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ALTERNATIVE MODELS FOR BUILDING ENERGY PERFORMANCE ASSESSMENT

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*La perseveranza è,
rispetto al coraggio,
ciò che è la ruota rispetto alla leva;
il perpetuo rinnovarsi del punto di appoggio*

Victor Hugo

*Perseverance is,
with respect to courage,
what is the wheel with respect to lever;
the perpetual renewal of the support point*

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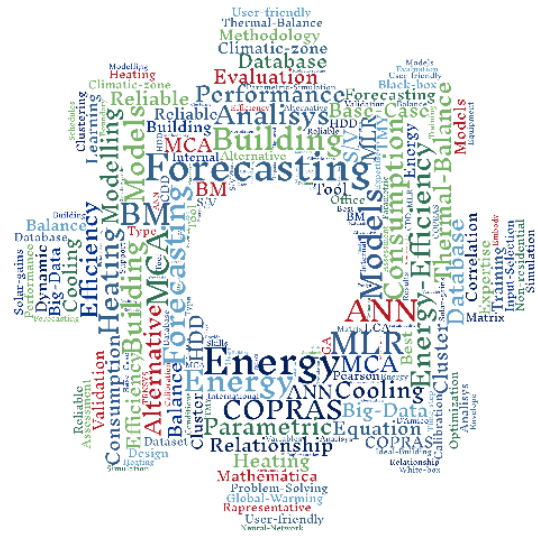
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RESEARCH INTRODUCTION & METHODOLOGY

RESEARCH INTRODUCTION

The research activity carried out during the three years of the PhD course attended, at the Engineering Department of the University of Palermo, was aimed at the identification of an alternative predictive model able to solve the traditional building thermal balance in a simple but reliable way, speeding up any first phase of energy planning. Nowadays, worldwide directives aimed at reducing energy consumptions and environmental impacts have focused the attention of the scientific community on improving energy efficiency in the building sector. The reduction of energy consumption and CO₂ emissions for heating and cooling needs of buildings is an important challenge for the European Union, because the buildings sector contributes up to 36% of the global CO₂ emissions [1] and up to 40% of total primary energy consumptions [2].

Despite the ambitious goals set by the Energy Performance of Buildings Directive (EPBD) at the European level [1], which states that, by 2020, all new buildings and existing buildings undergoing major refurbishments will have to be Nearly Zero Energy Buildings (NZEB) [3,4], the critical challenge remains the improvement of the efficiency when upgrading the existing building stock to standards of the NZEB level [5]. The improvement of the energy efficiency of buildings and their operational energy usage should be estimated early in the design phase to guarantee a reduction in energy consumption, so buildings can be as sustainable as possible [6]. While a newly constructed NZEB can employ the “state of the art” of available efficient technologies and design practices, the optimization of existing buildings requires better efforts [7]. One way or the other, the identification of the best energy retrofit actions or the choice of a better technological solution to plan a building is not so simple. It has become one of the main objectives of several research studies, which require deep knowledge in the field of the building energy balance.

The building thermal balance includes all sources and sinks of energy, as well as all energy that flows through its envelope. More in detail, the energy demand in buildings depends on the combination of several parameters, such as climate,

envelope features, occupant behaviour and intended use. Indeed, the assessment of building energy performance requires substantial input data describing structures, environmental conditions [8], thermo-physical properties of the envelope, geometry, control strategies, and several other parameters. From the first design phases designers and researchers, which are trying to respect the prescriptions of the EPBD directive and to simultaneously ensure the thermal comfort of the occupants, must optimize all possible aspects that represent the key points in the building energy balance.

As will be shown in **Chapter A**, the literature offers highly numerous complex and simplified resolution approaches [9]. Some are based on knowledge of the building thermal balance and on the resolution of physical equations; others are based on cumulated building data and on implementations of forecast models developed by machine-learning techniques [10].

Several numerical approaches are most widespread; these have undergone testing and implementing in specialised software tools such as DOE-2 [11], Energy Plus [12], TRNSYS [13] and ESP-r [14]. Such building modelling software can be employed in several ways on different scales; they can be simplified [15,16] or detailed comprehensively by different methods and numerical approaches [17]. Nevertheless, they are often characterised by a lack of a common language, which constitutes an obstacle for making a suitable choice. It is often more convenient to accelerate the building thermal needs evaluation and use the simplified methods and models. For example, a steady state approach for the evaluation of thermal loads is characterised by a good level of accuracy and low computational costs. However, its main limitation is that some phenomenon, such as the thermal inertia of the building envelope/structure, may be completely neglected.

On the other hand, the choice of a more complex solution, such as the dynamic approach, uses very elaborate physical functions to evaluate the energy consumption of buildings. Although these dynamic simulation tools are effective and accurate, they have some practical difficulties such as collecting detailed building data and/or evaluating the proper boundary conditions. The use of these tools normally requires an expert user and a careful calibration of the model and do

not provide a generalised response for a group of buildings with the same simulation, because they support a specific answer to a specific problem. Meanwhile the lack of precise input can lead to low-accuracy simulation. Anyway, in all cases it is necessary to be an expert user to implement, solve and evaluate the results, and these phases are not fast and not always immediately provide the correct evaluation, conducting the user to restart the entire procedure.

In the field of energy planning, in order to identify energy efficiency actions aimed at a particular context, could be more convenient to speed up the preliminary assessment phase resorting to a simplified model that allows the evaluation of thermal energy demand with a good level of accuracy and without excessive computational cost or user expertise.

The aim of this research, conducted during the three years of the PhD studies, is based on the idea of overcoming the limits previously indicated developing a reliable and a simple building energy tool or an evaluation model capable of helping an unskilled user at least in the first evaluation phase.

To achieve this purpose, the first part of the research was characterised of an in-depth study of the sector bibliography with the analysis of the most widespread and used methods aimed at solving the thermal balance of buildings. After a brief distinction of the analysed methods in White, Black and Grey Box category, it was possible to highlight the strengths and weaknesses of each one [9].

Based on the analysis of this study, some alternative methods have been investigated. In detail, the idea was to investigate several Black-Box approaches; mainly used to deduce prediction models from a relevant database. This category does not require any information about physical phenomena but are based on a function deduced only by means of sample data connected to each other and which describes the behaviour of a specific system. Therefore, it is fundamental the presence of a suitable and well-set database that characterise the problem, so that the output data are strongly related to one or more input data. The completely absence of this information and the great difficulty in finding data, has led to the creation of a basic energy database which, under certain hypotheses, is representative of a specific building stock.

For this reason, in the first step of this research was developed a generic building energy database that in a reliable way, and underlining the main features of the thermal balance, issues information about the energy performances.

In detail, two energy building databases representative of a non-residential building-stock located in the European and Italian territory have been created. Starting from a well-known and calibrated *Base-Case* dynamic model, which simulates the actual behaviour of a non-residential building located in Palermo, it was created an *Ideal Building* representative of a new non-residential building designed with high energy performances in accordance whit the highest standard requirements of the European Community. Taking into consideration the differences existing in the regulations and technical standards about the building energy performance of various European countries, several detailed dynamic simulation models were developed. Moreover, to consider different climatic characteristics, different locations were evaluated for each country or thermal zone which represent the hottest, the coolest and the mildest climate. The shape factor of buildings, which represents the ratio between the total of the loss surfaces to the gross heated volume of a building, was varied from 0.24 to 0.90.

To develop a representative database where the data that identify the building conditions are the inputs of the model linked to an output that describes the energy performances it was decided to develop a parametric simulation. In detail different transmittance values, boundary conditions, construction materials, and energy carriers were chosen and employed to model representative building stocks of European and Italian cities for different climatic zones, weather conditions, and shape factor; all details and the main features are described in **Chapter B**.

These two databases were used to investigate three alternative methods to solve the building thermal balance; these are:

- Multi Linear Regression (MLR): identification of some simple correlations that uses well known parameters in every energy diagnosis [18–20];
- Buckingham Method (BM): definition of dimensionless numbers that synthetically describe the relationships between the main characteristic parameters of the thermal balance [21]; and
- Artificial Neural Network (ANN): Application of a specific Artificial Intelligence (AI) to determine the thermal needs of a [22] building.

These methods, belonging to the Black-Box category, permit solving a complex problem easier with respect to the White-Box methods because they do not require any information about physical phenomena and expert user skills. Only a small amount of data on well-known parameters that represent the thermal balance of a building is required.

The first analysed alternative method was the MLR, described in **Chapter C**. This approach allowed to develop a simple model that guarantees a quick evaluation of building energy needs [19] and is often used as a predictive tool. It is reliable and, at the same time, easy to use even for a non-expert user since an in-depth knowledge in the use phase is not needed, and computational costs are low. Moreover, the presence of an accurate input analysis guarantees greater speed and simplicity in the data collection phase [23]. The basis for this model is the linear regression among the variables to forecast and two or more explanatory variables. The feasibility and reliability of MLR models is demonstrated by the publication of the main achieved results in international journals. At first, the MLR method was applied on a dataset that considered heating energy consumptions for three configurations of non-residential buildings located in seven European countries. In this way, it was developed a specific equation for each country and three equations that describe each climatic region identified by a cluster analysis; these results were published in [19]. In a second work [18], it was applied the same methodology to a set of data referring to buildings located in the Italian peninsula. In this case, three

building analysed configurations, in accordance to Italian legislative requirements regarding the construction of high energy performance buildings, have been employed. The achievement of the generalised results along with a high level of reliability it was achieved by diversifying each individual model according to its climate zone. It was provided an equation for each climate zone along with a unique equation applicable to the entire peninsula, obviously with different degrees of reliability. An improved version of the latest work concerning the Italian case study appeared in the paper published in [20]. The revised model provided an ability to predict the energy needs for both heating and cooling. Furthermore, to simplify the data retrieval phase that is required for the use of the developed MLR tool, an input selection analysis based on the Pearson coefficient has been performed. In this way the explanatory variables, needful for an optimal identification of thermal loads, have been identified. Finally, a comprehensive statistical analysis of errors ensured high reliability.

The second analysed alternative method represents an innovative approach in developing a flexible and efficient tool in the building energy forecast framework. This tool predicts the energy performance of a building based some dimensionless parameters implemented through the application of the Buckingham π theorem. A detailed description of the methodology and results is discussed in the **Chapter D** and is also published in [21]. The Buckingham theorem represents a key theorem of the dimensional analysis since it is able to define the dimensionless parameters representing the building balance [24]. These parameters define the relationships between the descriptive variables and the fundamental dimensions. Such a dimensional analysis guarantees that the relationship between physical quantities remains valid, even if there is a variation of the magnitudes of the base units of measurement [25]. The dimensional analysis represents a good model to simplify a problem by means of the dimensional homogeneity and, therefore, the consequent reduction in the number of variables. Therefore, this model works well with different applications such as forecasting, planning, control, diagnostics and monitoring in different sectors. The application of the BM for predicting the energy performance of buildings determined nine *ad hoc* dimensionless numbers. The

identification of a set of criteria and a critical analysis of the results allowed to immediately determine the dimensionless numbers and without using any software tool, the heating energy demand with a reliability of over 90%. Furthermore, the validation of the proposed methodology was carried out by comparing the heating energy demand that was calculated by a detailed and accurate dynamic simulation.

The last Black-Box examined model was the application of Artificial Neural Networks. The ANNs are the most widely used data mining models, characterised by one of the highest levels of accuracy with respect to other methods but generally have higher computational costs in the developing phase [26]. The design of a neural network, inspired by the behaviour of the human brain, involves the large number of suitably connected nodes (neurons) that, upon applications of simple mathematical operations, influence the learning ability of the network itself [27]. Also in this case, as described in **Chapter E**, this methodology was applied at the two different energy databases. In [22], the ANN was used to predict the demand for thermal energy linked to the winter climatization of non-residential buildings located in European context, while in another work under review, the ANN was used to determine the heating and cooling energy demand of a representative Italian building stock. The validation of the ANNs was carried out by using a set of data corresponding to 15% of the initial set which were not used to train the ANNs. The obtained good results (determination coefficient values higher than 0.95 and Mean Absolute Percentage Error lower than 10%) show the suitability of the calculation model based on the use of adaptive systems for the evaluation of energy performance of buildings.

Simultaneously, a deep analysis of the investigated problem, underlines how to determine the thermal behaviour of a building through Black-Box models, particular attention must be paid to the choice of an accurate climate database that along with thermophysical characteristics, strongly influence the thermal behaviour of a building [9].

In detail, to develop a predictive model of thermal needs, it is also necessary to pay close attention to the climate aspects. In the literature, many studies use the degree

day (*DD*) to predict building energy demand, but this assessment, through the use of a climatic index, is correct only if its determination is a function of the same weather data used for the model implementation. Otherwise, the predictive model is generally affected by a greater evaluation error; all these aspects are deeply discussed analysing a specific Italian case study in **Chapter F**, and the main results are published in [8].

The results achieved during the three years of PhD research, make it possible to affirm that each model can be used to solve thermal building balance by knowing merely a few parameters representative of the analysed problem. Nonetheless, some questions may be asked: Which of these models can be identified as the most efficient solution? Is it possible to compare the performances of these models? Is it possible to choose the most efficient model based on some specific phase in the evaluation?

To attempt to answer these questions, during the research period it was decided to compare the three selected alternative models by applying a Multi Criteria Analysis (MCA), that explicitly evaluates multiple criteria in decision-making. It is a useful decision support tool to apply to many complex decisions by choosing among several alternatives. The idea rising thanks to the scientific collaboration with the VGTU University of Vilnius, Lithuanian, in the person of Prof. A. Kaklauskas and Prof. L. Tupėnaitė, experts in the field of multi-criteria analysis. At the first time a multi-criteria procedure was applied to determine the most efficient alternative model among some resolution procedures of a building's energy balance. This application required extra effort in defining the criteria and identifying a team of experts. To apply the MCA, it was necessary to identify the salient phases of the evaluation procedure to explain the most sensitive criteria for acquiring conscious, truthful answers that only a pool of experts in the field can provide. Details of this work were carried out during the period of one-month research in Vilnius, from April to May 2019, where it was possible to improve the application of the Multiple Criteria Complex Proportional Evaluation (COPRAS) method for identifying the most efficient predictive tool to evaluate building thermal needs. These results are

collected in **Chapter G** and the main results are explained in a paper under review in the Journal “Energy” from September.

The identification of the most efficient alternative model to solve the building energy balance through the application of a specific MCA, allowed to deepen the identified methodology and improve research. In particular, the most efficient alternative resolution model was the subject of the research that took place during the research period at the RWTH in Aachen University, Germany with Prof. M. Traverso, Head of the INaB Department, from September 2018 to March 2019. The experience in the field of LCA and the possibility of identifying the environmental impacts linked to the building system, has led the research to investigate neural networks for a dual and simultaneous environmental-energy analysis. The results confirm that the application of ANNs is a good alternative model for solving the energy and environmental balance of a building and for ensuring the development of reliable decision support tools that can be used by non-expert users. ANNs can be improved by upgrading the training database and choosing the network structure and learning algorithm. The results of this research are collected in **Chapter H** and published in [28].

A more schematic and simple explanation of the entire work it is described in the **Methodology Section**.

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METHODOLOGY

For greater clarity and to guide the reader to a simpler and more schematic understanding of the investigated study, the following section illustrates the main line followed to achieve the research aim.

As displayed in the Fig.1, the entire research is described in 8 Chapters from A to H.

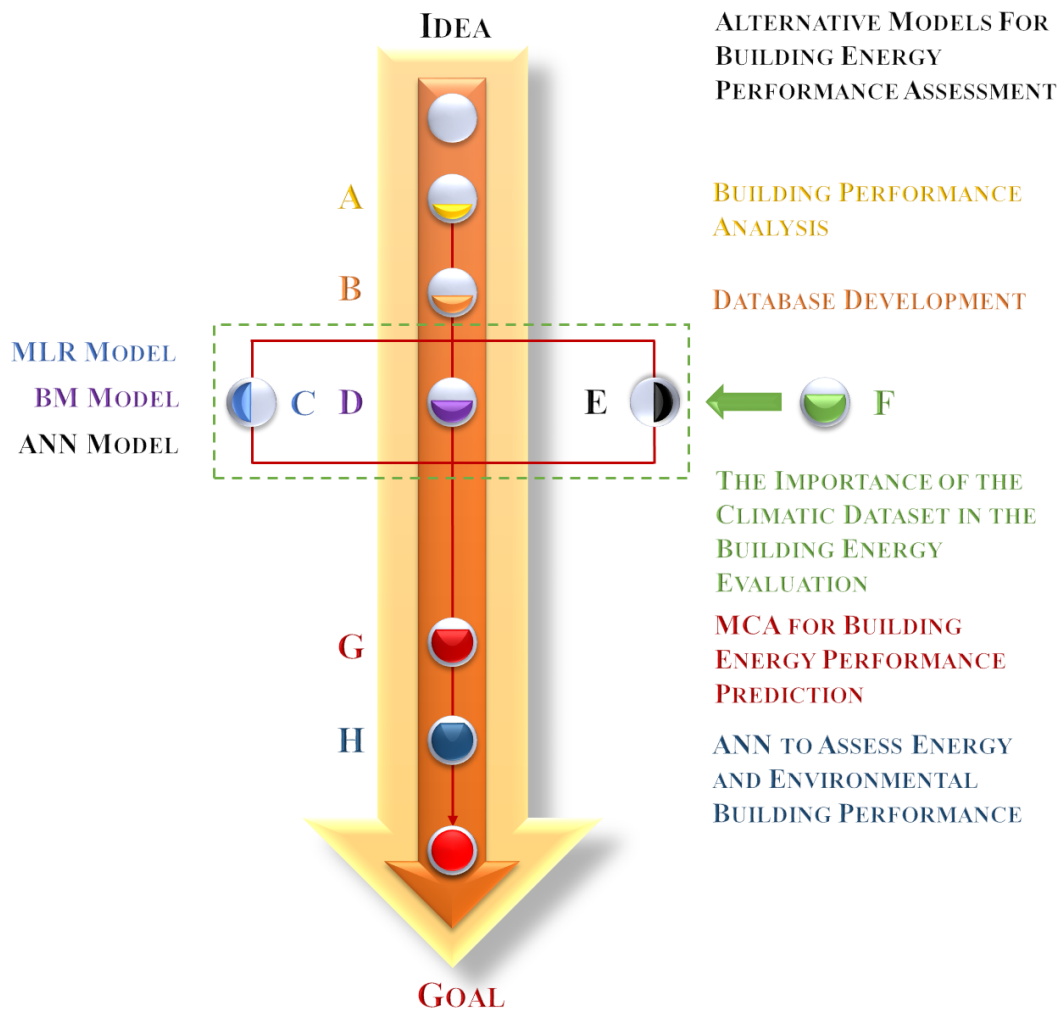


Fig. 1. Flow chart of the research work.

As briefly introduced in the **Research Introduction**, the research arises from the idea to provide a valid and simple to use alternative decision support tool for all those realities, such as administrations and institutions, which in the field of building energy planning do not always have always available to expert users and in which the evaluation times and computational costs effects can influence the success of a project.

As illustrated in **Chapter A**, after an introduction about the main features describing the building thermal balance, a brief discussion on the most used resolution methods and the identification of the main strengths and weaknesses of each of them, the research continues with the identification and development of some Black-Box models. To achieve the goal to solve the generic building thermal balance in any situation and for any boundary conditions, it is necessary to have a reliable and well-set database representative of the analysed problem. Owing to the difficulty in finding these data it was decided to create a specific database that could be used as a basis for the application and validation of alternative resolution models. **Chapter B** explains the procedure that was followed for the implementation of two building energy databases: a European and an Italian database.

From **Chapter C** to **Chapter E** are described the three Black-Box methods selected and investigated in this research. In particular, are described all details of each developed model and their application, underlining the results and the main steps followed. The three Chapters deal with:

- **Chapter C:** Identification of some simple correlations by MLR approach using certain parameters that are well known in every energy diagnosis [1–3];
- **Chapter D:** Definition of some dimensionless numbers that synthetically describe the relationships between the main characteristic parameters of thermal balance by applying the BM [4]; and
- **Chapter E:** Application of the ANN method [5–7] to determine the thermal needs of a building.

Details, hypothesis and boundary conditions are described in each chapter.

Furthermore, as pointed out in **Chapter B**, the thermal behaviour of a building is strongly influenced by climatic conditions and thermophysical characteristics. If from a thermophysical point of view, to ensure the design of high energy performance buildings, it is enough to follow the regulations in force in the field of energy efficiency, on the other hand, to develop a thermal model, it is also necessary to pay close attention to the climate aspects, to the choice of the climate database and to the calculation of the climatic indicators. In particular, in the literature, many studies use the degree day (*DD*) to predict building energy demand, but this assessment, through the use of a climatic index, is correct only if its determination is a function of the same weather data used for the model implementation. Otherwise, it is shown that the predictive model is affected by a greater evaluation error; these aspects are deeply discussed in **Chapter F** [8].

To identify the most efficient alternative model among some resolution procedures of a building's energy balance, it is necessary to compare, at the same level, the three selected Black-Box models.

For this reason, it was applied a comparison of the three alternative models by applying MCA, a sub-discipline of operations research that explicitly evaluates multiple criteria in decision-making. Thanks to the collaboration with the VG TU of the University of Vilnius, Lithuania, it was possible to apply the COPRAS method [9,10], a tested and reliable procedure developed and published by Prof. A. Kaklauskas, Head of the Department of Construction Management and Real Estate, and Prof. L. Tupénaitė; all details are explained in **Chapter G**.

The identification of the most efficient alternative model, allowed to deepen the identified methodology and improve the tool with the aim to make it more versatile. In particular, the most efficient alternative resolution model was the subject of the research that took place during the research period at the RWTH in Aachen University, Germany with the Prof. M. Traverso, Head of the INaB Department. As explained in **Chapter H**, the decision support tool used to evaluate the energy performance of a building has been integrated with an environmental analysis.

A brief description of the main contents of the thesis and a specific flow chart with the keywords of each chapter, are shown in the following Figs. 2 and 3.

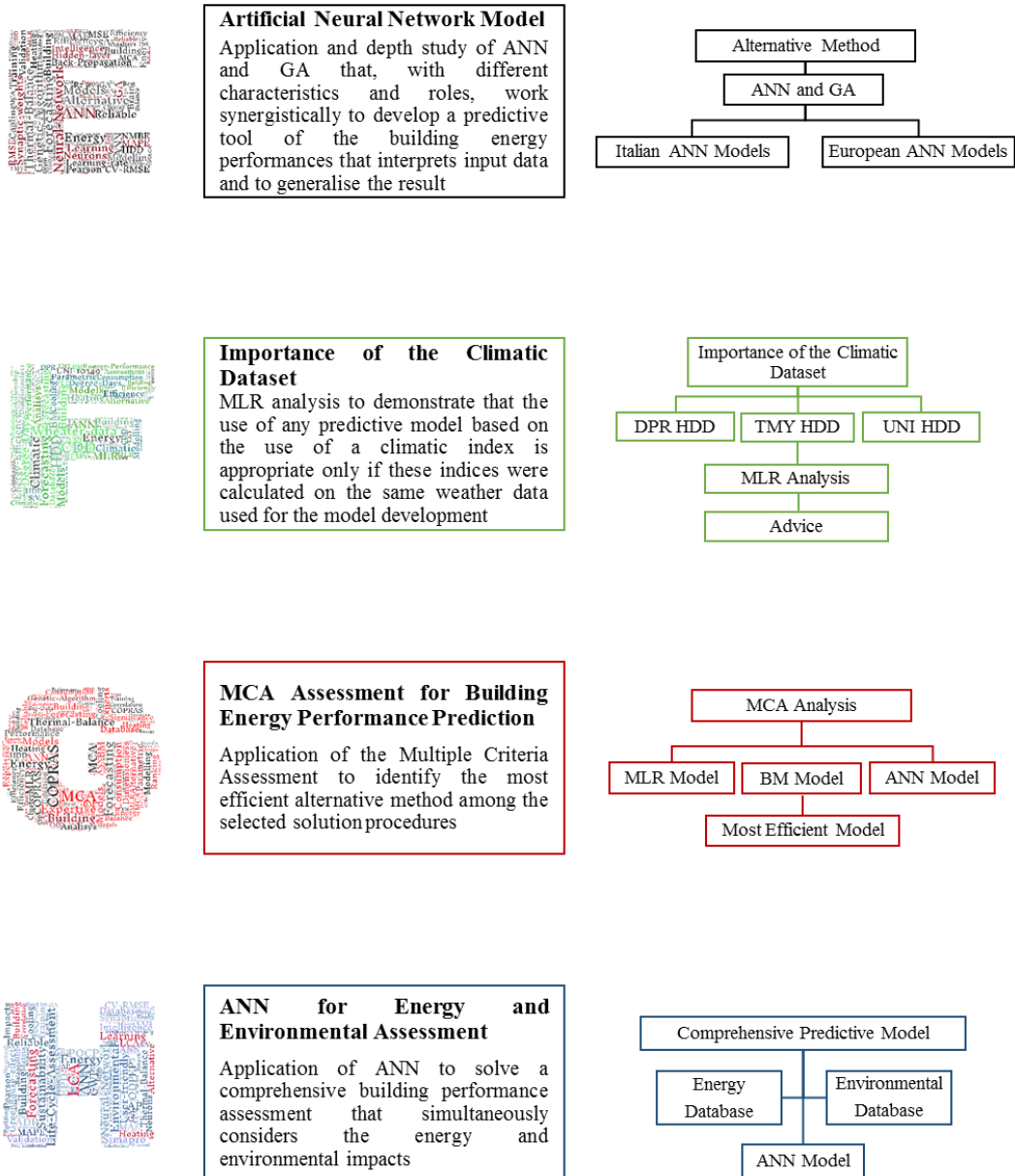


Fig. 3. Main description and keywords of Chapters E, F, G and H.

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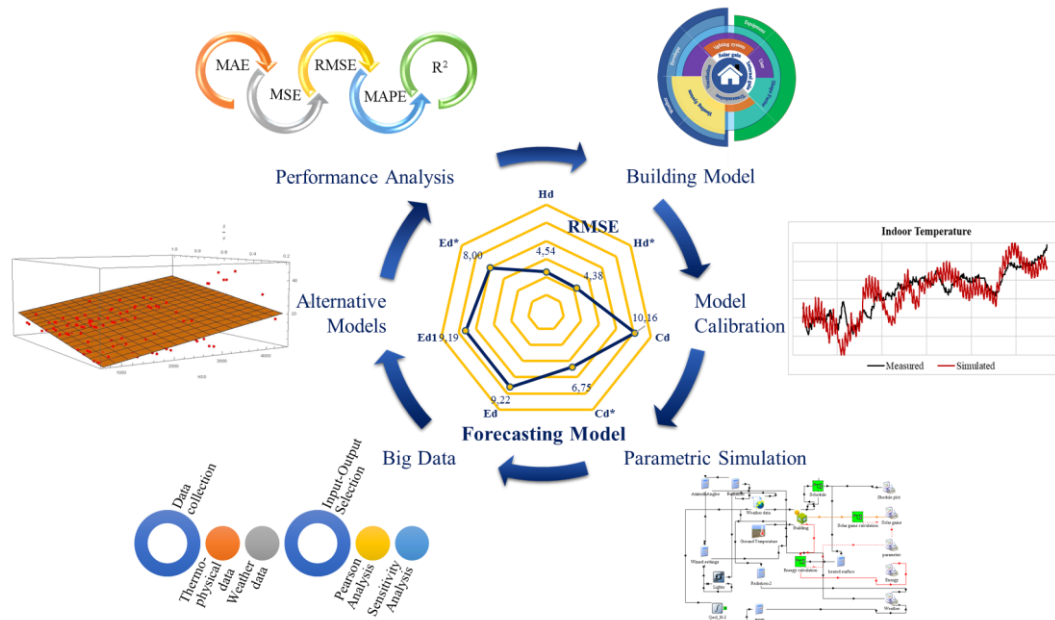
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CHAPTER A

BUILDING PERFORMANCE ANALYSIS

BUILDING PERFORMANCE ANALYSIS



ABSTRACT

The assessment of the building energy performance requires substantial input data describing constructions, environmental conditions, envelope thermo-physical properties, geometry, control strategies, intended use and several other parameters. This has been a very active area of research in recent years, and several numerical approaches for building simulation have been developed; furthermore, most of these approaches were tested and implemented in specialised software tools. In this first chapter, after a brief introduction to the building thermal balance, are described the main solution categories that can be found in the literature: Black, White and Grey-Box category. As in the following, the use of these tools poses many challenges in regards to the retrieval of reliable and detailed information, the knowledge of the physical phenomenon of the heat exchange, the expertise in the specific software use, the reduction computational costs and the increase of the reliability and generalization of the results, setting a steep learning curve for engineers and energy managers. The highlighting of the strengths and weaknesses of each method will be the starting point of the following research work that will try to propose an alternative solution that overcomes the limits listed above. Furthermore, as explained at the end of this chapter, to guarantees the reliability of the results it is highlighted that any evaluation tool chosen must in any case be subjected to a performance analysis and it is necessary to identify the parameters that can never be overlooked in a thermal balance of buildings.

NOMENCLATURE

Acronyms

ANN	Artificial Neural Network
CFD	Computational Fluid Dynamics
DH	District Heating
EPBD	Energy Performance of Buildings Directive
GA	Genetic Algorithm
HVAC	Heating, Ventilation, Air Conditioning
MLR	Multiple Linear Regression
ML	Machine Learning
SVM	Support Vector Machine

Building Thermal Balance parameters

A	Surface area [m^2]
E_d	Energy demand [kWh]
CDD	Cooling Degree days [K day]
DD	Degree days [K day]
HDD	Heating Degree days [K day]
n	Number of air changes per hour/3600 [s^{-1}]
\dot{Q}_{nd}	Power supplied by the conditioning system [W]
\dot{Q}_{sol}	Heat power supplied by solar radiation [W]
\dot{Q}_{tr}	Heat power exchanged for transmission between indoor and external environment [W]
\dot{Q}_{ve}	Heat power exchanged with the air ventilation [W]
$Q_{H,nd}$	Building's thermal energy requirement for space heating [MJ]
$Q_{C,nd}$	Building's thermal energy requirement for space cooling [MJ]
Q_c	Heat gain to the air [W]
$Q_{H,ht}$	Heat exchange flows in heating mode [MJ]
$Q_{C,ht}$	Heat exchange flows in cooling mode [MJ]
$Q_{H,gn}$	Overall thermal inputs in heating mode [MJ]
$Q_{C,gn}$	Overall thermal inputs in cooling mode [MJ]
Q_{tr}	Transmission heat exchange [MJ]
Q_{ve}	Ventilation heat exchange [MJ]
Q_{int}	Overall indoor thermal inputs over a given period [MJ]
Q_{sol}	Overall solar gains over a given period [MJ]
s	Volumetric specific heat of air [$J/(m^3K)$]
S/V	Shape factor [m^{-1}]
T_{sp}	Indoor set point temperature [$^{\circ}C$]
T_0	Outdoor temperature [$^{\circ}C$]
U	Thermal transmittance [$W/(m^2K)$]
V	Ventilation loss term [W/K]
v	Volume flow into the building [m^3/s]
$V_{building}$	Building volume [m^3]
$\eta_{H,gn}$	Dimensionless factors of use of thermal contributions
$\eta_{C,ls}$	Dimensionless factors of use of the thermal dispersions

Performance parameters

MAE	Mean Absolute Error
MSE	Mean Square Error
RMSE	Root Mean Square Error
MAPE	Mean Absolute Percentage Error
R^2	Determination coefficient

A.1 INTRODUCTION

Buildings' energy consumption has become a relevant international issue and various policy measures for energy saving are under discussion in many countries [1]. In Europe, the building sector is considered to be the largest energy consumer being responsible for up to 40% of total energy use and 36% of total CO₂ emissions [2]; more specifically, the non-residential sector represents about 40% of total energy consumption in the building sector [3,4]. Energy is consumed for different purposes, but the dominant energy end-use (responsible for around 70% of total consumption in households) is represented by thermal needs [5]. Moreover, this trend in energy demand assumes a place as a relevant issue in the development of energy systems and energy policies. In order to achieve appropriate saving of primary energy, several potential mitigation measures can be implemented involving the building envelope, internal condition, heating/cooling systems, etc., as reported in Wan et al. [6].

In this context, the 91/2002 "Energy Performance of Buildings Directive" (EPBD) [7] to introduce several requirements for new and existing buildings within the European Union (EU) has been developed. Accordingly, designers and researchers must optimize all possible involved aspects (building envelope, shadowing, heating and cooling system components, regulation criteria, etc.), starting from the earliest design phase, in order to respect the prescriptions of the current directive and, at the same time, ensure the thermal comfort of the occupants [8,9]. The knowledge of the energy performance of existing building stocks and the prediction of the energy behaviour of newly designed buildings is fundamental to achieving the targets of the EPDB [2]. It is well-known that building energy assessment is quite complex owing to the influence of many factors, such as weather conditions, the building construction and its shape, the thermophysical properties of the materials used, the intended use, the occupancy and behaviour of the users, the lighting, the ventilation, and the heating/cooling systems along with their performance and operating schedules [10].

In general, the evaluation of the energy performance of an existing building and the design of new buildings integrating several energy-efficiency measures are made via software programs with the aim to identify the improvements that could be made. Based on these observations, for careful energy planning, new methods have to be explored in order to support engineers and architects in their efforts to improve design, reduce computational time and increase energy performance. Owing to the complexity of the problem, the prediction of the building energy consumptions is quite difficult and has become one of the main objectives of several research studies. In recent years, a large number of both elaborate and simplified predictive approaches have been proposed. Several of these cases are available, some based on knowledge of the building thermal balance and on the resolution of physical equations, and others on building data collection and on the implementation of predictive models developed for example by means of machine-learning techniques [11]. In the literature, it is possible to distinguish three main methods: White-Box or physical techniques, Black-Box or statistical and/or learning approaches and Grey-Box or hybrid approaches. As explained in the following, to solve the building thermal balance it is possible to choose, based on the problem investigated, the amount of data, the degree of detail and the user expertise, one or another method. In this chapter, after a brief introduction about the building thermal balance and the identification of the main involved parameters, a description of the most diffuse resolution methods is carried out.

A.2 BUILDING THERMAL BALANCE

The building system can be considered an open thermodynamic system which works, with due simplifications, in average stationary regime and it is influenced by the boundary conditions and its intended use. In fact, the building thermal energy demand is estimated by means the application of a thermal balance on the indoor building delimited by the surface envelope, which is subject to different thermal flows.

Thanks to the first law of thermodynamic, it is possible to write this energy balance as (Eq. (1)):

$$\dot{Q}_{nd} = f(\dot{Q}_{sol} + \dot{Q}_{int} + \dot{Q}_{tr} + \dot{Q}_{ve}) \quad (1)$$

where:

\dot{Q}_{nd} is the power supplied by the conditioning system [W];

\dot{Q}_{sol} is the heat power supplied by solar radiation, which can be directed (through windows), or indirect (absorption in opaque envelope) [W];

\dot{Q}_{int} is the heat power supplied by internal heat sources (people, lighting system, equipment and heating, cooling, domestic hot water and ventilation plants) [W];

\dot{Q}_{tr} is the heat power exchanged for transmission between the indoor and the external environment [W]; and

\dot{Q}_{ve} is the heat power exchanged with the air ventilation (air infiltration, natural and/or mechanical ventilation) [W].

To an immediate view, Fig. 1A displays the main energy flows involved in a building thermal balance.

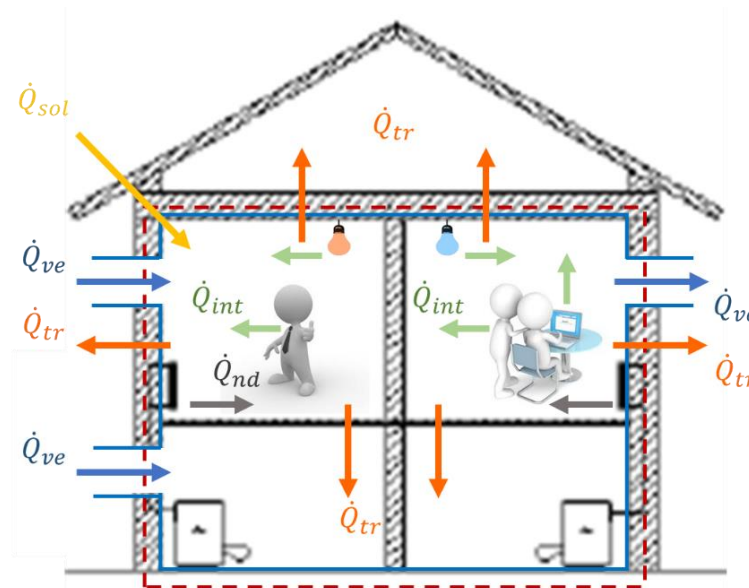


Fig. 1A. Building thermal balance.

The red dashed lines and the blue continuous lines, represent the boundaries of the open thermodynamic system to which the building is associated. In detail, the red line is the boundary for the thermal flows exchanged by transmission and for solar gains, the blue line for thermal exchanges involved with ventilation.

Obviously, higher is the need to have an energy balance that reproduces the real heat exchange dynamics, greater is the required detail degree. A deep analysis requires the definition of sufficiently small-time intervals (schedules or sub-schedules) and the decomposition of the building into homogeneous parts for thermophysical properties and boundary conditions. Fine temporal and geometric subdivisions (mesh) correspond to greater computational complexity but to a more accurate balance.

To solve the thermal balance, for each element is applied its own balance equation. The descriptive equations constitute a system, whose solution provides the temperatures values and unknown thermal flows. Among the unknown flows is included \dot{Q}_{nd} , which maintains the desired internal temperature. Based on the considered time-step (daily, monthly, seasonally, and yearly), the calculation must be repeated. This balance can essentially be solved followed three different calculation procedures: dynamic, semi-stationary and simplified approaches with decreasing order of precision and computational costs.

The dynamic calculation method foresees, as previously described, an application of the detailed thermal balance, with small time steps (generally hourly) and the subdivision of the entire building into several elements, in order to take into account, the thermal inertia, the accumulation and heat release from the mass. The methods used for the practical resolution of the thermal balance in dynamic regime are different; for example, the current international standard EN ISO 13790: 2008 [12] proposes two dynamic resolution methods: simplified and detailed timetable; in another way it is also possible to solve the balance through specific simulation software.

In fact, several simulation tools to evaluate building performance [13] based on different approaches have been developed, but often with a lack of common language to describe the thermal balance, representing an obstacle in choosing the

most suitable tool [14]. Moreover, Petersen and Svendsen in [15] underlined as many available tools are developed by researchers but for research purposes, making it difficult for building designers to use them. Design teams do not generally recognise these simulation tools as design support tools to the same extent as design tools, likely because of the required knowledge for using simulation tools, as well as the cost and time of simulations [16]. Indeed, depending on the objective, more than one kind of software could be required to carry out the simulation task [17]. In the last few years, several numerical approaches have been developed and tested [18], and most of them in software dedicated to building simulations have been implemented.

Another approach is the semi-stationary resolution method; this is a simplified approach compared to the previous one, based on sufficiently long calculation times (typically on a monthly or seasonal), but sufficiently detailed to be able to still take into consideration the dynamic effects through a factor of utilization of the inputs and/or losses determined empirically.

In detail, as reported in the standard, for each thermal zone of the building and each time-step (monthly or seasonally), the building's thermal energy requirement for space heating ($Q_{H,nd}$), and for space cooling ($Q_{C,nd}$), in continuous conditions, are obtained by means the application of the following equations:

$$Q_{H,nd} = Q_{H,ht} - \eta_{H,gn} \cdot Q_{H,gn} \quad (2)$$

$$Q_{C,nd} = Q_{C,gn} - \eta_{C,ls} \cdot Q_{H,ht} \quad (3)$$

where

$Q_{H,nd}$ and $Q_{C,nd}$ are the building's thermal energy requirements for heating and cooling seasons [MJ];

$Q_{H,ht}$ and $Q_{C,ht}$ represent total heat exchange flows in heating and cooling mode respectively [MJ];

$Q_{H,gn}$ and $Q_{C,gn}$ indicate the overall thermal inputs in heating and cooling mode respectively [MJ]; and

$\eta_{H,gn}$ and $\eta_{C,ls}$ represent the dimensionless factors of use of the contributions and of the thermal dispersions respectively.

Both in heating and cooling conditions the total heat exchange flows $Q_{H,ht}$ and $Q_{C,ht}$ are calculated following the Eq. (4).

$$Q_{ht} = Q_{tr} + Q_{ve} \quad (4)$$

where

Q_{tr} is the transmission heat exchange [MJ]; and

Q_{ve} is the ventilation heat exchange [MJ].

In the same way, the overall thermal inputs, both in heating and cooling mode, are expressed following the Eq. (5).

$$Q_{gn} = Q_{int} + Q_{sol} \quad (5)$$

Where

Q_{int} are the overall indoor thermal inputs over a given period [MJ]; and

Q_{sol} are the overall solar gains over a given period [MJ].

The detailed calculation of the individual thermal flow terms is stated in [12].

Ultimately, following the simplified calculation semi-stationary regime method, proposed by the aforementioned standard, the building energy heating and cooling requirements from the resolution of the heat balance, can be expressed by the following equations:

$$Q_{H,nd} = (Q_{H,tr} + Q_{H,ve}) - \eta_{H,gn} \cdot (Q_{int} + Q_{sol}) \quad (6)$$

$$Q_{C,nd} = (Q_{int} + Q_{sol}) - \eta_{C,ls} \cdot (Q_{C,tr} + Q_{C,ve}) \quad (7)$$

where

$Q_{H,tr}$ and $Q_{C,tr}$ are the transmission heat exchange for heating and cooling respectively [MJ]; and

$Q_{H,ve}$ and $Q_{C,ve}$ are the ventilation heat exchange for heating and cooling respectively [MJ].

The Fig. 2A shows the two balances represented by the previous equations for the heating and cooling regime.

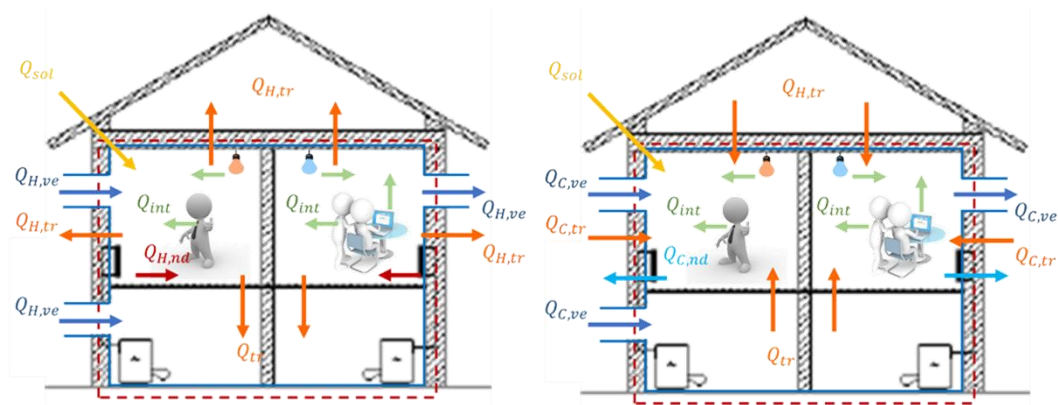


Fig. 2A. Heating and Cooling thermal balance of a building.

These simplified but reliable procedures permit the evaluation of heating/cooling loads with a good level of accuracy and without excessive computational costs [1]. Even steady state models a common standard for determining the energy performance of a building [12,19]. Thanks to fast calculations, this approach permits the energy performance assessment and long-term analysis of several energy efficiency measures [20,21]. The main limitation is that the thermal inertia of building envelope/structure is completely neglected; in particular conditions, this restriction severely limits the use of this approach, for example when the building is characterised by a massive envelope or integrates new technologies like free cooling [22–25] and phase change materials [26–28]. These simplified models are commonly used for preliminary building design and scenario analysis.

A.3 RESOLUTION METHODS

As explained in *Section A.1*, several approaches are available and, in the context of review articles on methods for buildings energy demand estimation, the study reported in [29] is one of the most exhaustive. They made a first broad distinction between:

- Top-down methods, whose outputs data are estimated based on aggregated input data through econometric or technological correlations; and
- Bottom-up methods, based on use of subordinated input data and highly detailed and reliable calculations. Bottom-up methods were in turn divided into:
 - Engineering methods, explicitly evaluate the energy consumption of end-uses, based on equipment power ratings and heat transfer laws and can be fully controlled across all calculation steps. They foresee the adoption of three alternative techniques:
 - Archetypes, energy modelling of a given building stock bases on its clustering through representative fictive buildings, leading to a computational time saving [30];
 - Samples, similar to the archetypes but with real selected buildings; and
 - Distributions, usually based on statistical information of the different appliances and related usage to calculate the energy consumption of each end-use. Even if they are closed to statistical methods.
 - Statistical methods, whose outcomes come from identified statistical correlations among considered variables (e.g. energy use, weather data, occupancy behaviour, buildings' features, etc). Since they are able to deal with uncertain and random data, their use sharply grown up in last decades. They were divided in:

- Regression, determining the coefficient of the model corresponding to the input parameters which are considered as affecting energy demand;
- Conditional demand analysis, regressing energy demand onto the list of appliances indicated with binary or count variable; and
- Neural networks, similar to regression and inspired to the biological neural networks.

Furthermore, in the literature, it is also possible to distinguish the Engineering and Statistical methods in White-Box and the Black-Box approach respectively. A solution that considers an intermediate approach is instead of Grey-Box. An example of this classification is displayed in the following flow-chart (Fig. 3A) reported by M. Bourdeau et. al. in [31].

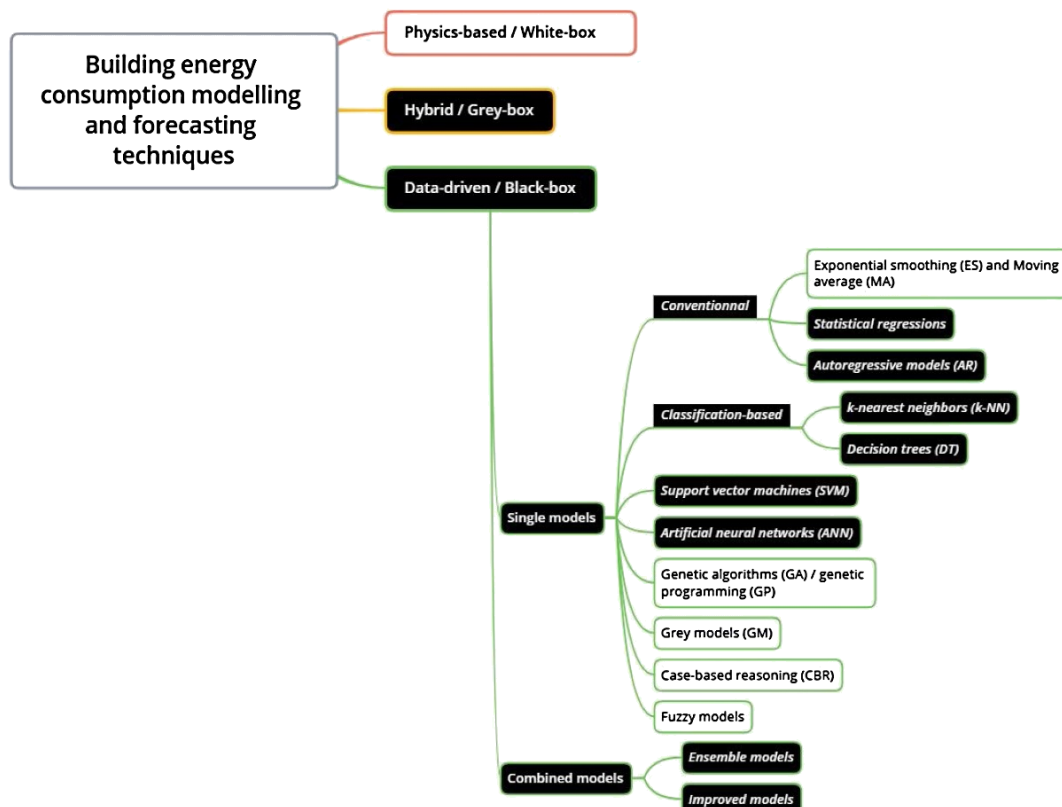


Fig. 3A. Classification of building energy consumption modeling and methods (Elsevier Licence Number: 4704240706214).

In the following a description of each category is explained, underling the main features, strengths and weaknesses and how the choice of one of this is function of several initial information that influence the quality of the response. The need to overcome the limits that the choice of one of these resolutions presents, has led the following research to investigate alternative, but at the same time reliable, methods for the resolution of a traditional problem such as the thermal balance of a building.

A.3.1 White-Box Methods

The White-Box approaches are used to model building thermal behaviour for several applications on different scales. These techniques, known also as engineering methods, are based on the use of physical principles to solve the equations describing the physical behaviour of heat transfer.

The adoption of engineering methods to assess the energy demand of buildings enables to have very accurate estimations, when based on dynamic energy simulation. Despite this, detailed building energy simulations could not be always time sustainable due to the required level of detail and quantity of information, therefore simplifications in the calculation methods or in the number and complexity of the modelled buildings are often adopted. In this category, it is possible to distinguish between simplified and detailed comprehensive methods.

In general, for deriving buildings thermal energy profiles, simplified calculation procedures were used. In [32] with reference to Beijing, a simplified method was developed for the prediction of buildings hourly cooling loads, to be applied on large-scale urban planning, which bases on linear correlation between cooling load components of the thermal balance and environmental parameters such as temperature and enthalpy differences. In [33] a simplified method was developed for heating, ventilation, air conditioning (HVAC) load estimation, assuming only one thermal zone building, neglecting internal gains and considering average solar radiation among exposures; the application of the method to a group of ten archetype buildings was reported. The EN ISO 13790 simplified hourly method [12] was adopted in [34–37]. In particular, in [34,35] a hybrid procedure was

defined, made of space heating/cooling profiles calculation for building archetypes defined for the Swiss context and their calibration with statistical data; in [36] buildings archetypes were defined with reference to a district in Manhattan and based on the DOE Commercial Prototype Buildings dataset [38] and the calculation method was corrected for considering buildings shadowing, urban heat island effects and occupancy.

Among the simplified methods, the degree day method is one of the most used; several research studies affirm that meteorological data provide an effective tool for determining the energy demand and for calculating heating or cooling building requirements [39–41]. Another simplified method is based on the temperature frequency, which can be used to model large buildings where internal gains dominate [42]. For example, White et al. [43] attempted to use average monthly temperatures to predict monthly building energy consumption and Westphal et al. [44] forecasted the annual heating and cooling loads of non-residential buildings based on certain weather variables. On the other hand, the detailed comprehensive methods use very elaborate physical functions to evaluate, step-by-step, the energy consumption of a building linked to its construction mode, operation of the plants, utility rate schedule of the equipment, external climate conditions and solar irradiance.

To solve such physical problems, a large number of numerical software programs are available and these have been compared [13,45]. Users can choose to select the mechanisms and the associated equations representing the system, but sometimes many software tools are badly adapted to taking into account moisture influences, and generally the effects of latent heat are neglected [45,46]. In the literature, three main thermal building methods can currently be found: Computational Fluid Dynamics (CFD), zonal methods and the multi-zone technique. CFD is a branch of fluid mechanics that is based on numerical analysis to analyse and solve problems that involve flows. Nowadays, a huge number of CFD software programs are available, such as FLUENT [47], COMSOL Multiphysics [48], MIT-CFD, PHOENICS-CFD [49], and so on.

The zonal method is the first degree of simplification of the CFD technique; it involves dividing each building zone into several cells detailing the indoor environment and estimating a thermal comfort zone [50,51]. Specifically, this technique presents its efficacy in the description of the flow profiles within the building. The multi-zone technique, or nodal method, is based on the assumption that each building zone is a homogeneous volume characterised by uniform state variables. The solution is based on the application of two main methods: transfer functions or the finite difference method. In the field of energy efficiency and sustainability in buildings, and based on this last technique, several software tools have been developed, such as, Energy Plus [52], ESP-r [53], TRNSYS, IDA-ICE [54], Clim2000 [55,56], BSim [57,58] and BUILDOPT-VIE [59].

In this case, within accurate studies, some of them were aimed at determining profiles for representative buildings. In particular, in [60] profiles of space heating and cooling for a parameterised office building representative of the UK building stock; in [61,62] of space heating for multi-thermal zones residential/office archetypes (defined based on different building sizes, envelopes, occupancy patterns and HVAC technologies) for the Austrian context; in [63] of space heating and cooling for multithermal zones residential/office archetypes (defined based on different geometry and envelope solutions) for several locations in Italy and in [64] of space heating and cooling for residential/office archetypes.

Although these simulation tools are effective and accurate, there are some practical difficulties in implementing a reliable model. Indeed, these tools require details of the building and environmental parameters which are not always simple to find and collect, and the lack of precise input can lead to a low-accuracy simulation; furthermore, to use these tools normally, an expert user is required, as is a careful calibration of the model.

A.3.2 Black-Box Methods

Statistical methods are also named data-driven or black-box methods, since the correlation among inputs and outputs is not always straightforward and is derived by assuming weights and bias. Despite a lower detail for the single data than in the engineering methods is required, their use allows to cope with data uncertainty, randomness and lack, therefore their application is suitable for prediction of stochastic phenomena, like consumers behaviour.

The Black-Box approaches are mainly used to deduce a prediction model from a relevant database (for example, to assess energy consumption or heating/cooling load in a given building). These models do not require any information about physical phenomena but they are based on a function deduced only by means of sample data connected to each other and which describe the behaviour of a specific system. The Black-Box methods mainly employed in the field of building energy prediction are: statistical regression model or Multiple Linear Regression (MLR) and Machine Learning (ML) method or rather Genetic Algorithm (GA), Artificial Neural Network (ANN) the Support Vector Machine (SVM) [10,11]; an overview of these method is described in Li et al. [65].

MLR methods correlate the building energy consumption or energy indices with the influencing variables in a simple way. These empirical models are developed based on energy performance data collected previously.

Typical examples of Statistical correlations are reported in [66–71]. In detail, space heating and cooling, Domestic Hot Water (DHW) and electricity consumption profiles were determined based on statistical analysis on data from direct survey and measurements overall Korea for department stores in [66], hotels, hospitals and office buildings in [67]; space heating profiles average per season were determined in [68] for residential, tertiary and industrial buildings based on measured District Heating (DH) consumptions in Sweden; in [69], for the six single-family houses case study, adopted electricity hourly load profiles were based on the ADRES-CONCEPT Austrian database [72], whose profiles have been determined for a set of building typologies and day-types since direct surveys and measurements; in

[70], hourly profiles of electricity, through probability distribution function, based on measured data in Trondheim (Norway), were determined for several building typologies, differing by use category (residential, office, educational, hospital, hotel, sports, retail), age and size; in [71], electricity profiles for the Sao Paulo end-use sectors were determined by means of probability distribution. With regard to the study [66], the overall electricity consumptions have been correlated with weather data in order to disaggregate the share due to appliances and artificial lighting from the one due to HVAC systems.

Studies explicitly referred to regression analysis are reported in [70,73,74]. In particular, hourly profiles of space heating, through regression analyses of measured energy consumptions and outdoor temperatures, were determined for different building archetypes, defined in terms of period of construction and use category in [70]. In [73], based on historical data of DH consumption and weather data for the Swedish town of Eskilstuna, computed regression coefficients were applied to a Test Reference Year (TRY) climatic data file in order to define a normalised heat load profile; then, heat demand profiles were dynamically simulated, and the daily difference was computed.

In certain simplified models, linear regression is used to correlate the energy consumption with climatic variables [75–77]; for example, Ansari et al. [78] calculated the total cooling load by adding up the cooling load of each building envelope component, while Dhar et al. [79,80] modelled heating and cooling loads using the outdoor dry bulb temperature as the only weather variable. In [74] a piecewise linear function between consumptions and outdoor temperatures plus a component dependant on consumers behaviour was defined and applied to predict the hourly heat load for two Domestic House networks in Stockholm. Parti et al. [81] were the first to propose a new method using linear regression for the prediction of building energy consumption. Instead, Kialashaki et al. [82] applied the regression and ANN models to evaluate the energy requirements of the residential sector.

The main advantage of this method is its ease of use; indeed, no specific expertise is required. As indicated in Aydinalp-Koksal et al. [83], regression models are

easier to use, against the engineering methods. However, the MLR presents a major limitation in that it is unable to treat non-linear problems. On the other hand, this method is increasingly adopted for predicting energy loads due to the ability of learning from past behaviour so returning in most robust outcomes. Various models, [84–88] to determine the building energy consumption have been developed. Existing research has mainly taken a trial-and-error approach by developing multiple models and identifying the best performer for a specific building [89].

Among these, GA is a stochastic optimisation technique based on Darwin's theory of evolution. In building simulation, GA is used to find a prediction model deducing a simple equation which can fit the problem. An important advantage of GA is the fact that it deals with a powerful optimisation method which is able to solve every problem and give several final solutions to a complex problem [11].

The ANNs are one of the most commonly adopted [90–92] and the most widely used in the prediction of building energy demand; they are capable of solving both non-linear and complex problems [93,94]. In [90] the authors presented a method for forecasting district heating and cooling loads, with the aim of improving previous tested ANN-based method predictions in periods affected by high fluctuations; past heat loads, as well as the day-type, the highest and lowest air temperatures of the predicted day were used as input data. In [91] after a comparison of some linear and nonlinear models, using past recorded weather data, occupancy data and hourly average measured energy consumptions as inputs, a method for estimation of day-ahead space heating, space cooling and electricity loads for a University campus in Austin (Texas) has been proposed. In [92] an unsupervised and supervised ANN based method was presented for the electric energy demand forecasting with a prediction time of one day. Input data were dry bulb temperature, relative humidity, global solar radiation, recorded electricity consumptions in a district of Palermo (Italy). The main advantage of ANN is its ability to determine non-linear relationships among different variables without any assumptions or any postulate of a model overcoming the discretisation problem. However, ANNs need to have a relevant database in order to obtain reliable solutions. In fact, it is really important to train an ANN with an exhaustive learning database with representative

and complete samples [10]. Among artificial intelligence techniques, SVM, introduced by Vapnik et al. [95], is usually used to solve classification and regression problems. These are highly effective models even with small quantities of training data. Many studies [96,97] of these models were conducted on building energy analysis and demonstrate that SVMs can perform well in predicting hourly and monthly building energy consumption. For example, in [98] a SVM was developed for short-term predicting the heat loads of domestic hot water connected consumers based on collecting the real data from a heating substation in the Serbian city of Novi Sad; in [99] an adaptive neuro-fuzzy inferences system model to forecast DH single consumers, based on real consumptions from a Serbian DH station is illustrated; while in [100] a Case Based Reasoning method for short-term predicting the electricity hourly energy demand of tertiary buildings, based on real and simulated data of an office building, on outdoor air temperature and relative humidity in the Canadian city of Varennes is described.

A.3.3 Grey-Box Methods

When a problem cannot be completely solved by applying one of the methods previously described, it is possible to use a Grey-Box method. These methods [101–104] are typically comprised of a hybrid structure and include advantages and disadvantage of the Black and White-Box methods, to try to overcome the limitations of each individual technique by coupling them so that the advantages of one method counteract the drawbacks of the other [11].

In the greater of big or large scale techniques, the residential building property is summarised according to an analogy of an energy path capable to establish and specify the power performance of the building sector [105]. Indeed, for well-defined systems and to estimate thermal characteristics of the building components, the Grey-Box method in building modelling has been used. For example, Madsen and Holst [106] and Madsen and Melgaard [107] model a test building using stochastic differential equations for the indoor air temperatures and the heat accumulating, while Norlén [108] estimates the thermal resistance and capacitance.

On the other hand, to obtain reliable estimates of thermal capacities and resistances, Hammarsten [109] uses the partial differential equations through lumped parameter models. Jonsson et al. [110] use ARX-models to estimate the hot tap water consumption. The convenience represented by the use of this technique as it exploits the advantages of the other two methods provides in any case a thorough knowledge not only of the problem but also of the various resolution techniques, so as to be able to select the right and most convenient calculation solution. Obviously, the main disadvantage is related to the need to be a highly expert user not only in the field of the thermal balance of the buildings but of several and different numerical resolution methods.

A.3.4 Comments

The detailed analysis of the characteristics of these methodologies has highlighted the favour points and not in each category. In the field of building energy planning, to answer at the necessity to have a reliable building energy evaluation in a not too long time, it would be convenient to identify a generic decision support tool, and therefore a resolute methodology, characterised by low calculation time, a non-complex data collection phase, high reliability and a simple calculation language that can be used even by a non-expert user.

The use of a White-Box method to solve the energy balance is a good solution but can be considered reliable only if the dynamic model is calibrated. As explained previously, the identification of the best software tool is not always simple and an expert user of the investigated problem and of the software language is necessary. Any simulation needs the collection of a multitude of parameters, which are not always easy to select or to implement. For careful building energy analysis, a preliminary collection and investigation phase are necessary. After calibrating the model and implementing other reliable scenarios with a parametric simulation, in order to extrapolate a generic relation that permits the identification of the energy demand of a generic building, all results must be analysed and elaborated because each single simulation is the answer to a specific condition.

Indeed, although the application of comprehensive methods by means of a dynamic simulation software tool represents the optimal solution for evaluating building energy performance, the high number of difficulties encountered in the implementation of the model has led many researchers to investigate other solutions. On the other hand, the use of a Grey-Box method requires a highly specialized user, not always easily available for an Administration or Institution. For this reason, it was decided to explore an alternative method belonging to the Black-Box category. Based on these considerations, this PhD thesis tries to investigate some Black-Box methods to solve the building thermal balance. As previously indicated, because the building thermal balance is a complex problem that considers several parameters, fluxes and dynamics, before of the selection and investigations of some alternative solutions, it was necessary a preliminary study about the main features that influence the building balance. In this way, it is possible to identify which of all the parameters that come into play are essential and which are the least, so as not to complicate the resolution for the user and at the same time not to lose important information.

A.4 PERFORMANCE ANALYSIS

To provide some information on the reliability of one model over another, it is necessary to carry out an analysis on the distribution of the residuals that highlights the differences between the expected and predicted values of the models, also through the representation in dispersion charts. Despite being a simplistic analysis, this type of control provides the first feedback on the goodness of fit of the model; a distribution of residues around zero is indicative of model accuracy in building energy needs.

In detail, a depth statistical analysis on the errors of a model should satisfy five evaluation criteria:

1. measurement validity;
2. reliability;
3. ease of interpretation;
4. clarity of presentation; and
5. support of statistical evaluation.

Hence, it necessary to evaluate the following statistical errors [111]:

- the Mean Absolute Error (MAE) represents the direct deviation between expected and predicted output values (Eq. (8)) [112]:

$$MAE = \frac{1}{N} \sum_{i=1}^N |x_i - y_i| \quad (8)$$

- the Mean Square Error (MSE) calculates the variance between the target of a model and what is going to be predicted (Eq. (9)) [113]:

$$MSE = \frac{1}{N} \sum_{i=1}^N (x_i - y_i)^2 \quad (9)$$

- the Root Mean Square Error (RMSE) represents the square root of the quadratic mean of the differences between predicted and expected values (Eq. (10)).

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (x_i - y_i)^2} \quad (10)$$

- the Mean Absolute Percentage Error (MAPE) evaluates the absolute percentage deviation between the predicted and expected values. It indicates the percentage error size that could be used as a measure of the quality of a model's output (Eq. (11)) [114]:

$$MAPE = 100 \cdot \frac{1}{N} \sum_{i=1}^N \frac{|x_i - y_i|}{x_i} \quad (11)$$

- the determination coefficient (R^2) evaluates the manner in which a model approximates the real data points, which is a measure of the predictability degree of the model [115]; the higher R^2 , the more efficient the developed model (Eq. (12)) [116]:

$$R^2 = 1 - \frac{\sum_{i=1}^N (x_i - y_i)^2}{\sum_{i=1}^N (x_i - \bar{x})^2} \quad (12)$$

where

x_i is the i^{th} expected output;

y_i is the i^{th} predicted output;

\bar{x} is the average of the whole desired output; and

N is the number of the identification set samples.

The MAE, MSE, RMSE and MAPE allow a comparison of the deviation between the predicted and expected values of the building energy demand [115,117]. However, because the first three are based on absolute errors, it is not possible to identify a specific criterion to find an optimal value for each of them, but smaller values correspond to more precise models. Instead, the MAPE, being independent of the scale, is more significant [117]. In this work, to guarantee the reliability of the results, every selected model to solve the investigated problem was subjected to a performance analysis.

A.5 MAIN PARAMETERS IN A BUILDING THERMAL BALANCE

As explained above, the heat balance of a building system is complex and characterized by the knowledge of many descriptive parameters of thermal exchanges. Of all the parameters that come into play, some are essential, that is, they cannot be neglected in any condition, while others under particular hypotheses and conditions, can be considered secondary and therefore neglected.

The analysis of the thermal balance of buildings in a simplified way has made it possible to identify the main parameters that can never be overlooked in a thermal balance of buildings. Obviously, as we will see later on, this first analysis is only a first step that has pushed the research to deepen and extend the search for essential parameters, while trying not to complicate the calculation procedure. As previously indicated, regarding the heating energy demand of a building is known that it is influenced by the transmission losses through the envelope (walls, window, roof, and floor), heat losses due to the ventilation and infiltration, and energy gains due to solar radiation, the presence of people, and heat from electrical appliances. For example, one of the simplified approaches implies the calculation of the instantaneous load on the heating system as [118]:

$$Q = (T_{sp} - T_0) \cdot (V + \sum A \cdot U) \quad (13)$$

where:

T_{sp} is the indoor set point temperature [$^{\circ}\text{C}$];

T_0 is the outdoor temperature [$^{\circ}\text{C}$];

V is the ventilation loss term [W/K];

A is the surface area [m^2]; and

U is the thermal transmittance [$\text{W}/(\text{m}^2 \text{K})$].

The ventilation loss conductance V is given as:

$$V = \frac{Q_c}{T_{sp} - T_0} = v \cdot s \quad (14)$$

where

Q_c is heat gain to the air [W];

v is the volume flow into the building [m^3/s]; and

s is the volumetric specific heat of air [$\text{J}/(\text{m}^3 \text{K})$].

Generally, it is common to express a required ventilation rate in terms of air changes per hour:

$$V = \frac{1}{3} \cdot n \cdot V_{building} \quad (15)$$

where

n is the number of air changes per hour/3600 [s^{-1}]; and

$V_{building}$ is the building volume [m^3].

The coefficient (1/3) comes from the ratio of volumetric specific heat of air (1200 $\text{J}/(\text{m}^3 \text{K})$ and 3600 s). The energy demand on the heating system, E_d , is the integral of instantaneous loads over time:

$$E_d \int Q dt = DD \cdot 86400 \cdot (V + \sum A \cdot U) \quad (16)$$

where DD is the degree day for the location, 86400 is the number of seconds in a day, and the temperature integral is the degree-day total:

$$DD = \int (T_{sp} - T_0) dt \quad (17)$$

The simplification of the temperature integral in the last equation is due to the reasonable assumption that heating systems do not operate on days where the average outdoor temperature exceeds the base temperature [119,120]. This makes the definition and calculation of DD simpler; it forms the standard definition defined by ASHRAE [121].

In this way, the heating energy demand in kWh can be estimated by:

$$E_d = \frac{86400}{3.6 \cdot 10^6} \cdot DD \cdot (V + \sum A \cdot U) = 0.024 \cdot DD \cdot U' \quad (18)$$

where

$$U' = V + \sum A \cdot U .$$

Eq. (18) shows that the energy demand is strongly correlated to the climate context (DD) and the thermo-physic parameter (U'). This last parameter represents the mean quality of the building envelope, but does not consider the geometry or orientation of the building, neglecting important parameters that influence the energy balance (e.g. does not evaluate the loss surface area to heated/cooled volume, shape). Indeed, to evaluate the heating or cooling energy demand, it is necessary to consider the Heating Degree Days (HDD) or Cooling Degree Days (CDD) and simultaneously the shape factor (S/V), an important factor that strongly influences heat loss and gain. Generally, greater the surface area, more heat will be gained or lost through the surface. A small S/V ratio implies minimum heat gain and minimum heat loss, and to minimize the losses and gains through the envelope of a building, a compact shape is desirable (the most compact shape is a cube). In this way, a more extensive calculation of the heating H_d or cooling C_d energy demand should be functions of:

$$H_d = f\left(HDD, \frac{S}{V}\right) \quad (19)$$

$$C_d = f\left(CDD, \frac{S}{V}\right) \quad (20)$$

Taking into account this observation, all methods, investigated in the following, consider always the effects of the shape factor on the thermal demand of buildings located in different climate contexts.

A.6 DISCUSSION

A detailed assessment of building energy performance requires a large amount of input data concerning building typology, environmental conditions, envelope thermophysical properties, geometry, control strategies, and several other parameters. Different numerical approaches for building simulations have been developed, and most of these approaches in specialised software tools have been tested and implemented. Notwithstanding, the use of these tools poses many challenges in regards to the retrieval of reliable and detailed information, setting a steep learning curve for engineers and energy managers. In this chapter after a brief description of the main characteristics of building thermal balance, a detailed review of the most useful and widespread numerical solutions developed in the literature is reported. As highlighted in several scientific studies, the determination of the building energy performance is a very active area of research; more in detail, it is possible to distinguish the Black-Box, the White-Box and the Grey-Box category.

For each category vantage and disadvantages of each method are described, and it was underlined how the use of these specific tools poses many challenges. Indeed, on the one hand the White-Box methods require the knowledge of the physical phenomenon, an expert user and long computational time in the use phase; on the other hand the Black-Box methods need the collection of detailed information and long computational time in the development phase; about the use of Grey-Box category their application it is complicated by the lack of uniform language among the different approaches, that complicates the resolution and it is necessary a highly

specialized user. Furthermore, to guarantee the reliability of the results obtained by any method, it is necessary a performance analysis and to identify the main parameters that can never be overlooked in a thermal balance of buildings.

Finally, the highlighting of the strengths and weaknesses of each method is the starting point of the following research that tries to propose an alternative model for the building thermal performance, overcoming the limits indicated above in order to provide a simple and reliable decision support tool able to help and to guide public bodies, administrations, institutions, engineers and technical staff in any first designer phase.

MY RELATED PUBLICATIONS

Part of the research covered in **Chapter A** were published in the following international Journals:

1. Ciulla, G., Brano, V. L., & **D'Amico, A.** (2016). Modelling relationship among energy demand, climate and office building features: A cluster analysis at European level. *Applied energy*, 183, 1021-1034.
2. Ciulla, G., & **D'Amico, A.** (2019). Building energy performance forecasting: A multiple linear regression approach. *Applied Energy*, 253, 113500.
3. Ferrari, S., Zagarella, F., Caputo, P., **D'Amico, A.** (2019). Results of a literature review on methods for estimating buildings energy demand at district level. *Energy*, 175, 1130-1137.

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CHAPTER B

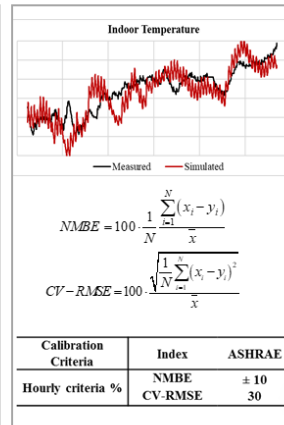
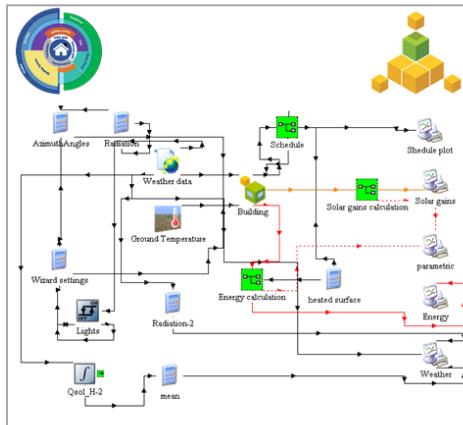
DATABASE DEVELOPMENT

DATABASE DEVELOPMENT

TRNSYS Building Model

Calibration

Simulation



Buildings Thermal Balance

ASHRAE
Guideline

Energy Database

ABSTRACT

The search of a solution for complex problems through the use of tools, capable of interpreting a generic case study, requires the presence of a reliable and well-set database. To achieve the goal of the research it was necessary to create an ad hoc energy database that is representative, allowing to interpret the actual behaviour of a generic building in any context and boundary conditions. The complexity and the enormous number of factors that influence the thermal behaviour of a building, has imposed the necessity to make some hypotheses that allow to identify a representative group of real buildings. In detail, it was developed an energy database of non-residential buildings, designed with high energy performance according to actual standard on energy consumption and located in several locations characterised by different weather conditions typical of the European and Italian climate. As described in the following, the building energy database was created thanks to a parametric simulation of an *Ideal Building* created from a detailed and calibrated *Base-Case* model.

NOMENCLATURE

<u>Acronyms</u>	
BPS	Building Performance Simulation
DH	District Heating
DHW	District Heating Water
TRY	Test Reference Year
<u>Building Thermal Balance parameters</u>	
C_d	Cooling energy demand [kWh/(m ² year)]
CDD	Cooling Degree Days [K day]
C_T	Normalised Thermal capacity [kJ/(m ³ K)]
DD	Degree Days [K day]
h	Heating operating hours [h]
HDD	Heating Degree Days [K day]
H_d	Heating energy demand [kWh/(m ² year)]
Q_g	Internal gains [kWh/(m ² year)]
Q_s	Solar gains [kWh/(m ² year)]
R_{w-op}	Glazed-opaque surface ratio
S/V	Shape factor [m ⁻¹]
S_w	Window surface [m ²]
S_{op}	Opaque Surface [m ²]
U	Thermal transmittance [W/(m ² K)]
U_{floor}	Floor thermal transmittance [W/(m ² K)]
U_{roof}	Roof thermal transmittance [W/(m ² K)]
U_o	Overall thermal transmittance [W/(m ² K)]
U_{wall}	Wall thermal transmittance [W/(m ² K)]
U_{window}	Window thermal transmittance [W/(m ² K)]
v	Wind speed
<u>Calibration Parameters</u>	
NMBE	Normalized Mean Bias Error
CV-RMSE	Coefficient of Variation of the Root Mean Square Error

B.1 INTRODUCTION

Energy saving is a high priority in developed countries, and buildings account for a substantial portion of the energy consumption in the world [1]. In recent years, significant efforts to improve the energy efficiency of buildings and to reduce energy consumption have been made. For these reasons, the topic of the building energy consumption has become a relevant international issue, and various policy measures for energy saving are under discussion in many countries [2,3]. The concept of energy efficiency in buildings is related to the energy supply needed to achieve the desirable indoor conditions that minimize energy consumption [4]. A careful heating and cooling design is one of the best methods to reduce energy costs in buildings [5]; to design energy-efficient buildings, the variables and construction parameters must be optimised [6] and, consequently, it is necessary to identify the variables that are directly related to the heat transfer process [7]. The preliminary design phase of a building is the best time to integrate suitable strategies aimed at reducing costs and accelerating the correct design for a high-performance building. As explained in **Chapter A**, to solve the building energy balance, several numerical approaches have been developed, and most of them were tested and implemented using specialised software tools for Building Performance Simulation (BPS). Nevertheless, these tools are often characterised by different numerical languages to solve the thermal balance, making more difficult to choose the most suitable tool [8,9]. Furthermore, the use of these tools poses many challenges regarding the recovery of reliable and detailed information and the creation of truthful models complicating the design phase. As previously described, to accelerate the preliminary assessment, it is more convenient to analyse simplified methods and models, e.g. those characterised by a steady state approach [2]. However, certain phenomena are completely neglected by those software [10], creating limitations and making them unsuitable. In contrast, the use of BPS tools or complete procedures [11,12] are characterised by excessive computational costs and high complexity. The results are reliable if the model is correctly calibrated and the data inserted in the model are obtained from a long and careful data collection phase. In

all cases, it is necessary to be an expert user to implement, solve evaluate the results, and to correct any possible mistakes.

Based on the idea to overcome these limits and to develop a reliable and simpler building evaluation tool, capable of helping an unskilled user at least in the first evaluation phase, during the PhD course were investigated some alternative methods to solve the traditional building energy balance. In detail, the idea was to investigate several Black-Box approaches that are mainly used to deduce a prediction model from a relevant database and that do not require any information about physical phenomena but are based on a function deduced only by means of sample data connected to each other and which describe the behaviour of a specific system. To try to investigate a predictive method, it is fundamental the presence of a suitable and well-set database that characterised the problem, so that the output data strongly relate to one or more input data. For this reason and based on the great difficulty in finding data in the first step of this research was developed a building energy database that under specific hypotheses, in a reliable way, underling the main features of a building energy balance, issued detailed information about the energy performance.

This chapter illustrates the main steps followed to create the building energy database; starting from a well-known and calibrated *Base-Case* dynamic model, which simulate the actual behaviour of an real non-residential building, it was created an *Ideal Building* representative of a non-residential building designed with high energy performance according to the minimum standard requirements of the European Community [11]. The creation of a generic database is ensured by a parametric analysis in which certain data, identifier of the building thermal balance and boundary conditions, have been varied. In this way, was obtained the building thermal behaviour of different scenarios, combining different shape, thermophysical features and weather conditions [13]. In the following, details and a careful description are illustrated.

B.2 METHODOLOGY

The current chapter describes the main steps followed to create an ad hoc building energy database. Indeed, to guarantee the reliability of the research results, it was necessary to use a big database based on well-known information: geometrical features, weather conditions, and typology of materials and components, including their thermophysical profiles. In the building sector, the energy demand regularity of non-residential buildings makes the energy assessment predictable. The reduction of random variables in fact make simpler to develop a building energy database of non-residential building stock than a residential. Furthermore, studying the factors affecting the energy performance of non-residential buildings and the energy characteristics of specific building constructions, is essential for an improved understanding of energy policies, and design principles, and operational strategies [14].

Focusing on current laws and standards on energy efficiency in buildings, a representative database of non-residential buildings designed with high energy performance and representative of the European and Italian context have been implemented. At first it was developed a detailed *Base-Case* model in TRNSYS environment [15], simulating the thermal behaviour of a well-known office building: the Building 9 of the University of Palermo, located in the city of Palermo, South of Italy. As explained in *Section B.3* specific information regarding the following items were collected and implemented in the model:

- geometric characteristics of the building: width, depth, height, heated volume, and loss surfaces;
- thermo-physical characteristics: transmittance and thermal capacity of opaque and glazed surfaces;
- boundary conditions of the building envelope: weather conditions, climatic indexes, solar radiations, latitude, altitude, wind speed, and relative humidity;
- heating periods and operating hours; lighting system; and

- intended use: employment rate, air infiltration, air change, and internal gains.

The validity of the dynamic model was guaranteed by a careful calibration on actual monitored internal temperatures as indicated in *Section B.6*. Starting from the Base-Case model, it was developed an Ideal Building model, demonstrative of a typical non-residential building designed following the limits law values of thermophysical features representative of a specific climatic context. Thanks to the parametric simulation (*Section B.7.1*), the *Ideal Building* was varied with different shape factors, heated volumes, and building construction types to represent Italian building stocks. To ensure the generality of the results, a deep examination of the Italian and European laws on construction and building energy efficiency [11,16] and a careful analysis of the climatic context were performed. Climatic indices such as the *HDD* were used to classify each country into harsh, mild, or warm climate, and to select several cities that represent the entire climate conditions; furthermore, the legal energy requirements of member states based on the standard for energy consumption of buildings were considered [11].

All possible combinations of thermophysical features, geometrical characteristics and climatic conditions were simulated, and the results were analysed and collected in a specific database. In detail, it is possible to identify the energy requirements of each building configuration: two different building energy databases were developed: a European (*Annexes 1 and 2*) and an Italian (*Annex 3*).

For the first energy database (*Section B.7.2*) the *Ideal Building* model was simulated in seven European countries: Belgium, Germany, Spain, France, Sweden, UK and Italy. For each country, three cities to take into account the maximum, minimum, and mean national *HDD* values have been chosen, and to generalise the results, the *Ideal Building* was varied, at first with three shape factors (*Annex 1*) and then, to generalize the results, with thirteen shape factors (*Annex 2*).

Similarly, based on the Italian national guidelines for building energy certification [17], the peninsula is characterised by 6 climatic zones that theoretically have the same climate, and for the new building imposes transmittance limit values. A total of 13 building models were simulated in five different climatic zones and for eight

orientations. To represent the entire climate condition accurately, three cities from each climatic zone were considered, representing harsh, mild, and warm climates, respectively, for a total of 1560 simulations reported in *Annex 3 (Section B.7.3)*. In the following, all details and a deep description of the procedure are described.

B.3 TRANSYS MODEL

In order to build a detailed database, required to achieve the research work purpose, it was necessary to implement, calibrate and simulate the energy behaviour of a real building, varying the boundary conditions and its constructive characteristics. The development of dynamic simulation models and the energy analyses were performed using TRNSYS 17 software [15], through which annual simulations on an hourly basis have been performed.

TRNSYS, available since 1975, is a complete and flexible computing environment designed for detailed analysis of the transient performance of any type of thermal energy system whose behaviour varies over time; including multi-zone buildings and building-plant systems. The software is widely used for the validation of new systems in the energy sector, ranging from the simple system for the DHW production for individual users, to the dynamic simulation of a complex building-plant system, including the regulation strategies of each component and the thermo-hygrometric well-being of the occupants and their habits. The strength of this software lies on its modular structure and programming code accessible to the user, who can modify the existing models, adapting them to his own design needs, or creates new ones, through FORTRAN and other various programming languages (C, C++, etc.). Furthermore, another aspect not to be underestimated is the possibility to connect the software with data pre- or post-processing tools (for example Microsoft Excel, Matlab, Wolfram Mathematica, etc.).

Key step for the realization of this research work was the preliminary modelling of an actual and well-known non-residential building located in Palermo, south of Italy, in the following indicate as *Base-Case*. The analysis of the thermal performance of the building, in free-floating conditions, and a calibration through

actual, monitored data, guaranteed the model reliability and the use of it to develop alternative and different scenarios. The variation of the building shape, boundary conditions and thermophysical characteristics, imposed by the law regulations, has allowed the creation of a buildings energy database able to identify a constructive panorama exhaustive for features and climatic conditions; “*conditio sine qua non*” is not possible to develop Black-Box models.

B.4 DESCRIPTION OF THE CASE STUDY

As previously indicated, the choice of the following building was based on the possibility of having precise information about the geometric and thermophysical characteristics, the intended use and energy consumption thanks to a census of these data in the field. The *Base-Case* reproduces the thermophysical behaviour of the Building 9 of the Engineering Department of the University of Palermo. The building was constructed between 1962 and 1965 and is characterised by five elevations: the mezzanine floor and the third floor are intended for laboratory use, the first and second floors are mainly used as offices, and the basement floor is the location of the technical room. Fig. 1B displays a rendering of the building.



Fig. 1B. Building 9 of the Engineering Department of the University of Palermo.

B.4.1 Thermophysical and Geometrical Features

From a structural point of view, the building has a load-bearing system framed with pillars and beams in reinforced concrete with foundations made of reinforced concrete plinths connected with beams. Each floor is characterised by a surface of about 1130 m² with thickness for the inter-floor slabs and for the roof slab of about 0.35-0.36 m and a height of 4.5 m. Fig. 2B represents a map of the standard floor of the Building 9.

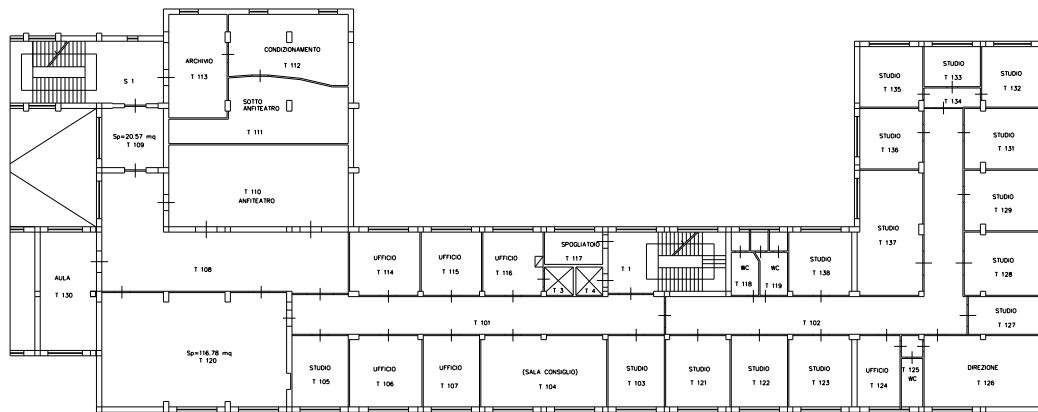
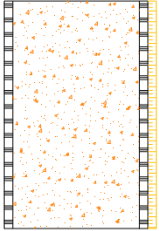


Fig. 2B. Planimetry of a standard floor of Building 9.

In the first and second floor of the building, the external walls are in limestone (tuff), a typical Sicilian material that possesses discrete characteristics of thermal and acoustic insulation, breathability and heat storage (Table 1B). Externally it is present the “Li Vigni” external plaster, a uniform medium-grained coating based on lime, cement and sands. Internally the walls are plastered and painted with water-based paint.

Table 1B

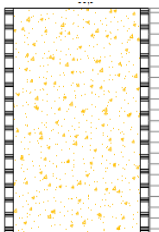
External wall stratigraphy of 1st and 2nd floor of *Base-Case* building.

1 st External Wall	Layer	Material	Conductivity	Density	Capacity	Thickness
			[W/(mK)]	[kg/m ³]	[kJ/(kgK)]	[m]
	1	Li Vigni	1.00	1800	0.84	0.02
	2	Lime cement plaster	0.90	1800	0.96	0.015
	3	Tuff block	0.63	1500	0.70	0.30
	4	Internal plaster	0.70	850	0.96	0.02
			U	W/(m²K)	1.412	

As shown in the Table 2B, a brick coating is found only for the external raised floor.

Table 2B

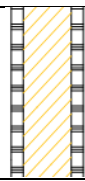
External wall stratigraphy of raised floor of *Base-Case* building.

2 nd External Wall	Layer	Material	Conductivity	Density	Capacity	Thickness
			[W/(mK)]	[kg/m ³]	[kJ/(kgK)]	[m]
	1	Brick	1.10	1900	0.82	0.03
	2	Lime cement plaster	0.90	1800	0.96	0.015
	3	Tuff block	0.63	1500	0.70	0.30
	4	Internal plaster	0.70	850	0.96	0.02
			U	W/(m²K)	1.391	

The interior walls are partitions with perforated bricks and cement mortar covered with plaster; the composition is described in Table 3B:

Table 3B

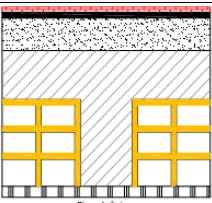
Internal wall stratigraphy of *Base-Case* building.

Internal Wall	Layer	Material	Conductivity	Density	Capacity	Thickness
			[W/(mK)]	[kg/m ³]	[kJ/(kgK)]	[m]
	1	Internal plaster	0.70	850	0.837	0.02
	2	Brick wall	0.28	800	1.00	0.08
	3	Internal plaster	0.70	850	0.837	0.02
			U	W/(m²K)	1.189	

The roof is horizontal with practicable terrace; it is made in brick-cement with 0.02 m waterproofing with floor in “Campigiana” (Table 4B).

Table 4B

Roof stratigraphy of *Base-Case* building.

Roof	Layer	Material	Conductivity	Density	Capacity	Thickness
			[W/(mK)]	[kg/m ³]	[kJ/(kgK)]	[m]
	1	Floor tiles	1.10	2100	0.84	0.02
	2	Bitumen	0.17	1200	1.4	0.02
	3	Lime cement	1.40	2000	1.2	0.06
	4	Concrete slab	1.91	1400	1.00	0.25
	5	Internal plaster	0.70	800	0.837	0.02
			U	W/(m²K)	2.085	

Almost all rooms are paved with pressed cement bricks with marble flakes, while the toilets have ceramic floors and coated walls, up to 1.6 m from the floor, with ceramic tiles; the typical stratigraphy is collected in Table 5B.

Table 5B

Floor stratigraphy of *Base-Case* building.

Floor	Layer	Material	Conductivity	Density	Capacity	Thickness
			[W/(mK)]	[kg/m ³]	[kJ/(kgK)]	[m]
	1	Marble brick	1.00	1120	0.84	0.02
	2	Cement screed	1.40	2000	1.20	0.06
	3	Concrete slab	1.91	1400	1.00	0.25
	4	Internal plaster	0.70	800	0.837	0.02
			U	W/(m²K)	2.549	

In general, the windows are made of aluminium and equipped with insulating thermoacoustic glass with plastic blinds. The windows on the mezzanine floor are located 2.5 m from the floor, and the large windows (one of the staircases and the other at the head of the corridors of the raised, 1st and 2nd floors), are made with aluminium window frames and external safety panels made of iron. In general, it is possible to find the window dimensions in Table 6B.

Table 6B

Windows typologies of *Base-Case* building.

Type	Width [m]	Height [m]
Window 1	1.6	1.2
Window 2	1.6	0.6
Window 3	2.85	1.3
Window 4	2.85	1.9
Window 5	2.85	2.9
Window 6	3.85	1.3
Window 7	1.4	1.9
Window 8	2.5	1.9

In the model, changing to the exposures, it was indicated the windows number and typology.

B.4.2 Indoor Lighting Features

The entire building is equipped with light fixtures consisting of ceiling lights equipped with fluorescent tubes of different sizes. The various models are:

- rectangular type with 1 neon light of 58 W;
- rectangular type with 2 neon light of 58 W;
- rectangular type with 2 neon light of 18 W;
- rectangular type with 3 neon light of 36W;
- squared type with 4 neon light of 18 W; and
- squared type with 4 neon lights of 36.

These specifications are summarised in Table 7B.

Table 7B

Indoor lights types of *Base-Case* building.

Model	Geometry	Number	Power [W]
1	Rectangular	1	58
2	Rectangular	2	58
3	Rectangular	2	18
4	Rectangular	3	36
5	Squared	4	18
6	Squared	4	36

B.4.3 Intended Use and State of Employment

The mainly intended use is for office activities, but because is characterised by the presence of classrooms and laboratories, the state of employment does not depend solely on the opening and closing time of the Department. For this reason, in the energy audit phase, the employment status was accurately recorded.

In general, all offices are occupied from Monday to Friday, from 8:30 AM to 6.00 PM, with a variable occupancy rate based on the size of the office. The classrooms and laboratories were considered occupied as indicated in the academic calendar.

For the entire building, the presence of the electrical equipment and the indoor lights has been surveyed. About electrical equipment it was supposed the presence of a complete work station for each office-person and the presence of several printers, rack, and other distributed along the various laboratories or computer rooms.

For each thermal load, based on the employment rate, distinguishing according to the users, a behavioural profile has been supposed; it allows to identify the switching on and off of the single equipment. In the following, are indicated detailed weekly and daily schedules regarding the utilisation of equipment, lighting systems, and presence of office users.

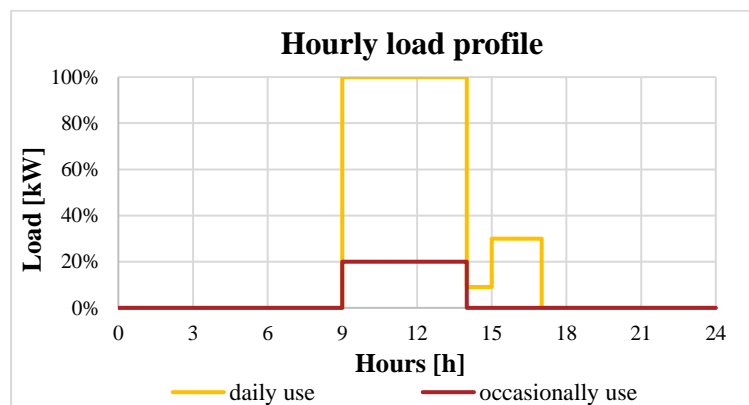


Fig. 3B. Hourly profile of equipment use.

For example, in Fig. 3B is represented the load hour profiles of the equipment during the working day, distinguishing the daily use respect the occasionally use. Furthermore, in the weekend it was hypothesised a residual consumption linked to the stand-by of the equipment. About the turn on of the lighting system it was hypothesised a daily use, during the working day, from 3:00 PM to 6:00 PM.

B.4.4 Weather Conditions

Based on the actual law, the city of Palermo belonged in B Climatic Zone. According to the actual law [16] and for office buildings, it is indicated the heating period from 1st December to 31st March, eliminating weekdays and holidays, for 8 hours per day based on the office occupancy rate. As is known, currently the Italian

legislation does not give any indication about the climatic zones for cooling, but it is indicated a generic cooling period from 1st June to 30th September. In detail, in the old Italian technical standards UNI 10349: 1994 [18] and DPR 412/93 [19] based on climatic data previous to 1994, the *CDD* values are absent. On the other hand, the new version of the standard, UNI 10349, published in 2016 [20], contains monthly average data calculated from TRY, developed by the Italian Thermo-Technical Committee for 110 Italian locations, and recalculates the *HDD* and *CDD* values without changing the previously stated heating and cooling periods for all Italian cities and without making any distinction between the climate zones. About the weather data, in the simulation model was implemented, for each location, the actual monitored data recorded from 2000 to 2009 (TMY2) elaborated by Meteonorm software [21].

B.5 THE *BASE-CASE* DYNAMIC MODEL

In this section is described the development of the *Base-Case* model. A system defined in TRNSYS is made up of a series of components, connected together in a suitable way in order to simulate the performance of the specified building-plant complex. As indicated in *Section B.3*, TRNSYS contains a series of subroutines written in FORTRAN language. Each subprogram contains a model of a system component marked by a number (Type); each Type has a specific function and can be configured specifying the parameters (time-independent values) and the input data (time-dependent values); the model can calculate the output time-functions. The outputs thus obtained can be used as inputs for other components (Types) which contain a different mathematical model. The modular technique minimizes the complexity of system simulation, since it reduces a big problem in a number of small problems, each of which can be solved independently and easily. To put together the overall system, or to assemble the types used in the specific project, the user generates an input file (*.dck) that guides TRNSYS in connecting the various subroutines.

Based on the input file, TRNSYS calls the components and iterates at each time step (sampling time set a priori by the user, with an extension between seconds and days depending on the duration of the expected transients for the studied process and on the level of desired approximation), up to solve the global system of equations. The user can easily and independently generate a component of TRNSYS to model any new technological component, even innovative. Fig. 4B displays the TRNSYS model with the connection scheme of the different types that make up the model.

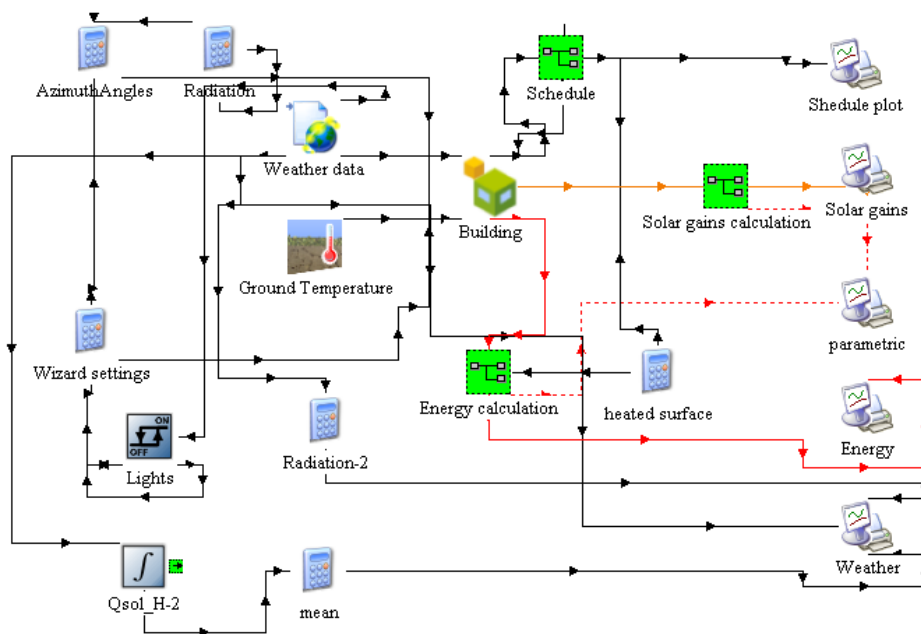


Fig. 4B. TRNSYS schema [22].

The main component of the developed model is represented by Type 56 called “Building” in Fig. 4B; this component allows to implement any kind of multi-zone building and simulate its thermal behaviour.

To use this component, it is necessary to execute a data pre-processing program (TRNBuild), which reads and processes the file containing the building description and generates two files that will be used by the Type 56 component during the TRNSYS simulation. Alternatively, the file containing the building implementation can be generated directly by the user within the TRNBuild itself [15]. As previously

indicated, for the weather data, which represent the boundary conditions of the building, the Meteonorm software was used. Meteonorm using the most recent climate databases, provides a TMY2 file which refers to the desired location. These files are characterised by a range of meteorological phenomena and hourly temperature trends in line with the long-term average values (generally at 20 years) for the location and are read by the Type “Weather data” with regular time intervals, interpolating them with time steps lower than one hour.

Based on information on the intended use and employment status, specific programs have been created, that determine the switching on and off of electrical equipment and internal lighting, both weekly and hourly.

B.6 MODEL CALIBRATION

After implementing the *Base-Case* model, it is necessary to calibrate it and then, to generalise the results, to develop a parametric simulation. For the model calibration, data recorded by two-channel Hobo-U10 Temp / RH temperature sensors positioned in many office rooms of the building, was used.

For example, the data relating to an area for office use located on the second floor is reported. This office was unoccupied for the entire period and, therefore, characterised by a low air turnover and negligible temperature changes induced by erratic use. In Fig. 5B, for a period from 25th February to 17th May 2006, the indoor air temperature and the indoor air average relative humidity trends were monitored.

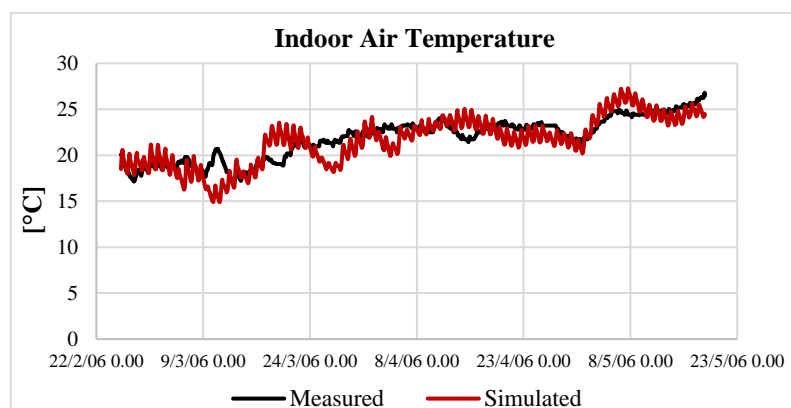


Fig. 5B. Comparison between the measured and simulated indoor air temperature trend.

The comparison between the hourly measured and simulated indoor air temperature is illustrated. As reported in Mustafaraj et al. [23] and Royapoor et al. [24], according to the main standards or guidelines (ASHRAE Guideline 14 [25], Measurement and Verification of Federal Energy Projects (FEMP) [26] and International Performance Measurement and Verification Protocol (IPMVP) [27]), it was possible to validate the *Base-Case* model. In particular, two error indices have been calculated: the Normalized Mean Bias Error (NMBE) and the Coefficient of Variation of the Root Mean Square Error (CV-RMSE):

- the NMBE (Eq. (1)) is a normalisation of the Mean Bias Error and provides the global bias between the expected and predicted data. Positive values of this index mean that the model provides an underestimated value with respect to the expected data. Negative values mean that the model provides an overestimated output data [28,29];

$$NMBE = 100 \cdot \frac{1}{N} \cdot \frac{\sum_{i=1}^N (x_i - y_i)}{\bar{x}} \quad (1)$$

- the CV-RMSE (Eq. (2)), providing a measure of the variability of the error between the expected and predicted data, is one of the most important measurements for evaluating the goodness-of-fit of the model [30]. It provides a clear indication of the prediction ability of the model in the field of building energy evaluation [29,31].

$$CV - RMSE = 100 \cdot \frac{\sqrt{\frac{1}{N} \sum_{i=1}^N (x_i - y_i)^2}}{\bar{x}} \quad (2)$$

In Table 8B, the limit values and ranges of applicability of all criteria for both indexes for hourly calibration are reported; furthermore, in the last column the NMBE and the CV-RMSE calculated for the *Base-Case* model are indicated.

Table 8B

Criteria and error indices for the model calibration.

Calibration Criteria	Index	FEMP	ASHRAE	IPMVP	<i>Base-Case</i>
Hourly criteria %	NMBE	± 10	± 10	± 5	+1.33
	CV-RMSE	30	30	20	8.13

For all criteria the *Base-Case* model was calibrated; the NMBE is within the applicability ranges required and CV-RMSE is lower than the specified limit values.

B.7 BUILDING ENERGY DATABASE

To create a valid and reliable database it is thought to start from the knowledge of the *Base-Case* properly calibrated and to implement a parametric simulation. Indeed, basing on the calibrated model, it was possible to develop several scenarios, varying different boundary conditions and several geometrical properties. Indeed, from the *Base-Case*, it was possible to construct an *Ideal Building*; a non-residential building designed with high energy performance according to actual standard on energy consumption of office buildings, EN ISO 13790: 2008 [11]. In detail, it was developed an *Ideal Building*, one for each different weather condition, indeed, varying the climatic zones change the limit transmittance values of the envelope surfaces. The *Ideal Building* model, by means of the parametric simulation, was simulated several times, each time varying the shape factors, the heated volume, the building construction type, the thermo-physical features, internal gains, the heating/cooling operational period, the climatic zones, the cities and the building orientation. In this way, it was possible to generate a large building energy database representative of non-residential building stocks designed with high energy performance. In the following, after a brief definition of the parametric simulation,

it is described the development of two different building energy database representative of the European and Italian building stock.

B.7.1 Parametric Simulation

The parametric modelling allows the designer to define entire classes of shapes, not just specific instances: the designer need only alter one parameter; the other parameters get adjusted automatically. Parametric models are built from a set of mathematical equations. For parametric models to have any legitimacy, they must be based on real project information. As explained previously, to obtain a generic database useful for developing a reliable model, it was necessary to perform a parametric simulation in a TRNSYS environment. From the *Base-Case*, it was possible to construct an *Ideal Building* model that, by means of a parametric simulation, was simulated several times, each time varying the shape factors, the heated volume, the building construction type, the thermo-physical features, the heating/cooling operational period, the climatic zones, the cities and the building orientation. It was, therefore, possible to generate a big building energy database representative of non-residential building stocks designed with high energy performance [13].

B.7.2 European Building Energy Database Development

In this section the main features selected to develop the European building energy database is described. In detail, the boundary conditions identified to determine a representative European building stock issued to obtain a at the first a database characterised by 504 simulations and then a database characterized by 2184 simulations.

B.7.2.1 European Climate

Europe is a region that includes a continental portion and peninsulas, interrupted by the Black Sea and the Baltic Sea. It is one of the smallest continents, but it is the third

most populous continent. The natural border of Europe is largely made up of its seas: on the north, it is bounded by the Arctic Ocean, and to the west and south by the Atlantic Ocean, the Mediterranean and the Black Sea. In contrast, Eastern Europe borders Asia. In general, Europe lies in the northern temperate climate zone, but more in detail, the western part of the European continent is characterised by a climate called Temperate Oceanic climate, strongly influenced by the Gulf Stream. This marine current coming from central American regions carries a great quantity of heat, keeping a moderate air temperature (considering the latitude) over North-Western Europe during the winter. On the contrary, Eastern Europe is characterised by a drier, continental climate with four distinct seasons, while Southern Europe enjoys a Mediterranean climate characterised by distinct wet and dry seasons with prevailing hot and dry conditions during the summer months. Parts of the Central European plains have a hybrid oceanic/continental climate [32,33].

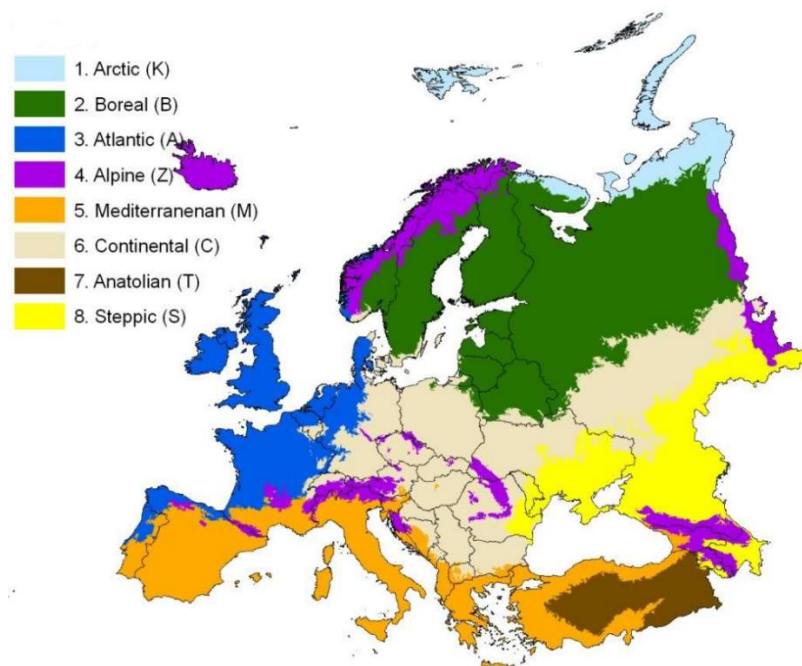


Fig. 6B. European Climate (Elsevier Licence Number: 4705881491934) [33].

Schematically, the European continent could be characterised by five different climatic regions (Fig. 6B), mainly due to the wide extension in latitude of the continent:

1. Subarctic climate or high mountain: It is typical of the north of Europe (Iceland and much of Norway), and is characterised by low rainfall, mostly snowy; with cold temperatures, that exceed 0°C only in spring and summer and with cold winds. The combination of these phenomena determines the scarcity of vegetation;
2. Continental climate (which is divided into cool continental climate and cold continental climate): In the lower (much of the Commonwealth of Independent States, Sweden and Finland) are the cold continental climate, which differs from the continental fresh to the lowest temperatures. The latter is typical of south-western and south-eastern Europe. The continental climate generally has a short season hot and muggy and a long cold and snowy;
3. Atlantic climate: The Atlantic climate is typical of Great Britain and Ireland, part of Sweden and Norway, Portugal, the coast of Spain, French, Polish and German, the Netherlands, Belgium and Denmark. Presents abundant rainfall with rare snowfall and mild temperatures that can occasionally drop below 0 °C;
4. Mountain climate: Typical of the mountain ranges of Central and South Asia, and snowy winters and cool summers and rainy; and
5. Mediterranean climate: The Mediterranean climate is characterised by short, mild winters and long, hot summers. In spring and autumn rainfall is scarce, and the rare snowfall. Between May and September are frequent long periods of drought. It is typical of Spain, Italy, Greece and of all south part of the continent.

As previously described, the *DD* value is an indicator that can be used in the assessment and analysis of weather related to the energy consumption of a building. To limit the study to a selected group of states, which are representative of different geo-climatic conditions and design characteristics in the EU, an initial classification

was made using of *HDD* and *CDD* indicators, provided by Eurostat and shown in Table 9B.

Table 9B

HDD, *CDD* and Solar Irradiation (Insolation) for the EU States (Elsevier Licence Number: 4705881491934) [33].

Countries	<i>HDD</i>	<i>CDD</i>	Insolation
	[K day]	[K day]	[kWh/(m ² year)]
Finland	5078	27	869
Sweden	4735	33	876
Estonia	4396	39	964
Latvia	4212	38	998
Lithuania	4116	37	998
Luxembourg	3534	63	1037
Poland	3494	83	1011
Denmark	3482	32	976
C. Republic	3268	125	1022
Slovakia	3100	201	1088
Germany	3095	91	1000
Romania	3088	290	1351
Austria	3060	158	1077
Slovenia	2904	207	1205
Hungary	2834	254	1226
Ireland	2806	0	952
Bulgaria	2706	304	1460
U. Kingdom	2669	42	949
Netherlands	2669	70	988
Belgium	2619	110	923
France	2265	202	1278
Italy	1442	561	1424
Spain	1161	748	1588
Greece	1155	958	1460
Portugal	886	325	1570
Malta	634	916	1763
Cyprus	512	1290	1738

In order to simplify the analysis, and at the same time to preserve the significance of the study, it was considered only few countries among the EU group are taken into account. These countries are chosen trying to represent different climatic and

representative European areas; in Fig. 7B are identified by different colour and are: Sweden, Germany, United Kingdom, Belgium, France, Italy and Spain.



Fig. 7B. States selected for the study and its *HDD* and *CDD* average values (Elsevier Licence Number: 4705881491934) [33].

In Fig. 8B the values of the selected Countries (Table 10B) in a histogram chart have been plotted. The figure shows how the values of the *HDD* are inversely proportional to the value of solar radiation, while the values of the *CDD* are directly proportional.

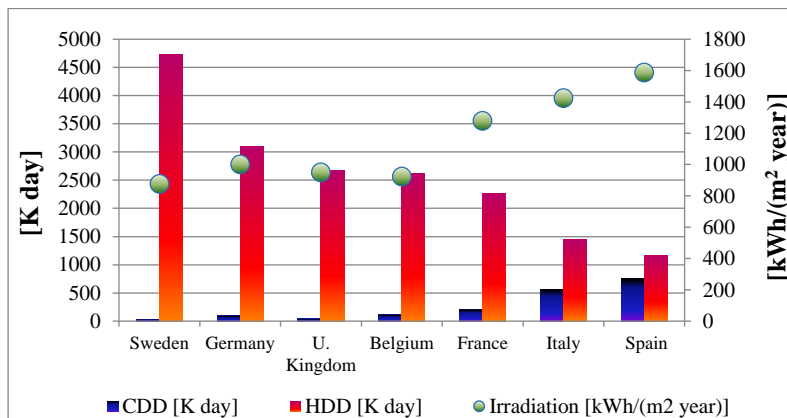


Fig. 8B. Average *HDD*, *CDD* and Solar Irradiation for selected Countries (Elsevier Licence Number: 4705881491934) [33].

This study attempts to collect at least one example of all possible climatic situations that can be observed in the EU and for this reason three different locations for each of the aforementioned countries were chosen. The three cities were chosen by identifying three different *HDDs* representing the maximum, minimum, and mean national values. Table 10B shows the selected cities, and the *HDD* values respectively.

Table 10B

Heating period of examined European cities.

European Countries	City	Heating period			
		From	To	Days	h
Sweden	Kiruna	1 st September	30 th June	223	1784
	Umea	1 st September	30 th June	212	1696
	Lund	15 th October	15 th May	155	1240
Germany	Fichtelberg	1 st September	15 th June	212	1696
	Hof	15 th October	15 th May	166	1328
	Frankfurt	15 th October	15 th May	155	1240
U. Kingdom	Aviemore	1 st September	15 th May	189	1512
	Birmingham	1 st October	15 th May	167	1336
	Camborne	1 st November	15 th May	136	1088
Belgium	St.Hubert	1 st September	15 th May	189	1512
	Bruxelles	15 th October	30 th April	144	1152
	Leigè	1 st November	31 st March	103	824
France	Bourges	1 st November	30 th April	133	1064
	Bordeaux	1 st November	31 st March	111	888
	Nice	15 th November	31 st March	100	800
Italy	Sestriere	15 th September	15 th June	201	1608
	Venezia	15 th October	15 th April	101	808
	Palermo	1 st December	31 st March	89	712
Spain	Salamanca	15 th October	15 th May	155	1240
	Madrid	1 st November	31 st March	111	888
	Sevilla	15 th November	15 th March	61	488

The *HDD* indexes, listed in Table 11B, were calculated using the TMY2 files [21] and by defining the heating periods and the hours of the heating period in each day [10,34]. Details about the calculation procure are deeply described in **Chapter F**.

Table 11B

HDD indexes of selected European cities.

Belgium		France		Germany		Italy		Spain		Sweden		U. Kingdom	
City	HDD	City	HDD	City	HDD	City	HDD	City	HDD	City	HDD	City	HDD
Hubert	3190.7	Bordeaux	1602.1	Fichtelberg	4982.2	Palermo	662.7	Seville	702.8	Lund	3202.4	Camborne	2026.3
Bruxelles	2239.3	Bourge	2226.7	Frankfurt	2829.5	Venice	2077.8	Madrid	1615.3	Umea	5299.1	Birmingham	2773.7
Liège	1975.2	Nice	1123.4	Hof	3425.5	Sestriere	5265.2	Salamanca	2379.3	Kiruna	6986.2	Aviemore	3483.3

B.7.2.2 European models: Thermophysical Features

As explained in **Chapter A**, concerning the building dimension, the shape factor of a building influences the solar energy that it receives as well as its total energy consumption [35]. The radiation hitting a building can significantly decrease the heating energy requirements [36]. The shape factor determines not only the total areas of the facade and roof that receive solar radiation but also the surface exposed to the outside and thus the heating energy losses [37]. At first, only three models with different shape factors were considered ($S/V = 0.24, 0.5$ and 0.9), than for a more general assessment, thirteen building configurations characterised by the geometrical dimensions listed in Table 12B have been investigated.

Table 12B

Geometric characteristics of building models.

Case study	S/V	Width	Depth	Height	Loss surface	Heating surface	Heated volume
	[m ⁻¹]	[m]	[m]	[m]	[m ²]	[m ²]	[m ³]
A	0.24	45	39	13.5	5797	7050	23793
B	0.27	60	22	13.5	4854	4854	17820
C	0.32	40	40	9	4640	3200	14400
D	0.35	15	30	13.5	2115	1800	6075
E	0.40	25	15	10.5	1590	1125	3938
F	0.50	106	50	4.5	11987	5293	23793
G	0.56	100	50	4	11200	5000	20000
H	0.58	50	50	4	5800	2500	10000
I	0.62	25	20	4.5	1405	500	2248
L	0.64	40	25	3.16	2411	1000	3160
M	0.69	90	20	3.5	4370	1800	6300
N	0.70	45	60	3.2	6072	8640	2700
O	0.90	118	8	3.16	2673	940	2970

Among the parameters that influence the passive solar design of buildings, orientation is very important. The intensity of beam solar radiation received on the building facade depends on the wall azimuth and building orientation. For these reasons, each model for each city was simulated eight times, varying the orientation of the building by 45° and averaging all the obtained results. Each model was built based on EN ISO 13790: 2008 [11] and by implementing detailed information concerning the thermophysical characteristics of the building envelope: glazed-opaque surface ratio, employment rate, internal gains, heating period, and turning on/off of the heating system. The glazed-opaque surface ratio R_{w-op} for each country is defined, and it is evaluated in [38]. For a non-residential building, it is supposed that the heating system is turned on eight hours per day, Monday through Friday, from 06.00 AM to 12.00 AM and from 3.00 PM to 5.00 PM; only for Sweden, it is a different period from 06.00 AM to 06.00 PM.

Solar gains were evaluated directly inside the dynamic simulation as a function of weather data, geometrical features of the building and surface orientations. Further, the occupancy was estimated to be from 07:00 AM to 5:00 PM, considering the reference values reported in Annex G of the specific technical standards [11]. Internal heat gains due to electrical equipment and lighting systems were implemented taking into account an estimated utilization rate. The lighting system was modelled considering fluorescent lamps with a specific thermal heat flow of 5 W/m². The electrical equipment contribution was implemented with partial or total use according to working hours, evaluating the radiative and convective contributions. Weekly schedules regarding the utilization of the equipment, lighting system and occupancy of office were implemented considering the time period, the fractions of load used and the number of users.

In a non-residential building model, the total floor surface is principally used for offices (14%), meeting rooms (56%) and other uses (30%). It was estimated that there are approximately 0.07 persons per m² of office spaces and 0.5 persons per m² of meeting room spaces. Furthermore, the infiltration losses were determined following Annex C of the standard [11]. Regarding the internal gains due to occupants, the presence of office workers with sedentary activity was estimated

(120 W/person, 65 W sensible and 55 W latent). Concerning typical office equipment, we estimated a heat gain of 230 W/equipment, one piece for each office worker and one piece per 50 meeting people. For each model, it was defined the stratigraphy of the walls, roofs, floors and windows, ensuring that each U-value respects the standard national limits [33].

To take into account different legal constraints imposed by national legislations, the variation of the thermal transmittance was achieved by changing the thickness and materials composing the building envelope, as shown in Table 13B.

Table 13B

U-value and thickness of building wall, floor, and roof.

European Countries	Components	<i>U</i>	Thickness
		[W/(m ² K)]	[m]
Sweden	Wall	0.140	0.605
	Floor	0.153	0.590
	Roof	0.152	0.490
Germany	Wall	0.263	0.475
	Floor	0.458	0.420
	Roof	0.246	0.490
U. Kingdom	Wall	0.345	0.440
	Floor	0.236	0.500
	Roof	0.152	0.490
Belgium	Wall	0.535	0.400
	Floor	0.709	0.390
	Roof	0.470	0.415
France	Wall	0.444	0.415
	Floor	0.371	0.440
	Roof	0.246	0.490
Italy	Wall	0.454	0.413
	Floor	0.458	0.420
	Roof	0.345	0.445
Spain	Wall	0.575	0.395
	Floor	0.709	0.390
	Roof	0.415	0.426

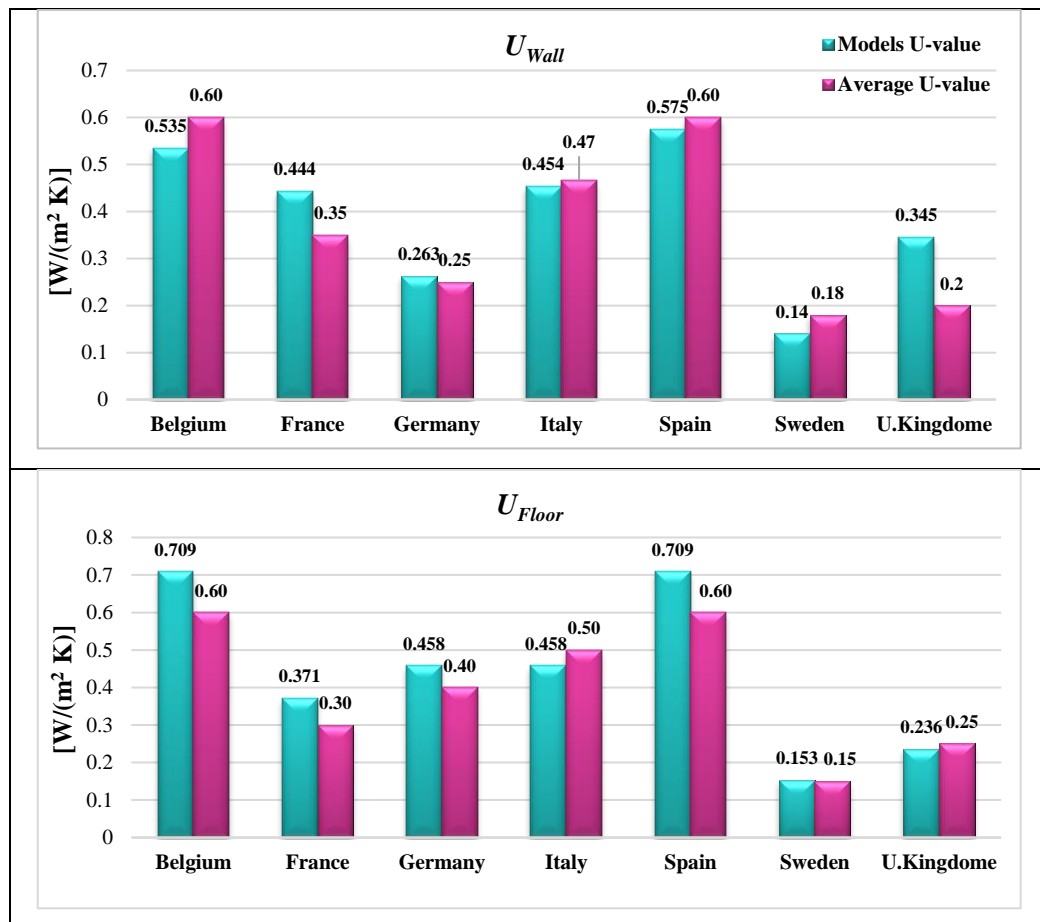
Each model has aluminium window frames and double panes with air or argon, depending on the U value defined by the national standard, as depicted by Table 14B. Furthermore, for each Country the optimum R_{w-op} is indicated.

Table 14B

Thermo-physical parameters used for the deployment of TRNSYS models.

European Countries	U_{window}	R_{w-op}
	[W/(m ² K)]	
Sweden	1.27	0.48
Germany	1.27	0.64
U. Kingdom	1.4	0.64
Belgium	1.4	0.64
France	1.4	0.64
Italy	2.76	0.61
Spain	2.76	0.61

In the following graphs (Fig. 9B), the comparisons between the average national thermal transmittance of each envelope surface and the respective thermal transmittance implemented in the models are shown.



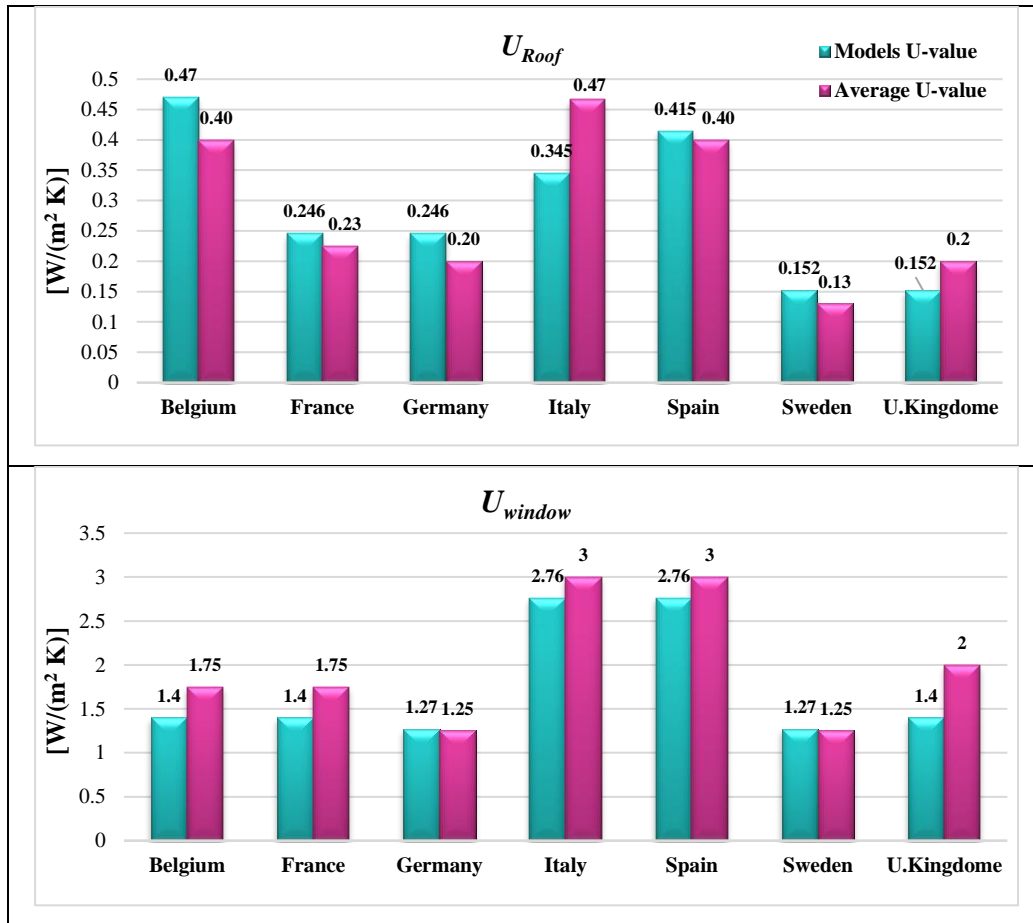


Fig. 9B. Comparisons between the implemented and standard national U -values.

Furthermore, it was evaluated the overall U_o -value that quantifies heat losses through the whole building envelope [39], as shown by the following equation:

$$U_o = \frac{\sum_{i=1}^n U_i S_i}{\sum_{i=1}^n S_i} \quad (3)$$

This index depends on the value of the thermal transmittance of the i^{th} surface (U_i) and the respective surface area (S_i) and for each model and each county, the overall U_o -values are collected in Table 15B.

Table 15B

Overall U_o for each model in each country.

European Country	U_o [W/(m ² K)]												
	A	B	C	D	E	F	G	H	I	L	M	N	O
Belgium	0.70	0.72	0.68	0.75	0.74	0.62	0.62	0.63	0.67	0.64	0.62	0.64	0.67
France	0.51	0.60	0.37	0.45	0.40	0.46	0.58	0.47	0.54	0.40	0.36	0.38	0.36
Germany	0.47	0.49	0.45	0.53	0.51	0.39	0.38	0.39	0.44	0.41	0.39	0.40	0.44
Italy	0.76	0.82	0.69	0.93	0.89	0.51	0.50	0.53	0.67	0.56	0.50	0.56	0.68
Spain	0.89	0.95	0.82	1.05	1.01	0.66	0.65	0.68	0.80	0.71	0.66	0.71	0.81
Sweden	0.29	0.31	0.26	0.36	0.34	0.19	0.19	0.20	0.25	0.21	0.19	0.21	0.26
U.K.	0.41	0.45	0.37	0.52	0.49	0.26	0.25	0.27	0.36	0.29	0.26	0.29	0.36

The total thermal capacity C_T for each model was evaluated (Table 16B). More in detail, the specific thermal capacity of each envelope element of each model was evaluated knowing the mass and the specific heat of each layer.

Table 16B

Total thermal capacity for each model in each country.

European Country	C_T [kJ/(m ³ K)]												
	A	B	C	D	E	F	G	H	I	L	M	N	O
Belgium	248.18	235.76	81.21	662.70	200.46	296.08	379.88	324.58	314.10	378.02	424.9	157.96	436.66
France	247.99	235.83	80.94	662.60	210.07	296.30	380.26	324.61	313.69	377.84	424.31	157.80	435.25
Germany	247.41	235.11	82.86	661.87	204.75	296.14	380.09	324.51	313.66	377.6	424.11	156.83	435.05
Italy	248.45	236.29	81.42	662.69	210.70	296.51	380.24	324.79	314.47	378.58	425.15	143.83	437.39
Spain	248.66	236.38	80.82	662.89	208.36	296.31	380.06	323.1	314.41	378.46	425.11	158.12	437.55
Sweden	247.91	236.83	90.44	660.31	217.03	299.00	382.08	326.26	317.76	382.29	427.55	159.48	443.81
U.K.	247.83	235.9	82.08	662.54	211.83	296.79	380.57	324.84	314.22	378.44	425.05	157.07	435.94

The combination of all variations in these parameters results in the development of: 504 simulations in the first case study, obtained from the simulation of 3 cities in 7 countries for 3 models and 8 orientations, and 2184 simulations in the second, from the simulation of 3 cities in 7 countries for 13 models and 8 orientations.

Integrating and averaging the simulation results, heating energy demands are summarised in *Annex 1 and 2* respectively.

In detail, in *Annex 1* the matrix is characterised by the following columns:

1. HDD [K];
2. S/V [m^{-1}];
3. $\frac{m_w^2}{m_{op}^2}$ window/opaque surface ratio;
4. U_w window transmittance [$W/(m^2K)$];
5. U_{op} global average of opaque surface transmittance [$W/(m^2K)$];
6. U_0 overall U-value [$W/(m^2K)$];
7. Q_s solar gains [kWh/year];
8. v_s wind speed [m/s]; and
9. h hours of heating operation per year [h].

In *Annex 2* the matrix considered the following parameters:

1. HDD : Heating Degree Days [K day];
2. S/V : Shape factor [m^{-1}];
3. S_w : Window surface [m^2];
4. S_{op} : Opaque Surface [m^2];
5. U_w : Window thermal transmittance [$W/(m^2 \cdot K)$];
6. U_{op} : Overall opaque thermal transmittance [$W/(m^2 \cdot K)$];
7. U_o : Overall thermal transmittance [$W/(m^2 \cdot K)$];
8. Q_s : Solar gains [kWh/year];
9. h : Heating operating hours [h];
10. C_T : Total thermal capacity [kWh/($m^3 \cdot K$)];
11. Q_G : Internal gains [kWh/year];
12. v : Wind speed [m/s]; and
13. H_d : Heating energy demand [kWh/($m^2 \cdot year$)].

B.7.3 Italian Building Energy Database Development

In this case each model was simulated for 13 geometrical configurations in 5 climatic zones represented by 3 Italian cities; also, in this case, each model was simulated eight times, varying the orientation by 45° each time, and averaging the results, for a total of 1560 simulations.

B.7.3.1 Italian Climate

The Italian region is between the 47th and the 36th parallel north, located almost in the centre of the temperate zone of the northern hemisphere.

From a general perspective Italian climate is also favoured by the influences of the Mediterranean Sea that surrounds almost every side. Mediterranean Sea can be considered as a beneficial reservoir of heat and humidity that determines a particular zone often called “temperate zone” (Fig. 10B).

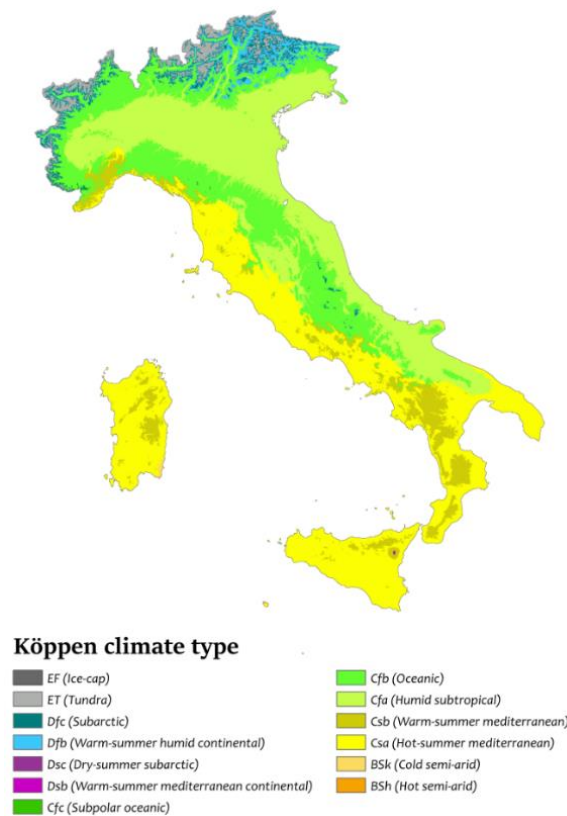


Fig. 10B. Köppen climate map of Italy [40].

The climate varies considerably from the north to the south of Italy. In the north of the country, the climate is harsh, with very cold winters and very hot and particularly humid summers, due to the presence of Alps and Apennines. The Alps, not only are a sort of barrier for cold currents coming from the Arctic regions of northern Europe, but also for the temperate but wet air masses from the North Atlantic. In addition, the Alps surround (along with facing the Northern Apennines), a closed basin, subject to atmospheric subsidence, with stagnant air in the lower layers. This basin area called “Po-Venetian”, have an independent climate, different from that of the surrounding areas of south-eastern France, Switzerland and Austria. Also in this context, the presence of the Adriatic Sea, long and shallow (especially near the coast) and between two peninsulas (the Italian and Balkan) gives a limited beneficial effect: its influence is much less important than that exercised by the wider and deeper Tyrrhenian Sea, on the western side of the Italian peninsula.

In central Italy, the climate is milder, with a smaller difference in temperature between summer and winter and a shorter and less intense cold season than in the north; summers are longer, but the climate of the northern cities is mitigated by the sea. In southern Italy and the islands, winters are never particularly harsh, and spring and autumn temperatures are similar to those reached in the summer in other areas of Italy [41]. Temperatures vary widely in Italy, in the north, centre or south of the country. The summer can be quite hot, mainly in the south of the peninsula, with high nocturnal temperatures of usually 28-33°C, but sometimes-even 40°C. Thunderstorms are quite common especially in the northern areas. Hot air rising from the sea can cause heavy thunderstorms especially in early fall, but these bring often the only summer rain that rapidly evaporates. In spring and fall, the Scirocco or Sirocco, a warm wind from Africa, raises the temperature of the peninsula. In the summer these winds can bring very hot, unpleasant weather, sometimes even up to the northern districts of Italy [42].

According to the Italian national guidelines for building energy certification [17], the peninsula is characterised by different climatic zones, which theoretically have the same climate [19]. As indicated in Table 17B, employing *HDD*, it is possible to

identify six different climatic zones, where zone A represents the hottest and zone F represents the coolest. For each zone, the daily hours of heating system activity and the consequent yearly period has been published.

Table 17B

Features of Italian Climatic Zones.

Climatic Zone	From HDD	To HDD	During of heating season		Daily hours
			From	To	
A	0	600	1 st December	15 th March	6
B	601	900	1 st December	31 st March	8
C	901	1400	15 th November	31 st March	10
D	1401	2100	1 st November	15 th April	12
E	2101	3000	15 th October	15 th April	14
F	3001	∞	No limit		

Each model was simulated in different climate zones and characterised by specific internal gains [8]. Furthermore, three cities were selected for each zone, to take into account the maximum, minimum, and mean *HDD* values [10]. Table 18B presents the *HDD* values for the 15 selected locations according to actual Italian law [19].

Table 18B

Selected Italian cities and DPR 412/94 HDD values.

Italian climatic zones									
B		C		D		E		F	
Location	HDD	Location	HDD	Location	HDD	Location	HDD	Location	HDD
Messina	707	Cagliari	990	Genova	1435	Trieste	2102	Cuneo	3012
Palermo	751	Bari	1185	Firenze	1821	Torino	2617	Cortina	4433
Crotone	899	Termoli	1350	Forlì	2087	Bolzano	2791	Sestriere	5165

Climatic zone A was not simulated, because it is not representative. In Italy, only two cities belong to this zone, with very similar *HDD* values: Lampedusa (*HDD* = 568) and Porto Empedocle (*HDD* = 579). Fig. 11B displays the climatic zone distribution on the Italian territory and the location of all cities selected to build the database.



Fig. 11B. Location of the selected cities and climatic zone distribution.

B.7.3.2 Italian models: Thermophysical Features

Also in this case, a non-residential base model was designed, with high-energy performance, according to the Italian standard requirements and the *Ideal Building* was simulated with different shape factors ($0.24 < S/V < 0.9$) and heated volumes, thereby creating 13 different building models.

Regarding the geometrical configurations, the shape factor influences the solar energy received by each location, as well as its total energy consumption [35]; indeed, the radiation hitting a building can increase the cooling energy requirements by up to 25% [36]. Moreover, the shape factor determines not only the total area of the facade and roof receiving solar radiation, but also the surface exposed to the outside, and thus, to energy losses [37]. In detail, in the following Table 19B are collected the thirteen models developed for the Italian case study, indicating the main geometrical features.

Table 19B

Geometric characteristics of the investigated building models.

Case study	<i>S/V</i>	Width	Depth	Height	Loss surface	Heating surface	Heated volume
	[m ⁻¹]	[m]	[m]	[m]	[m ²]	[m ²]	[m ³]
1	0.24	45	39	13.5	5797	7050	23793
2	0.50	106	50	4.5	11987	5293	23793
3	0.90	118	8	3.16	2673	940	2970
4	0.35	15	30	13.5	2115	1800	6075
5	0.62	25	20	4.5	1405	500	2248
6	0.76	40	25	3.16	2411	1000	3160
7	0.40	25	15	10.5	1590	1125	3938
8	0.32	40	40	9	4640	3200	14400
9	0.27	60	22	13.5	4854	5280	17820
10	0.69	90	20	3.5	4370	1800	6300
11	0.70	45	60	3.2	6072	2700	8640
12	0.58	50	50	4	5800	2500	10000
13	0.56	100	50	4	11200	5000	20000

Based on the same considerations about the building orientation [1], each model for each location was simulated eight times, with the building orientation varied by 45° each time, and all of the obtained results were averaged. In this manner, the mean energy performance of a building was evaluated as a function of the incident solar radiation calculated by averaging the eight simulation results. For each model, it was defined the stratigraphy of the walls, roofs, and floors, by ensuring that the transmittance values (*U-values*) conformed to the standard national limits (Table 20B) [8]. Indeed, based on this climatic zone classification, the current Italian law imposes transmittance limit values for the design of high-performance buildings.

Table 20B

Limit and model thermal transmittance values used in TRNSYS models.

Climatic zone	A-B		C		D		E		F	
	limit	model	limit	model	Limit	model	limit	model	Limit	model
<i>U_{wall}</i>	0.45	0.444	0.38	0.379	0.34	0.336	0.30	0.297	0.28	0.276
<i>U_{roof}</i>	0.38	0.377	0.36	0.353	0.30	0.303	0.25	0.249	0.23	0.234
<i>U_{floor}</i>	0.46	0.445	0.40	0.385	0.32	0.307	0.30	0.287	0.28	0.268
<i>U_{window}</i>	3.2	2.76	2.40	2.26	2.00	1.76	1.80	1.76	1.50	1.40

From the climatic point of view, also in this case, it was used TMY2 generated by the Meteororm software [21]. Regarding the utilisation of equipment, lighting system, and presence of office users Table 21B describes the weekly schedules.

Table 21B

Weekly schedules of equipment, lighting systems and attendance of office users.

Week day	Equipment Schedule	Lighting system Schedule	Users Schedule
Monday	equip. work day	lighting work day	people work day 1
Tuesday	equip. work day	lighting work day	people work day 2
Wednesday	equip. work day	lighting work day	people work day 1
Thursday	equip. work day	lighting work day	people work day 2
Friday	equip. work day	lighting work day	people work day 1
Saturday	equip. weekend	weekend	weekend
Sunday	equip. weekend	weekend	weekend

Each daily schedule is described in Fig. 12B; based on the time period, the load fractions used and number of users are reported.

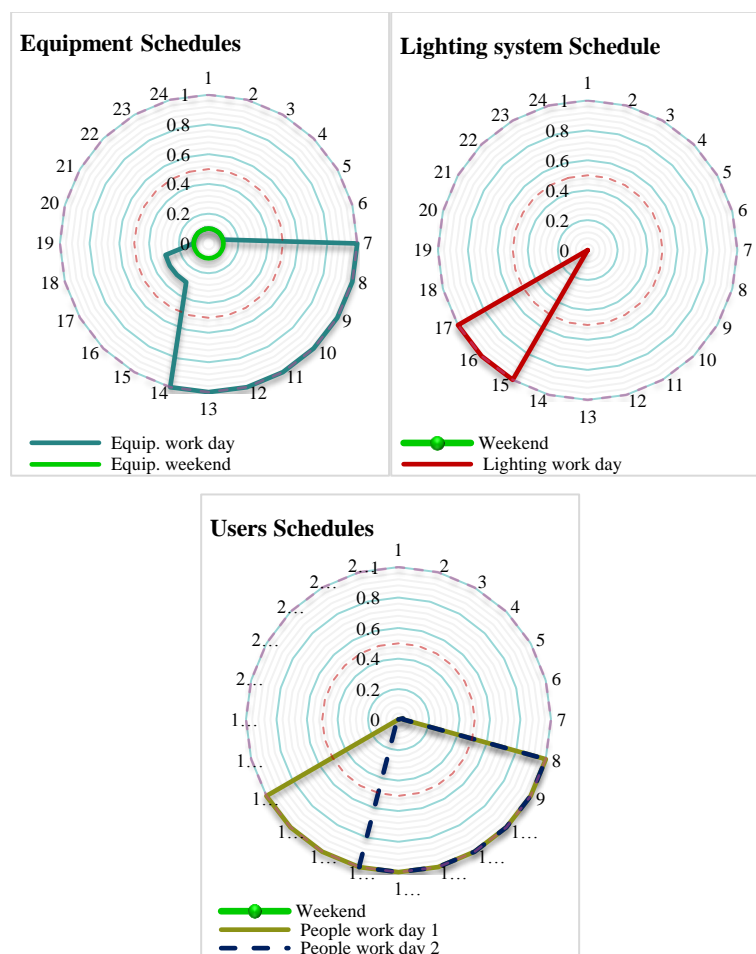


Fig. 12B. Daily schedules: fraction of load used and of the number of people [13].

In this model, the total floor surface has three different uses: offices (14%), meeting rooms (56%), and other uses (30%). The authors estimated that there are approximately 0.07 people per square metre of office space and 0.5 people per square metre of meeting room space [43,44]. Furthermore, the infiltration losses were determined according to Appendix C of [11]. Concerning the typical office equipment, a heat gain of 230 W per piece of equipment, with one piece for each office worker and one piece per 50 meeting people, was estimated; the presence of office workers with sedentary activity was also estimated (1 met).

Integrating and averaging the all simulation results, heating and cooling energy demands are summarised in *Annex 3*; in this case the matrix is characterised by the following columns:

1. *HDD*: Heating Degree Days [K day];
2. *CDD*: Cooling Degree Days [K day];
3. *T*: Mean outdoor temperature [K];
4. *RH*: Mean relativity humidity [%];
5. v_s : Wind speed [m/s];
6. I_h : Horizontal global solar irradiation [W/m^2]
7. *S/V*: Shape factor [m^{-1}];
8. H_s : Heated surfaces [m^2];
9. S_w : Glazed losses surface [m^2];
10. S_{op} : Opaque losses surfaces [m^2];
11. U_w : Glazed thermal transmittance [$\text{W}/(\text{m}^2\text{K})$];
12. U_{op} : Opaque thermal transmittance [$\text{W}/(\text{m}^2\text{K})$];
13. U_o : Overall thermal transmittance [$\text{W}/(\text{m}^2\text{K})$];
14. $Q_{s,H}$: Solar gains for heating period [kWh/year];
15. $Q_{s,C}$: Solar gains for cooling period [kWh/year];

16. h_H : Operating hours for heating period [h];
17. h_C : Operating hours for cooling period [h];
18. C_T : Thermal capacity [kWh/(m³K)]; and
19. Q_G : Internal gains [kWh/(m² year)].

B.8 DISCUSSION

In general, to develop a predictive tool capable of providing a solution to a generic problem, a reliable and well-set database representative of the analysed case study is required. Therefore, the search for the building energy predictive tool is based on the use of an energy building database describing the main characteristics of their thermal behaviour and capable of issuing a solution in any condition.

To achieve this goal, two energy databases have been developed representative of non-residential building stocks with high energy efficiency: a European and an Italian database.

Starting from a detailed *Base-Case* model, representative of a real office building located in Palermo, simulated in TRNSYS environment and calibrated on monitored data, it was possible to develop an *Ideal Building*. This last model describes a non-residential building designed with high energy performance according to actual standard on energy consumption, built with specific thermophysical features representative of a definite climatic zone; indeed, varying the climatic zones change the limit transmittance values of the envelope surfaces. Thanks to a parametric simulation that permitted to change the shape factor and the weather conditions, it was possible to simulate simultaneously several models in different boundary conditions. In detail, for the European context, in a first work, seven countries were considered, and to simulate all possible weather conditions, for each country three cities that represent the harsh, warm and mild climate were considered; in total 504 simulations were developed (*Annex I*). To generalize the results, the database was improved simulating other geometrical configurations; in

detail thirteen shape factor were analysed obtaining in this way 2184 simulations (*Annex 2*).

In the same way, an Italian non-residential building stock energy database was created. Based on current legislation in the field of energy certification, the Italian peninsula is divided into climate zones. In this case, for 5 different climatic zones, the model has been simulated; for each climate zone three cities have been identified, each of which represents the coldest, warmest and mildest condition. Every single model in each specific city has been simulated, for thirteen shape factor and for eight orientations, obtaining a dataset of 1560 simulations (*Annex 3*). In general, for each individual simulation it is possible to highlight a series of main parameters that characterize the single case study. In particular, for each simulation it was possible to explain the following main parameters:

- Heating Degree Days HDD [K day]
- Cooling Degree Days CDD [K day]
- Shape factor S/V [m^{-1}];
- Window surface S_w [m^2];
- Opaque Surface S_{op} [m^2];
- Window thermal transmittance U_w [$W/(m^2 K)$];
- Overall opaque thermal transmittance U_{op} [$W/(m^2 K)$];
- Overall thermal transmittance U_o [$W/(m^2 K)$];
- Solar gains Q_s [kWh/m^2 year];
- Heating operating hours h [h];
- Total thermal capacity C_T [$kWh/(m^3 K)$];
- Internal gains Q_g [$kWh/(m^2$ year)];
- Wind speed v [m/s];
- Heating energy demand H_d [$kWh/(m^2$ year)]

- Cooling energy demand C_d [kWh/(m²year)]

These datasets represent the solid and reliable basis on which to investigate different alternative models and achieve the purpose of the research.

MY RELATED PUBLICATIONS

Part of the research covered in **Chapter B** were published in the following international Journals:

4. Ciulla, G., Brano, V. L., & **D'Amico, A.** (2016). Modelling relationship among energy demand, climate and office building features: A cluster analysis at European level. *Applied energy*, 183, 1021-1034.
5. Ciulla, G., Brano, V. L., & **D'Amico, A.** (2016). Numerical assessment of heating energy demand for office buildings in Italy. *Energy Procedia*, 101, 224-231.
6. Ciulla, G., **D'Amico, A.**, & Brano, V. L. (2017). Evaluation of building heating loads with dimensional analysis: Application of the Buckingham π theorem. *Energy and Buildings*, 154, 479-490.
7. **D'Amico, A.**, Ciulla, G., Panno, D., & Ferrari, S. (2019). Building energy demand assessment through heating degree days: The importance of a climatic dataset. *Applied energy*, 242, 1285-1306.

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- [13] D’Amico A, Ciulla G, Panno D, Ferrari S. Building energy demand assessment through heating degree days: The importance of a climatic dataset. *Applied Energy* 2019;242:1285–306. doi:10.1016/J.APENERGY.2019.03.167.
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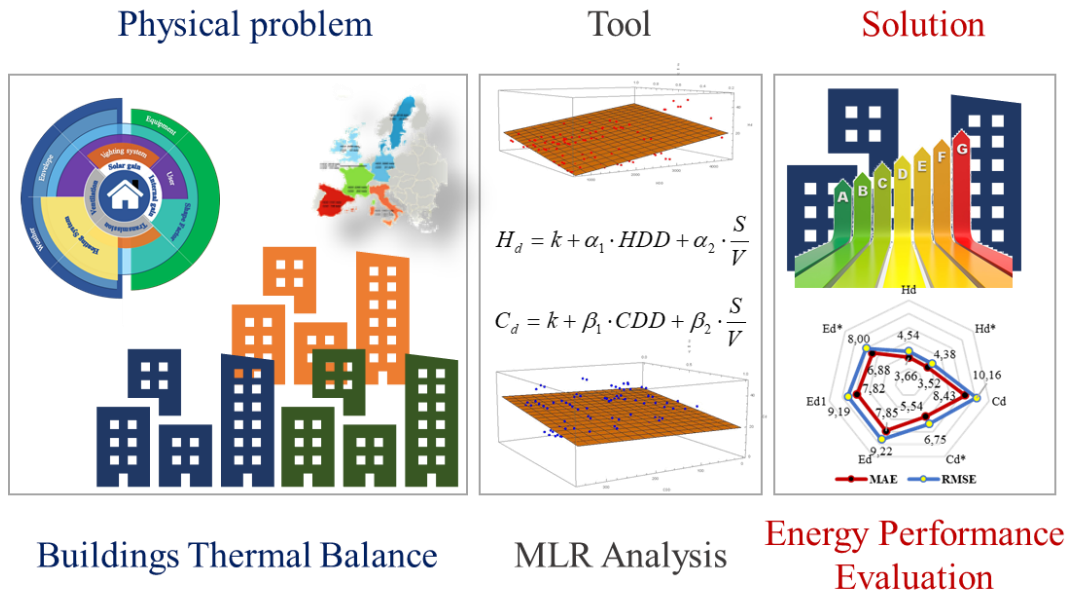
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CHAPTER C

MULTIPLE LINEAR REGRESSION MODEL

MULTIPLE LINEAR REGRESSION MODEL



ABSTRACT

More than one-third of the energy demand of industrialised countries is due to achieving acceptable conditions of thermal comfort in buildings. Indeed, assessing a building's energy performance has become a very active area of research in recent years, and different ways to evaluate the building energy balance can be found in literature, including comprehensive techniques, statistical and machine-learning methods and hybrid approaches. The identification of the most suitable approach is important to accelerate the preliminary energy assessment. In the first category, several numerical methods have been developed and implemented in specialised software using different mathematical languages. However, these tools require an expert user and a model calibration. In order to overcome these limitations, an alternative, reliable linear regression model to determine building energy needs was developed. Furthermore, the lack of general results, provide by White-Box methods, has led to investigate a statistical method also capable of supporting an unskilled user in the estimation of the building energy demand. To guarantee high reliability and ease of use, a selection of the most suitable variables was conducted by careful sensitivity analysis using the Pearson coefficient. The Multiple Linear Regression procedure allowed the development of some simple relationships to determine the thermal heating or cooling energy demand of a generic building as a function of only a few, well-known parameters. Deep statistical analysis of the main error indices underlined the high reliability of the results. This approach is not targeted at replacing a dynamic simulation model, but it represents a simple decision support tool for the preliminary assessment of the energy demand related to any building and any weather condition.

NOMENCLATURE

<u>Acronyms</u>	
MLR	Multiple Linear Regression
<u>Multiple Linear Regression parameters</u>	
y_i	i^{th} independent variable
x_i	i^{th} explanatory variable
b_0	Intercept of the linear regression
b_i	i^{th} regression coefficient
<u>MLR model parameters: explanatory variables</u>	
CDD	Cooling Degree Days [K day]
HDD	Heating Degree Days [K day]
h	Hours of heating operation per year [h]
Q_s	Solar gains [kWh/year]
Q_G	Internal gains [kWh/year]
S_{op}	Opaque surface [m ²]
S_w	Surface of the glazed component [m ²]
S/V	Shape factor [m ⁻¹]
U_0	Overall U-value [W/(m ² K)]
U_{op}	Global average of opaque surface transmittance [W/(m ² K)]
U_w	Window transmittance [W/(m ² K)]
v_s	Wind speed [m/s]
T	Outdoor temperature [°C]
$\frac{m_w^2}{m_{op}^2}$	Window/opaque surface ratio
<u>MLR model parameters: regression parameters</u>	
α_i	Regression parameters for the Italian model; H_d unknown
β_i	Regression parameters for the Italian model; C_d unknown
γ_i	Regression parameters for the Italian model; E_d unknown
θ_i	Regression parameters for the European model
k	Intercept of the linear equations
<u>Error and performance parameters</u>	
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MSE	Mean Squared Error
RMSE	Root Mean Square Error
R^2	Determination coefficient
<u>Other parameters</u>	
r	Pearson correlation coefficient
σ_{xy}	Covariance between the x and y variables
σ	Standard deviation
<u>Outputs of the models</u>	
C_d	Cooling energy demand [kWh/(m ² · year)]
E_d	Energy demand [kWh/(m ² · year)]
H_d	Heating energy demand [kWh/(m ² · year)]

C.1 INTRODUCTION

In this chapter, it is described the adoption of the Multi Linear Regression model to solve the traditional building energy balance; a valid and alternative decision support tool useful in every preliminary phases of an energy planning, when the user is not an expert or when it is necessary to speed up the decision-making phases. A comprehensive analysis of the energy performance of a specific building, although correctly interpreting the energy balance problem, requires a skill user with a knowledge of the physical problems associated and who is capable of constructing a model, collecting and implementing a large number of parameters, performing careful calibrations and explaining the results. All of these steps require high computational time and do not always provide an immediately correct evaluation; and in the case of an incorrect assessment, the procedure must be restarted. Moreover, although a parametric simulation allows the simultaneous analysis of the energy needs of several case studies, the results cannot be generalised: a dynamic simulation of each individual case corresponds to a specific result. To try to overcome these limits and to accelerate the preliminary assessment phase, the reliability of the MLR to solve the building energy balance was investigated. With the implementation of the detailed, reliable energy database representative of high energy performance non-residential building stocks, it was possible to apply this Black-Box method and to compare the obtained results with the previous comprehensive analysis. As explained in **Chapter B**, were investigated two different case study, referring to the European and Italian context. Furthermore, in the second case study, with the aim to improve and simplify the evaluation carry out in the Italian context, a careful sensitivity analysis through examination of the Pearson coefficient was done, which permitted the identification of the most suitable variables that influence the building energy balance during the heating/cooling period. The application of the MLR method to the energy database resulted in the definition of some simple correlations that identified heating (H_d), cooling (C_d) or comprehensive (E_d) energy demand with a high degree of reliability, valid for a representative building stock. These correlations, validated thanks to a

deep statistical error analysis, solve the building energy balance knowing only a few well-known parameters and without any computational time or physical knowledge.

Although, the literature reports Black-Box methods being applied to determine the energy needs of a specific building or a district, in this work a methodology is proposed to allow the identification of a more flexible tool that can assess the energy requirements of any generic building belonging in the non-residential buildings class. Indeed, once the correlations valid at a general level have been determined, it was provided an easy-to-use tool that identifies the needs of a building, simply by solving a linear equation. The high degree of reliability achieved from the results guarantees that this methodology can be replicated in any other climatic and building context, representing a predictive tool to support decisions. Furthermore, this solution could be used as a supplementary evaluation criterion/tool to support standards and/or laws in the field of building energy performance. Another strength of the presented model is that the application of the MLR method does not require, during the use phase, any calculation tool such as a personal computer or software program, but it is characterised by the resolution of a simple linear equation.

C.1.1 Contribution of the Work

The aim of this part of the research it was achieved thanks to the exploitation of the MLR model at two energy databases explained in **Chapter B**. In detail, in the following is underlined as the MLR model solves the complex problem of the building thermal balance with high reliability degree and high determination coefficients (R^2). Furthermore, the good results are guaranteed by a deep statistical analysis of the error indices. Details and main phases to achieve the aim of this work is explained in the *Section C.2*, furthermore because are investigated two different case study, in *Section C.4* and *Section C.5* are displayed the steps followed in each case.

C.2 METHODOLOGY

In the flow chart, displayed in Fig. 1C, the entire procedure followed is represented.

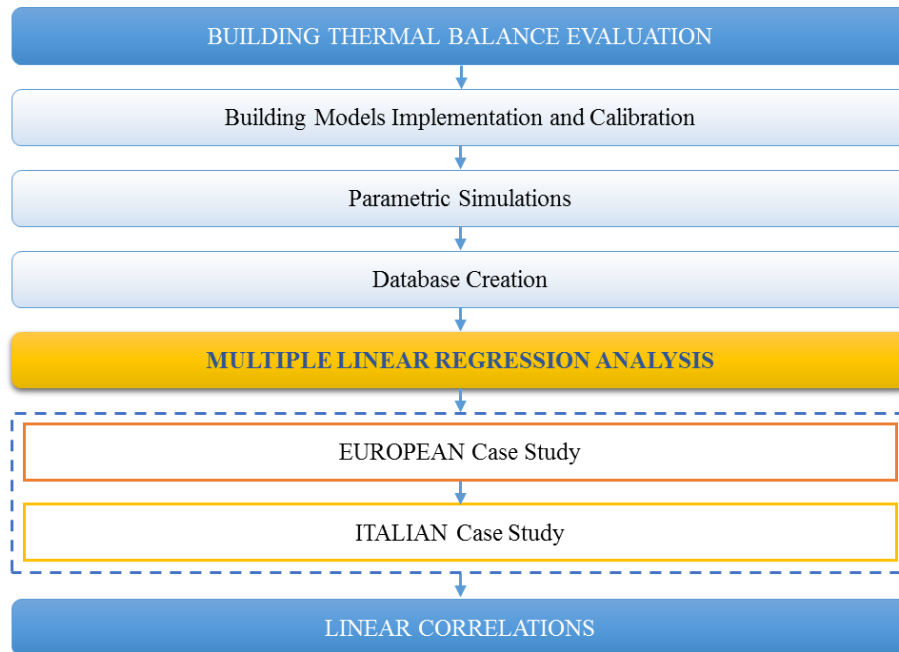


Fig. 1C. Flow chart of the procedure method.

The idea is to develop a generic decision support tool that, without an expert user and with a high reliability degree, immediately solves the traditional building energy balance in any case and in any conditions. In order to achieve this goal, it is necessary to develop a generic solution of a representative building stock which includes all possible building topologies and weather conditions. For this reason, it was decided to investigate, as representative, a non-residential building stock designed with high energy performance according to current energy efficiency laws and standards. As described in **Chapter B**, thanks to a parametric simulation it was possible to develop two building energy databases of high energy performance building stocks, one valid for a more general and broader context, such as the European, and one valid for a national context represented by the Italian case; the first one is characterised by 63 scenarios distributed in 7 European countries; the second one by 195 scenarios entirely located in Italy.

The identification of a series of restrictions related to the White-Box methods, such as the data collection, the knowledge of the physical problems, the tool language, the computational time and the lack of generality of results, prompted the research to investigate other alternative methods that overcome these limits. In this context, a good alternative for resolving this problem is represented by the Black-Box methods (*Section A.3.2*). Although they do not take into account the physics of the problem, they are able to identify a correlation or a dependence between the input and output data. The strong correlation or dependence between the data is guaranteed by the identification of the main parameters that characterise the building energy balance. The exploration of the MLR method on the two databases (*Section C.4* and *Section C.5*), allowed the modelling of some linear relationships between two or more explanatory variables (input of the model) and a response variable (building energy performance) through a fitting procedure. The performance analysis is illustrated by means of an error metric analysis (*Section C.5.1* and *Section C.5.3*), which provides the most used error indices. Owing to the reliability and flexibility of the energy database, this model was investigated with good results.

C.3 MULTIPLE LINEAR REGRESSION

The MLR model allows an immediate assessment of building energy requirements and is one of the easiest and most intuitive approaches of prediction. This method, excluding a knowledge of the physical phenomena, still allows the prefixed objective to be reached without excessive computational cost. Nonetheless, a knowledge of a large survey database on which the model can be constructed is necessary. Therefore, if compared to the physical model, MLR models have the advantage of minimising the amount of input data, avoiding tedious work and the necessity for powerful informatics equipment [1]. The aim of this method is to explain the relationship between the dependent variable (annual heating, cooling or comprehensive energy demand) and two or more explanatory variables or regressors (climate and thermophysical parameters) using linear combinations of

the latter [2]. The MLR models were developed according to the most general equation form (Eq. (1)) [3]:

$$y_i = b_0 + b_1x_1 + b_2x_2 + \dots + b_px_p + e \quad (1)$$

where

y_i represent the i^{th} independent variable (output);

x_i represent the i^{th} explanatory variable (input);

b_0 is the intercept of the relationship;

b_i is the i^{th} regression coefficient that determines the used weight by the equation on the i^{th} explanatory variable to provide the estimate output; and

e is the error related to the i^{th} observation.

The objective function for constructing the MLR model is the least square method, with the goal of minimising the sum of the least square errors between the expected and predicted outputs as illustrated in the following equation Eq. (2) [2]:

$$\text{Min} \sum_{i=1}^n \left(y_i - \sum_{j=1}^p x_{ij}b_j - b_0 \right)^2 \quad (2)$$

C.4 MLR ENERGY PREDICTIVE TOOL FOR THE EUROPEAN BUILDING STOCK

At the first, stems from previous considerations, it was investigated the MLR procedure to assess the energy performance of a non-residential building-stock for the European case study. Owing to the predominance of the demand for thermal energy for the heating compared to that for the cooling, in this case study, the possibility to develop a predictive model for the only determination of the heating energy requirement was evaluated. The use of a single equation with a good degree of approximation eliminates the necessity of the use of a simulation software, and thereby accelerating the entire diagnosis process. As explained in **Chapter B**, to ensure a high reliability of the data used to deploy the following correlations, a

specific energy building database was created. The *Ideal Building* were built according to the legal energy requirements of seven different European countries and based on the European standard for energy consumption in buildings [4]. In this first work, the database on which the linear regression model was built, provides the selection of three cities, for seven European Countries, that represent the harsh, mild, and warm climate of the overall national territory, and, for each location, the simulation of only three building models with the following shape factors: $S/V = 0.24$, 0.5 and 0.9 (Fig. 2C).

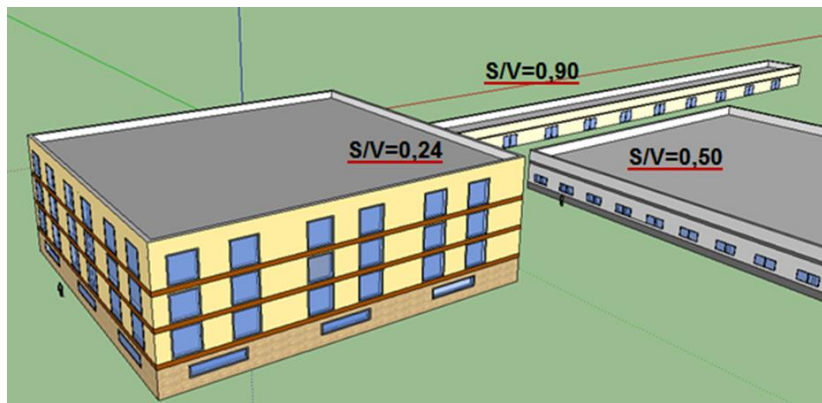


Fig. 2C. Schema of the three shape factor values.

The geometry characteristics of these models are collected in Table 1C.

Table 1C

Geometric characteristics of building models.

S/V	Wide [m]	Depth [m]	Height [m]	Loss Surface [m ²]	Heated Surface [m ²]	Heated Volume [m ³]
0.24	44.76	39.38	13.5	5796.53	7049.78	23793
0.50	105.85	50	4.5	11986.72	5292.73	23793
0.90	117.49	8	3.16	2672.82	939.92	2969.72

Detailed information is deeply described in **Chapter B**, *Section B.7*.

The results collected in Table 2C were employed to establish a relationship among the thermal energy demand for heating a non-residential building, HDD, and S/V values.

Table 2C

Specific heating energy demand for each building.

European Countries	City	H_d [kWh/(m ² year)]		
		$S/V=0.24$	$S/V=0.50$	$S/V=0.90$
Sweden	Kiruna	6.96	11.40	46.99
	Umea	5.70	10.06	39.16
	Lund	4.03	8.07	25.56
Germany	Fichtelberg	7.00	11.15	46.42
	Hof	5.10	9.01	36.79
	Frankfurt	4.87	8.46	35.29
U. Kingdom	Aviemore	16.01	27.78	59.39
	Birmingham	13.59	24.84	48.53
	Camborne	9.99	21.08	32.48
Belgium	St.Hubert	13.89	21.97	83.94
	Bruxelles	11.41	17.33	65.50
	Liegè	9.98	13.30	60.08
France	Bourges	12.83	22.90	43.08
	Bordeaux	8.84	19.31	29.46
	Nice	3.52	16.15	15.19
Italy	Sestriere	23.08	19.21	69.37
	Venezia	11.38	11.37	37.62
	Palermo	0.16	4.30	4.87
Spain	Salamanca	2.40	4.65	21.19
	Madrid	2.04	3.46	17.36
	Seville	0.49	2.34	9.05

To better generalize the results, data were clustered into three *HDD* ranges [5] determining three equations with a high R^2 . To obtain a more generalizable result, it was investigated a more complex correlation, obtaining a function of nine crucial parameters for the assessment of a building's energy balance. Even with a cluster analysis it was possible to obtain three correlations characterized by a high R^2 value from this function. To guide the reader in understanding the current case study, the flow chart and the main steps performed are displayed in Fig. 3C.

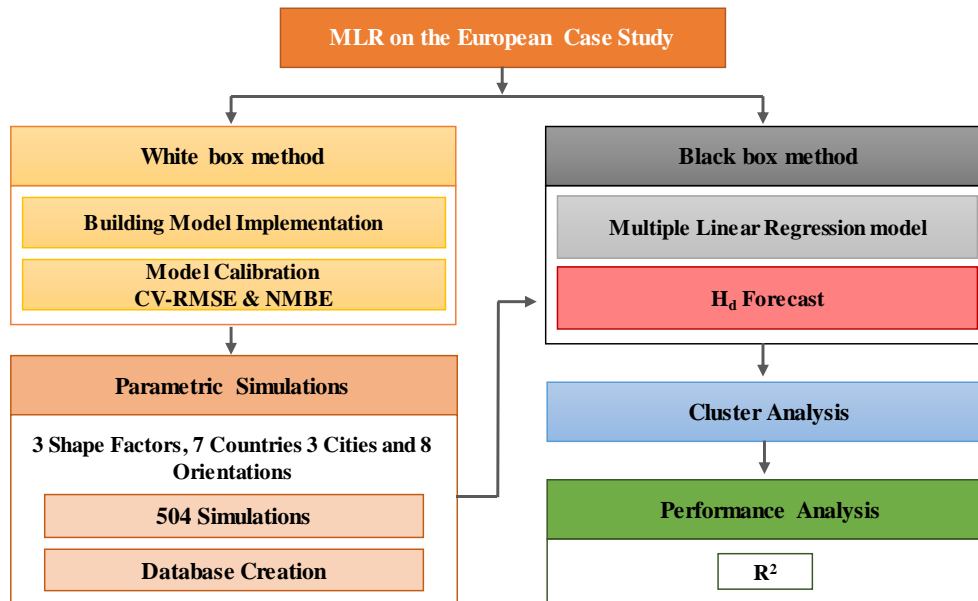


Fig. 3C. Flow chart of the procedure model for the European case study.

C.4.1 Results and Discussion of the European Case Study

The results obtained from the simulations, and collected in *Annex 1*, were then further processed; at first, the possibility to identify a simple relationship to evaluate the thermal energy performance of an office building in a specific country was evaluated; then the identification of a general correlation useful for all of the countries surveyed, and thus generally valid for the entire European area, was investigated. As a first attempt, data were analysed for each country, and seven correlation functions of *HDD* and *S/V* values were extrapolated. Each correlation has the general form of a plane in a 3D space:

$$H_d = k + \theta_1 \cdot HDD + \theta_2 \cdot \frac{S}{V} \quad (3)$$

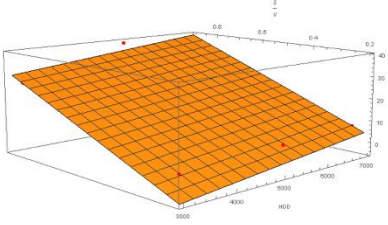
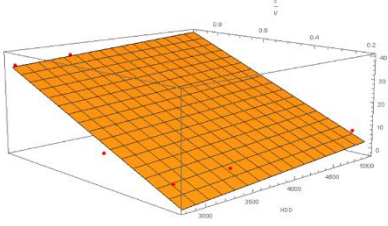
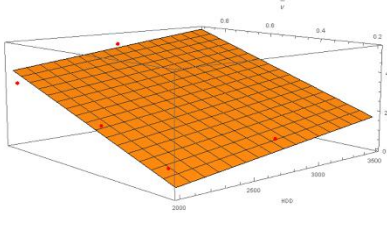
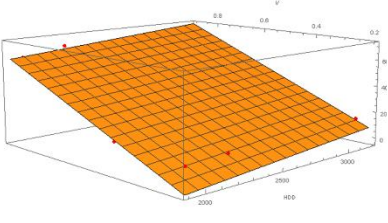
where

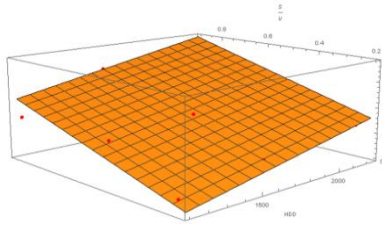
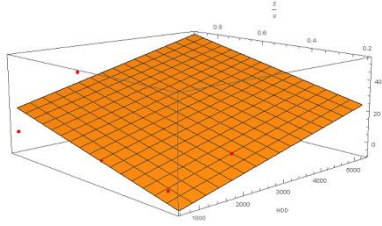
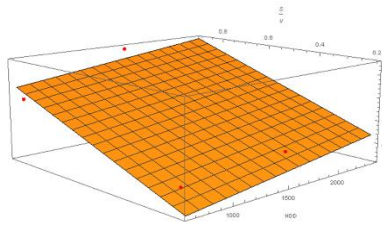
- k is the intercept [kWh/(m² year)];
- θ_1 is the 1st regression coefficient [kWh/(m² year K day)]; and
- θ_2 is the 2nd regression coefficient [kWh/ (m year)].

For each country, data related to the specific heating energy demand, HDD , and S/V are fitted to Eq. (3) using the least square method. The results of the fitting procedures are shown in Table 3C; for each country, the correlation, graphic representation, and R^2 value are provided.

Table 3C

H_d correlations for seven European countries.

European Countries	H_d equation	Plan plot	R^2
Sweden	$H_d = 0.0025HDD + 49.71\frac{S}{V} - 22.28$		0.948
Germany	$H_d = 0.0025HDD + 53.27\frac{S}{V} - 20.49$		0.959
United Kingdom	$H_d = 0.0091HDD + 51.31\frac{S}{V} - 24.93$		0.984
Belgium	$H_d = 0.0097HDD + 91.63\frac{S}{V} - 41.04$		0.957

European Countries	H_d equation	Plan plot	R^2
France	$H_d = 0.0132HDD + 30.99\frac{S}{V} - 19.67$		0.965
Italy	$H_d = 0.0071HDD + 41.14\frac{S}{V} - 21.19$		0.867
Spain	$H_d = 0.0033HDD + 22.36\frac{S}{V} - 10.34$		0.927

The proposed correlations are seven simple linear equations that are functions of only two parameters; the good reliability of the provided correlations is confirmed by high R^2 (coefficient of determination). To generalize the results to most if not all of Europe, all data were collected in a matrix with 63 rows and three columns, where:

- the HDD values are contained in the first column;
- the S/V values are provided in the second column;
- the simulated H_d values are presented in the third column; and
- the cities (21 cities for each S/V value) are given in the rows.

To obtain mathematical relationships that fit the energy demand values for all of the country surveyed, data results with a cluster analysis were preliminarily examined.

C.4.1.1 Cluster Analysis

The cluster analysis is a convenient method for identifying homogeneous groups of data called clusters. Data in a specific cluster share many characteristics, but are very dissimilar to objects not belonging to that cluster. This means that data within each cluster are similar to each other with respect to variables or attributes of interest, and the clusters themselves stand apart from one another. The aim of this analysis was to identify three clusters of similar data and then to identify three correlations universally valid throughout the European area. Several clustering methods exist and, as already discussed, cluster analysis is also used to group variables into homogeneous and distinct groups requiring a more precise definition of “similarity” of observations and clusters [5]. When the grouping is based on variables, it is natural to employ the familiar concept of distance. In this case the distance in the space \mathbb{R}^3 should be considered. Perhaps the simplest method is to treat the distance between the two nearest points, one from each cluster, as the distance between the two clusters.

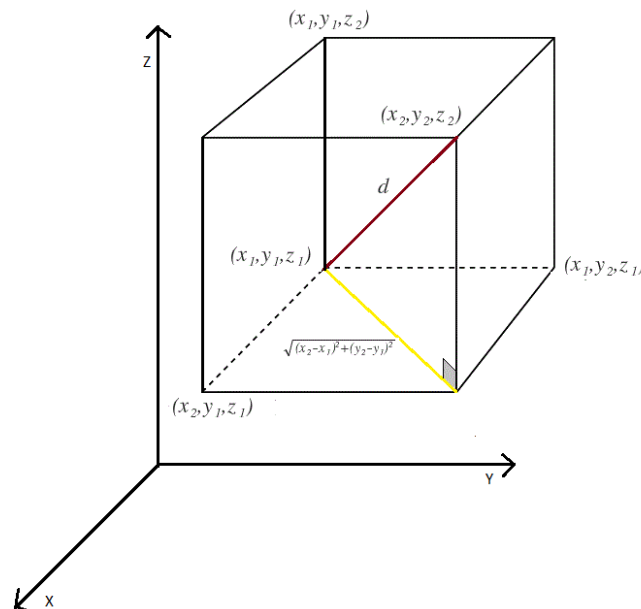


Fig. 4C. Distance between two points.

Fig. 4C presents a map showing two points with coordinates $j (x_1; y_1; z_1)$ and $i (x_2; y_2; z_2)$, respectively, so that the Euclidean distance between the two points is:

$$d(i, j) = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2 + (z_2 - z_1)^2} \quad (4)$$

A point i is declared to be closer (more similar) to j with respect to point k if:

$$d(i, j) < d(i, k) \quad (5)$$

An alternative measure is the squared Euclidean distance; in Fig. 4C the squared distance between the two points 1 and 2 is:

$$d^2(i, j) = (x_2 - x_1)^2 + (y_2 - y_1)^2 + (z_2 - z_1)^2 \quad (6)$$

Given a distance measure, a reasonable procedure for grouping n points starts with as many clusters as there are points, with each observation forming a separate cluster. The pair of observations that are nearest one another are then merged, leaving $n-1$ clusters for the next step. This merging of the two nearest clusters is then repeated, leaving $n-2$ clusters for the next step. The process continues in this way, reducing the number of clusters by one at each step, until a predetermined number of clusters is reached. This clustering methodology belongs to those so-called “hierarchical clustering” methods, and more specifically is called the “single-linkage” or “nearest neighbour” method. This clustering analysis is then applied to the available data in the space $\mathbb{R}^3 \rightarrow \left(H_d; \frac{S}{V}; HDD \right)$ to identify the following three clusters based on the HDD values:

- Cluster 1: $650 < HDD < 2550$;
- Cluster 2: $2551 < HDD < 4200$; and
- Cluster 3: $4201 < HDD < 7000$

The list of cities belonging to each cluster are collected in Table 4C.

Table 4C

List of cities belonging to each cluster.

Cluster 1		Cluster 2		Cluster 3	
City	HDD	City	HDD	City	HDD
Bruxelles	2239	St. Hubert	3191	Fichtelberg	4982
Liege	1975	Frankfurt	2830	Sestriere	5265
Bordeaux	1602	Hof	3426	Umea	5299
Bourges	2227	Lund	3202	Kiruna	6986
Nice	1123	Birmingham	2774		
Palermo	663	Aviemore	3483		
Venezia	2078				
Seville	703				
Madrid	1615				
Salamanca	2379				
Camborne	2026				

It must be emphasized that the clustering on the basis of the *HDD* parameter was not predetermined, but is the result of the analysis. Fig. 5C depicts the results of the cluster analysis; the orange points represent the first cluster, the blue points are the second cluster, and the green points represent the third cluster.

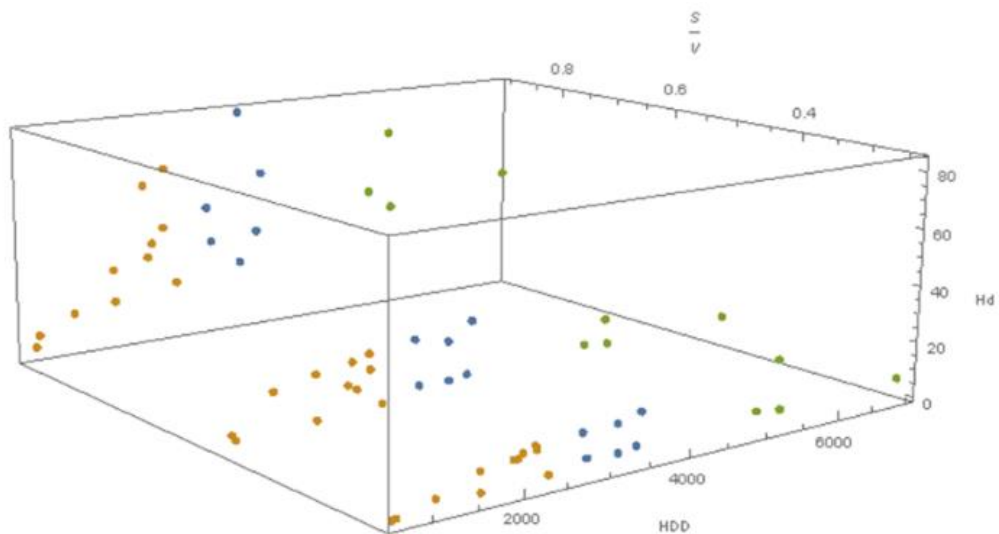


Fig. 5C. 3D plot of the three clusters.

Once the three clusters were identified, it was applied the fitting procedures of a generic linear mathematical relationship, represented by Eq. (4), and the obtained θ_i values are as follows (Table 5C), respectively:

Table 5C

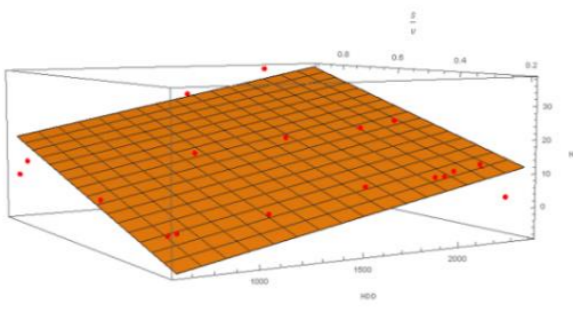
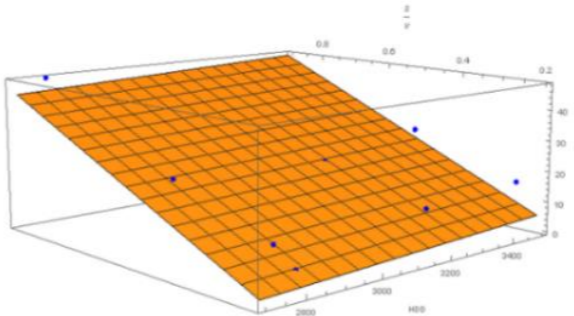
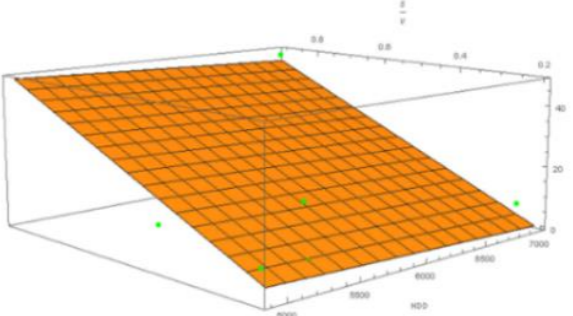
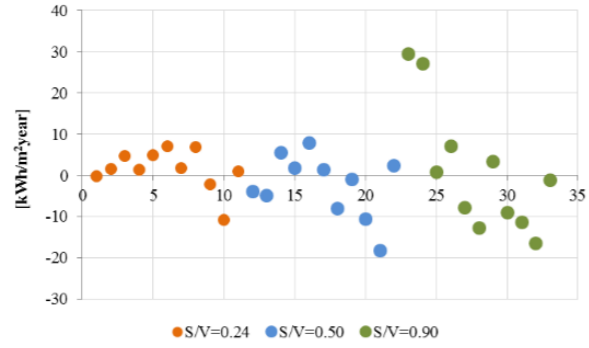
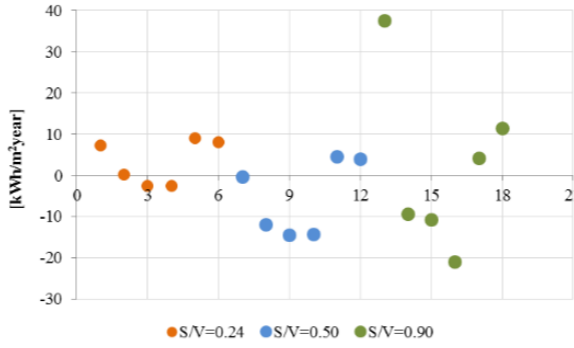
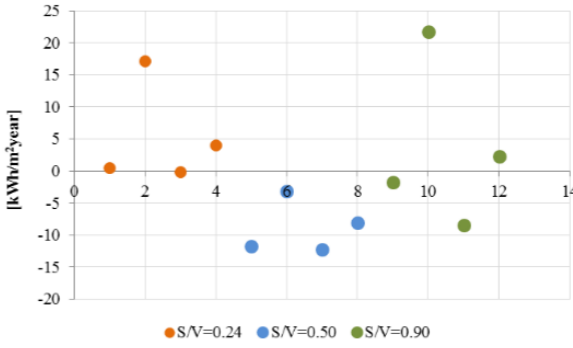
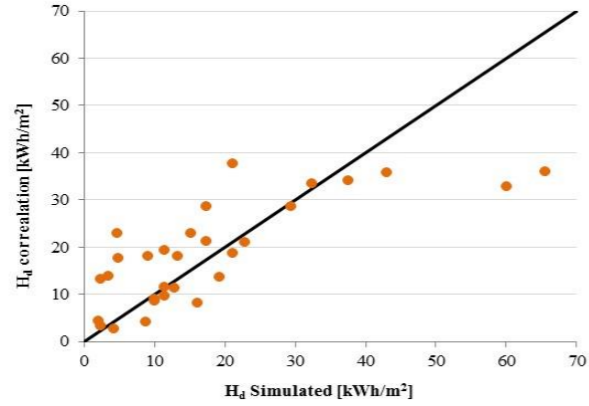
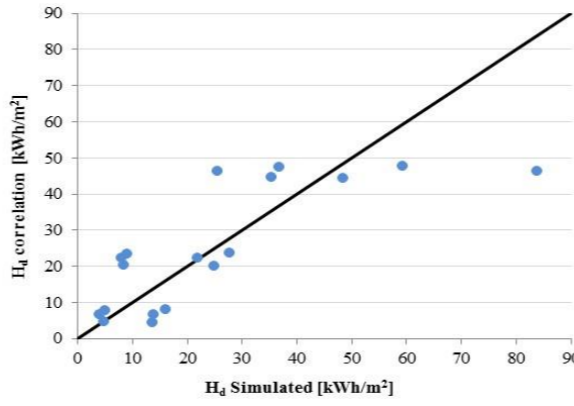
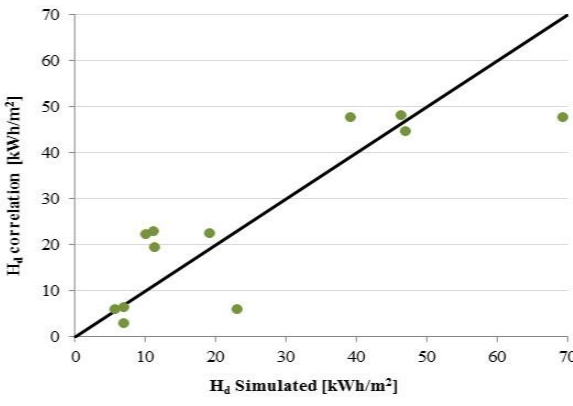
θ_i values for each cluster.

θ_i	Cluster 1	Cluster 2	Cluster 3
k	-23.48	-23.99	-0.012
θ_1	0.012	0.005	-0.002
θ_2	36.98	60.30	63.13

The results concerning to the first, second, and third clusters are presented in Table 6C.

Table 6C

The three correlations pertaining the 1st, 2nd, and 3rd clusters.

	Cluster 1	Cluster 2	Cluster 3
H_d	$H_d = 0.012 \cdot HDD + 36.98 \cdot \frac{S}{V} - 23.48$	$H_d = 0.005 \cdot HDD + 60.30 \cdot \frac{S}{V} - 23.99$	$H_d = -0.002 \cdot HDD + 63.13 \cdot \frac{S}{V} - 0.012$
Surface			
Fit Residual			
Correlation degree			
R^2	0.808	0.841	0.900

The following details are available for each cluster:

- the form of correlation;
- the surface that represents the equation and best fits the data;
- the distribution of the fit residuals in which each colour corresponds to a different S/V value ($S/V = 0.24$ for orange points; $S/V = 0.5$ for blue points; $S/V = 0.9$ for green points);
- the correlation degree between the simulated data obtained by TRNSYS and by correlations; and
- the evaluation of the determination coefficient R^2 .

In all cases, the determination coefficients are higher than 0.80.

C.4.1.2 A More Extensive Correlation to Obtain H_d

To better exploit the information related to the constructive typology, the intended use, and the climate context, and thus obtained a more generalizable result it was investigated a more complex and extensive correlation. Several parameters were studied, and among those who in the end were not selected because they did not give rise to significant improvements in the quality of prediction: global thermal capacity, floor surface, air flow, geometric dimensions. In this way, the specific heating energy demand is a function of nine parameters decisive for the assessment of the building's energy balance. The parameters considered in the hypothesized function are:

10. HDD [K day];
11. S/V [m^{-1}];
12. $\frac{m_w^2}{m_{op}^2}$ window/opaque surface ratio;
13. U_w window transmittance [$W/(m^2K)$];
14. U_{op} global average of opaque surface transmittance [$W/(m^2K)$];
15. U_0 overall U-value [$W/(m^2K)$];
16. Q_s solar gains [kWh/year];

17. v_s wind speed [m/s]; and
18. h hours of heating operation per year [h].

The data in *Annex 1* were subjected to a fitting procedure adapted to a form of a linear relationship as in the following equation:

$$H_d = k + \theta_1 HDD + \theta_2 \frac{S}{V} + \theta_3 \frac{m_w^2}{m_{op}^2} + \theta_4 U_w + \theta_5 U_{op} + \theta_6 U_0 + \theta_7 Q_s + \theta_8 v_s + \theta_9 h \quad (7)$$

where the θ_i values are collected in Table 7C.

Table 7C

θ_i values of the generic H_d correlation between nine parameters.

θ_i	Value	θ_i	value	θ_i	value
k	-87.2611	θ_4	-10.9847	θ_8	1.4992
θ_1	0.0045	θ_5	-45.1921	θ_9	0.0248
θ_2	18.6261	θ_6	72.8352		
θ_3	116.4940	θ_7	-0.0032		

In detail:

- k is the intercept [kWh/(m² year)];
- θ_1 is the 1st regression coefficient [kWh/(m² year K day)];
- θ_2 is the 2nd regression coefficient [kWh/(m year)];
- θ_3 is the 3rd regression coefficient [kWh/(m² year)];
- θ_4, θ_5 and θ_6 are 4th, 5th and 6th regression coefficient [10^3 (K h)/ year];
- θ_7 is the 7th regression coefficient [1/m²];
- θ_8 is the 8th regression coefficient [(kWh s)/(m³ year)]; and
- θ_9 is the 9th regression coefficient [kW/(m² year)].

In Fig. 6C, the distribution of the residual fit, obtained from the difference between the simulated data by TRNSYS software and the calculated data by the correlation, is plotted, with the three colours representing the three different shape factor values.

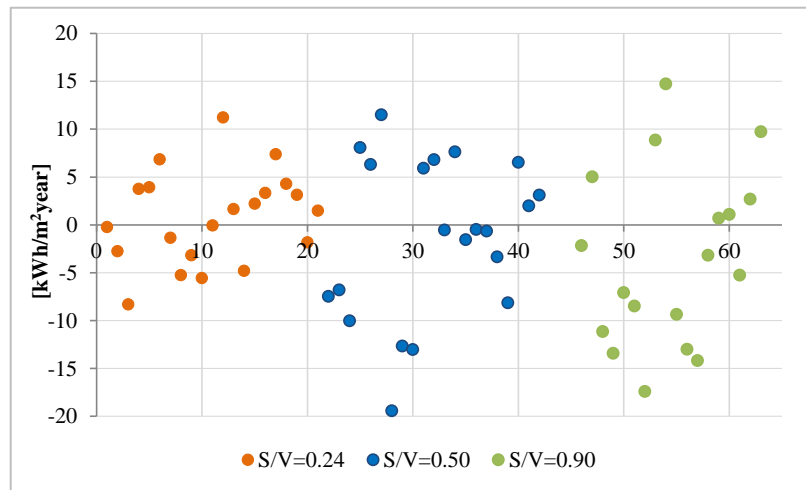


Fig. 6C. Residuals related to $S/V=0.24$, $S/V=0.5$ and $S/V=0.90$.

The reliability of the discovered correlation is characterised by a high value of $R^2=0.889$; in Fig. 7C it is possible to see the distribution of the simulated H_d (obtained from TRNSYS) versus those obtained from correlation.

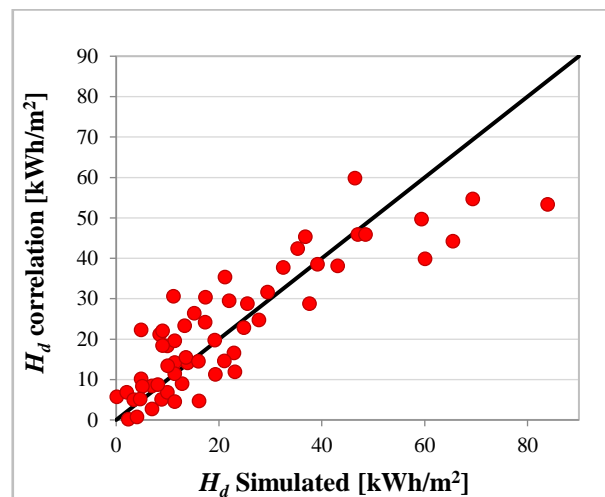


Fig. 7C. Simulated H_d obtained by TRNSYS versus those obtained by correlations.

To better understand the results obtained in this last case, a cluster range was imposed on the clusters previously indicated using a previous equation form (Eq. (7)); in this way it was possible to identify the following solutions for three general and extensive correlations (Table 8C):

Table 8C

θ_i values of the generic H_d correlation between nine parameters based on cluster classification.

θ_i	HDD		
	<2550 Cluster 1	2551-4200 Cluster 2	>4201 Cluster 3
k	6.5879	1155.59	-72.8245
θ_1	0.0115	-0.2954	0.0112
θ_2	24.643	-45.1637	45.2433
θ_3	14.498	2490.46	43.5629
θ_4	-12.722	-3313.56	18.9247
θ_5	-22.463	-492.338	-416.241
θ_6	33.237	225.87	123.892
θ_7	-0.0002	-0.0001	-0.0001
θ_8	-1.0471	109.122	17.812
θ_9	-0.0032	1.7878	-0.0311
R²	0.886	0.973	0.995

In Figs. 8C, 9C and 10C it is possible to observe the correlation degrees and the residual values pertaining to the first, second, and third clusters, respectively.

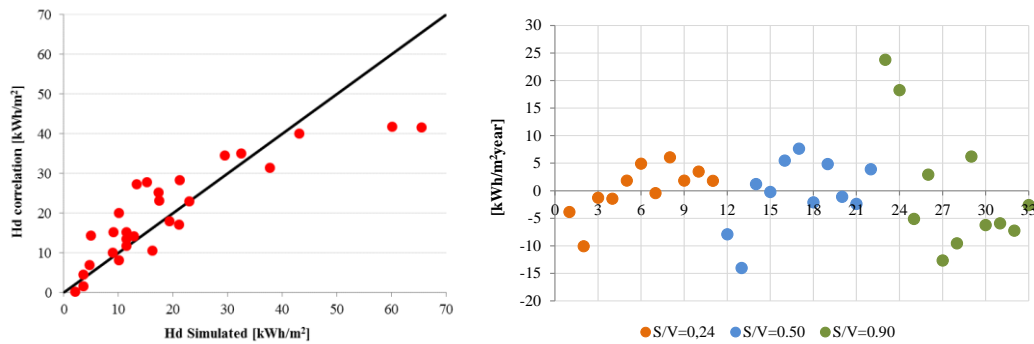


Fig. 8C. Correlation degree and residual values for cluster 1.

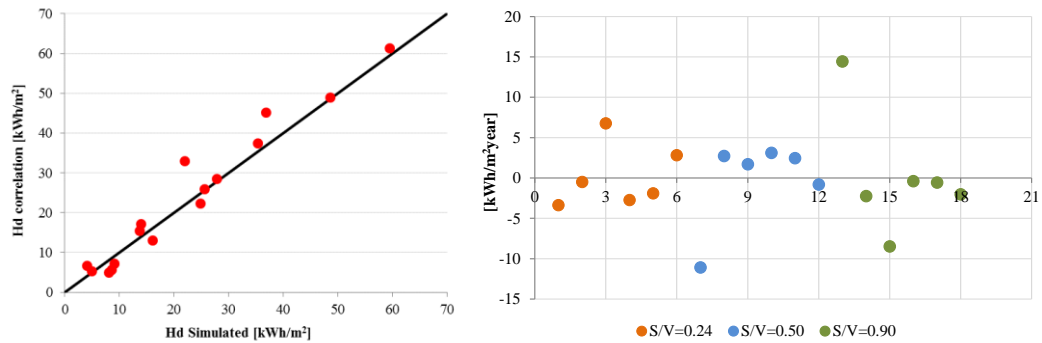


Fig. 9C. Correlation degree and residual values for cluster 2.

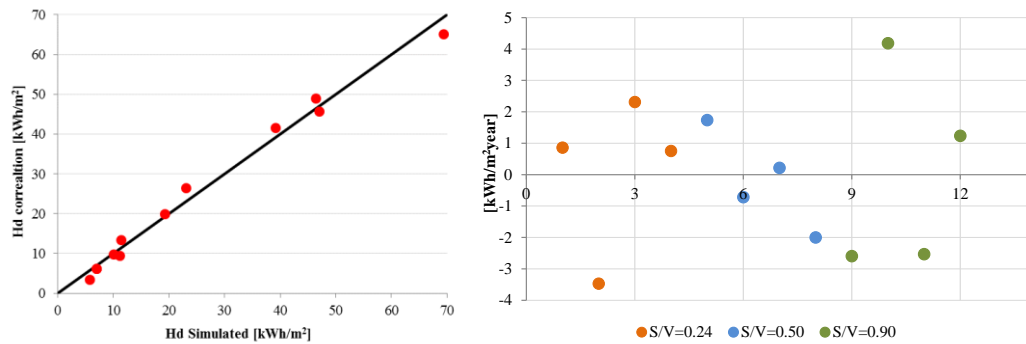


Fig. 10C. Correlation degree and residual values for cluster 3.

In all cases, the data obtained from TRNSYS simulations and the H_d values obtained from correlations are in accordance. The correlation coefficients are high for all clusters and are 0.886, 0.973 and 0.995, respectively.

C.5 MLR ENERGY PREDICTIVE TOOL FOR THE ITALIAN BUILDING STOCK

To provide an improved tool that allows the prediction of overall building energy demand immediately in any situation and boundary conditions, it was evaluated the applicability of a MLR analysis in the Italian context with the possibility to determine some correlation that are able to evaluate also the cooling and overall energy demand of any non-residential building. This context was chosen because of the high cooling thermal load required and the deep knowledge of the Italian legislation on the subject.

Thanks to the availability of a wider and more general database, in this case built through the application of a parametric simulation of 1560 simulations on 195 scenarios implemented in the TRNSYS; this alternative approach could be applied with optimal results using the strong correlations between the dependent and selected explanatory variables. [6].

As explained in **Chapter B**, the simulated scenarios represent the all possible combination of 13 building model built with different shape factor and thermo-physical parameters located in 5 climatic zones and 15 cities. In this general condition, all main parameters that describe the building thermal energy balance and all thermal energy requirements obtained from the parametric simulations were collected in a matrix of 197 rows and 21 columns (*Annex 3*). The identification of the best variables for calculating the building energy demand with high reliability is guaranteed thanks to preventive input selection performed by means a sensitivity analysis of the calculated Pearson coefficient, which allowed to identify the more correlate parameters with the heating and cooling demand, and so too the optimal input data for determining the building energy requirements.

Fig. 11C shows the flowchart of the main involved steps.

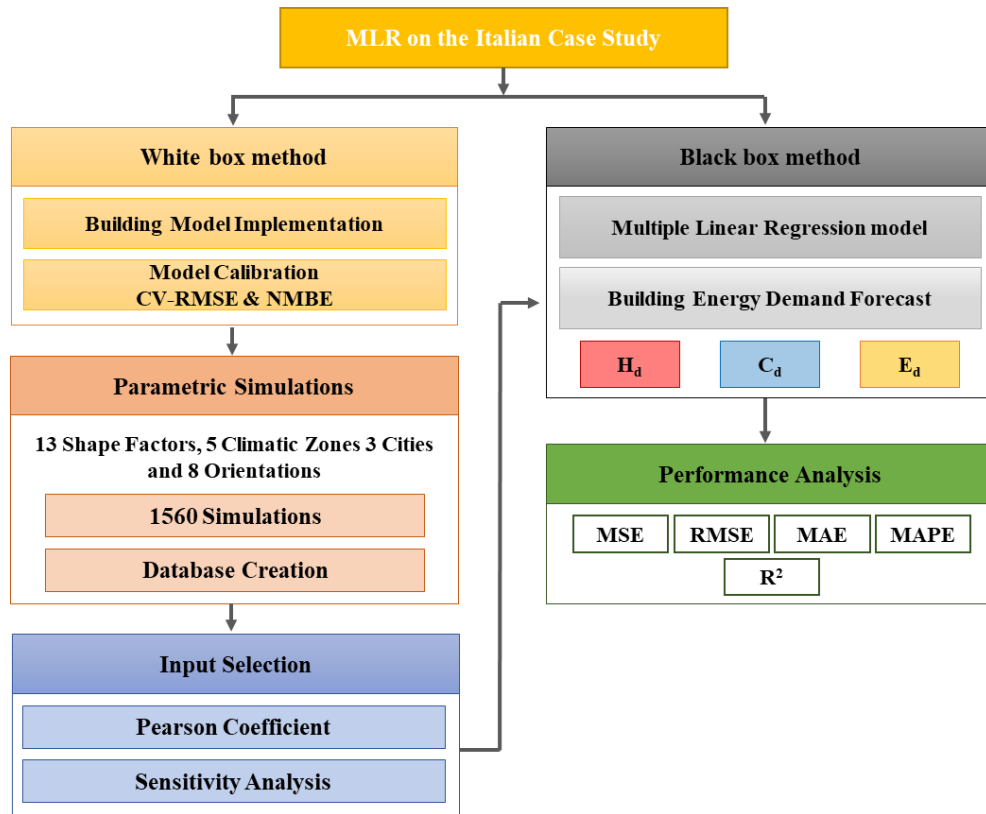


Fig. 11C. Flow chart of the procedure model for the Italian case study.

In order to validate this model, for the procedure were used 85% of the available data for the determination of the MLR model equations, while the remaining 15% was used to evaluate and test the reliability achieved by each relationship. To provide some information on the reliability of each model, a first analysis on the distribution of residuals (differences between expected and predicted values by the models) through their representation in scatter plots was conducted. Despite being a simplistic analysis, this provides the first feedback on the goodness of fit of the built model; a distribution of the residuals around zero is indicative of model accuracy in the prediction of building energy needs. Furthermore, for this case study, an error metric analysis was conducted, considering the error indices explained in *Section A.4*: MAE, MSE, RMSE, MAPE and R^2 . This statistical analysis was applied for all correlation forms proposed: for the heating, cooling and comprehensive energy demand assessment.

C.5.1 Sensitivity Analysis and Input Variable Selection

Owing to the complexity of the building energy balance resolution, selection of the phenomenon explanatory variables is a crucial step in the modelling of predictive models, because the input data determines both the equation form and the partial regression coefficient values that affect the results [7]. This is widely recognised by the scientific community and input data selection is applied in many works: in Lahouar et al. [8], an autocorrelation plot was used to identify the input that most influences the output variables; in Gunay et al. [9] and Kapetanakis et al. [10], the Pearson and Spearman correlation coefficients were applied to identify the strongest correlation between the building load and weather parameters. Other input selection methods are represented by the clustering methods; for example, Yan Ding et al. [11] applied the K-means and hierarchical clustering methods to study the accuracy of cooling load prediction models in office buildings influenced by the input data. In the same manner, David Hsu [12] used the K-means and clusterwise regression methods for an energy needs prediction model. To identify the mean parameters that mostly influence the heating and cooling energy demands of the building stock studied, it was applied the Pearson correlation coefficient (r) analysis. This method, deducing simple correlations between the explanatory variables and the dependent variable, is one of the simplest and fastest methods for selecting and identifying the most influential input variables useful for forecast models [7]. Given two statistical variables, the Pearson correlation r coefficient is defined as the ratio between the covariance of the two variables and the standard deviation of each as indicated in the following (Eq. (8)):

$$r = \frac{\sigma_{xy}}{\sigma_x \cdot \sigma_y} \quad (8)$$

where σ_{xy} is the covariance between the x and y variables and is calculated as:

$$\sigma_{xy} = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x}) \cdot (y_i - \bar{y}) \quad (9)$$

σ_x and σ_y are the standard deviation of each variable and are calculated as:

$$\sigma_x = \sqrt{\frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n}} \quad (10)$$

$$\sigma_y = \sqrt{\frac{\sum_{i=1}^n (y_i - \bar{y})^2}{n}} \quad (11)$$

The r coefficient measures the linear correlation between the two analysed variables and it may assume a value between $(-1 < r < 1)$; the value 1 represents a total positive linear correlation, the value -1 indicates a total negative linear correlation and 0 means that there is not a linear correlation. It was calculated the r coefficient for each parameter representative of the energy database constructed in **Chapter B**, *Section B.7.3* and then applied a sensitivity analysis to identify those parameters that affect the building thermal balance more and that can be used in the MLR model. In the following graphs (Figs. 12C to 17C), the linear regression of the main variables affecting the dynamic behaviour of the *Ideal Building* model both for heating and cooling energy demand are illustrated: *HDD*, *CDD*, outdoor temperature (T), S/V , glazed surface (S_w), opaque surface (S_{op}) and internal gains (Q_G). For each trend, the R^2 and the r coefficients are also displayed.

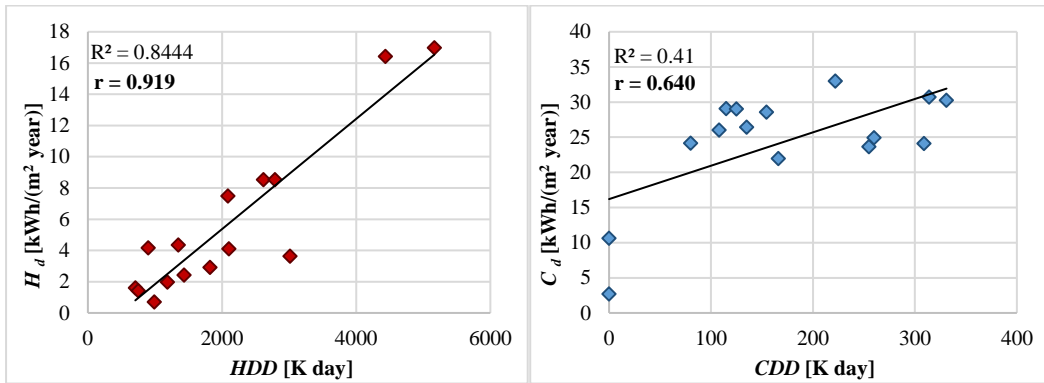


Fig. 12C. Linear regression analysis between the H_d and HDD (a) and between the C_d and CDD (b).

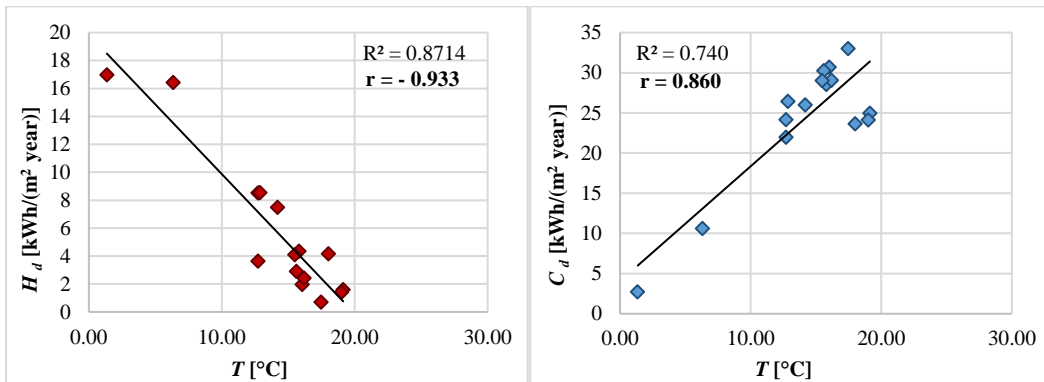


Fig. 13C. Linear regression analysis between the H_d and T (a) and between the C_d and T (b).

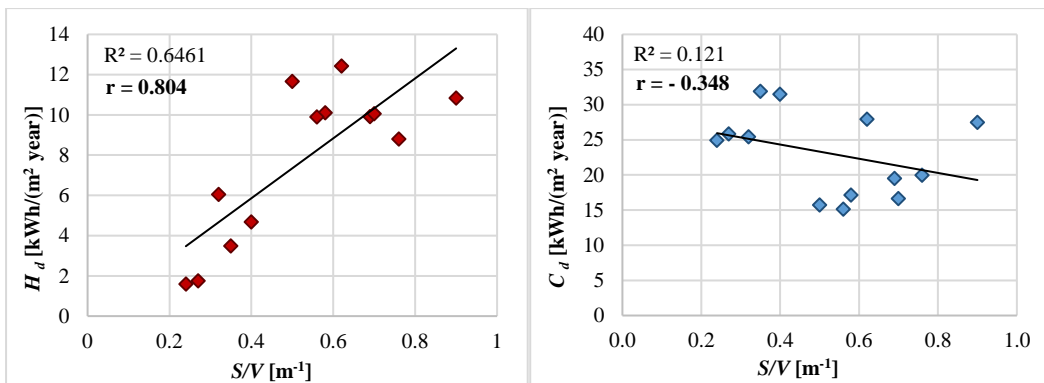


Fig. 14C. Linear regression analysis between the H_d and S/V (a) and between the C_d and S/V (b).

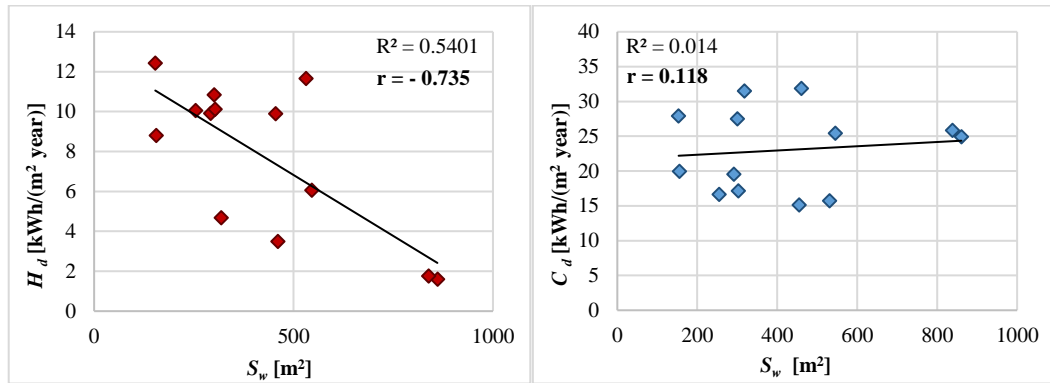


Fig. 15C. Linear regression analysis between the H_d and S_w (a) and between the C_d and S_w (b).

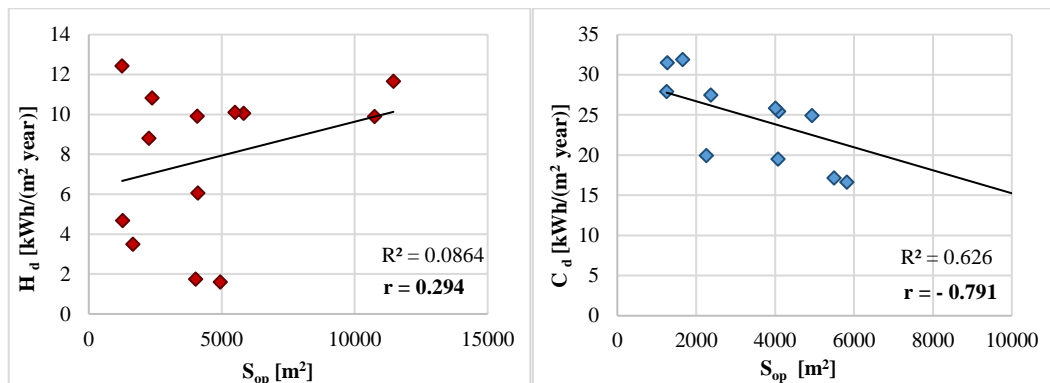


Fig. 16C. Linear regression analysis between the H_d and S_{op} (a) and between the C_d and S_{op} (b).

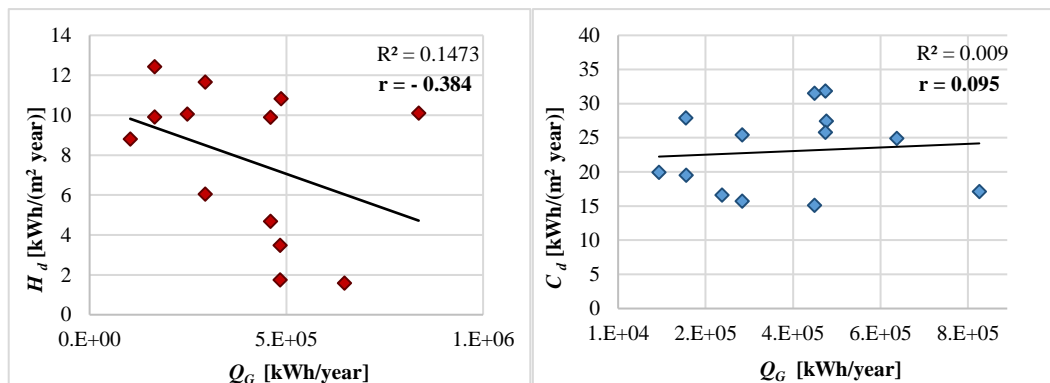


Fig. 17C. Linear regression analysis between the H_d and Q_G (a) and between the C_d and Q_G (b).

A first criterion for the identification of the significant variables for the studied phenomenon could be that of sorting the variables in descending order of the absolute value of the coefficient r and selecting those that have a value of r significantly different from zero. Another identification criterion is represented by

an empirical rule that (for high value of n) selects those variables in which the value of r is greater than $2/\sqrt{n}$ [13]. In Fig. 18C, sensitivity analysis among the input variables and the heating/cooling energy demand based on the r coefficient is displayed.

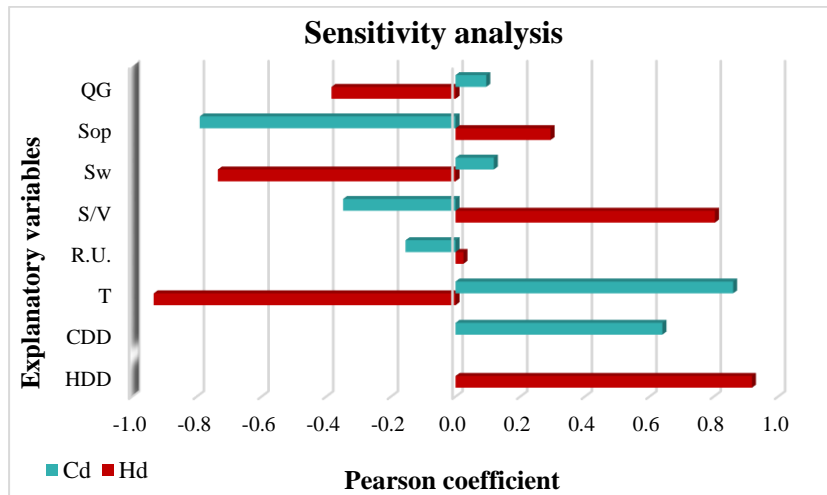


Fig. 18C. Pearson correlation coefficients of input variables for H_d and C_d .

To calculate the r correlation coefficient, the values assumed in each selected city (for the climatic parameters) and the values assumed in each *Ideal Building* model (for the thermophysical and geometric parameters) were considered. In this manner, applying the empirical selection criterion previously described, only the values with an r correlation coefficient greater than 0.55 can be considered for the implementation of the regression model. Based on these considerations and on the sensitivity analysis emphasised in Fig. 18C, the *HDD*, *T*, *S/V* and *Sw* for the heating energy demand determination and *CDD*, *T* and *Sop* for the cooling energy demand evaluation should be selected. However, based on the previous results obtained in Ciulla et al. [14,15] and in D’Amico et al. [16], also for the building cooling load evaluation, it was considered the *S/V* parameter indispensable (*Section A.5*). Instead, because the two climatic indices are a function of the external temperatures, it was decided to exclude the temperature from input variables in the linear regression model because of its redundancy. Further, the determination of *HDD* and *CDD* data, often tabulated in laws and standards, is easier than determining the

average monthly temperatures Regarding the high values of linear correlation assumed by the glazed and opaque surfaces for the heating and cooling energy demand respectively, it is possible to affirm that, fixing all other conditions, with increases of the glazed surface the solar gain increases and obviously H_d decreases and C_d increases.

C.5.2 MLR Evaluation

The investigation of the MLR method allowed the identification of the best correlation form for determining H_d , C_d and E_d . For the heating and cooling demand two correlations were identified for each of them; the first is a function of the weather index and the shape factor, and the second is also a function of S_w for H_d and S_{op} for C_d . Regarding E_d evaluation, it was possible to propose two equation forms that considered HDD , CDD and S/V simultaneously, and another correlation in which the dependence from S_w and S_{op} are also indicated.

C.5.2.1 MLR and Heating Energy Demand Evaluation

The first form of the heating energy demand as a function of HDD and S/V is represented by Eq. (12):

$$H_d = k + \alpha_1 \cdot HDD + \alpha_2 \cdot \frac{S}{V} \quad (12)$$

where

α_1 is the first regression coefficient [kWh/(m² year K day)];

α_2 is the second regression coefficient [kWh/(m year)]; and

k is the intercept [kWh/(m² year)].

The graphical representation of Eq. (12) is plotted in Fig. 19C.

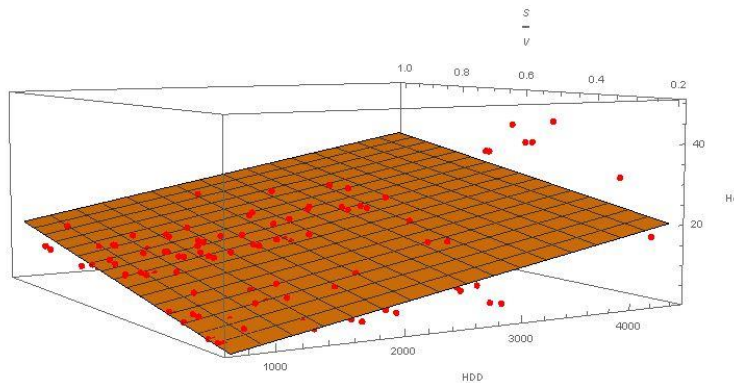


Fig. 19C. Scatter plot and regression plan for the H_d .

While the second form of H_d as a function of HDD , S/V and S_w is represented by Eq. (13):

$$H_d^* = k + \alpha_1^* \cdot HDD + \alpha_2^* \cdot \frac{S}{V} + \alpha_3^* \cdot S_w \quad (13)$$

where

α_1^* is the first regression coefficient [kWh/(m² year K day)];

α_2^* is the second regression coefficient [kWh/(m year)];

α_3^* is the third regression coefficient [kWh/(m⁴ year)]; and

k is the intercept [kWh/(m²year)].

The values of all regression coefficients, intercepts and R^2 for both equations, obtained from the application of the least square method between the expected and predicted outputs for 85% of the database values are collected in Table 9C; in both cases R^2 is close to 0.9.

Table 9C

Partial regression coefficient and R^2 for the H_d .

	k	α_1	α_2	α_3	R^2
H_d	-7.3203	0.0053781	19.4008	-	0.898
H_d^*	-2.3015	0.0053839	14.4288	-0.0056909	0.900

C.5.2.2 MLR and Cooling Energy Demand Evaluation

In the same way, the first form of the cooling energy demand as a function of CDD and S/V is represented by Eq. (14) and is plotted in Fig. 20C:

$$C_d = k + \beta_1 \cdot CDD + \beta_2 \cdot \frac{S}{V} \quad (14)$$

where

β_1 is the first regression coefficient [kWh/(m² year K day)];

β_2 is the second regression coefficient [kWh/(m year)]; and

k is the intercept [kWh/(m² year)].

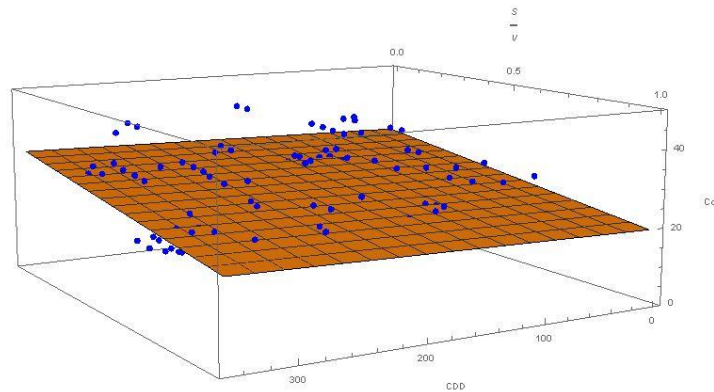


Fig. 20C. Scatter plot and regression plan for the C_d .

The second form is represented by Eq. (15):

$$C_d^* = k + \beta_1^* \cdot CDD + \beta_2^* \cdot \frac{S}{V} + \beta_3^* \cdot S_{op} \quad (15)$$

where

β_1^* is the first regression coefficient [kWh/(m² year K day)];

β_2^* is the second regression coefficient [kWh/(m year)];

β_3^* is the third regression coefficient [kWh/(m⁴ year)]; and

k is the intercept [kWh/(m² year)].

Also in this case, the values of all regression coefficients, intercepts and R^2 for both equations were obtained from the application of the least square method for 85% of the data. It should be noted that some of the data from the sample was purged due to an inconsistency between the value of CDD and the demand value for cooling calculated with the TRNSYS models. More specifically, for the cities where the CDD value was not initially provided, the parameter was calculated according to the procedure explained in **Chapter F**, and in particular for Cortina and Sestriere, the value of CDD was assessed as zero. These values could imply the non-ignition of the cooling system, but since the current standard establishes a standard cooling period valid for all Italian cities without distinction of area, the simulation in TRNSYS has provided an unjustified cooling requirement. Therefore, for the determination of the cooling energy demand, it was eliminated the values linked to the models of the cities of Cortina and Sestriere (26 fewer scenarios). In Table 10C, all parameters of Eq. (14) and Eq. (15) are collected and, in general, the R^2 values are higher than 0.9.

Table 10C

Partial regression coefficient and R^2 for the C_d .

	k	β_1	β_2	β_3	R^2
C_d	30.5767	0.0064923	-11.0297	-	0.906
C_d^*	41.4031	0.0041604	-13.0856	-0.0020440	0.962

C.5.2.3 MLR and Comprehensive Energy Demand Evaluation

To determine the comprehensive energy demand, two different forms of correlation were investigated. As indicated in Eq. (16), the first form considers, as a first explanatory variable, the sum of the HDD and CDD indices and the regression plan is plotted in Fig. 21C:

$$E_d = k + \gamma_1 \cdot (HDD + CDD) + \gamma_3 \cdot \frac{S}{V} \quad (16)$$

where

γ_1 , is the first regression coefficient [kWh/(m² year K day)];

γ_2 is the second regression coefficient [kWh/(m year)]; and

k is the intercept [kWh/(m²year)].

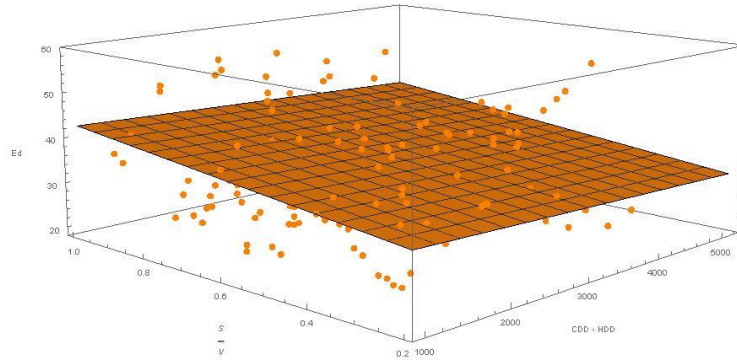


Fig. 21C. Scatter plot and regression plan for the E_d .

The second correlation form, instead, considers the two weather indices in two different explanatory variables (Eq. (17)):

$$E_{d1} = k + \gamma_1 \cdot HDD + \gamma_2 \cdot CDD + \gamma_3 \cdot \frac{S}{V} \quad (17)$$

where

γ_1, γ_2 are the first and second regression coefficients [kWh/(m² year K day)];

γ_3 is the third regression coefficient [kWh/(m year)]; and

k is the intercept [kWh/(m² year)].

Finally, to consider the strong correlation among the energy demand and the S_w and S_{op} parameters, a more complicated correlation is proposed in which the value of E_d is a function of five parameters (Eq. (18)):

$$E_d^* = k + \gamma_1^* \cdot HDD + \gamma_2^* \cdot CDD + \gamma_3^* \cdot \frac{S}{V} + \gamma_4^* \cdot S_w + \gamma_5^* \cdot S_{op} \quad (18)$$

where

γ_1^*, γ_2^* are the first and second regression coefficients [kWh/(m² year K day)];

γ_3^* is the third regression coefficient [kWh/(m year)];

γ_4^*, γ_5^* are the fourth and fifth regression coefficients [kWh/(m⁴ year)]; and

k is the intercept [kWh/(m² year)].

The collection of the regression coefficients and the intercept values for each correlation, and the comparison of the determination coefficients is reported in Table 11C.

Table 11C

Partial regression coefficient and R² for the E_d .

	k	γ_1	γ_2	γ_3	γ_4	γ_5	R²
E_d	32.5597	-0.0006188	10.7855	-	-	-	0.950
E_{d1}	33.6326	-0.0008445	-0.0041735	10.8133	-	-	0.950
E_d^*	49.342	-0.0008874	-0.0058240	-1.35286	-0.0131923	-0.0007279	0.959

The results confirm that the use of *HDD* and *CDD* as a unique explanatory variable or two distinct variables is indifferent, so much so that the determination coefficient is the same; in all cases higher than 0.95.

C.5.3 Results and Discussion of Italian Case Study

The analysis of the results obtained from the application of the MLR model to the evaluation of building energy performance confirms that this procedure is a valid alternative to a more complex model. All correlations identified for the heating, cooling and comprehensive energy demand are characterised by optimal determination coefficients higher than 0.9. In all cases, the more complex correlations (H_d^* , C_d^* and E_d^*) are the best. For these correlations, in the following graphs (from Fig. 22C to Fig. 24C), the residual values calculated for the identification and validation set are displayed. As previously explained, only 85% of the total data was used to determine the correlations, while 15% was used to validate these.

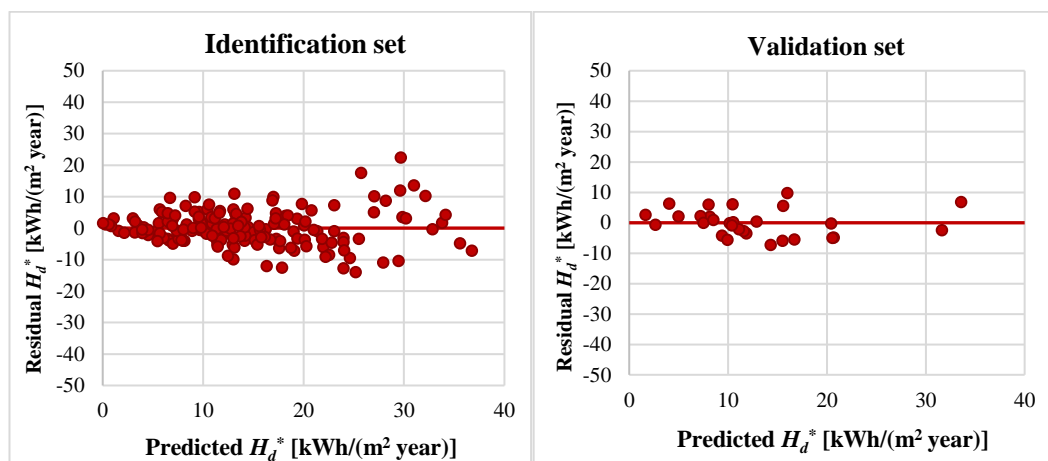


Fig. 22C. Residual trend of H_d^* correlation for identification and validation set.

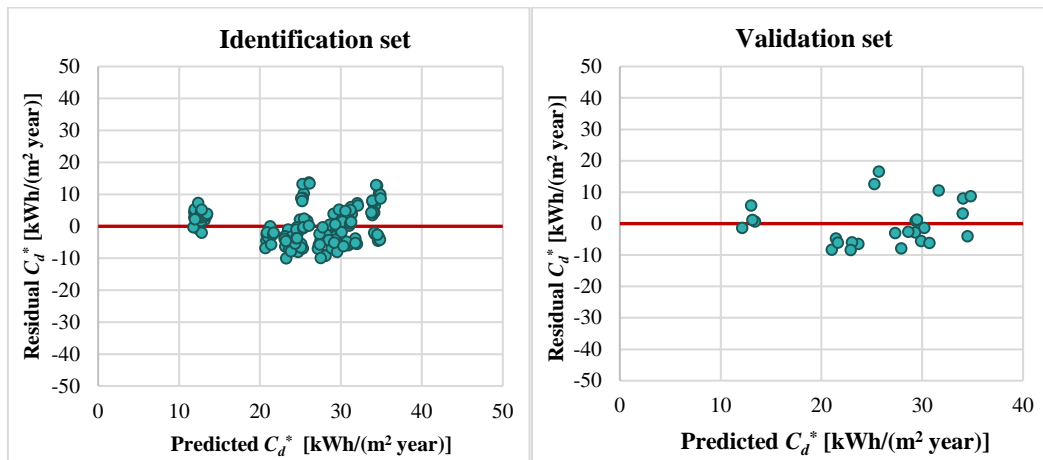


Fig. 23C. Residual trend of C_d^* correlation for identification and validation set.

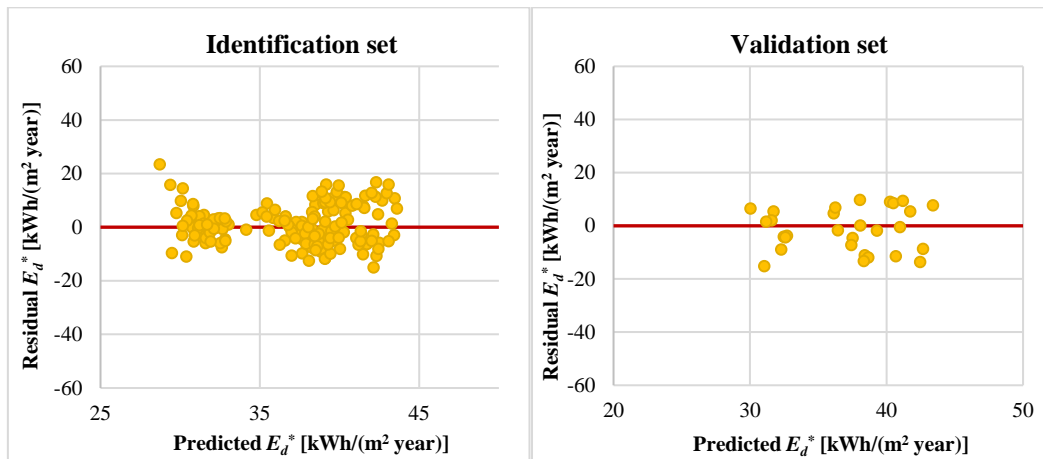


Fig. 24C. Residual trend of E_d^* correlation for identification and validation set.

Simply, a residual is the error in a result and in these cases the value is between $\pm 20\%$, both in the identification and validation sets. In Fig. 22C, the residual trends of H_d^* correlation for all data from the identification and validation set are plotted, whereas in Fig. 23C, there are the residual trends of C_d^* correlation. In this second case, the data sample is represented by a lower number of cases because there are no model results related to the cities of Cortina and Sestriere. In Fig. 24C, the residual trends of E_d^* correlation are plotted. In addition to the calculation of R^2 values, to validate the reliability of the MLR models, four other statistical errors were calculated: the MSE, MAE, RMSE and MAPE. In Fig. 25C, the statistical analysis of the error based on the validation dataset is represented.

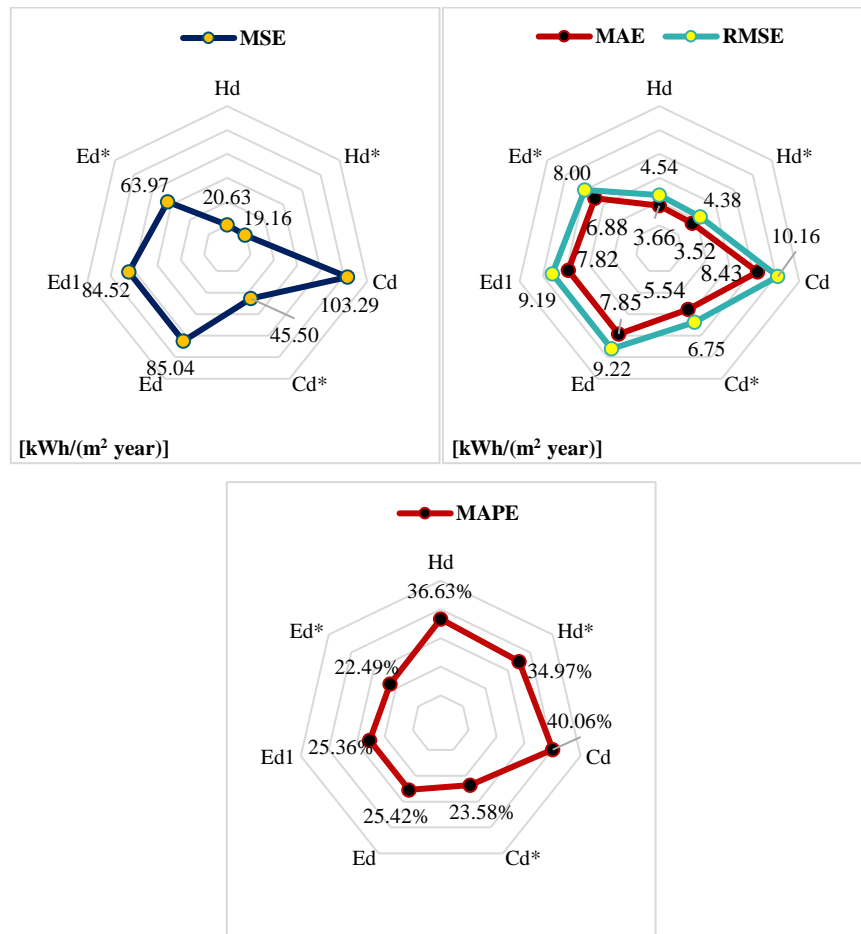


Fig. 25C. Statistical analysis of the Validation set for the MLR models.

The MSE distribution highlighted as the best performance is related to the heating energy demand correlations (Eq. (12) and Eq. (13)), while the worst is the cooling energy demand C_d (Eq. (14)). Among the energy comprehensive correlations, the best is E_d^* (Eq. (18)). The same considerations are valid for MAE and RMSE. As for MAPE, the best results are indicated by E_d^* , while the heating energy demand correlations are less efficient. Generally, in all cases, the solution E_d^* , H_d^* and C_d^* are the best correlations for solving the thermal energy balance of a building; these results are also confirmed by the high R^2 values determined in Section C.5.2. In the following (Table 12C), all correlations and respective statistical errors are collected.

Table 12C

MLR correlations and respectively statistical errors.

Correlations	R ²	MAE	MSE	RMSE	MAPE
$H_d = -7.3203 + 0.0053781 \cdot HDD + 19.4008 \cdot \frac{S}{V}$	0.90	3.66	20.63	4.54	37 %
$H_d^* = -2.3015 + 0.0053839 \cdot HDD + 14.4288 \cdot \frac{S}{V} - 0.0056909 \cdot S_w$	0.90	3.52	19.16	4.38	35 %
$C_d = 30.5767 + 0.0064923 \cdot CDD - 11.0297 \cdot \frac{S}{V}$	0.91	8.43	103.3	10.16	40 %
$C_d^* = 41.4031 + 0.004604 \cdot CDD - 13.0856 \cdot \frac{S}{V} - 0.002044 \cdot S_{op}$	0.96	5.54	45.50	6.75	24 %
$E_d = 32.5597 - 0.0006188 \cdot (HDD + CDD) + 10.7855 \cdot \frac{S}{V}$	0.95	7.85	85.04	9.22	25 %
$E_{d1} = 33.6326 - 0.0008445 \cdot HDD - 0.0041735 \cdot CDD + 10.8133 \cdot \frac{S}{V}$	0.95	7.82	84.52	9.19	25 %
$E_d^* = 49.342 - 0.0009 \cdot HDD + -0.0058 \cdot CDD - 1.3527 \cdot \frac{S}{V} - 0.0132 \cdot S_w - 0.0007 \cdot S_{op}$	0.96	6.88	63.97	8.00	22 %

As explained previously, the more complicated correlations are characterised by better quality and reliability; in general, the high value of R² and the low values of MAE and RMSE justify the use of the MLR methodology as a good alternative for determining the building energy performance. The MLR model represents a simple and immediate tool which can solve a complex problem, such as the building energy balance, and can accelerate and help some aspects of energy planning.

C.6 DISCUSSION

The aim of this Chapter was to determine simple and reliable mathematical correlations that allow a preliminary assessment of a non-residential building's energy performance to be in accordance with European energy standards.

Accurately describing a building energy balanced is a complex and composite procedure; an accurate knowledge of the physical phenomena is necessary. A generic thermal energy balance is a function of the climatic context, thermal characteristics of the envelope, orientation of the building, ratio between the opaque surface and glass surface, and many other variables. The selection of the most suitable model for solving a problem, like the building thermal balance, is important

because it allows to overcome certain limits, in order to identify a generic solution able to interpret any condition and to accelerate the resolution with high reliability. From the review of the main types of models for solving the building energy balance widespread in the literature, a comprehensive analysis with a dynamic software, belonging to the White-Box category, allows the most reliable determination of the building energy performance if the model is correctly developed and calibrated. Indeed, as known, a high reliability is a function of a detailed data collection phase (representative of the model), careful calibration, and the presence of an expert user who knows the software tool language and the studied physical phenomena. These conditions permit the development an accurate model which represents the actual conditions well. However, although a dynamic parametric simulation simultaneously solves several scenarios, it is not able to give a generic indication because each single simulation gives a single specific response for a model under certain boundary conditions and characterised by specific thermophysical choices. Indeed, to generalise the results, it is necessary to analyse all of the thermal energy results obtained from the parametric simulation, to develop a consistent database and to implement one of the several Black or Grey-Box methods. For this reason, in this Chapter it was analysed and applied the MLR method in order to provides planners and designers with a reliable and easy to use tools for a preliminary assessment of the energy demand of non-residential buildings, taking into account the European and Italian regulations on energy efficiency in building. This method allowed a linear relationship among two or more explanatory variables, which represent the inputs of the model and a response variable through a fitting procedure. In this way, the use of a single equation with a good reliability and accuracy determines the thermal energy requirements, allowing the designer to avoid using simulation software, accelerating the entire diagnosis process.

In the first case study, were used the building energy database representative of the European building stock (*Section B.7.2*). First, elaborating the TRNSYS simulation data it was possible to determine seven simple correlations for each surveyed country. With only the buildings shape factor S/V and HDD values, the correlations allow the immediate assessment of the heating energy demand of an office building

with an $R^2 > 0.86$. With a subsequent cluster analysis of all results, three generic correlations were discovered for three different *HDD* ranges; even in these cases the R^2 value was not less than 0.80.

In a second phase, it was investigated a more complex and extensive correlation to ensure the data's generalizability. In this case, the heating energy demand is a function of nine parameters: *HDD*, *S/V*, the window/opaque surface ratio, the window transmittance, the global average of opaque transmittance surfaces, the global average of transmittance, the solar gains, the wind speed, and the yearly number of hours of heating operation. A simple linear correlation is proposed, achieving a satisfactory reliability with R^2 values higher than 0.89; furthermore, applying a cluster analysis, three different correlations as function of *HDD* value were discovered with R^2 values between 0.89 and 0.995. In this way, the knowledge of the shape factor *S/V* and *HDD* values enables engineers to determine the heating energy demand of a non-European building. Finally, by exploiting more data input, these correlations allow for the evaluation of heating energy performance with a very high degree of reliability, but they need a depth data collection phase. In the second case study, with the objective to also explore a correlation able to determine the cooling energy demand it was developed the MLR model based on the Italian case, using the energy database of Italian building stock (*Section B.7.3*).

Furthermore, to simplify and accelerate the data collection phase, but still ensuring a high level of reliability a careful sensitivity analysis on the 1560 simulation results, based on the identification of the Pearson coefficient was performed. This analysis, allowing the identification of the main parameters that influence the building thermal balance during the heating, cooling and entire climatization periods, guarantees a good compromise between the good predicting ability and the ease of use of the calculation tool. As a result, some simple correlations, valid for the entire national territory, were developed knowing only a few groups of well-known parameters, and identifying the heating, cooling and comprehensive energy needs of a building with a high degree of reliability. Indeed, these correlations are characterised by optimal statistical error values; for example, the determination coefficients are higher than 0.9 and the MAE and RMSE are lower than 10

kWh/(m²year). The reliability and flexibility of the energy database allowed the identification of solutions that simultaneously respond to changes in climate and building shape factor, obtaining generic solutions which can explain any possible building topology in any conditions.

The promising results justify the use of MLR as an alternative model, issuing a simple and immediate tool that can solve a complex problem like building energy balance, thereby accelerating and helping some evaluation phases in energy planning on local, national, and international levels, presenting a valid criterion that could be indicated in standards and laws in the field of the building energy performance. This type of approach is not targeted to replace a dynamic simulation model of a building. On the contrary, it represents a decision support tool, easy to use, for a preliminary assessment of energy requirements related to European non-residential building stocks or to a specific country. Thus, the provided correlations could be useful in the field of energy planning at the urban, national and European scale.

MY RELATED PUBLICATIONS

The research covered in **Chapter C** was published in the following international Journals:

8. Ciulla, G., Brano, V. L., & **D'Amico, A.** (2016). Modelling relationship among energy demand, climate and office building features: A cluster analysis at European level. *Applied energy*, 183, 1021-1034.
9. Ciulla, G., Brano, V. L., & **D'Amico, A.** (2016). Numerical assessment of heating energy demand for office buildings in Italy. *Energy Procedia*, 101, 224-231.
10. Ciulla, G., & **D'Amico, A.** (2019). Building energy performance forecasting: A multiple linear regression approach. *Applied Energy*, 253, 113500.

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BUCKINGHAM MODEL

Physical problem



Buildings Thermal Balance

Tool

$$\pi_1 = \frac{H_d \cdot h \cdot \left(\frac{S}{V}\right)}{HDD \cdot C_T} \quad \pi_2 = S_v \cdot \left(\frac{S}{V}\right)^2$$

$$\pi_3 = S_{op} \cdot \left(\frac{S}{V}\right)^2 \quad \pi_4 = \frac{U_w \cdot h \cdot \left(\frac{S}{V}\right)}{C_T}$$

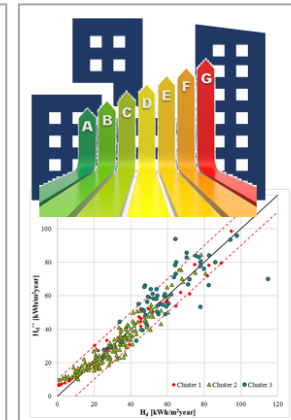
$$\pi_5 = \frac{U_{op} \cdot h \cdot \left(\frac{S}{V}\right)}{C_T} \quad \pi_6 = \frac{U_o \cdot h \cdot \left(\frac{S}{V}\right)}{C_T}$$

$$\pi_7 = \frac{I_s \cdot h \cdot \left(\frac{S}{V}\right)^3}{HDD \cdot C_T} \quad \pi_8 = \frac{Q_g \cdot h \cdot \left(\frac{S}{V}\right)^3}{HDD \cdot C_T}$$

$$\pi_9 = h \cdot V \cdot \left(\frac{S}{V}\right)$$

Buckingham π
Theorem

Solution



Energy Performance
Evaluation

ABSTRACT

In this chapter, a second numerical approach, based on an unconventional use of the Buckingham π theorem, was explored. In detail, this approach allows to determine the energy performance of a building through the application of a non-linear regression model on dimensionless parameters obtained by a dimensional analysis performed by means the Buckingham π theorem. Dimensional analysis is a means of simplifying a physical problem by appealing to dimensional homogeneity to reduce the number of relevant variables. In this way, it was possible to define some dimensionless numbers that synthetically describe the links between the main characteristic parameters of the thermal balance. The proposed methodology has been validated by the comparison of the thermal heating energy demand calculated by the dimensionless parameters and the heating energy demand obtained by detailed dynamic simulations carried out in TRNSYS according to the standards and laws of building energy requirements in seven different European countries. Finally, some numerical correlations that allow for the calculation of the heating energy demand have been derived. The reliability is characterized by an R^2 index greater than 0.9.

NOMENCLATURE

Buckingham Theorem Parameters

D	Independent variable dimension
L	Length (identified as primary dimension) [m]
P	Thermal power (identified as primary dimension) [kWh]
t	Time (identify as primary dimension) [s]
T	Temperature (identified as primary dimension) [K]
π	generic dimensionless parameter

Error and performance parameters

MPE	Mean Percentage Error [%]
R^2	Determination coefficient

BM parameters

C_T	Total thermal capacity [kWh/(m ³ K)]
h	Heating operating hours [h]
HDD	Heating Degree Days [K day]
Q_s	Solar gains [kWh/year]
Q_g	Internal gains [kWh/year]
S_{op}	Opaque losses surface [m ²]
S_w	Window losses surface [m ²]
S/V	Shape factor [m ⁻¹]
U_o	Overall U-value [W/(m ² K)]
U_w	Window thermal transmittance [W/(m ² K)]
U_{op}	Overall opaque thermal transmittance [W/(m ² K)]
v	Average wind speed [m/s]

Other parameters

CDD	Cooling Degree Days [K day]
R_{w-op}	transparent surface-to-opaque surface ratio

Outputs of the models

H_d	Heating energy demand [kWh/(m ² ·year)]
-------	--

D.1 INTRODUCTION

As aforementioned, the energy saving in building is a high priority in developed countries and significant efforts have been made to find and develop alternative way to predict the energy needs. In particular, the evaluation of the heating energy demand in an unconventional way and with an easy to use tool is very important, mostly in the design phase. The current chapter, through the development of a new method, permits a fast preliminary assessment of heating energy demand of non-residential buildings located in Europe, taking into account regulations dictated by law in each considered country [1]. Because in some countries, as Italy, *CDD* has not yet accurately been defined and for others the climate does not require the satisfaction of a cooling load, also in this work, it was analysed only the link between heating energy demand and *HDD*. To achieve the aim of the work, it was investigated an approach to assess the heating energy demand of a high-performance, non-residential building, i.e., applying the Buckingham π theorem. The dimensional analysis represents a good method to simplify a problem by means of the dimensional homogeneity and, therefore, the consequent reduction in the number of variables. Buckingham π theorem is a key theorem that permits to define dimensionless parameters representing the physics of the studied phenomenon [2]. For this reason, is well used for different purposes and, in the literature, it is possible to find some applications such as forecasting, planning, control, diagnostics and monitoring in different fields. For example, Russo et al. [2] used the Buckingham π theorem to define non-dimensional parameters that scale up the modelling of a fuel cell. Toh and Lim [3] applied the Buckingham π theorem, in the same manner, to determine two dimensionless numbers useful for developing two dimensionless correlations able to characterize the heat exchange in a pulsating fluidized bed to a high correlation degree. To develop a forecast model, Salmani and Mahpeykar [4] applied the dimensional analysis to create a method for predicting a droplet radius and wetness fraction in the wet steam equipment design.

To make the concept clearer, similar to the most known dimensional analysis in thermo-fluid dynamics, the identified dimensionless numbers allow for the

determination of the heating energy demand knowing only some lumped parameters always available in energy audits. In detail, it was therefore possible to define some dimensionless numbers ($\pi_1, \pi_2, \dots, \pi_{n-1}$) that summarise the heating energy balance with only some widely known and used parameters.

After a detail description of the Buckingham π theorem and, its application for the solution of the building thermal balance, the steps that conduct to the identification of 9 dimensionless numbers have been described. To identify the numbers that better describe the heating energy demand were used and analysed the results related to data collected in *Annex 2*. In this way, applying a set of criteria, it was possible to identify a set dimensionless numbers that allowed to determine, immediately and without any calculation or use of steady/dynamic software, the heating energy demand with a reliability $> 90\%$.

D.2 METHODOLOGY

As indicated in the following flow chart (Fig. 1D), also in this case to achieve the aim of this research it was necessary to use the reliable building energy database described in **Chapter B**.

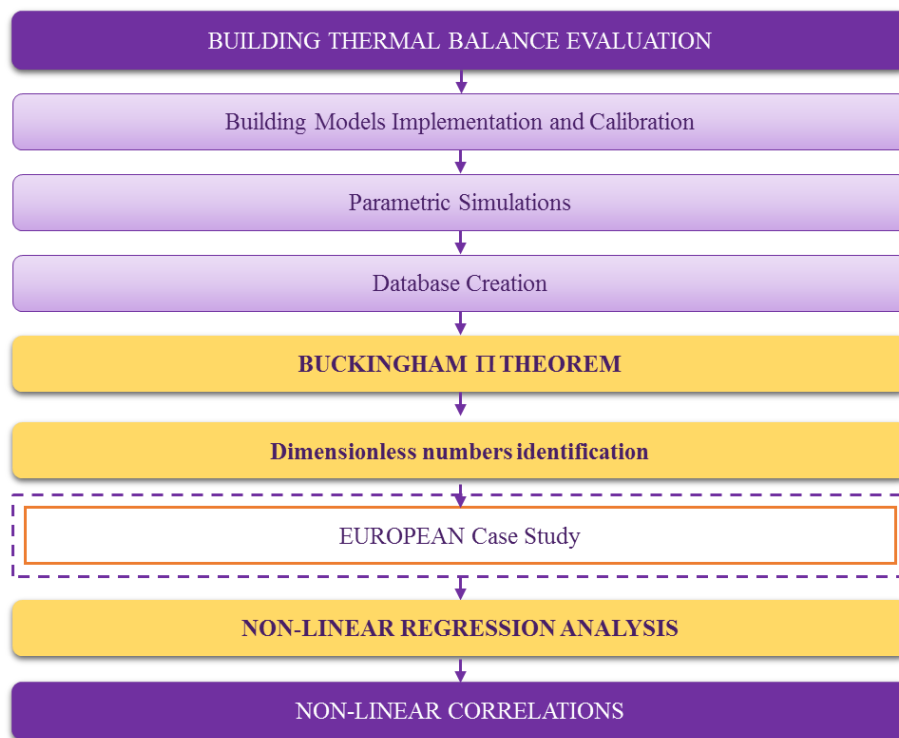


Fig. 1D. Flow chart of the procedure method.

After a detailed description of the Buckingham theorem and of its application concerning the evaluation of the building energy balance, it is explained how to identify 9 *ad hoc* dimensionless numbers that summarize the heating energy balance with only some widely known and used parameters. This approach represents a first and innovative application of the Buckingham π theorem in the field of buildings thermo-physics. Indeed, in literature it is possible to find original applications of the Buckingham theorem concerning materials or building plants, but none concerning the overall thermal balance of a building.

The proposed methodology, by the comparison of the heating energy demand calculated by detailed dynamic simulations carried out in TRNSYS according to

the standards and laws of building energy requirements in 7 different European countries, has been validated. Applying a set of criteria, it was possible to employ a dimensionless number to determine, immediately and without any calculation or use of steady/dynamic software, the heating energy demand with a reliability >90%. All details, numerical manipulations, evaluations and choices are explained in the following sections. Considering the obtained results, the proposed model is a good alternative solution for the quick determination of the heating energy demand of a building with a good level of accuracy and without excessive computational costs or user expertise.

D.3 BUCKINGHAM II THEOREM

The Buckingham π theorem is a means of simplifying a physical problem by appealing to dimensional homogeneity to reduce the number of relevant variables. The premise of dimensional analysis is that the form of any physically significant equation must be such that the relationship between the actual physical quantities remains valid independent of the magnitudes of the base units [5]. Regardless of the application field, the theorem allows writing the original correlation, which governs the physical phenomenon analysed by means of a set of non-dimensional parameters $(\pi_1, \pi_2, \dots, \pi_{n-1})$ obtained by manipulating the original variables. To simplify and schematize the entire procedure, in the following it is possible to identify 7 main steps.

To accomplish that, as explained in [5], first of all, it is necessary to identify a complete set of independent variables (Q_1, Q_2, \dots, Q_n) that are likely to influence the physical quantity of interest Q_0 , which is considered the dependent variable (**Step 1**).

The functional equation can be written as:

$$Q_0 = (Q_1, Q_2, \dots, Q_n) \quad (1)$$

The relationship expressed symbolically in Eq. (1) is the result of the physical laws that govern the phenomenon of interest.

Since the variables describing the physical phenomenon have been identified, the dimensions D for each of them shall be determined. In particular, each variable must be represented by its primary dimensions. For example, if the primary dimensions are mass M , length L and time t , each variable can be expressed as:

$$[Q_i] = L^{l_i} \cdot M^{m_i} \cdot t^{\tau_i} \quad (2)$$

where

the exponents l_i , m_i and τ_i are dimensionless numbers with $i = (0, n)$ and n is the number of independent variables (**Step 2**).

Accordingly, a “complete” and “dimensionally independent” subset $r \leq v$ will be selected from the entire set of identified independent variables, where v is the number of involved fundamental dimensions. These variables will, therefore, be present in each group π_i and, among them, will contain all fundamental dimensions. The remaining variables, including the dependent variable, will be a function of the variables of this subset [2]. The number of the variables r belonging to the “complete” and “dimensionally independent” subset corresponds to the rank of the matrix displayed in Eq. (3). This matrix contains all the variables that describe the physics phenomenon in its column and the fundamental dimensions identified by the entire set of variables in its rows.

The identification of each element inside the matrix is a number that takes into account the number of occurrences of the fundamental dimension in the analysed variable and its position by the sign (**Step 3**):

$$\begin{matrix}
 & Q_0 & Q_1 & \dots & Q_n \\
 D_1 & \left[\begin{matrix} a_{11} & a_{12} & \dots & a_{1n} \\
 D_2 & \left[\begin{matrix} a_{21} & a_{22} & \dots & a_{2n} \\
 \dots & \left[\begin{matrix} \dots & \dots & \dots & \dots \\
 D_v & \left[\begin{matrix} a_{v1} & a_{v2} & \dots & a_{vn} \end{matrix} \right] \end{matrix} \right] \end{matrix} \right] \end{matrix} \end{matrix} \cdot \quad (3)$$

Therefore, the number of dimensionless parameters will be $i = n - r$ and is indicated as $\pi_1, \pi_2, \dots, \pi_i$. Finally, the calculation of each dimensionless parameter π_i is given by multiplying each excluded variable X from the previously identified subset to all included variables S as indicated in Eq. (4) (**Step 4**):

$$\pi_i = S_1^a \cdot S_2^b \cdot \dots \cdot S_r^z \cdot X \quad (4)$$

since π_i is a dimensionless number:

$$S_1^a \cdot S_2^b \cdot \dots \cdot S_r^z \cdot X = D_1^0 \cdot D_2^0 \cdot \dots \cdot D_v^0 \quad (5)$$

The solution of the resulting system identifies the exponents of Eq. (4) and, therefore, determines the dimensionless numbers. The determination of all dimensionless parameters permits writing the entire problem with a group of $n - r$ equations with the following forms (**Step 6**):

$$\begin{cases}
 Q_1 = \pi_1 \cdot Q_2^{a_1} \cdot Q_3^{b_1} \cdot \dots \cdot Q_n^{m_1} \\
 Q_2 = \pi_2 \cdot Q_1^{a_2} \cdot Q_3^{b_2} \cdot \dots \cdot Q_n^{m_2} \\
 \dots \\
 Q_{n-r} = \pi_{n-r} \cdot Q_1^{a_{n-r}} \cdot Q_2^{b_{n-r}} \cdot \dots \cdot Q_n^{m_{n-r}}
 \end{cases} \quad (6)$$

The a, b, \dots, m parameters are arbitrary exponents [6]. This system of equations fully describes the problem. Therefore, by applying the Buckingham π theorem,

π_0 may be expressed by a functional relationship between the other π_i parameters as:

$$\pi_0 = f(\pi_1, \pi_2, \dots, \pi_{n-1}), \quad (7)$$

where π_0 is the dimensionless number defined from the variable Q_0 (**Step 7**).

The π theorem can be seen as a scheme for non-dimensionalisation because it provides a model for computing sets of dimensionless parameters from the given variables, even if the form of the equation is still unknown [7,8].

In the following, the π theorem is applied to the complex physical phenomena that affect the energy balance of a building. Furthermore, the dependent variable object of this study is the heating energy demand H_d . This model allows the determination of some correlations in the form of Eq. (7).

D.3.1 Buckingham π Theorem and Building Thermal Balance

Transmission losses through the envelope (walls, window, roof, and floor), heat losses due to ventilation and infiltration, and energy gains due to solar radiation, the presence of people, and heat from electrical appliances influence the assessment of the heating energy demand of a building. It is a difficult physical problem to resolve owing to the many physical variables involved. In this section, even taking into account the experience gained in the field of buildings thermo-physics, it was decided to consider the following complete set of independent variables. If it is supposed that the determination of the heating energy demand H_d is a function of:

$$H_d = f\left(HDD, \frac{S}{V}, R_{w-op}, S_w, S_{op}, U_w, U_{op}, U_o, Q_s, h, v, C_T, Q_g\right) \quad (8)$$

The list of the 13 parameters considered in Eq. (8) is presented in Table 1D:

Table 1D

List of variables and fundamental dimensions that affect the building thermal balance.

n.	Parameters	Symbol	Units	Fundamental dimensions
1	Heating Energy demand	H_d	[kWh/(m ² year)]	[P/L ²]
2	Heating Degree Days	HDD	[K day]	[T]
3	Shape factor	S/V	[m ⁻¹]	[L ⁻¹]
4	Window Surface	S_w	[m ²]	[L ²]
5	Opaque Surface	S_{op}	[m ²]	[L ²]
6	Window transmittance	U_w	[W/(m ² K)]	[P/(L ² T)]
7	Opaque transmittance	U_{op}	[W/(m ² K)]	[P/(L ² T)]
8	Overall transmittance	U_o	[W/(m ² K)]	[P/(L ² T)]
9	Solar gains	Q_s	[kWh/year]	[P]
10	Operating hours	h	[h]	[t]
11	Average wind speed	v	[m/s]	[L/t]
12	Thermal Capacity	C_T	[kWh/(m ³ K)]	[P t/(T L ³)]
13	Internal Gains	Q_g	[kWh/year]	[P]

In Table 1D, there is no value for R_{w-op} (ratio of glazed surface to opaque surface) because it is a dimensionless parameter. In this way, the number of considered variables is $n = 13$, and the number of variables belonging to the “complete” and “dimensionally independent” subset is $r = 4$ (temperature T , length L , power P and time t). Consequently, the number of independent dimensionless groups is $i = n - r$ or equal to 9. The 9 dimensionless parameters are symbolised $\pi_1, \pi_2, \dots, \pi_9$, and to define these groups, a core of r variables must be chosen. From the above list, were chosen four variables that globally contain all primary dimensions: HDD , S/V , h and C_T . The origin of all dimensionless numbers can be written as:

$$\pi_i = HDD^a \cdot \left(\frac{S}{V}\right)^b \cdot h^c \cdot C_T^d \cdot X \quad (9)$$

that can be rewritten as:

$$\pi_i = T^a \cdot \left(\frac{1}{L}\right)^b \cdot t^c \cdot \left(\frac{P \cdot t}{L^3 \cdot T}\right)^d \cdot X \quad (10)$$

where X represents a variable excluded from the previously identified subset.

In this way, the nine π_i groups and the primary dimension form can be derived and are collected in Table 2D:

Table 2D

List of π_i groups and primary dimension forms.

π_i independent group	π_i in primary dimension form
$\pi_1 = HDD^{a_1} \cdot (S/V)^{b_1} \cdot h^{c_1} \cdot C_T^{d_1} \cdot H_d$	$\pi_1 = T^{a_1} \cdot \left(\frac{1}{L}\right)^{b_1} \cdot t^{c_1} \cdot \left(\frac{P \cdot t}{L^3 \cdot T}\right)^{d_1} \cdot \left(\frac{P}{L^2}\right)$
$\pi_2 = HDD^{a_2} \cdot (S/V)^{b_2} \cdot h^{c_2} \cdot C_T^{d_2} \cdot S_w$	$\pi_2 = T^{a_2} \cdot \left(\frac{1}{L}\right)^{b_2} \cdot t^{c_2} \cdot \left(\frac{P \cdot t}{L^3 \cdot T}\right)^{d_2} \cdot L^2$
$\pi_3 = HDD^{a_3} \cdot (S/V)^{b_3} \cdot h^{c_3} \cdot C_T^{d_3} \cdot S_{op}$	$\pi_3 = T^{a_3} \cdot \left(\frac{1}{L}\right)^{b_3} \cdot t^{c_3} \cdot \left(\frac{P \cdot t}{L^3 \cdot T}\right)^{d_3} \cdot L^2$
$\pi_4 = HDD^{a_4} \cdot (S/V)^{b_4} \cdot h^{c_4} \cdot C_T^{d_4} \cdot U_w$	$\pi_4 = T^{a_4} \cdot \left(\frac{1}{L}\right)^{b_4} \cdot t^{c_4} \cdot \left(\frac{P \cdot t}{L^3 \cdot T}\right)^{d_4} \cdot \left(\frac{P}{L^2 \cdot T}\right)$
$\pi_5 = HDD^{a_5} \cdot (S/V)^{b_5} \cdot h^{c_5} \cdot C_T^{d_5} \cdot U_{op}$	$\pi_5 = T^{a_5} \cdot \left(\frac{1}{L}\right)^{b_5} \cdot t^{c_5} \cdot \left(\frac{P \cdot t}{L^3 \cdot T}\right)^{d_5} \cdot \left(\frac{P}{L^2 \cdot T}\right)$
$\pi_6 = HDD^{a_6} \cdot (S/V)^{b_6} \cdot h^{c_6} \cdot C_T^{d_6} \cdot U_0$	$\pi_6 = T^{a_6} \cdot \left(\frac{1}{L}\right)^{b_6} \cdot t^{c_6} \cdot \left(\frac{P \cdot t}{L^3 \cdot T}\right)^{d_6} \cdot \left(\frac{P}{L^2 \cdot T}\right)$
$\pi_7 = HDD^{a_7} \cdot (S/V)^{b_7} \cdot h^{c_7} \cdot C_T^{d_7} \cdot Q_s$	$\pi_7 = T^{a_7} \cdot \left(\frac{1}{L}\right)^{b_7} \cdot t^{c_7} \cdot \left(\frac{P \cdot t}{L^3 \cdot T}\right)^{d_7} \cdot P$
$\pi_8 = HDD^{a_8} \cdot (S/V)^{b_8} \cdot h^{c_8} \cdot C_T^{d_8} \cdot Q_g$	$\pi_8 = T^{a_8} \cdot \left(\frac{1}{L}\right)^{b_8} \cdot t^{c_8} \cdot \left(\frac{P \cdot t}{L^3 \cdot T}\right)^{d_8} \cdot P$
$\pi_9 = HDD^{a_9} \cdot (S/V)^{b_9} \cdot h^{c_9} \cdot C_T^{d_9} \cdot v$	$\pi_9 = T^{a_9} \cdot \left(\frac{1}{L}\right)^{b_9} \cdot t^{c_9} \cdot \left(\frac{P \cdot t}{L^3 \cdot T}\right)^{d_9} \cdot \left(\frac{L}{t}\right)$

The application of the abovementioned method leads to the definition of a 9-equations system whose resolution allows for the calculation of the value of the exponents for each dimensionless group π_i .

To facilitate the understanding of the applied method, we described the calculation steps for determining the exponents that define the first dimensionless number π_1 :

- a) writing π_i taking into account the fundamental variables:

$$\pi_1 = HDD^{a_1} \cdot \left(\frac{S}{V}\right)^{b_1} \cdot h^{c_1} \cdot C_T^{d_1} \cdot H_d \quad (11)$$

- b) writing π_1 taking into account the primary dimensions:

$$\pi_1 = T^{a_1} \cdot \left(\frac{1}{L}\right)^{b_1} \cdot t^{c_1} \cdot \left(\frac{P \cdot t}{L^3 \cdot T}\right)^{d_1} \cdot \left(\frac{P}{L^2}\right) \quad (12)$$

- c) since π_1 is dimensionless:

$$T^{a_1} \cdot \left(\frac{1}{L}\right)^{b_1} \cdot t^{c_1} \cdot \left(\frac{P \cdot t}{L^3 \cdot T}\right)^{d_1} \cdot \left(\frac{P}{L^2}\right) = T^0 \cdot L^0 \cdot t^0 \cdot P^0 \quad (13)$$

- d) writing the equation system involving the exponents:

$$\begin{cases} T: a_1 - d_1 = 0 \\ L: -b_1 - 3d_1 - 2 = 0 \\ t: c_1 + d_1 = 0 \\ P: d_1 + 1 = 0 \end{cases} \quad (14)$$

- e) solving the system:

$$\begin{cases} T: a_1 = -1 \\ L: b_1 = 1 \\ t: c_1 = 1 \\ P: d_1 = -1 \end{cases} \quad (15)$$

- f) finally, it is possible to define the dimensionless number π_1 :

$$\pi_1 = \frac{H_d \cdot h \cdot \left(\frac{S}{V}\right)}{HDD \cdot C_T} \quad (16)$$

Iterating this method, were obtained all the π_i numbers, resumed in Table 3D.

Table 3D

List of π_i dimensionless numbers.

Dimensionless numbers		
$\pi_1 = \frac{H_d \cdot h \cdot \left(\frac{S}{V}\right)}{HDD \cdot C_T}$	$\pi_2 = S_w \cdot \left(\frac{S}{V}\right)^2$	$\pi_3 = S_{op} \cdot \left(\frac{S}{V}\right)^2$
$\pi_4 = \frac{U_w \cdot h \cdot \left(\frac{S}{V}\right)}{C_T}$	$\pi_5 = \frac{U_{op} \cdot h \cdot \left(\frac{S}{V}\right)}{C_T}$	$\pi_6 = \frac{U_o \cdot h \cdot \left(\frac{S}{V}\right)}{C_T}$
$\pi_7 = \frac{Q_s \cdot h \cdot \left(\frac{S}{V}\right)^3}{HDD \cdot C_T}$	$\pi_8 = \frac{Q_g \cdot h \cdot \left(\frac{S}{V}\right)^3}{HDD \cdot C_T}$	$\pi_9 = h \cdot v \cdot \left(\frac{S}{V}\right)$

Because some sets of variables, such as the thermal transmittances of opaque, transparent and global elements or the opaque and transparent surface losses, are identical from the dimensional perspective, some of the π_i numbers are formally identical (π_4 , π_5 and π_6 or π_2 and π_3). However, to identify which of the dimensionless numbers are more significant in the building energy balance, all of them were analysed. In the following, it is applied the calculation procedure of the above dimensionless numbers to a large number of scenarios, to generalise the calculation of H_d by deriving the type correlations in Eq. (7).

D.4 DATABASE CREATION

For this work the European database built in *Section B.7.3* was used. In detail, as explained in **Chapter B**, 13 calibrated building models were considered and simulated in 21 cities, 3 for each of the 7 Countries selected to consider a generic wheatear condition. Furthermore, to respect the standards guidelines and law values

in each Country, each of the 13 models was modified varying the thermophysical features.

The obtained results and some of the input data to create a matrix of data that contains all 13 variables have been used. The matrix (*Annex 2*) has 273 rows (3 cities in 7 countries for 13 models) and 13 columns that contain the following:

1. Heating Degree Days HDD [K day];
2. Shape factor S/V [m^{-1}];
3. Window surface S_w [m^2];
4. Opaque Surface S_{op} [m^2];
5. Window thermal transmittance U_w [$W/(m^2 K)$];
6. Overall opaque thermal transmittance U_{op} [$W/(m^2 K)$];
7. Overall thermal transmittance U_0 [$W/(m^2 K)$];
8. Solar gains Q_s [kWh/year];
9. Heating operating hours h [h];
10. Total thermal capacity C_T [kWh/($m^3 K$)];
11. Internal gains Q_g [kWh/year];
12. Wind speed v [m/s]; and
13. Heating energy demand H_d [kWh/(m^2 year)].

To standardize all units of measurement, C_T in kWh/ m^3K has been expressed. The choice of a large database with 273 scenarios and 2184 simulations, considering that to obtain an average value of the results each model was also simulated for eight different orientations, arises from the need to get a generic and representative result of European building context, versatile and reliable also for other not analysed cases.

D.5 CORRELATIONS THROUGH DIMENSIONLESS NUMBERS

The value of the dependent variable, the heating energy demand H_d , is the object of the study. As mentioned, the conventional determination of the H_d value requires a deep understanding of the phenomena that govern the energy balance of a building and, eventually, the use of special and expensive dedicated software that requires a long phase of operator training. Having a substantial database available from which it is possible to calculate all the above-defined dimensionless numbers, it was possible to research the existence of correlations similar to those in the field of thermal fluid-dynamics [9]. In detail, because only the expression

$$\pi_1 = \frac{H_d \cdot h \cdot \left(\frac{S}{V}\right)}{HDD \cdot C_T}$$

is function of H_d , it is possible to state that there is a relationship

among π_1 and the other π_i values as:

$$\pi_1 = f(\pi_2, \pi_3, \pi_4, \pi_5, \pi_6, \pi_7, \pi_8, \pi_9) \quad (17)$$

that could be expressed in the following exponential form:

$$\pi_1 = K \cdot (\pi_2^a, \pi_3^b, \pi_4^c, \pi_5^d, \pi_6^e, \pi_7^f, \pi_8^g, \pi_9^p) \quad (18)$$

where K is a constant, and a, b, c, d, e, f, g and p , are exponents.

Using the matrix data in *Annex 2*, it was possible to calculate for each row the respective values of the nine dimensionless numbers. Assuming that between π_1 and the other π_i there is the relationship shown by Eq. (18), it was applied a regression analysis that is a statistical process for estimating the relationship among variables. For this problem of data fitting, it was used the method of least squares and obtained the following results:

$$\pi_1 = \frac{0.00233299 \cdot \pi_3^{0.620096} \cdot \pi_6^{1.464978} \cdot \pi_7^{0.150075}}{\pi_2^{0.592283} \cdot \pi_4^{0.227490} \cdot \pi_5^{0.296717} \cdot \pi_8^{0.159663} \cdot \pi_9^{0.042780}} \quad (19)$$

The correlation shown in Eq. (19) has a high R^2 value ($R^2 = 0.943$). Nevertheless, the use of this correlation implies the calculation of eight dimensionless numbers that are a function of several other variables. It would be more suitable to have a more compact and short correlation for calculating the value of H_d from only two π_i numbers or, rather, from only some characteristic parameters of the building thermos-physics field, as:

$$\pi_1 = Z \cdot \pi_x^m \cdot \pi_y^q \quad (20)$$

where Z is a constant, and m and q are exponents.

Were investigated all possible combinations between π_1 and the other dimensionless π_i , looking for the most correlated triplet. Using the matrix data and iterating the regression analysis already employed to obtain Eq. (19), were listed these combinations with the associated R^2 values in Table 4D. The most reliable combinations ($R^2 > 0.90$) are marked with bold values.

Table 4D

List of the investigated combinations with R^2 values.

Combination	R^2	Combination	R^2	Combination	R^2
$\pi_1 = f(\pi_2, \pi_4)$	0.867	$\pi_1 = f(\pi_3, \pi_6)$	0.936	$\pi_1 = f(\pi_5, \pi_8)$	0.925
$\pi_1 = f(\pi_2, \pi_5)$	0.927	$\pi_1 = f(\pi_3, \pi_7)$	0.774	$\pi_1 = f(\pi_5, \pi_9)$	0.929
$\pi_1 = f(\pi_2, \pi_6)$	0.917	$\pi_1 = f(\pi_3, \pi_8)$	0.659	$\pi_1 = f(\pi_6, \pi_7)$	0.918
$\pi_1 = f(\pi_2, \pi_7)$	0.822	$\pi_1 = f(\pi_3, \pi_9)$	0.682	$\pi_1 = f(\pi_6, \pi_8)$	0.917
$\pi_1 = f(\pi_2, \pi_8)$	0.661	$\pi_1 = f(\pi_4, \pi_7)$	0.848	$\pi_1 = f(\pi_6, \pi_9)$	0.911
$\pi_1 = f(\pi_2, \pi_9)$	0.683	$\pi_1 = f(\pi_4, \pi_8)$	0.866	$\pi_1 = f(\pi_7, \pi_8)$	0.753

Combination	R ²	Combination	R ²	Combination	R ²
$\pi_1 = f(\pi_3, \pi_4)$	0.876	$\pi_1 = f(\pi_4, \pi_9)$	0.866	$\pi_1 = f(\pi_7, \pi_9)$	0.751
$\pi_1 = f(\pi_3, \pi_5)$	0.933	$\pi_1 = f(\pi_5, \pi_7)$	0.928	$\pi_1 = f(\pi_8, \pi_9)$	0.699

In Table 5D, are list the form of the most accurate correlations:

Table 5D

Correlation forms.

n.	Combination	R ²	Correlation form
1	$\pi_1 = f(\pi_3, \pi_5)$	0.933	$19.3647 \cdot 10^{-4} \cdot \pi_3^{0.130757} \cdot \pi_5^{0.951992}$
2	$\pi_1 = f(\pi_3, \pi_6)$	0.936	$6,0250 \cdot 10^{-4} \cdot \pi_3^{0.247225} \cdot \pi_6^{1.009550}$
3	$\pi_1 = f(\pi_5, \pi_9)$	0.929	$4.9897 \cdot 10^{-4} \cdot \pi_5^{0.893489} \cdot \pi_9^{0.146550}$

In the plots of the surfaces in 3D space (π_1, π_x, π_y) that originate from the three best correlations, $\pi_1 = f(\pi_3, \pi_5)$ (Fig. 2D), $\pi_1 = f(\pi_3, \pi_6)$ (Fig. 3D) and $\pi_1 = f(\pi_5, \pi_9)$ (Fig. 4D), show a good fit with the data points.

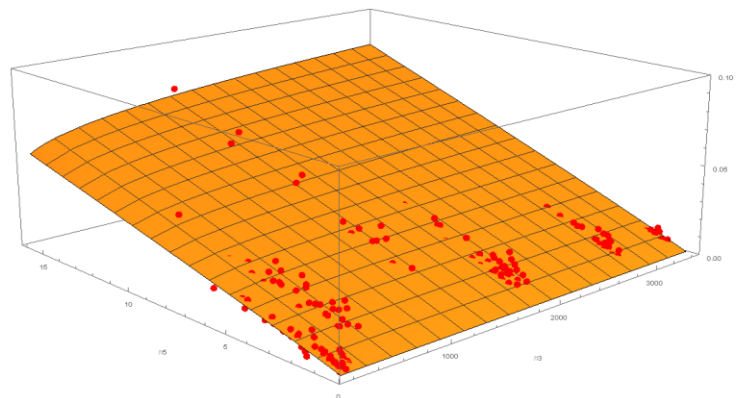


Fig. 2D. Plot of surface area of $\pi_1 = f(\pi_3, \pi_5)$.

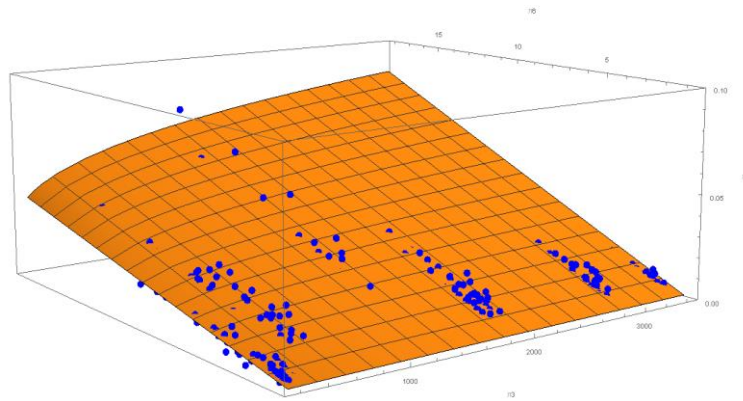


Fig. 3D. Plot of surface area of $\pi_1 = f(\pi_3, \pi_6)$.

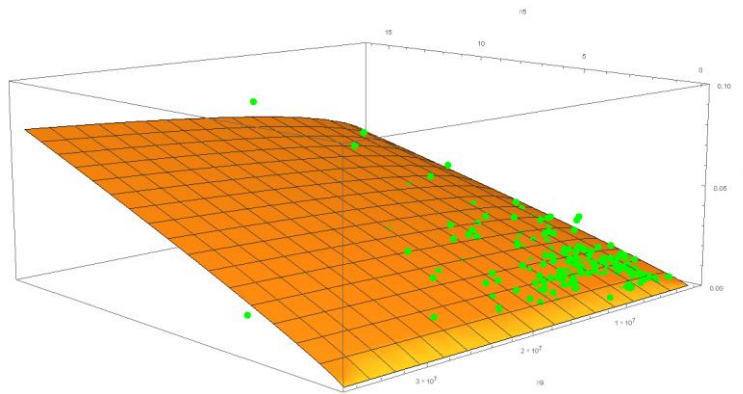


Fig. 4D. Plot of surface area of $\pi_1 = f(\pi_5, \pi_9)$.

D.6 IMPROVEMENT OF THE CORRELATION RELIABILITY USING A CLUSTER ANALYSIS

Similar to the convection problem, it is reasonable to assume that some transition phenomena identify some validity ranges for correlations of the same triplet of π_1 in the building thermos-physics. A detailed analysis of the validity of the correlations presented above is carried out using a comparison between the H_d values obtained from the simulations used to build the database (considered as exact values) and the H_d^* values (considered as approximate value) calculated using the

dimensionless numbers. To retrieve the value of H_d^* from the above correlations, it is sufficient to apply the definition of π_1 :

$$H_d^* = \pi_1 \cdot \frac{HDD \cdot C_T}{h \cdot \left(\frac{S}{V}\right)} = f(\pi_x, \pi_y) \cdot \Psi \quad (21)$$

where Ψ represents the ratio of the parameters among HDD , C_T , h and S/V and π is calculated using one of the equations listed in Table 5D, calculating the heating energy demand employing an approximate value determined by the correlations of π_1 . This model eliminates the need to use specialized and expensive software or to solve the detailed energy balance of a building.

Carrying out a comparison between H_d and its approximated value H_d^* from the best correlations $\pi_1 = f(\pi_3, \pi_5)$, $\pi_1 = f(\pi_3, \pi_6)$ and $\pi_1 = f(\pi_5, \pi_9)$, it is possible to obtain the following distributions (Figs. from 5D to 7D):

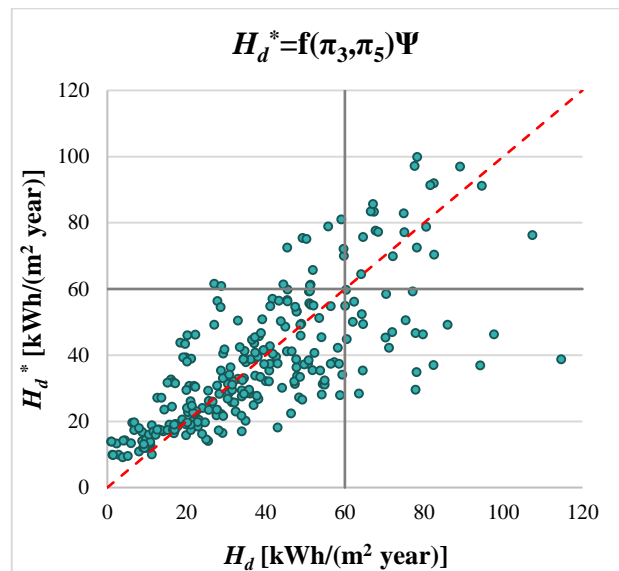


Fig. 5D. Comparison between H_d and approximated H_d^* values for $\pi_1 = f(\pi_3, \pi_5)$.

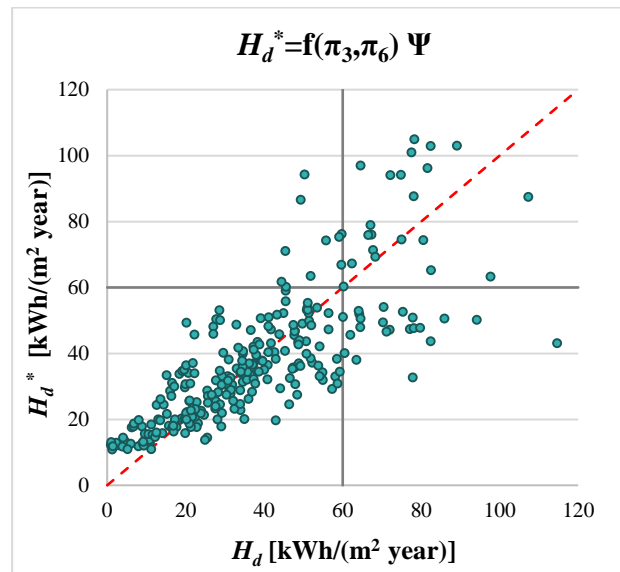


Fig. 6D. Comparison between H_d and approximated H_d^* values for $\pi_1 = f(\pi_3, \pi_6)$.

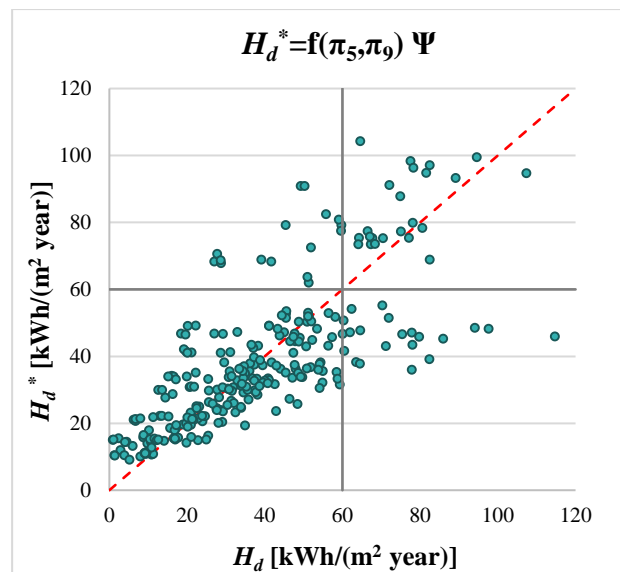


Fig. 7D. Comparison between H_d and approximated H_d^* values for $\pi_1 = f(\pi_5, \pi_9)$.

In each case is reported the 1:1 line that underlines the deviation; in all cases it is possible to see how for $H_d > 60$ kWh/(m² year) (when the buildings are characterised by the worst energy performance) there is a greater points dispersion. Furthermore, employing the general correlation from Eq. (19), it is possible to appreciate the

same behaviour for H_d versus H_d^* (Fig. 8D); the same observation is valid in the generic case reported in Fig. 9D.

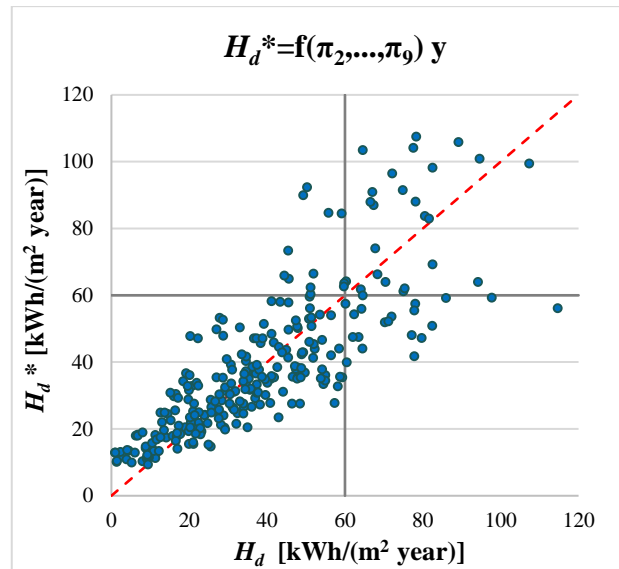


Fig. 8D. Comparison between simulated H_d versus H_d^* calculated considering all π_i .

A more detailed analysis of the best correlation function $\pi_1 = f(\pi_3, \pi_6)$, characterised by an $R^2 = 0.94$, was carried out to determine the best confidence range of H_d value. Trying to minimize the mean percentage error (< 0.25) and trying to minimize dispersion of points (more than 60% of points inside the confidence interval) leads to define a confidence interval of ± 7 kWh /(m^2 year) around the red line.

This assumption gives rise, in the graph of H_d versus H_d^* , to the identification of three regions:

- Red Region (over): the approximated values H_d^* are overestimated;
- Green Region (optimal): the approximated values H_d^* are optimal; and
- Blue Region (under): the approximated values H_d^* are underestimated.

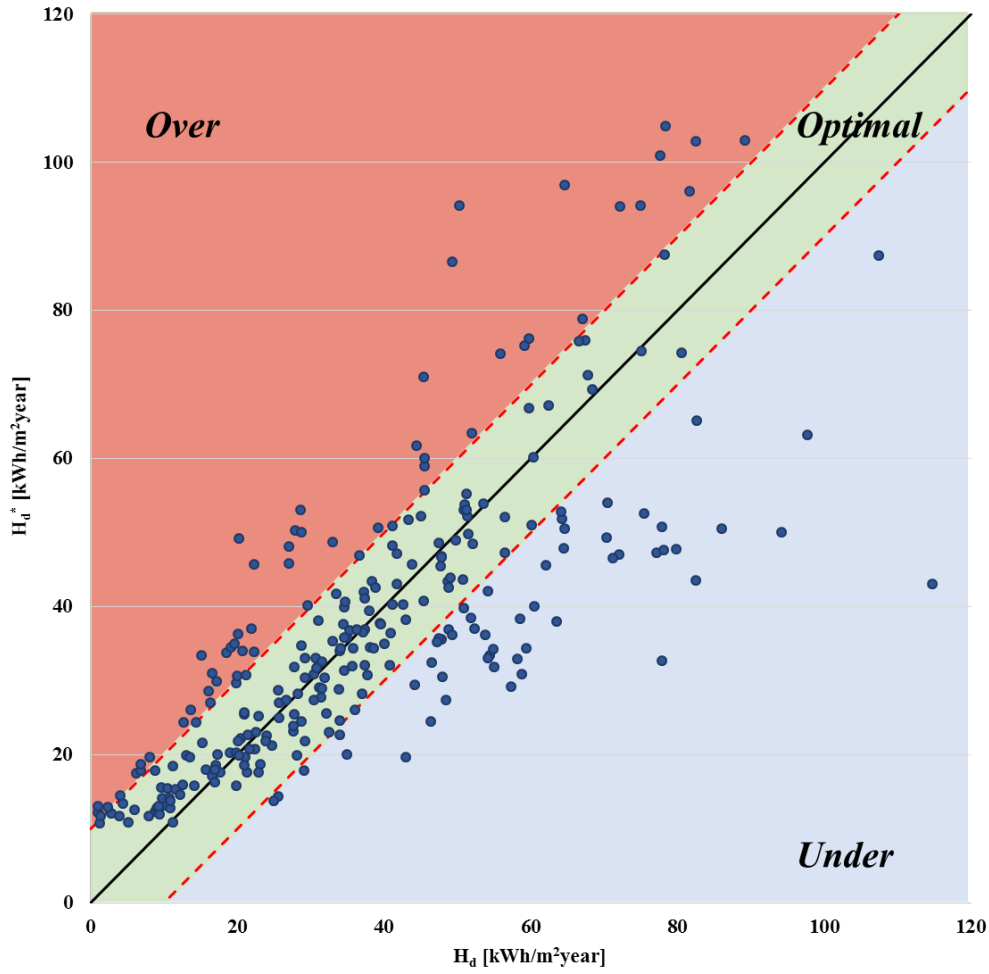


Fig. 9D. H_d versus H_d^* for $\pi_1 = f(\pi_3, \pi_6)$.

Defining the Mean Percentage Error MPE as:

$$MPE = \frac{100\%}{n} \cdot \sum \frac{|H_d - H_d^*|}{H_d} \quad (22)$$

where n is the number of samples, the points within the green region in Fig. 9D are characterised by an $MPE < 25\%$. Fig. 10D presents the 273 case studies split into 3 clusters:

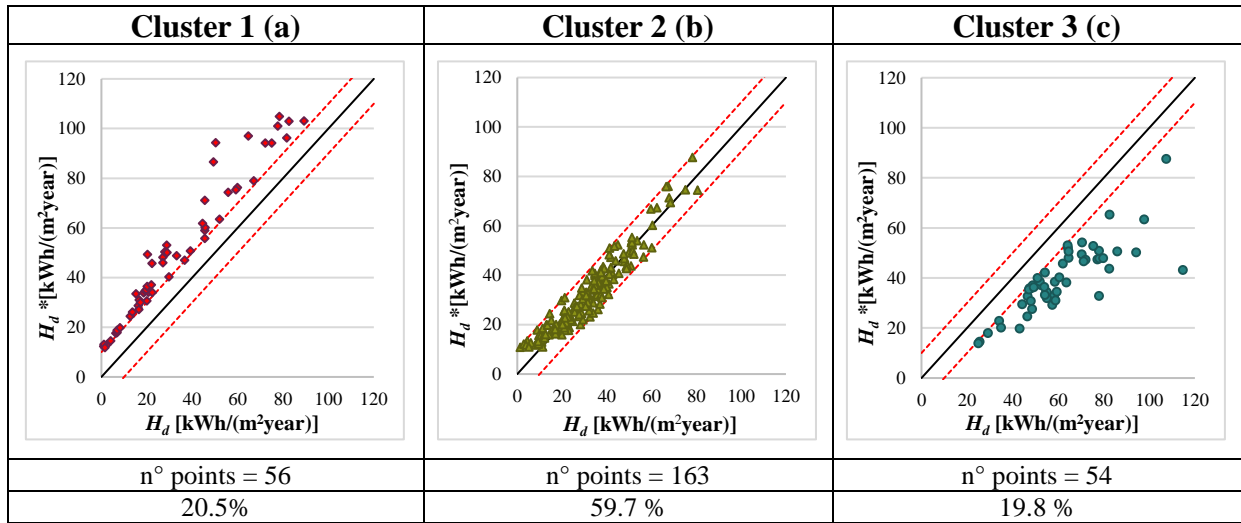


Fig. 10D. Data point distributions of $\pi_1 = f(\pi_3, \pi_6)$ within its cluster.

The analysis of Fig. 9D shows how the single correlation used to approximate the value of H_d does not have global validity, i.e., the correlation $\pi_1 = f(\pi_3, \pi_6)$ over- and under-estimates the values of H_d in 56 and 54 cases, respectively (approximately 20% each). The characteristics of the case studies represented in Fig. 10D have been carefully examined, confirming the existence of transition phenomena, and discovering two criteria that perfectly identify the case studies represented by the data points in Fig. 10Da and Fig. 10Dc.

Generally, the case studies of Fig. 10Da are well identifiable by the following criteria:

$$\left\{ \begin{array}{l} \frac{S}{V} \leq 0.3 \\ U_{op} \geq 0.2 \end{array} \right. \quad \text{or} \quad \left\{ \begin{array}{l} \frac{S}{V} > 0.3 \\ U_{op} \geq 0.2 \\ HDD > 3500 \end{array} \right. \quad (23)$$

while the case studies of Fig. 10Dc are well identifiable by the following criteria:

$$\begin{cases} \frac{S}{V} > 0.3 \\ U_{op} < 0.2 \\ HDD > 3500 \end{cases} \quad (24)$$

By using these criteria emerges that the value of $S/V < 0.3$ is a sort of threshold always very relevant for the determination of the heating energy demand of a building. Case studies related to Fig. 10Da are buildings with an $S/V \leq 0.3$ or with an $S/V > 0.3$ but located in more a severe climate condition. Case studies related to Fig. 10Dc are buildings with an $S/V > 0.3$ but located in colder countries and characterized by a high-insulated envelope. All the remaining case studies pertain to cluster 2. The above-mentioned criteria allow clustering of the 273 study cases into three groups for which it is appropriate to derive three specific correlations of the type $\pi_1 = f(\pi_3, \pi_6)$.

Table 6D

Equation of π_1 correlation for each cluster.

Cluster	Correlation	R ²	Equation form	Validity range
1	$\pi_1 = f(\pi_3, \pi_6)$	0.992	$1.75243 \cdot 10^{-4} \cdot \pi_3^{0.344663} \cdot \pi_6^{1.13441}$	$\begin{cases} \frac{S}{V} \leq 0.3 \\ U_{op} \geq 0.2 \end{cases}$ or $\begin{cases} \frac{S}{V} > 0.3 \\ U_{op} \geq 0.2 \\ HDD > 3500 \end{cases}$
2	$\pi_1 = f(\pi_3, \pi_6)$	0.979	$4.56136 \cdot 10^{-4} \cdot \pi_3^{0.276275} \cdot \pi_6^{1.03367}$	All other cases
3	$\pi_1 = f(\pi_3, \pi_6)$	0.986	$14.4352 \cdot 10^{-4} \cdot \pi_3^{0.205224} \cdot \pi_6^{0.896594}$	$\begin{cases} \frac{S}{V} > 0.3 \\ U_{op} < 0.2 \\ HDD > 3500 \end{cases}$

Table 6D collects the three equations of the π_1 correlations and representative data points in the three clusters; the R² value is > 0.97 in all cases.

Plotting the heating energy demand H_d values obtained by the TRNSYS simulations versus the approximated H_d^{**} values calculated by the three π_1 correlations shown in Table 6D, it is possible to see the following distribution.

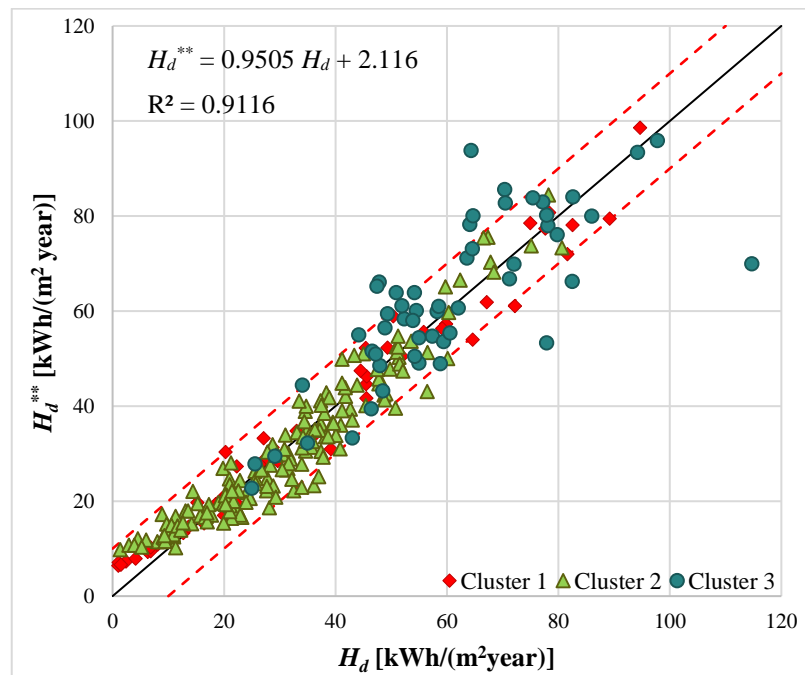


Fig. 11D. H_d versus H_d^{**} obtained from π_1 calculated for each cluster.

The application of the criteria permitted to obtain the points distributions represented in Fig. 11D. All points are included in the confidence range previously indicated with an $MPE < 0.25$. Only some points, generally related to the Cluster 3 are out of the range; they represent buildings with an $S/V > 0.3$ but located in colder countries and characterized by a high-insulated envelope.

Indeed, comparing Fig. 9D and Fig. 11D permits the assessment of the validity of the model: all case studies lie in the optimal range where the approximate values of H_d are very close to the real ones. The high values of R^2 for these final correlations indicate that this approach is very reliable for quickly determining the thermal energy needs of a non-residential building designed for high performance.

D.6.1 Error Analysis

The analysis of the results obtained from the application of the BM underlines that this model can be applied to solve the complex problem of the building thermal balance. More in detail, the use of the regression analysis on dimensionless numbers is characterised by a R^2 value, between the heating energy demand expected and calculated by BM, equal to 0.91. The calculation of the residual values calculated for the entire dataset is displayed in Fig. 12D

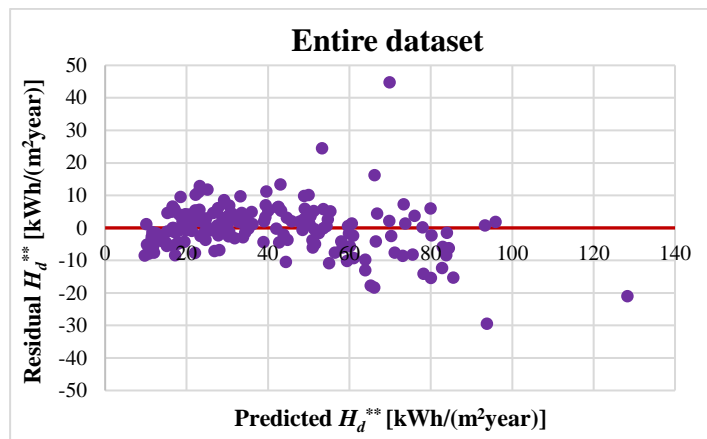


Fig. 12D. Residual trend of H_d^{**} correlation for entire dataset.

To guarantee a comparison with other investigated models, also in this case were defined the four error indexes:

Table 7D

Error indexes for BM.

	MSE	MAE	MAPE	RMSE
BM	[kWh/(m ² year)]	[kWh/(m ² year)]	[%]	[kWh/(m ² year)]
	44.512	4.621	24.669	6.672

D.7 DISCUSSION

In this chapter, to find an alternative methodology that simplifies the calculation of the heating energy demand, a non-linear regression procedure applied after a dimensional analysis through the Buckingham π theorem has been exploited. The application of the Buckingham π theorem allows the determination of 9 dimensionless numbers (π_i) that synthesize and group the principal variables affecting the thermal balance. Only one of these nine numbers (π_1) is a function of the thermal energy needs H_d and is the base to retrieve a simplified assessment procedure.

To validate this model, it was applied the procedure for the definition of the above dimensionless numbers to several scenarios to generalize the calculation of H_d by deriving a correlation in the form of Eq. (7). In detail it was used the database that considers the H_d values obtained from the dynamic simulation of 13 models of non-residential building designed for high-energy performance and located in 3 different cities of 7 European countries (Section B.7.2). Each model was designed according to the national legislation of each country and simulated by the TRNSYS software. The results of the simulations, validated by a careful calibration of the models (Section B.6) have allowed for the generation of the matrix in Annex 1 that for the evaluation of the dimensionless numbers has been used.

It was possible to determine a relationship among π_1 and the other π_i by applying the Buckingham π theorem. In Eq. (19), π_1 is a function of all other π_i with a correlation coefficient $R^2 = 0.94$. Nevertheless, the use of this correlation implies the calculation of eight dimensionless numbers that are a function of several other variables. For a simpler mathematical formula, were investigated more compact and simpler correlations for calculating the H_d value based on only two π_i numbers. In this way, it was possible to identify the best three correlations with $R^2 > 0.929$ (Table 5D). Among the ten discovered correlations, it was paid more attention to the best correlation: $\pi_1 = f(\pi_3, \pi_6)$ with $R^2 = 0.94$. Assuming a good approximation of H_d is in the range of ± 7 kWh/(m²year) with respect to the real value calculated

by TRNSYS, were identified three different regions that overestimate, underestimate or optimally estimate H_d . The case studies belonging to these regions can be defined by specific criteria (Eq. (23) and Eq. (24)). These criteria allow for the clustering of the 273 case studies into three groups for which it is appropriate to derive three specific correlations of the type (Table 6D), improving the reliability of the correlations. The Buckingham π theorem and the described methodology allow the approximation of the H_d values using a single equation that is a function of only HDD , C_T , h and S/V and one dimensionless number π_1 . This approach, validated for non-residential buildings in Europe, permits the assessment of the thermal energy need using only one equation and five principal variables (Eq. 22). Four of these variables (HDD , C_T , h and S/V) are well known and available during any energy audit phase. The number π_1 was determined with a good degree of reliability, greater than 90%, with three correlations (Table 6D).

The proposed model is a good alternative solution for the quick determination of the heating energy demand of a building with a good level of accuracy and without excessive computational costs or user expertise. Indeed, the collection of all data described in *Section D.4* and the detailed implementation of all these data in a software, such as that done in this work using TRNSYS, is not necessary because the H_d value is determined using only one dimensionless number. Furthermore, this approach represents a first and innovative application of the Buckingham π theorem in the field of buildings thermos-physics. This approach will have promising developments in the future. A possible further improvement of this work could be the analysis of the cooling energy demand and/or a multi-objective optimization of the energy demand determination with a comparison of this model with other non-linear transforms such as artificial intelligence.

MY RELATED PUBLICATIONS

The research covered in **Chapter D** was published in the following international Journal:

11. Ciulla, G., **D'Amico, A.**, & Brano, V. L. (2017). Evaluation of building heating loads with dimensional analysis: Application of the Buckingham π theorem. *Energy and Buildings*, 154, 479-490.

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- [1] Ciulla G, Lo Brano V, D'Amico A. Modelling relationship among energy demand, climate and office building features: A cluster analysis at European level. *Applied Energy* 2016;183:1021–34. doi:10.1016/j.apenergy.2016.09.046.
- [2] Russo L, Sorrentino M, Polverino P, Pianese C. Application of Buckingham π theorem for scaling-up oriented fast modelling of Proton Exchange Membrane Fuel Cell impedance. *Journal of Power Sources* 2017;353:277–86. doi:10.1016/J.JPOWSOUR.2017.03.116.
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CHAPTER E

ARTIFICIAL NEURAL NETWORK

MODEL

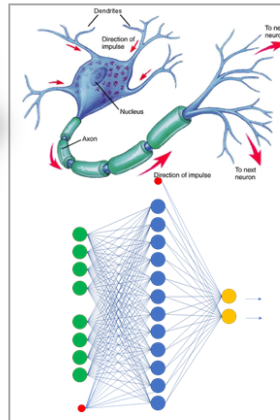
ARTIFICIAL NEURAL NETWORK MODEL

Physical problem



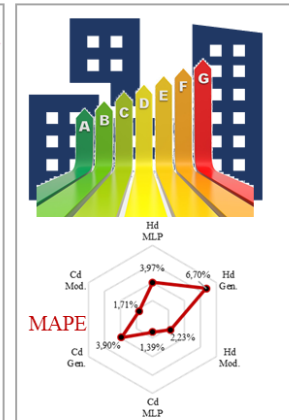
Buildings Thermal Balance

Tool



AI Applications

Solution



Energy Performance Evaluation

ABSTRACT

Among the efforts made to achieve the main objective pursued during the whole period of the PhD, the most difficult challenge was represented by the application of artificial intelligences. In detail, this chapter involves the application and in-depth study of Artificial Neural Networks and Genetic Algorithms that, with different characteristics and roles, work synergistically in order to develop a predictive tool of the building energy performances with great ability to interpret input data and to generalise the result. For these reasons, the suitability of neural networks in developing a tool for thermal energy demand assessment linked to the winter and summer climatization of non-residential buildings was investigated. In this regard, by means of the application on a European and an Italian building-stock, of artificial neural networks optimised by the application of Genetic Algorithms were explored, and were also carefully validated by a deep statistical error analysis. The strengths of the artificial neural networks are the generalisation ability, improvable by upgrading the training database, speed and ease of use, low number of input parameter and low computational cost or knowledge of the thermal balance by the user.

NOMENCLATURE

<u>Acronyms</u>	
AI	Artificial Intelligence
AF	Activation function
ANN	Artificial Neural Network
BEA	Building Energy Analysis
BPS	Building Performance Simulation
DT	Decision Tree
GA	Genetic Algorithm
GD	Gradient Descendent algorithm
HL	Hidden layer
HVAC	Heating, Ventilation, and Air Conditioning
LM	Levenberg Marquardt algorithm
MLP	Multi-Layer Perceptron
MLR	Multiple Linear Regression
QP	Quick Prop algorithm
SR	Step Rule algorithm
SVM	Support Vector Machine
<u>ANN parameters</u>	
A_i	Activation potential
E_w	Error function
h	Hidden layers
k	Scale parameter
K	Tanh-sigmoid function shape
T	Number of iterations
t_i	Output pattern
v_{jk}	Interconnection synaptic weights between j^{th} and k^{th} layers
w_{ij}	Interconnection synaptic weights between i^{th} and j^{th} layers
Δw_{ij}	Variation of the interconnection synaptic weights
x_i	Input data
y_i	Output data
α	Momentum
η	Learning rate
μ	Specific input pattern
θ_i	Neuron activation threshold
<u>Model Parameters</u>	
C_T	Normalised total thermal capacity [kWh/(m ³ ·K)]
CDD	Cooling Degree Days [K day]
HDD	Heating Degree Days [K day]
Q_G	Internal gains [kWh/year]
Q_S	Solar gains [kWh/year]
Q_T	Heat transmission losses [kWh/year]
Q_V	Ventilation losses [kWh/year]
S_{op}	Opaque losses surface [m ²]
S_w	Window losses surface [m ²]
S/V	Shape factor [m ⁻¹]
U	Thermal transmittance [W/(m ² ·K)]
U_0	Overall U-value [W/(m ² ·K)]
U_w	Window thermal transmittance [W/(m ² ·K)]
U_{op}	Overall opaque thermal transmittance [W/(m ² ·K)]
V	Heated volume [m ³]

Error and performance parameters

CV-RMSE	Coefficient of Variation of the Root Mean Square Error
MAE	Mean Absolute Error
MSE	Mean Square Error
RMSE	Root Mean Square Error
MAPE	Mean Absolute Percentage Error
NMBE	Normalized Mean Bias Error
R ²	Determination coefficient

Other parameters

r	Pearson correlation coefficient
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Outputs of the models

C_d	Cooling energy demand [kWh/(m ² year)]
H_d	Heating energy demand [kWh/(m ² · year)]

E.1 INTRODUCTION

A careful analysis of building energy demands in the preliminary design and/or renovation stage allows the technician to identify the criticalities of the building-plant system and to select the most appropriate design choices; furthermore, this action strongly affects the consumption of energy and could improve the energy performance of the building. To simplify the calculation procedures, many efforts are directed to the development of a wide variety of approaches for performing BPS [1]. Among these, a third alternative Black-Box approach to the traditional methods, for the definition of the building energy balance (e.g. those characterised by a steady state approach [2,3] or those characterised by a dynamic approach of the problem [4]), is here presented through the use of evolutionary algorithms that are based on the operating logic of Artificial Intelligence (AI) [5]. Although the evolutionary algorithms do not know in detail the mathematical equations that analytically describe the dynamic behaviour of the systems, they exploit the correlations existing between large amounts of data in order to identify functional connections between input and output. Indeed, one of the most representative strengths of the systems based on this type of model lies in their inherent ability to build a strong relationship between input and output, when in another way this would be difficult, or even impossible. These kinds of models are very useful whenever the phenomenon to be studied is characterised by considerable complexity and interdependence of many factors for which the identification, and in particular calibration, of an analytical deterministic and/or statistical (or otherwise) model is rather complicated; furthermore, often these tools are not validated decreasing their reliability. If it is considered that, among the Black-Box methods, there is a greater propensity of the scientific community towards the utilisation of an Artificial Neural Networks (ANNs) instead of MLR model or other numerical approach, support vector machine (SVM) and/or decision trees (DT), the choice to use the ANN as base AI is widely justified. Confirming this, in the building sector, ANNs are applied more often by researchers [6,7] as opposed to other AI methods, owing to their high prediction reliability, interchangeability with

several building energy simulation software, and their ability to overcome the nonlinearity between the inputs' and outputs' energy data. In more detail, ANNs are the most widely used AI models in the application of Building Energy Analysis (BEA) prediction; indeed, several studies have shown that ANNs achieve better results as compared with other approaches [8,9]. The reason for this tendency is also owing to the embedded strengths of ANNs, such as good approximation capabilities and fast processing times [10,11].

A brief review of the state-of-the-art shows that several researchers have applied ANNs to analyse energy applications in buildings. For example, Kalogirou et al. [12] used back propagation neural networks to predict the required heating loads of a building, whereas Ekici and Aksoy [13] used the same model to predict heating loads in three buildings. Olofsson et al. [14] predicted the annual heating demand of small single residential buildings in the north of Sweden. In another work Kalogirou [15] analysed the use of ANN models for simulating the behaviour of heating, ventilation, and air conditioning (HVAC) energy systems and predicting a building energy demand, whereas Fan et al. [16] used machine learning models to forecast next-day building energy consumption for a shopping centre in Hong Kong. In the Canadian residential sector, Aydinalp et al. estimated and simulated consumptions of space heating, domestic hot water and appliances, lighting, and cooling energy using an ANN by [17,18]. Similarly, Kialashaki et al. [19] applied ANN models to determine the energy demand of a residential sector in the United States. Recently are several review papers [20,21] in which it is possible to compare different predictive models for building energy consumption prediction, underling as the ANN are in most cases the best solution to help the energy planning and management.

The main advantage of the ANN is its ability to determine the relationships between different variables without any assumptions or any postulate of a model, overcoming the discretisation problem. An ANN is constituted by a group of units called “neurons” that are analogous to human neurons. All neurons are connected to each other by synaptic weights, which are identified by an inductive learning process through the presentation of input and output patterns. A neural network,

instead of being programmed so as to perform specific tasks with respect to a dataset, is trained until it independently learns the relationships between the patterns presented [22]. Neural networks can be identified as a technology offering an alternative model for tackling complex problems or problems that are not well-specified. The power of neural networks in modelling complex problems and in system identification since 1984 has been demonstrated [23,24], encouraging many researchers to explore the possibility of using neural network models in real world applications, such as in control systems, classification, and modelling complex process transformations [25,26].

E.1.1 Contribution of the Work

Based on the previous considerations, in this chapter is proposed the application of ANNs and genetic algorithms (GA) to determine the energy performances of a non-residential building located in any weather conditions and characterised by any geometrical and thermophysical features for any boundary conditions. In detail, as the first was examined the European case study (*Section B.7.2*) in which a predictive model will be developed for the determination of the thermal energy to winter climatization (*Section E.4*), subsequently, an in-depth study will be carried out on the Italian case study (*Section B.7.2*) developing a model that can simultaneously determines the heating and cooling loads (*Section E.5*).

In the two case studies, different topologies of neural networks are developed and suitably optimised by applying a GA, and are evaluated according to the variation of the learning algorithm. The reliability of the model is evaluated by means of a deep statistical error analysis, and is validated by following the guidelines of the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE), i.e. ASHRAE Guideline 14 [27].

The results obtained are excellent, and confirm the full potential of ANNs for building energy performance evaluation.

E.2 METHODOLOGY

To achieve the aim of this application, were followed the main steps indicated in Fig. 1E. As indicated in the **Chapters C and D**, the first part of the research (from the building models implementation and calibration to the database creation, discussed in **Chapter B**) is essential to the development of this alternative tool.

In the current chapter, after a detailed explanation of the third selected method, and a brief description of the principal characteristics and the operation algorithm of the neural network (*Section E.3*), the ANN was applied in the two different building energy databases based on European (*Annex 2*) and Italian (*Annex 3*) contexts (*Sections E.4 and E.5*). In each case study were identified several ANN configurations with different features and design. Furthermore, to improve the quality of the results, each examined ANN was optimised by the application of the GA (*Section E.3.1*).

The high performance of the models (*Sections E.4.3 and E.5.3*) confirms, as this approach is a very reliable alternative model to solve the building thermal balance.

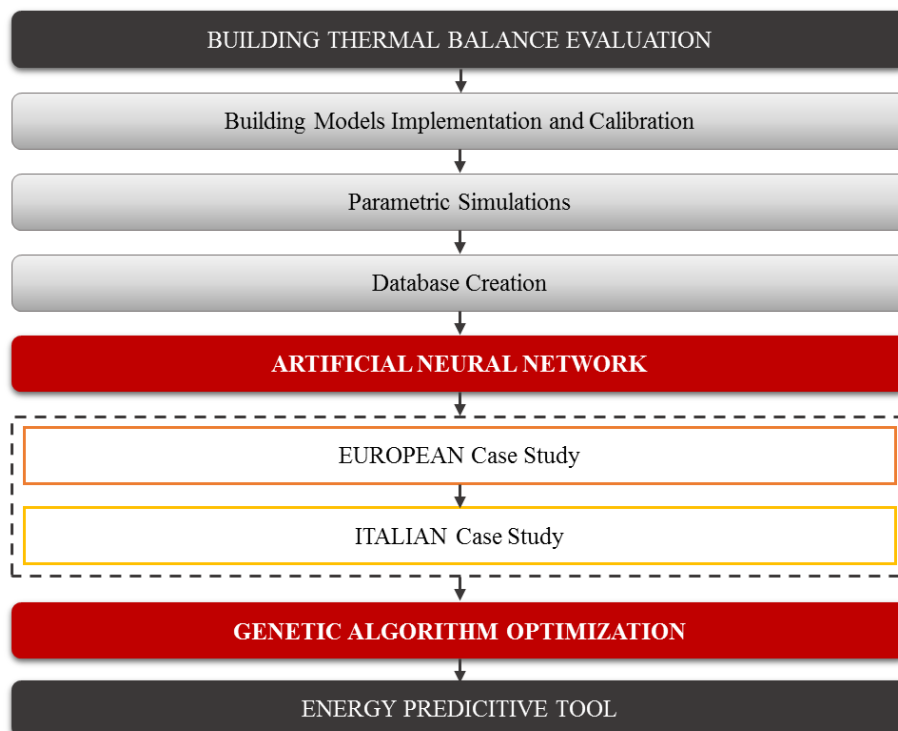


Fig. 1E. Flow chart of the procedure method.

Furthermore, only for the Italian case study, to reduce the number of input variables, it was applied a sensitive analysis for the selection of the explanatory variables (Sections E.5.4 and E.5.5).

In this way a complex problem like an energy balance of the building has been simplified, guaranteeing a high degree of reliability of the results only if a careful evaluation of the performances and a careful selection of the neural network configuration are made.

E.3 ARTIFICIAL NEURAL NETWORK

AI techniques are implemented in several applications due to their strong reasoning, fault tolerance, flexibility and generalization capabilities. As well documented in Zhao et al. [28], ANNs are the most widely employed artificial intelligence models owing to their capability to solve non-linear and complex applications, and are the most effective tool in the field of building energy prediction. ANNs are a mathematical paradigm inspired by the learning behaviour of the human brain, and their structure provides an artificial version of neurons, axons, dendrites, and biological synaptic connections. In order to better understand these systems, a basic understanding of the biological neuron is required. A biological neuron can be seen as a cell (nucleus) that has many inputs (dendrites) and one output (axon). A biological neural network is composed of many neurons whose axons are linked to the dendrites of other neurons through links which are called synapses (Fig. 2E).

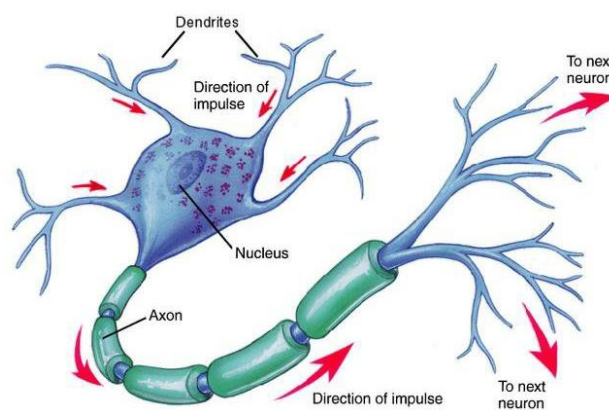


Fig. 2E. Biological neuron [29].

Therefore, an ANN is a collection of individually interconnected processing units acting as parallel-distributed computing networks. Unlike conventional computers that are programmed to carry out specific functions, ANNs, working as human brain-like mathematical models, can learn from examples and remove the need to use complex mathematical formulas or expensive physical models. ANNs are fault tolerant and can work with noisy data, providing high-speed generalization capabilities for unseen input [30]. Furthermore, ANNs have particular adaptation characteristics that also allow the resolution of highly non-linear problems where it is particularly difficult to find analytical formulations that link the input data to the output data [31]. Different to other statistical or parametric methods, ANNs are able to derive non-explicit relationships from a large mass of correlated data by exploiting the high computing capabilities of current computers; in this way, ANNs have become a particularly successful approach to solving different problems in fields that are very different from each other [32]. Application of neuro-computing does not require the provision of particular hypotheses on the investigated physical phenomenon, they can simply be linked to a black box whose internal functioning is not known [33].

In particular, an ANN simulates the behaviour of the human brain in two ways: first, it reaches knowledge through a learning process based on a determination of the existing relationship between submitted input and output pattern pairs; second, the synaptic weights, which are the interconnections between each neuron, memorise the previously acquired knowledge [34]. This ability to learn, regardless of knowledge of the system or of the physical phenomena, is one of their strengths. ANNs have a distributed memory structure, are adaptive, able to modify themselves independently in response to the stimuli received during training, and their learning does not suffer from the existence of possible non-linear links between the input/output pairs used for training. They also possess high elasticity of input interpretation, and extrapolation and generalization capabilities. For these reasons, Haykin [33] defines an ANN as a parallel distributed processor that learns from experience, stores, and makes available its knowledge in forecasting and/or classification tools. The capacity to create parallel structures that allow uninterrupted computing, training, learning, and implementing with high flexibility

[8,35] and their ability to solve non-linear problems makes them preferable over other statistical prediction tools, such as those based on regression models [36]. In the literature, different strategies of neural networks have been developed, depending on the complexity and/or type of the problem to be solved. Example strategies include static feed forward, recurrent, Elman, Hopfield, radial basis, and convolutional neural networks. As suggested in Ahmad et al. [37], a static feed forward ANN with a back propagation learning algorithm is the most generic and widely used network for solving most parts of problems. For this reason, in this work, the authors compare three prediction models based on a static feed forward back propagation ANN. Regardless of the type of ANN, each ANN is composed of simple individual neurons or perceptrons arranged in layers and connected with each other to exchange information. Each perceptron is characterised by an input signal x , a synaptic weight w , and a bias function b , which is the threshold activation value of each neuron and produces an output signal y [36]. Fig. 3E illustrates the individual components of an ANN.

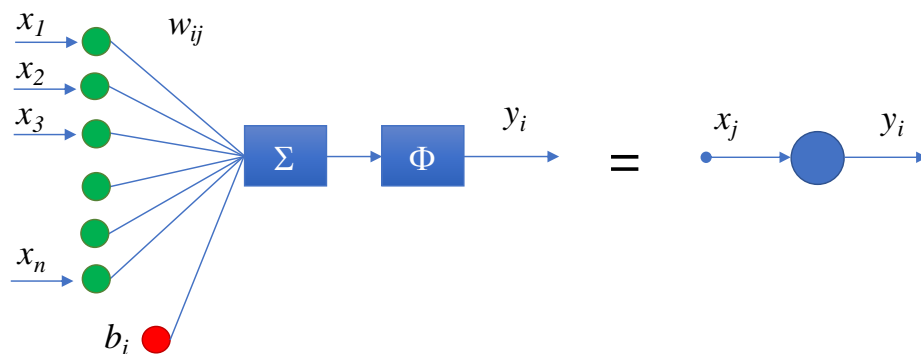


Fig. 3E. Artificial neuron or perceptron scheme.

Each neuron sums up the weighted contributions coming through other synaptic connections, filters them by means of the activation function (AF), and produces a unique response. In general, the effect of an input signal x_j on the i^{th} postsynaptic neuron is simply equal to the product $(w_{jk} \cdot x_j)$ where w_{ij} is the weight of the

corresponding connection. The net input of this neuron, defined as activation potential A_i , is equal to:

$$A_i = \sum_{j=1}^n w_{ij}x_j - b_i \quad (1)$$

where

x_j is the j^{th} input signal to the neuron;

w_{ij} is the synaptic weight of the connection; and

b_i is the bias unit (equal to -1), in other words is the threshold activation value of the neuron.

The output is obtained only if the input signal is propagated through the activation, function as shown in Eq. (2) [38].

$$y_i = \Phi \left(\sum_{j=1}^n w_{ij}x_j - b_i \right) \quad (2)$$

where

y_i is the output signal from the neuron; and

Φ is the activation function, which is able to scale, convert and limit the range that the output signal can take [38].

In fact, the values of input and output variables are often normalised to reduce certain numerical instabilities and to improve ANN performance. Typically, the same activation function is used for all neurons in the network, even if it is not necessary [39]. Among the most common mathematical functions which can be used for activation threshold in ANNs, there are linear, step, sigmoid, and hyperbolic tangents. As already mentioned, the ANN is made up of blocks of neurons connected to each other so as to discover the relationships between correlated data [40–43]. Through the training process, the neural network determines the functions that describe the separation lines between the various categories (decision *boundaries*).

The characteristics of the separation functions are linked to the network weights. At each training step, the weights are updated directly according to the characteristics of the data presented to the network, regardless of any hypothesis about the statistical distribution of the data or knowledge of the physical laws governing the phenomenon.

In this work, it was used two continuous activation functions: linear and hyperbolic tangent functions (tanh-sigmoid) [44].

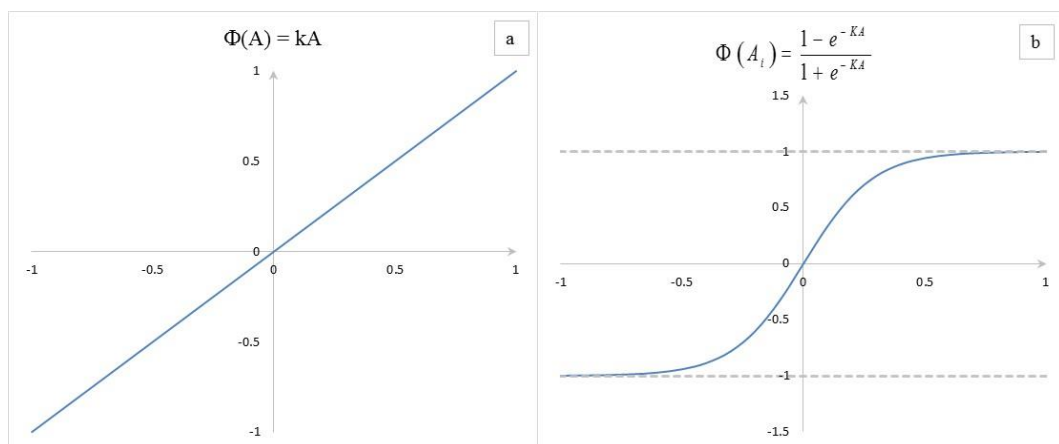


Fig. 4E. Linear (a) and tanh-Sigmoid (b) activation functions.

In a linear function (Fig. 4E.a), a number of such linear neurons perform a linear transformation of the input vector:

$$y_i = \Phi(A_i) = kA_i \quad (3)$$

in which k is a scale parameter.

A tanh-sigmoid function (Fig. 4E.b) instead produces an output value between -1 and 1; furthermore, the tanh-sigmoid function is continuous and differentiable. Generally, the tanh-sigmoid function is defined by the following formula:

$$\Phi(A_i) = \frac{1 - e^{-KA}}{1 + e^{-KA}} \quad (4)$$

where K is a constant that controls the shape of the curve.

As previously explained, the objective of this chapter is to evaluate, by means of ANNs, the H_d and C_d of a generic non-residential building. A base scheme for the analysed networks is illustrated in Fig. 5E, where the links between each neuron are specified.

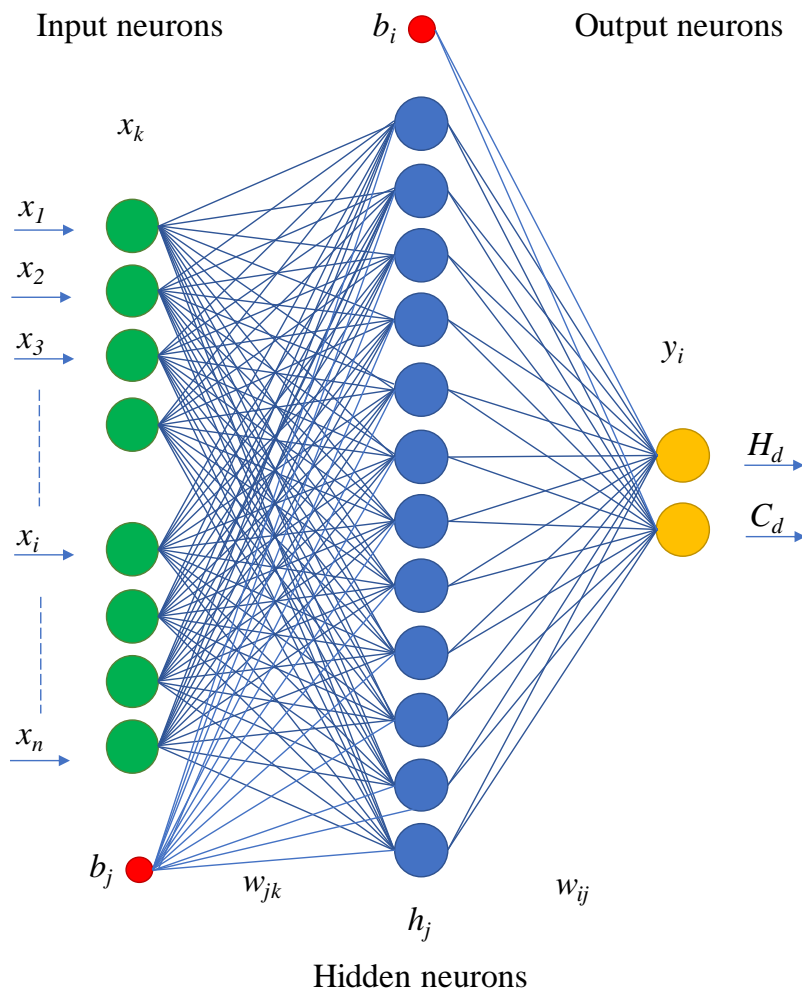


Fig. 5E. Base MLP scheme with only one hidden layer.

Considering a generic network scheme with only one hidden layer (HL), where the output unit y_i receives the w_{ij} synaptic connections from all hidden units h_j , whereas each h_j unit receives the synaptic connections w_{jk} from input unit x_k , the values of each output provided by the ANNs are given by the composition of the

signals coming out of each layer of neurons. The generic output of the individual hidden units is given by:

$$h_j = \Phi_j \left(\sum_{k=0}^{n_k} w_{jk} x_k - b_j \right) \quad (5)$$

while for the output unit:

$$y_i = \Phi_i \left[\sum_{j=1}^{n_j} w_{ij} \cdot h_j - \sum_{i=1}^{n_i} b_i \right] \quad (6)$$

Therefore, the final equation is given by:

$$y_i = \Phi_i \left[\sum_{j=1}^{n_j} w_{ij} \cdot \Phi_j \left(\sum_{k=0}^{n_k} w_{jk} x_k - b_j \right) - \sum_{i=1}^{n_i} b_i \right] \quad (7)$$

where

y_i is the generic output of the ANN;

x_k is the k^{th} input to the ANN;

w_{jk} is the synaptic weight between the input and hidden layers;

w_{ij} is the synaptic weight between the hidden and output layers;

b_j is the bias unit of the hidden neurons;

b_i is the bias unit of the output neurons;

Φ_j is the activation function of the hidden layer; and

Φ_i is the activation function of the output layer.

The ANN knowledge is obtained and stored by means of the final values achieved by the synaptic weights. Indeed, the learning phase is an iterative process, in which these values are dynamically and gradually updated at each iteration or epoch,

through a presentation of patterns related to 85 % of the entire analysed database. Each training pattern is composed of two vectors; the input vector and the real response vector. The initial values of the synaptic weights are randomly assigned within a small range, e.g. [-0.1, 0.1]. In this work, the synaptic weights are updated at the end of the presentation of all database patterns (training for an epoch). The new value of the synaptic weight is obtained by adding the weight modification to the previous synaptic weight configuration, as indicated in Eq. (8):

$$w_{ij}^t = w_{ij}^{t-1} + \Delta w_{ij}^t \quad (8)$$

where

w_{ij} are the weights between the generic i^{th} and j^{th} connections;

Δw_{ij} is the synaptic weight updated; and

t is the epoch number.

To avoid deletion of acquired knowledge owing to the updated Δw_{ij} values, the learning process recursively and gradually proceeds, adding only a fraction of the synaptic weight modification. Indeed, the learning speed is regularised by the introduction of a learning rate coefficient (η) that reduces the Δw_{ij} values. If the learning coefficient ($0 < \eta \leq 1$) rate is high, the network can train very quickly but giving rise to greater inaccuracy; if the learning rate is small, the synaptic weights change more slowly; usually, it decreases during the learning process.

There are two main methods of learning: supervised learning and self-organisation learning. In this work, each ANN was trained following a supervised learning back propagation algorithm, in which the synaptic weights modifying process was performed using MSE minimisation between the ANN response at each iteration and the provided target output for each input pattern. Backward error propagation algorithm is one of the most widely used and reliable learning rules used with Multi-Layer Perceptron (MLP) ANNs. The error function is described by Eq. (9):

$$E_w = \frac{1}{2} \sum_{\mu} \sum_i (t_i^{\mu} - y_i^{\mu})^2 \quad (9)$$

where

y_i is the generic output of the ANN;

t_i is the target output; and

μ is a specific input pattern.

Referring to the generic ANN scheme (Fig. 5E), with only one hidden layer, the error function takes the form of Eq. (10):

$$E_w = \frac{1}{2} \sum_{\mu} \sum_i \left[t_i^{\mu} - \Phi_i \left[\sum_j w_{ij} \cdot \Phi_j \left(\sum_k w_{jk} x_k^{\mu} - b_j \right) - \sum_i b_i \right] \right]^2 \quad (10)$$

Because the objective is to minimise the MSE, the synaptic weights modification must occur in the opposite direction of the gradient E_w . Considering two layers of synaptic weights, the synaptic weight modifications are the following:

$$\Delta w_{ij}^t = -\frac{\partial E_w}{\partial w_{ij}} = \eta \sum_{\mu} (t_i^{\mu} - y_i^{\mu}) \dot{\Phi} \left(\sum_j w_{ij} h_j^{\mu} - b_i \right) h_j^{\mu} + \alpha \Delta w_{ij}^{t-1} \quad (11)$$

$$\Delta w_{jk}^t = -\frac{\partial E_w}{\partial w_{jk}} = \eta \sum_{\mu} \sum_i (t_i^{\mu} - y_i^{\mu}) \dot{\Phi} \left(\sum_j w_{ij} h_j^{\mu} - b_i \right) w_{ij} \dot{\Phi} \left(\sum_k w_{jk} x_k^{\mu} - b_j \right) x_k^{\mu} + \alpha \Delta w_{jk}^{t-1} \quad (12)$$

where

h_j^{μ} is the input signal to the output layer of a specific input pattern;

x_k^{μ} is the input signal to the hidden layer of a specific input pattern;

$(0 < \eta \leq 1)$ is the learning rate coefficient; and

$(0 < \alpha \leq 1)$ is the momentum.

As previously explained, too small learning rate values involve very long training times; on the other hand, very large values cause instability problems and oscillations of the errors. To overcome this problem, the last term of the previous two equations (Eq. (11) and Eq. (12)) provides the inertia to the synaptic weights variation, and is introduced to improve the stability of the learning algorithm. In this way, the α coefficient allows for use of higher η values, and consequently leads to a lower computational time in the learning phase. The back-propagation algorithm is thus characterised by the following steps:

1. Random initialization of the synaptic weights connections;
2. Setting η and α values;
3. Calculation of the signal coming out from the output node (Eq. (7));
4. Calculation of the error function (Eq. (10));
5. Calculation of each synaptic modification Δw_{jk}^f (Eq. (12)); and
6. Modification of weights (Eq. (8)).

The algorithm is iteratively repeated until a minimum set error value is reached. Finally, the introduction of a noise level allows to avoid local minimum condition during the training phase and therefore the inaccurate convergence of the network.

E.3.1 ANN Optimization through the GA Application

GA is a heuristic algorithm based on natural selection and on the principles of biological evolution that is a family of optimization techniques that operate on a population of artificial chromosomes reproduced in a selective way on the basis of the performances of the corresponding phenotypes. During the reproduction process, the chromosomal replication of the best individuals (genotype) is coupled at random and a part of their genetic material is exchanged, further some small random mutations that alter the structure of the genetic code are introduced locally. The new genetic structures then replace the old structures with a new generation. This process continues until a new genotype is born which represents an acceptable solution to the problem

under consideration. GA is based on three main phases: selective reproduction of the best individuals, genetic recombination (crossover) and random chromosome mutation. These operators rely on two important mechanisms necessary to solve the problem: genetic coding and evaluation function (or fitness function). Genetic coding refers to the type of representation that is used to encode problem solutions within artificial chromosomes; while the fitness function judges the performance of each phenotype with respect to the problem to be solved. That is to say, the fitness function plays a role similar to that of the physical environment for biological organisms; provides a numerical value for each population phenotype proportional to the goodness of the solution supply, or a measure of individual performance [44]. The application of GA to the ANN architecture permitted to discover a better combination of number of neurons, type of activation function, weights and so on.

E.4 ANN ENERGY PREDICTIVE TOOL FOR THE EUROPEAN BUILDING STOCK

As performed for the models developed in the previous chapters, this section provides the application of the ANN and the evaluation of its performance applied to the European case study. Consequently, by referring to the database developed in *Section B.7.2*, the ability of the ANNs to predict only the heating consumption of a non-residential building located in any city belonging to the European territory will be evaluated. The database on which the network will be trained will be composed by 12 input columns and one output column (H_d) and 273 lines representing the simulated scenarios.

Regarding the development and training of the ANNs, it was used the Peltarion Synapse software [45], which, to identify the best configuration of the analysed ANNs, performed a GA optimisation. The flow chart representing the main steps of the work are displayed in the Fig. 6E:

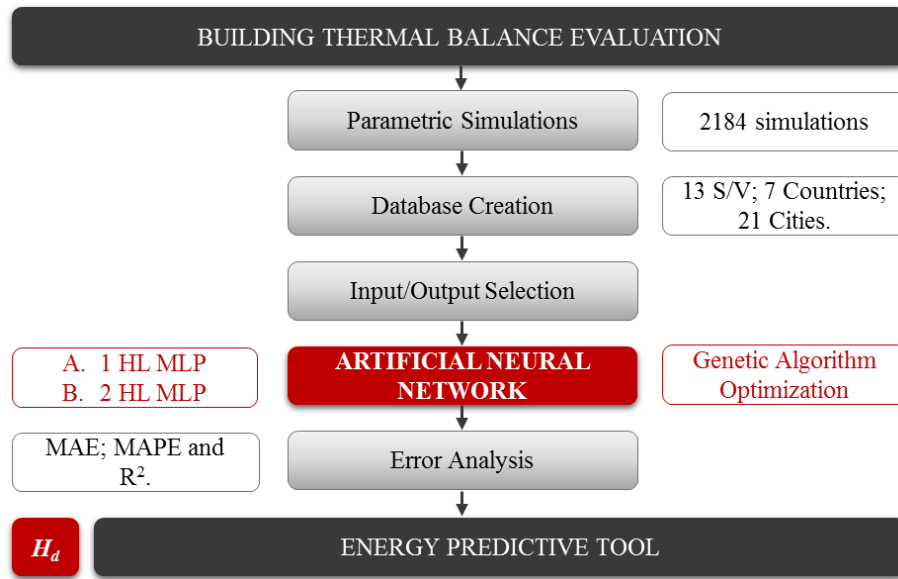


Fig. 6E. Flow chart of the procedure model for the European case study.

E.4.1 Database Creation

Generally, the implementation of an ANN to solve a problem requires the presence of a suitable database set in which the output data wanted by the network is strongly related to one or more data considered as input. In this case, the output data is represented by the H_d , while the input data are the most part of data that describe the building thermal balance, such as: the constructive typology, the intended use, the climate context and so on. In detail, the collected data are related to the following parameters (*Annex 2*):

1. HDD : Heating Degree Days [K day];
2. S/V : Shape factor [m^{-1}];
3. S_w : Window surface [m^2];
4. S_{op} : Opaque Surface [m^2];
5. U_w : Window thermal transmittance [$W/(m^2 \cdot K)$];
6. U_{op} : Overall opaque thermal transmittance [$W/(m^2 \cdot K)$];
7. U_o : Overall thermal transmittance [$W/(m^2 \cdot K)$];

8. Q_S : Solar gains [kWh/year];
9. h : Heating operating hours [h];
10. C_T : Total thermal capacity [kWh/(m³·K)];
11. Q_G : Internal gains [kWh/year];
12. v : Wind speed [m/s]; and
13. H_d : Heating energy demand [kWh/(m²·year)].

E.4.2 Design of the ANNs

As previously explained, in an ANN, the link between input and output is not defined by explicit interdependence relationships but is obtained through an empirical training process based on declared corresponding inputs/outputs. The neural network learns and builds the function that binds output with the input through the presentation of a large number of input/output examples correlated with each other. For each input example presented to the network during the learning process, a calculated output that differs by a certain amount from the exact output is provided. The training algorithm modifies some network parameters at each iteration to bring the output to the exact system response. These parameters are the numerical weights associated with the synaptic connections between the neurons of the network.

Based on this approach, the previous database was used to train an ANN to immediately identify the H_d value without the solution of an energy balance. After the pre-processing phase, were explored different topologies of ANN and four ANNs were developed in this study for the evaluation of heating energy demand. For the modelling of physical systems and the resolution of regression problems, a feed-forward Back-Propagation MLP structure is commonly used. Therefore, the basic configuration of ANN was an MLP investigating two different topologies and for each of them two different configurations, varying the number of hidden layers and the number of neurons. The main advantages of MLP structures are that, they are easy to use and they require relatively little memory and are generally fast; also,

MLP structures have the ability to learn non-linear and complex relationships between input and output patterns, which would be difficult to model with conventional methods. A topology: MLP with one hidden layer (Fig. 7E):

- A1: hidden layer with 8 neurons; and
- A2: hidden layer with 30 neurons.

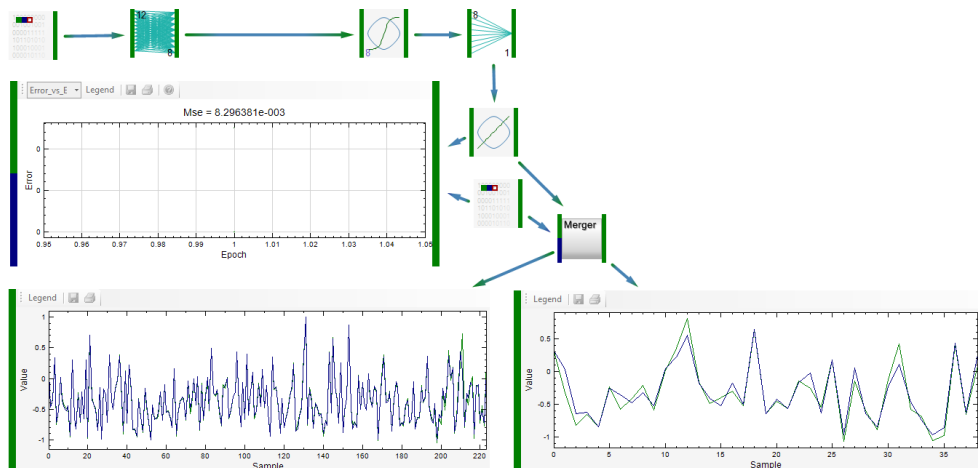


Fig. 7E. “A1-ANN” topology.

B topology: MLP with two hidden layers (Fig. 8E):

- B1: first hidden layer with 400 neurons and second hidden layer with 120 neurons; and
- B2: first hidden layer with 500 neurons and second hidden layer with 250 neurons.

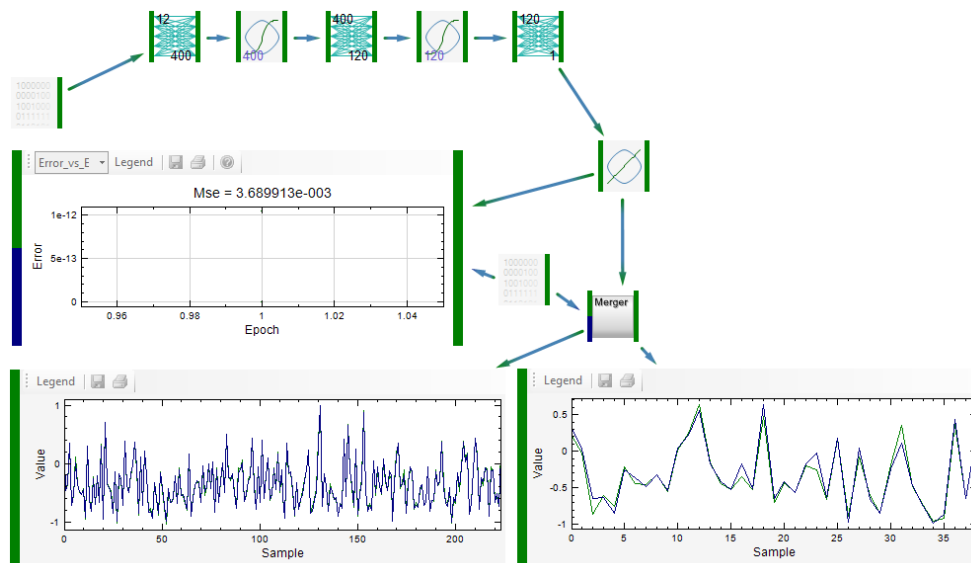


Fig. 8E. “B1-ANN” topology.

Figs. 7E and 8E represent the schemas of A1 and B1 topologies respectively, and in these configurations, it is possible to identify different activation functions. As previously explained, an activation function determines the response that a neuron is capable of delivering. In this work, it was used two continuous activation functions: linear and hyperbolic tangent functions (tanh-sigmoid) [44].

In the A-ANN configuration there is one tanh-sigmoid activation function after the hidden layer, and one linear activation function after the output layer (Fig. 7E); in the B-ANN configuration there are two tanh-sigmoid activation functions each after the two hidden layers and one linear activation function after the output layer (Fig. 8E). All topologies are characterised by a Back-Propagation learning algorithm (Section E.3). Furthermore, in each figure, in addition to a simple scheme of the network, are displayed the trends of training and validation phase, plotting the comparison between the target outputs of each sample against the outputs provided by the ANN for each iteration. In a third graph, it is possible to plot the trend of the MSE, varying the epochs.

To better analyse the reliability of the selected ANNs, different simulations were carried out changing the time of the training phase and/or the epochs; in all cases, in order to avoid over-fitting, the training phase has been suspended. Each ANN

was trained and validated; the validation data are extracted from the database before the training phase and represent 15% of the total data. The main characteristics of the four ANNs are shown in Table 1E:

Table 1E

ANN Design and characteristics.

Models	Topology	ANN Design				Learning
		HL	Input layer	1° HL	2° HL	
A1	Feed forward MLP	1	12	8	-	Backpass: Step rule
A2	Feed forward MLP	1	12	30	-	Backpass: Step rule
B1	Feed forward MLP	2	12	400	120	Backpass: Step rule
B2	Feed forward MLP	2	12	500	250	Backpass: Step rule

Given the complexity of the building system to analyse, it would be interesting to investigate the interaction between the different intelligent algorithms in order to exploit the advantages of each technique and get an optimised result. A hybrid system capable of matching the characteristics of intelligent algorithms can be constituted by ANN and a GA. The aim is to obtain a computing system that possesses a greater adaptive power with respect to that supplied individually by each of the two approaches; this combination implies a genetic model for the ANN. Indeed, the GA algorithm is used to optimize the ANN architectures. The optimisation GA algorithm is based on a population of artificial chromosomes in which the basic characteristics of each ANN configuration containing the starting population are encoded (*Section E.3.1*). Each network is different from the others with an absolutely random variation of some parameters. Among these parameters are: the initialization of the weight layer, the learning rate, the momentum of the weight layers and of the activation functions, and the numbers of neurons of the hidden layers. The networks that provide an output that most closely matches the optimal output have the greatest reproduction probability and this permits the selecting of the best configuration [44].

In the initial optimization phase based on the use of the evolutionary process of the GA, a population of 20 networks, each of which has random weight values, it was

identified. The evolutionary process is done iteratively for 500 steps or generations to obtain the best configuration network that delivers the optimal combination of key parameters. It was possible to identify the best solution of the problem in a shorter computing time. Thus, the optimization phase processed 10,000 different ANNs each of them trained for only 1,000 epochs: a total of 10,000,000 epochs for the entire process. The simulations were carried out with Peltarion synapse software [45] installed on a machine with Intel Core i5 3460 4 core with 3.2 GHz processor and 12 GB of RAM. These features have led to a long time for the optimization phase of the neural network: about 8 days for the most complex (B2-ANN) and about 28 minutes for the simplest network configuration (A1-ANN).

E.4.3 Results

In the following tables the features of the two best ANN architectures, after the optimization phase, are shown. In Table 2E the values of learning rate η , the momentum α and the noise level for each weight layers and activation function for A-ANN topologies are reported. Similarly, in Table 3E the values of η , α and noise level are collected for each weight and activation layers for B-ANN topologies.

Table 2E

Features of the best A-ANN configurations.

Model	1° WL			2° WL			1° AF		2° AF	
	η	α	Noise level	η	α	Noise level	η	α	η	α
A1	0.295	0.077	0.569	0.271	0.042	0.787	0.196	0.014	0.155	0.051
A2	0.173	0.05	0.668	0.077	0.095	0.553	0.261	0.097	0.072	0.046

Table 3E

Features of the best B-ANN configurations.

Model	1° WL			2° WL			3° WL			1° AF		2° AF		3° AF	
	η	α	Noise level	η	α	Noise level	η	α	Noise level	η	α	η	α	η	α
B1	0.1	0.7	0.289	0.1	0.7	0.05	0.1	0.7	0.091	0.1	0.7	0.1	0.7	0.1	0.7
B2	0.001	0.037	0.052	0.222	0.08	0.186	0.003	0.084	0.292	0.001	0.004	0.012	0.001	0.1	0.7

After the optimization phase, the best four ANN topologies were trained and validated for a total of 100,000 epochs and, based on the machine previously described, the training times are shown in Table 4E; the A1 topology is the fastest (1 min and 7 seconds), and the B2 topology the slowest (about 8 hours).

Table 4E

Data of training phase.

ANN Training		
Models	Epoch	Training time [s]
A1	100,000	67
A2	100,000	188
B1	100,000	12,000
B2	100,000	28,500

The post processing phase allows the statistical evaluation of the accuracy of the tested ANNs and the error results are summarised in Table 5E in terms of:

- Mean: the mean value of difference between the expected value and the value predicted by the ANN;
- Median: the intermediate value between all calculated deviations between the expected value and the value predicted by the ANN; and
- Standard Deviation (StDv): an estimation of the dispersion of data related to the difference between the expected value and the value issued by the ANN.

Each statistical index is calculated for training and validation data.

Table 5E

Post processing error data of ANNs.

Post processing error							
Models	Training			Validation			Confidence range
	Mean	Median	StD	Mean	Median	StD	[kWh/(m ² .year)]
A1	-0.869289	-0.960003	2.292850	0.767037	0.812436	5.082879	± 9.947962
A2	0.048863	0.230784	3.641756	0.839429	0.951314	6.318410	± 12.33428
B1	0.000326	0.039369	1.979777	1.028433	0.531214	4.837094	± 9.572819
B2	0.000239	0.000914	2.628834	0.270659	1.056509	4.866031	± 9.429152

The 95% confidence range values are summed in the last column of Table 5E; the bold values indicate the lower absolute values, and generally, the B-ANN architecture has the best results, despite being characterised by longer computational times. Between the two B topologies there are no strong differences; the results are similar. However, the lower computational time of B1 makes it preferable. Meanwhile, between the two A topologies, the best is A1 which is also characterised by a shorter computational time. Comparing the confidence range values of A1 and B1 and simultaneously considering the computational time, the A1 topology is preferable. To better understand the validity of these results, in the following figures the error frequency distribution for the training (Fig. 9E) and validation phases (Fig. 10E) of A1 topology are shown.

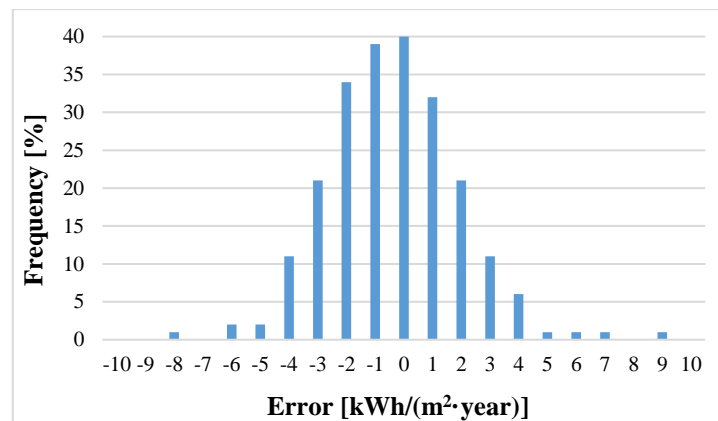


Fig. 9E. Error frequency in the training phase of A1 topology.

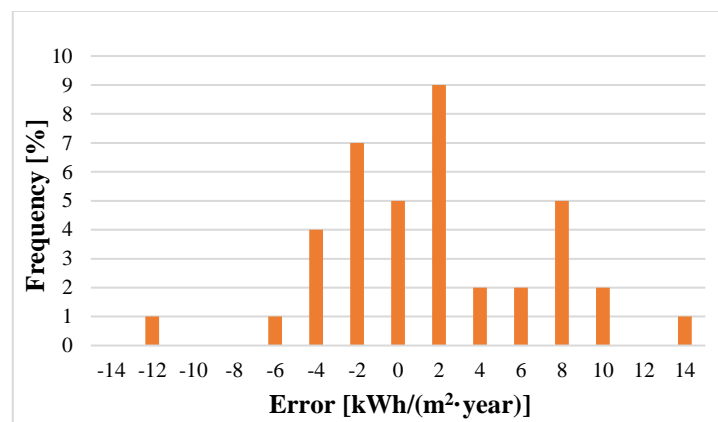


Fig. 10E. Error frequency in the validation phase of A1 topology.

After the post processing phase, it is possible to assess the quality of the prediction issued by the ANNs. The statistical analysis performed on the deviation between expected values of heating demand and values predicted by the ANNs confirm the reliability of the neuro-computing approach because the MAE, calculated for validation phase, is equal to 3.527 for A1 ANN and 3.308 for B1 ANN. Networks that required a longer time to be trained generally show better performance with regard to the accuracy of the calculated values. Nevertheless, the topology A1 network shows an excellent performance in the results belonging to the validation dataset, as can be seen from the 95% confidence plot in Fig. 11E.

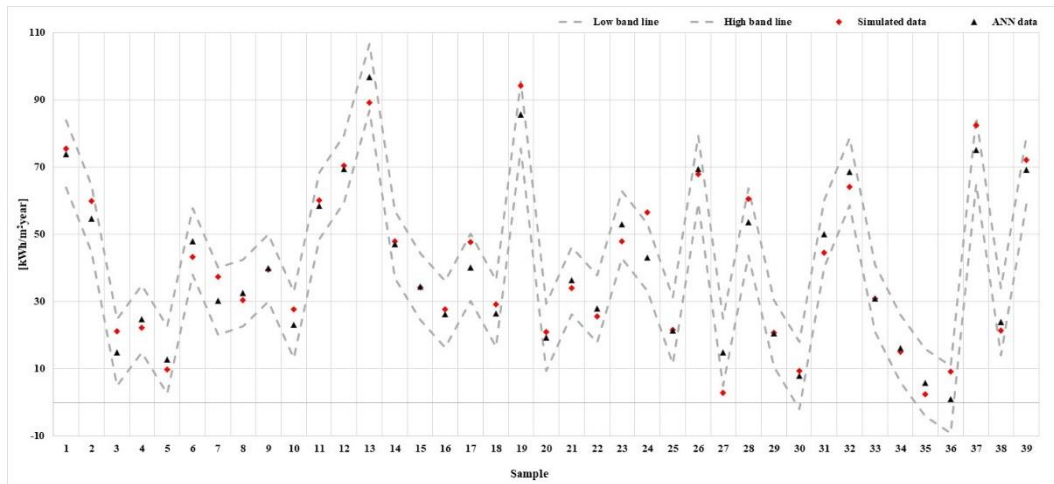


Fig. 11E. Confidence plot of MLP A1 topology.

In Fig. 11E, the H_d values of simulated data with the ANN data of the validation data set (the 15% of 273 H_d data) are compared. In Fig. 12E, is displayed the learning curve of this topology where it is illustrated the trend of the error function of the epochs; an optimal convergence is achieved from about 100 epochs.

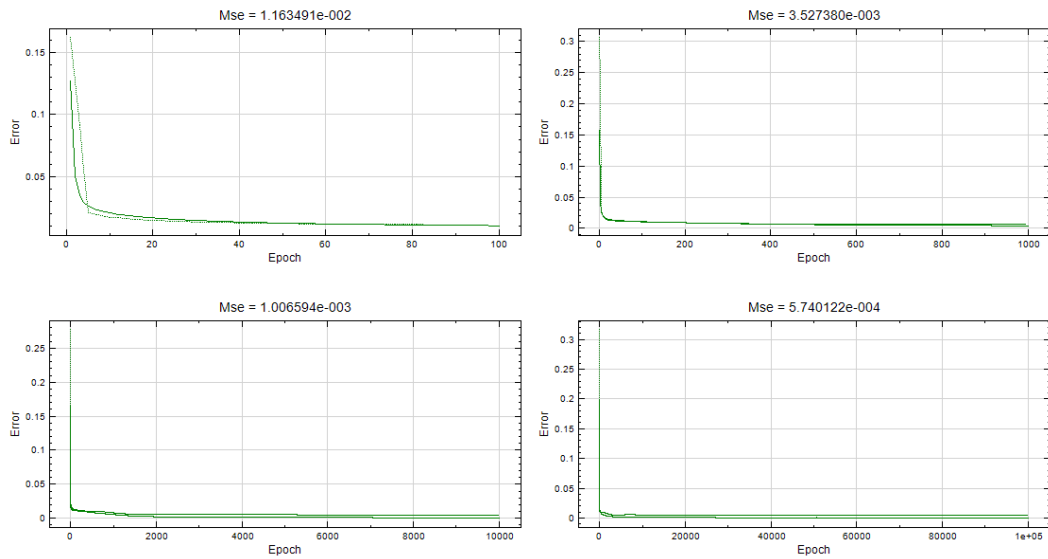


Fig. 12E. Learning curves of MLP A1 topology at 100, 1,000, 10,000 and 100,000 epochs.

To better understand the validity of these results, in the following graphs (Figs. 13E and 14E) the Absolute Percentage Error (APE), and MAPE, between the simulated data with respect to the ANN data are plotted. Regarding the A1 ANN results the Fig. 13E illustrates a MAPE of about 9 % instead the B1 ANN presents a MAPE of about 8.5 % (Fig. 14E).

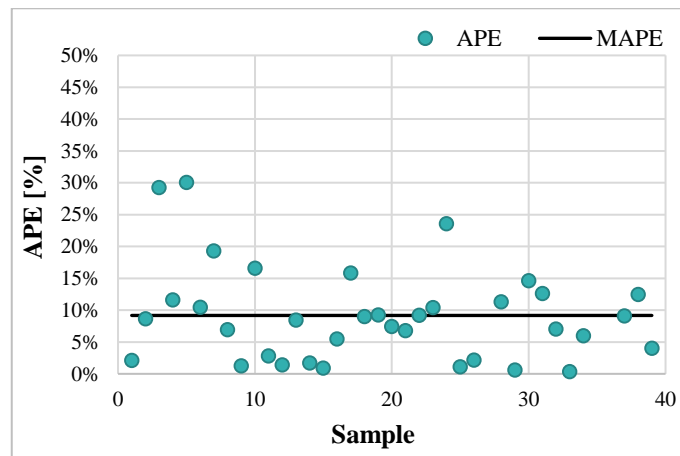


Fig. 13E. APE and MAPE of MLP A1 validation samples.

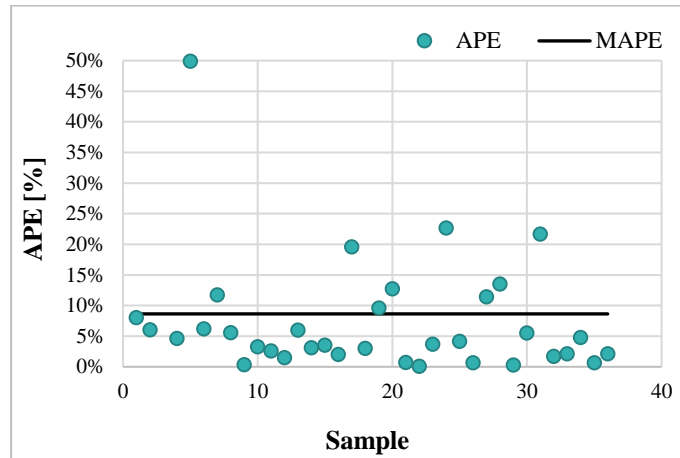


Fig. 14E. APE and MAPE of MLP B1 validation samples.

The high reliability of the ANNs, configured for the solution of the building thermal balance, are shown in the following figures: the distribution of the desired H_d versus the provided A1-ANN is shown, in Fig. 15E; the desired H_d versus B1-ANN is shown in Fig. 16E. In both cases, the data are well distributed on the diagonal of the first quadrant with determination coefficient values (R^2) higher than 95 %.

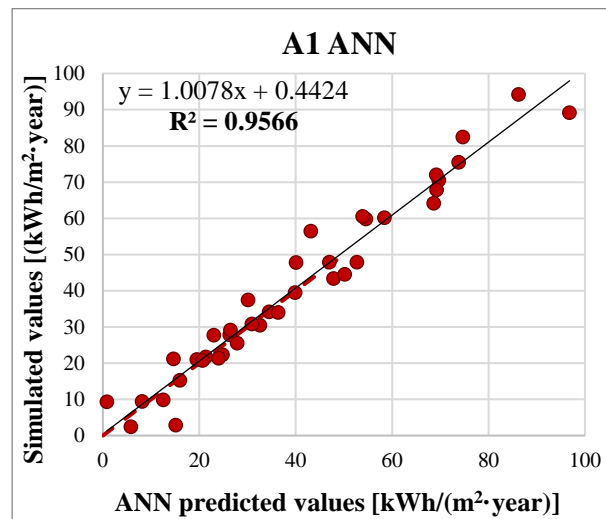


Fig. 15E. The distribution of the desired H_d versus the provided A1-ANN.

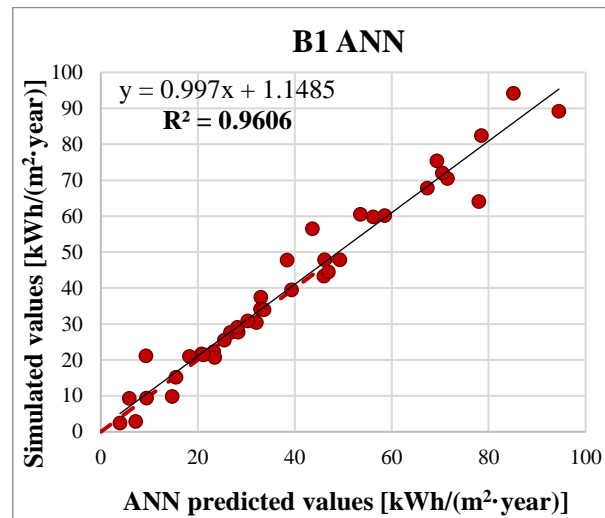


Fig. 16E. The distribution of the desired H_d versus the provided B1-ANN.

E.5 ANN ENERGY PREDICTIVE TOOL FOR THE ITALIAN BUILDING STOCK

This case study represents a deepening of the previous application because, its aim is to investigate the suitability of ANNs as tools for a simultaneous estimation of heating (H_d) and cooling (C_d) building loads while minimising the set of input data, to facilitate the work of design engineers in the field of building energy efficiency [12]. In this way, an attempt is made to develop a tool that has greater versatility, applicability and generalization than that obtained with the work previously discussed in this thesis and compared to those in the literature. Indeed, even if in the literature it is possible to find different works that have used the ANNs for the evaluation of the energy performance of buildings, most of these predict the electric and non-thermal consumption [46,47], or evaluate the thermal loads only for heating [48,49] or only for cooling [50,51]. Few papers deal simultaneously the determination of both thermal loads, but are characterised by a greater number of inputs, higher value of errors and/or by a single output [9,52–54].

As for the previous case, to develop an alternative predictive model based on the use of an ANN, it is necessary to resort to a large, consistent, generalised and reliable database. For this case, using the implementation of the reliable energy database representative of an entire Italian building stock that is explained in the

Chapter B Section B.7.3, it was decided to train different ANNs, with the goal of simultaneously determining heating and cooling building thermal loads, using the data collected in *Annex 3*. Therefore, this dataset represents a reliable dataset to train an ANN, and is characterised by 19 input columns representing the building thermal balance, 2 output columns representing the heating and cooling loads, and 195 rows representative of all possible scenarios. As for the previous case study, to develop the ANN model, it was used the Peltarion Synapse software [45]. The main steps of this work are displayed in the following flow chart (Fig. 17E):

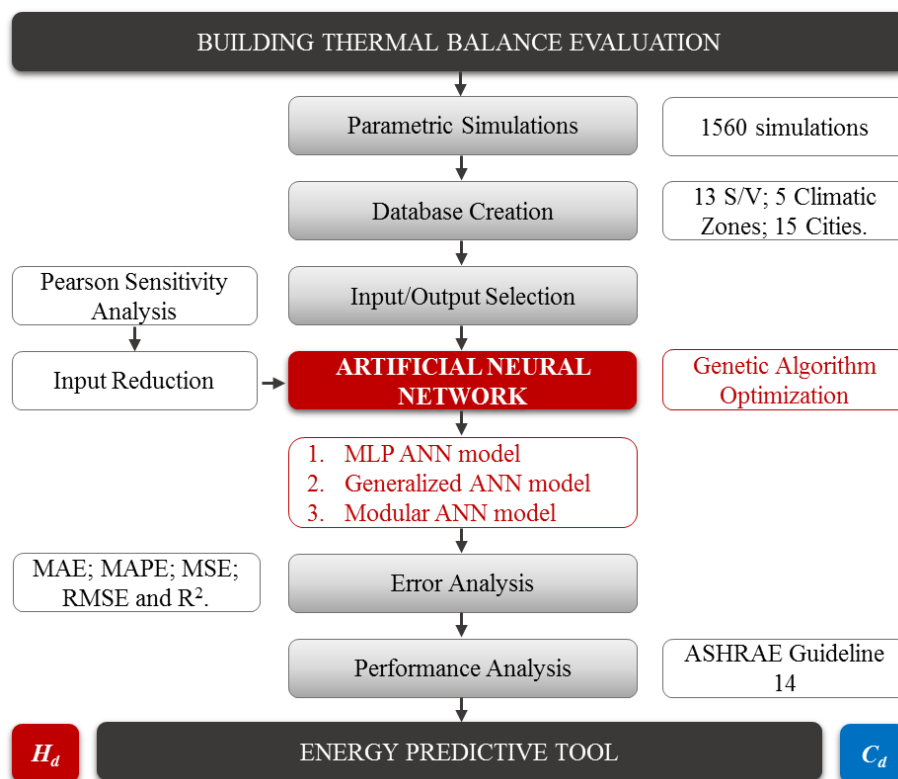


Fig. 17E. The main steps of the work.

After a detailed description on the database creation (*Section E.5.1*) and of the principal characteristics and operation algorithms of the selected ANNs (*Section E.5.2*), the results of the best three ANNs that solve the comprehensive building thermal balance will be illustrated (*Section E.5.3*). In detail, three different static ANN configurations, optimised through the GA application, are analysed: a multi-

layer perceptron, a generalised configuration, and a modular configuration. Also in this case, all of these networks were trained with 85% of the total dataset, whereas the remaining 15% was used for validation. The reliability of the results is guaranteed, owing to a deep statistical error analysis evaluating the MAE, MSE, RMSE, R^2 , and MAPE between the predicted and target values of the building energy demand [55,56] (*Section E.5.3.1*). Furthermore, according to ASHRAE Guideline 14 [27], and to validate the performance of the ANN models, two other errors were calculated, i.e. the NMBE and the coefficient of variation of CV-RMSE indices [57] (*Section E.5.3.2*).

To minimise the number of inputs needed for application of the ANN model, it was applied an input selection analysis that identified the main parameters primarily influencing the heating and cooling energy demands of a building stock. In detail, as performed for the second MLR model (**Chapter C**), a Pearson analysis was applied to deduce simple correlations between the involved explanatory variables and the dependent variables (H_d and C_d) [58] (*Section E.5.4*). The input data reduction was conducted for exploring new configurations of ANNs. The best two of the previous three ANNs were trained with only 5 inputs and 2 outputs (*Section E.5.5*). All results are discussed in the last part of the case study (*Section E.5.5*), and demonstrate the high degree of reliability of this model. Thus, it is anyway permitted to affirm that the ANN represents an optimal decision support tool in the field of building energy assessment. However, the simplification of the use phase, deriving from the reduction of the parameters necessary to obtain an optimal prevision, requires a careful evaluation of the network chosen, the selected learning algorithm, and the number of neurons involved. In fact, as evidenced by the results, downstream in the input reduction process, only one of the analysed networks continues to show optimal results.

E.5.1 Database Creation

As explained in **Chapter B**, after a deep analysis of the principles of a traditional building balance, it is possible to identify the parameters that best represent (or have

a greater influence on) the thermal energy needs of a building. Collecting these parameters and the data provided by the parametric simulation of the Italian case study, the following variables was identified as the main features for determining the heating H_d and cooling C_d loads:

1. HDD : Heating Degree Days [K day];
2. CDD : Cooling Degree Days [K day];
3. T : Mean outdoor temperature [K];
4. RH : Mean relativity humidity [%];
5. v_s : Wind speed [m/s];
6. I_h : Horizontal global solar irradiation [W/m^2]
7. S/V : Shape factor [m^{-1}];
8. H_s : Heated surfaces [m^2];
9. S_w : Glazed losses surface [m^2];
10. S_{op} : Opaque losses surfaces [m^2];
11. U_w : Glazed thermal transmittance [$W/(m^2 K)$];
12. U_{op} : Opaque thermal transmittance [$W/(m^2 K)$];
13. U_o : Overall thermal transmittance [$W/(m^2 K)$];
14. $Q_{S,H}$: Solar gains for heating period [kWh/year];
15. $Q_{S,C}$: Solar gains for cooling period [kWh/year];
16. h_H : Operating hours for heating period [h];
17. h_C : Operating hours for cooling period [h];
18. C_T : Thermal capacity [$kWh/(m^3 K)$]; and
19. Q_G : Internal gains [$kWh/(m^2 year)$].

Therefore, it was obtained a matrix with 195 rows (scenarios), 19 input columns and 2 output columns (H_d and C_d), on which the ANN will be trained (*Annex 3*).

E.5.2 ANNs Selection

In this case study, three ANNs have been explored. The first is a simple feed forward MLP with two hidden layers, and the others are improved versions of the first (simple) one. As these are MLP ANNs or improved versions thereof, each ANN does not present any recurrent connection to neurons of the same level or previous levels; the input signal only travels from the input to the output units. Moreover, they are characterised by at least one hidden layer of neurons and non-linear, continuous, and differentiable activation functions. The non-linear units allow for processing of complex and non-linear input information, and are continuous and differentiable for the back propagation of the error. In this study, all analysed networks are characterised by non-linear, continuous, and differentiable tanh-sigmoid activation functions for the hidden layers, and a linear activation function after the output layer. The first function enables the ANN to learn the correlation between the input–output samples and provides a bounded output within the range (-1 to 1) [59]; the second function linearizes the output signal, allowing the ANN to provide non-bounded output values [60]. Fig. 18E displays the two-layer MLP ANN layout, whereas the layouts of the improved versions of the ANN are illustrated in the following Fig. 19E and Fig. 20E.

The first ANN, represented in Fig.18E, is characterised by 4 neuron layers (an input layer with 19 neurons, 2 hidden layers with 19 neurons and one output layer with 2 neurons), two tanh-sigmoid activation functions and one linear activations function.

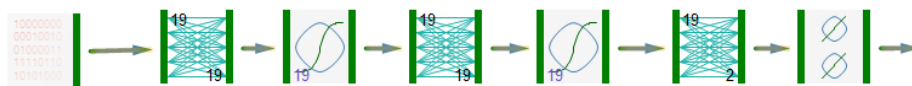


Fig. 18E. Schema of the two layers MLP ANN.

The first improved version (Fig. 19E) is a generalised two-layer neural network; in many cases, it is a more efficient extension of the standard two-layer MLP neural network. It is suitable for function modelling problems where many data are available. Compared to the previous configuration, the second ANN is also

characterised by 4 layers with 2 hidden layers, with 10 and 16 neurons respectively, but with a different connection scheme. In this case, the input layer is simultaneously connected with the first and the second hidden layer, whereas the first hidden layer is in turn simultaneously connected with the second hidden layer and with the output layer. Obviously, the input and output layers present the same number of neurons.

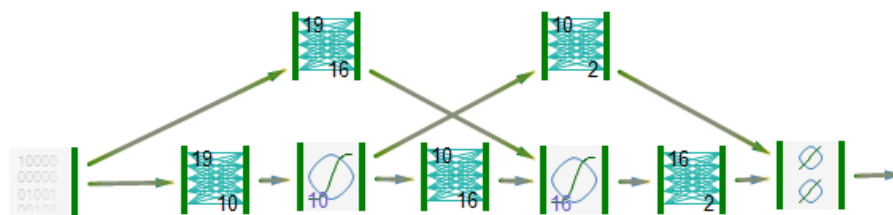


Fig. 19E. Schema of the Generalized two layers ANN.

The second improved version (Fig. 20E) is a modular neural network. This is also an improved version of the MLP neural network, and is capable of better generalisation of the results. This feature is guaranteed, owing to the behaviour that this particular structure engages during the training phase. In fact, during the modification of the synaptic weights, the two branches compete against each other, improving the learning ability. In this case, the input layer is simultaneously connected to 2 separate branches that each presenting two hidden layers of neurons. The first branches (the top one) presents two hidden layers respectively of 16 and 13 neurons, the second branches (the down one) has two hidden layers respectively of 16 and 6 neurons. Afterwards, the two branches again converge in another hidden layer of 15 neurons that is in turn connected to the output layer.

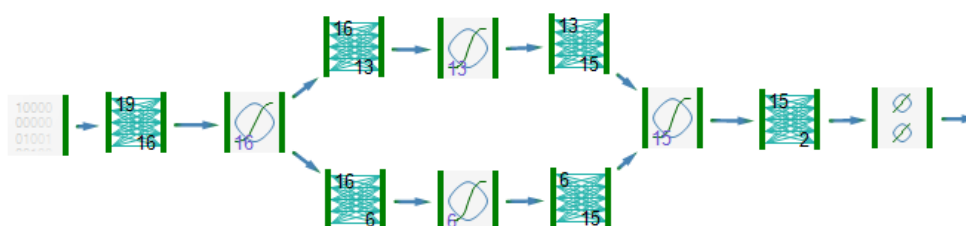


Fig. 20E. Schema of the Modular ANN.

For each analysed configuration, the neuron numbers of each hidden layer, learning rate and momentum values, and synaptic weight initialisation are determined and optimised using an evolutionary GA, allowing for identification of the best configuration for each ANN topology. To perform the genetic optimisation, 20 active populations and 30 generations that are trained for 100,000 epochs has been set. The number of populations represents the set of data proposed to the training phase of the GA application, whereas the generations represent the number of steps for which the training phase is iterated. The selected rules for the parameter's crossover, mutation type, and selection of the population parameters are double point, uniform, and tournament, respectively. The features of the best ANN configurations are reported in Table 6E, which also indicates the number of signal paths and neurons in each hidden layer.

Table 6E.

Features of the ANNs schema.

ANN Design								
MLP Models	Total HL	Signal path	HL for each line	N° of Neurons			AF	
				1° HL	2° HL	3° HL	Tanh-sigmoid	Linear
MLP ANN	2	Line 1	2	19	19	-	2	1
		Line 1	2	10	16	-	2	1
Generalized ANN	2	Line 2	1	16	-	-	1	1
		Line 3	1	10	-	-	1	1
Modular ANN	5	Line 1	3	16	13	15	3	1
		Line 2	3	16	6	15	3	1

For the learning process, a BP algorithm with the Step Rule (SR) was employed [38]. The “step rule” is an improved version of the standard Gradient Descendent (GD) algorithm with momentum and stabilization regularization, in which the network weights are moved along the negative gradient of the performance function [61]. This improved rule allows for local minima to be avoided, stabilizing and regularizing convergence, and speeding up the learning process of the ANN [60]. Furthermore, the learning speed is regulated by the learning rate, which acts on the percentage of change of the synaptic weights.

In this case, in addition to the SR, each configuration of the ANN was trained with a different learning algorithm, i.e. Levenberg Marquardt (LM), and Quick Prop (QP) [60,61]. In that regard, it was verified that the QP is not adaptable for these ANN configurations and for this type of data and problem. Indeed, in all cases, the networks do not converge. However, the other two algorithms showed good resolution abilities that were able to reach convergence, and an excellent capability to generalise new data. However, the SR better explains the behaviour of the MLP and the generalised ANN, whereas the LM better explains the behaviour of the modular ANN.

E.5.3 ANN Models Results

As previously indicated, only 85% of the total dataset was used in the training phase, and the other 15% was used for validation. For each ANN and for each output (H_d and C_d), the minimum and maximum values of the difference (deviation) between the predicted and target output are obtained. These results for the training and validation phases are collected in Table 7E.

Table 7E

Post processing data: minimum and maximum deviations from the target output values for the training and validation dataset.

Models	Training dataset				Validation dataset			
	H_d		C_d		H_d		C_d	
	Min	Max	Min	Max	Min	Max	Min	Max
MLP ANN	3.30E-04	2.60	4.80E-04	0.82	0.04	1.34	0	0.73
Generalized ANN	9.76E-06	2.76	2.20E-04	1.7	0	1.07	0	1.65
Modular ANN	8.50E-05	0.13	6.10E-04	0.09	0	1	0	1.3

The following figures illustrate the values of the Mean, Median, and Standard Deviation (StD). In particular, Fig. 21E is related to the training phase, whereas Fig. 22E is related to the validation phase.

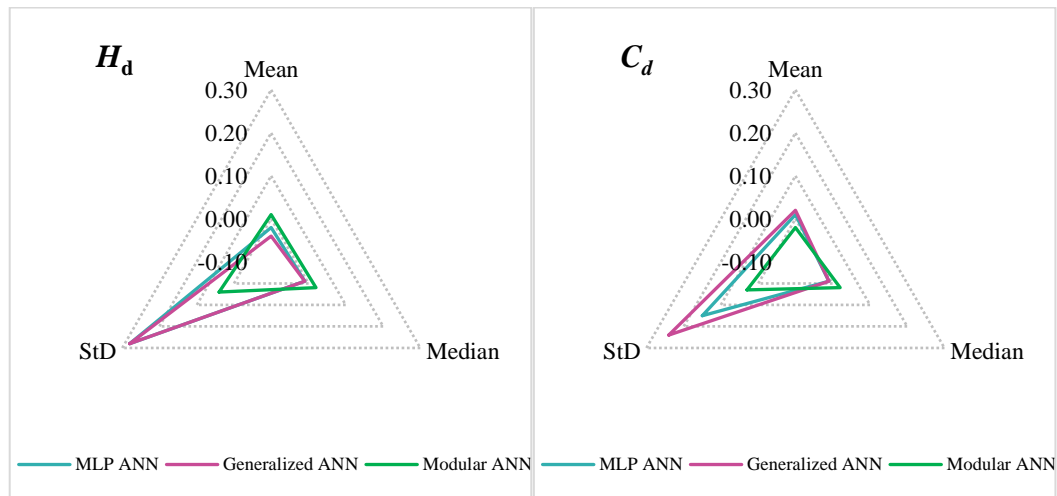


Fig. 21E. Post processing data: Mean, Median and StD deviations from the target output values for the training phase.

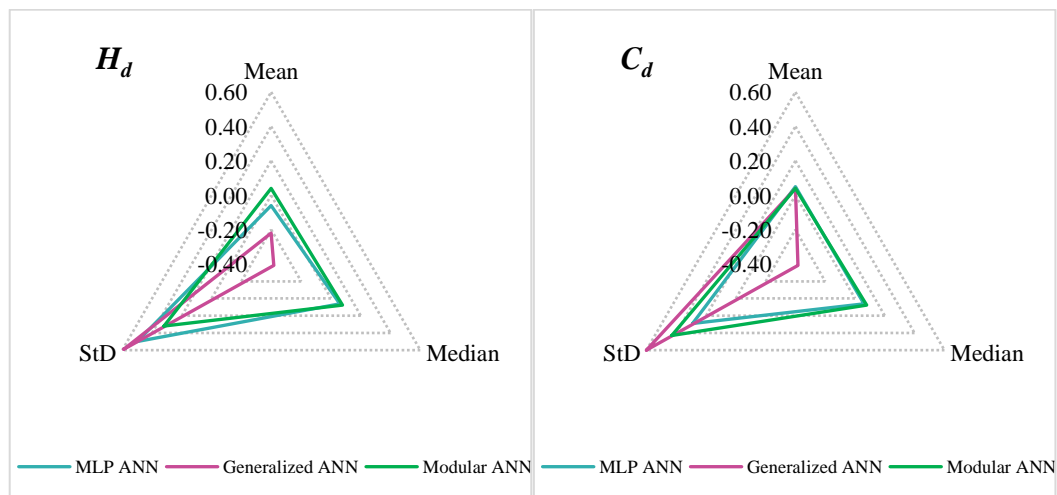


Fig. 22E. Post processing data: Mean, Median and StD deviations from the target output values for the validation phase.

Evidently, comparing the validation data results with the training data results, all indexes are higher. In detail, the mean value increases from 1.7 to 1.9 times, the median from 2 to 2.5 times, and the StD increases approximately 10 times. The plot deviation between the target data obtained from the simulation and the predicted data obtained from the ANN, for all database samples, allows for identification of which data are not well-fit by the ANN. Figs. 23E to 25E plot all of the deviations for the heating (ΔH_d) and cooling loads (ΔC_d) for the training and validation set and for each ANN.

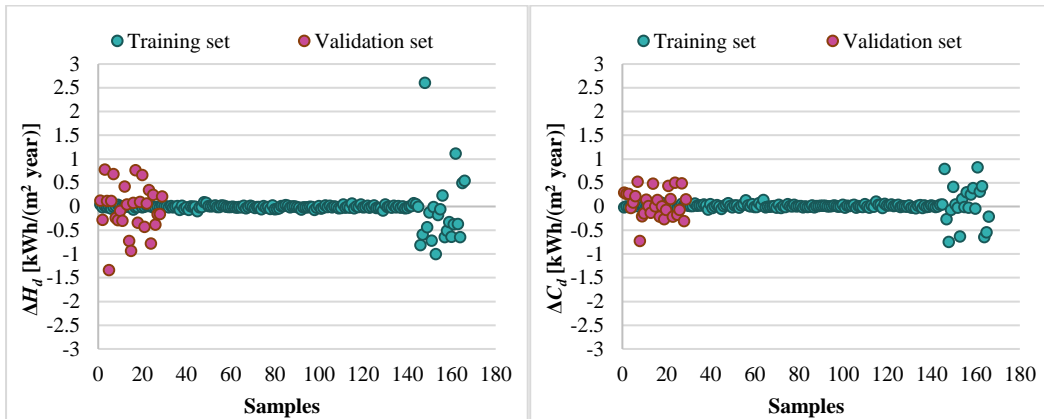


Fig. 23E. Deviation of the predicted heating (a) and cooling (b) energy demands for the two layers MLP ANN with SR learning algorithm.

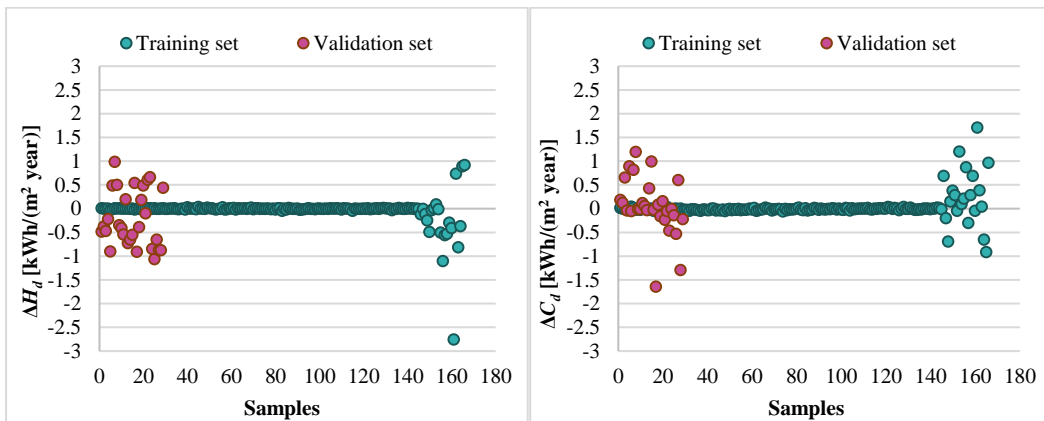


Fig. 24E. Deviation of the predicted heating (a) and cooling (b) energy demands for the Generalized two layers ANN with SR learning algorithm.

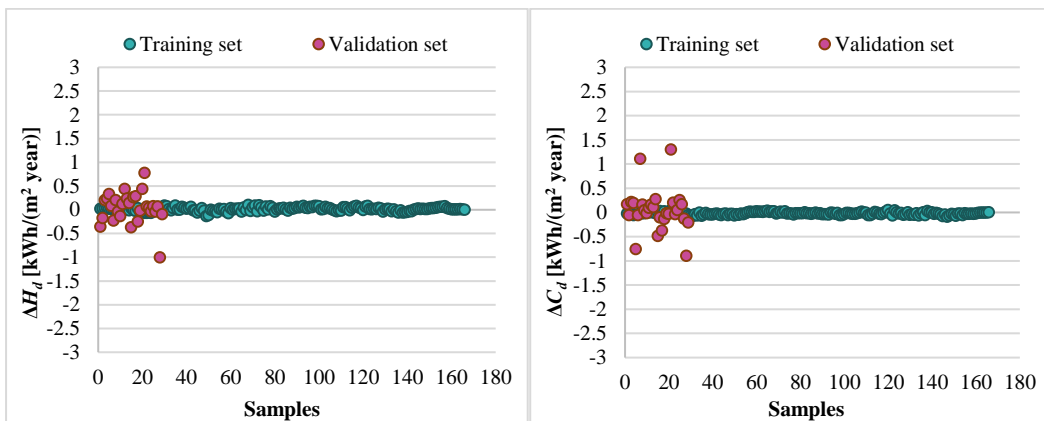


Fig. 25E. Deviation of the predicted heating (a) and cooling (b) energy demands for the Modular ANN with LM learning algorithm.

In general, in all cases, the ΔH_d and ΔC_d distributions are near zero (kWh/(m² year)) for the training set and are between ± 1.5 (kWh/(m² year)) for the validation set. For the first two ANNs only, the last part of the training dataset (approximately 12% of all data) is distributed in a range of ± 1.5 (kWh/(m² year)). At any rate, all deviation values are very low, with respect to a mean heating consumption of approximately 15 (kWh/(m² year)) and a mean cooling consumption of approximately 23 (kWh/(m² year)). Although the scatter plot deviation is a simple and fast way to discern the suitability of predictive models, a deep statistical error analysis was conducted to determine the best solution among the different developed models.

E.5.3.1 ANN Error Analysis

An error measure is often defined in terms of the forecasting error, which is the difference between the actual (target) and predicted values [62]. In the literature, there are several number of error measures and in this case were used those described in *Section A.4*. The MAE, MSE, MAPE and RMSE indices allow a comparison of the deviation between the predicted with the target building energy performances [55,56]. In general, smaller values of these indices correspond to more precise models; among these, the MAPE is independent of the scale [55]. Furthermore, a model is often selected if it presents an optimal value of a statistical indicator, such as the R².

Fig. 26E illustrates the MSE, MAE, RMSE, and MAPE for each ANN, and for the evaluation of the H_d and C_d for the validation set.

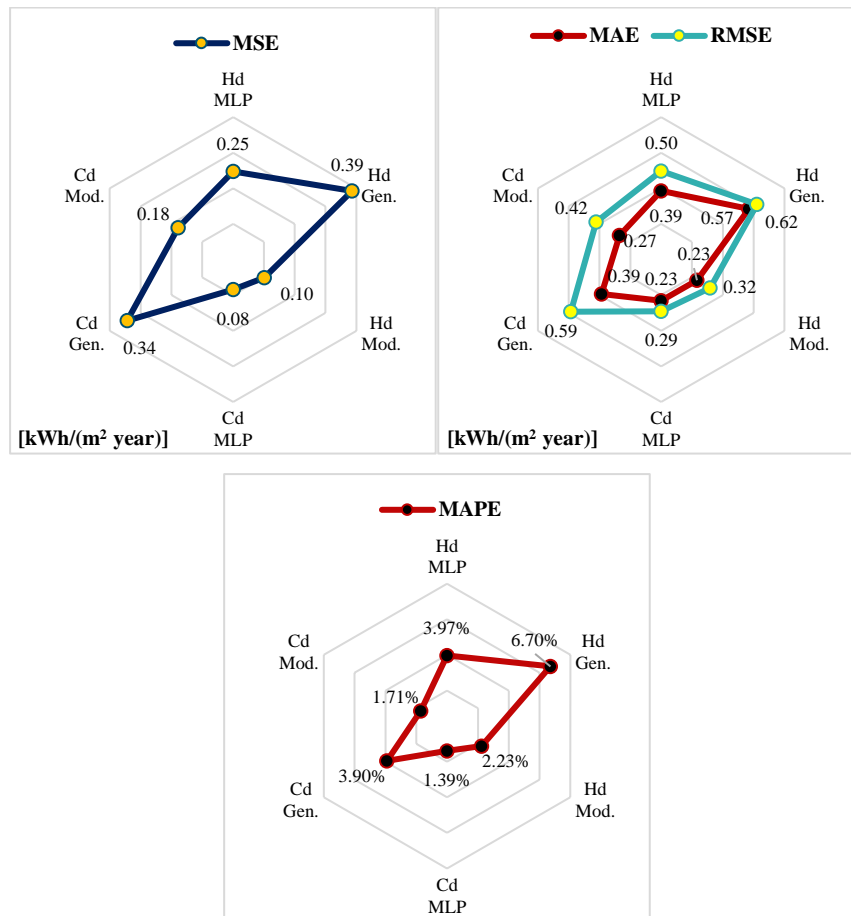


Fig. 26E. Error analysis of the Validation set; MAE, MSE, RMSE and MAPE representation for the ANN models.

Analysing the results for all indices, the best values are related to the modular ANN for the heating load, and to the MLP ANN for the cooling evaluation. As previously indicated, the R^2 index between the predicted and target values was also calculated for all three ANN configurations. Therefore, Figs. 27E to 29E illustrate the distribution results of a linear regression analysis for each ANN, and further display the R^2 values and linear equations, distinguishing the heating from the cooling loads.

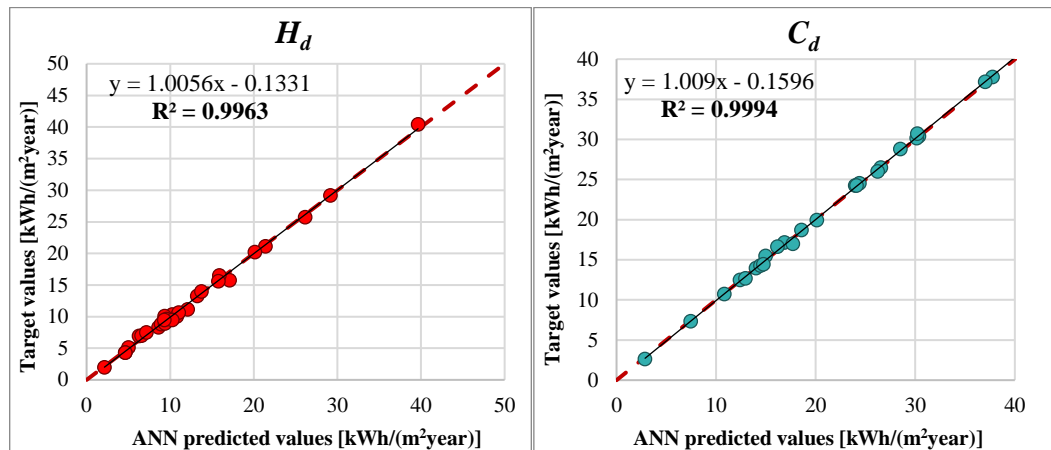


Fig. 27E. Regression between target versus predicted H_d and C_d values for the MLP ANN for validation set.

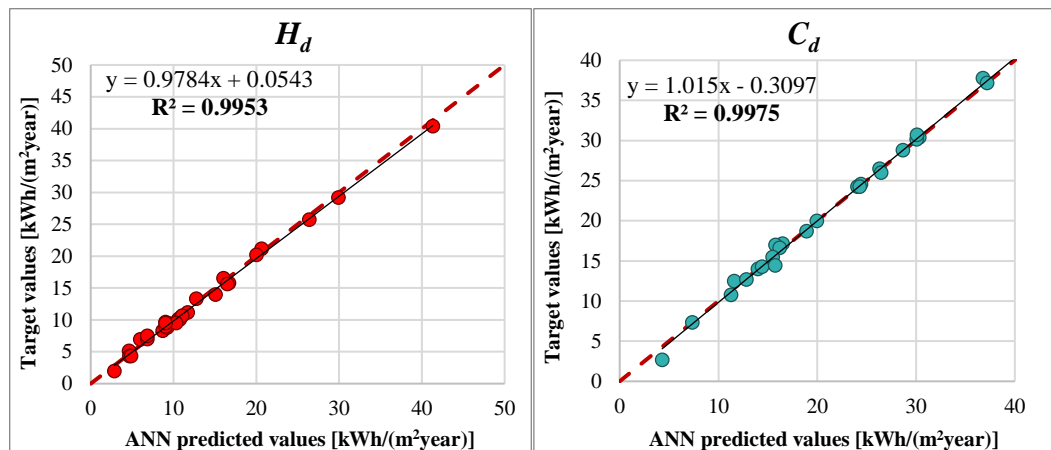


Fig. 28E. Regression between target versus predicted H_d and C_d values for the Generalized two layers ANN for validation set.

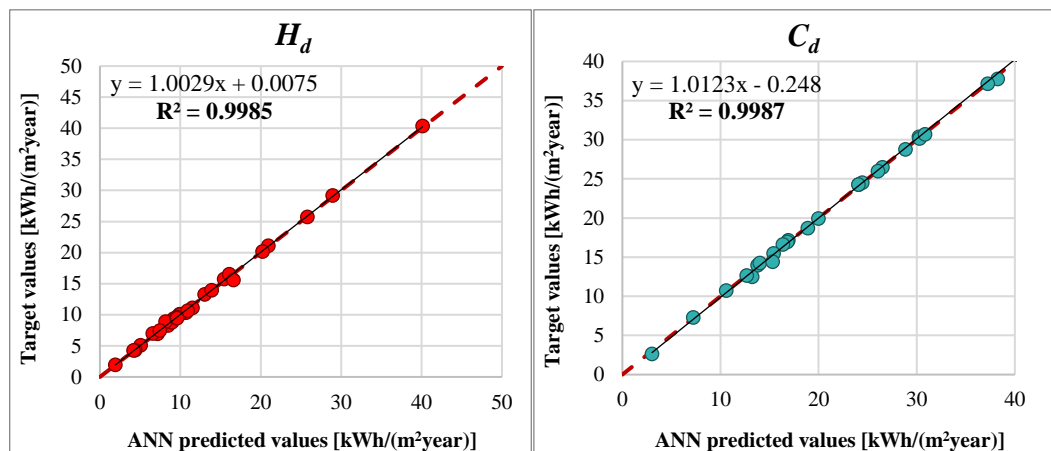


Fig. 29E. Regression between target versus predicted H_d and C_d values for the two layered Modular ANN for validation set.

In all cases, the R^2 values are close to one, indicating that this model is a good alternative for solving a complex problem such as a building thermal balance. Regarding the best two ANNs, the learning curves of the MLP and Modular ANNs are displayed in Figs. 30E and 31E, respectively. These show the trend of the error function of the epochs; an optimal convergence is achieved from approximately 60,000 epochs.

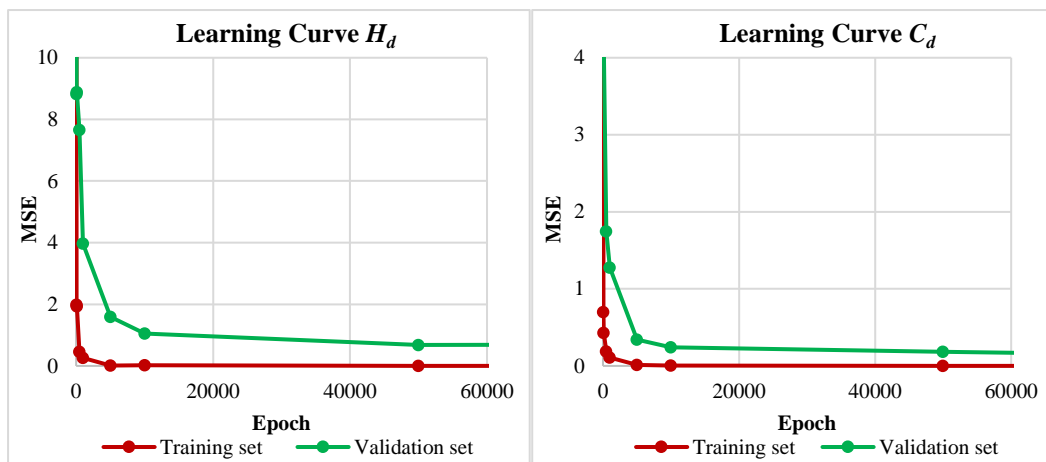


Fig. 30E. Learning curves of the predicted heating (a) and cooling (b) energy demands for the two layered MLP ANN with GD learning algorithm.

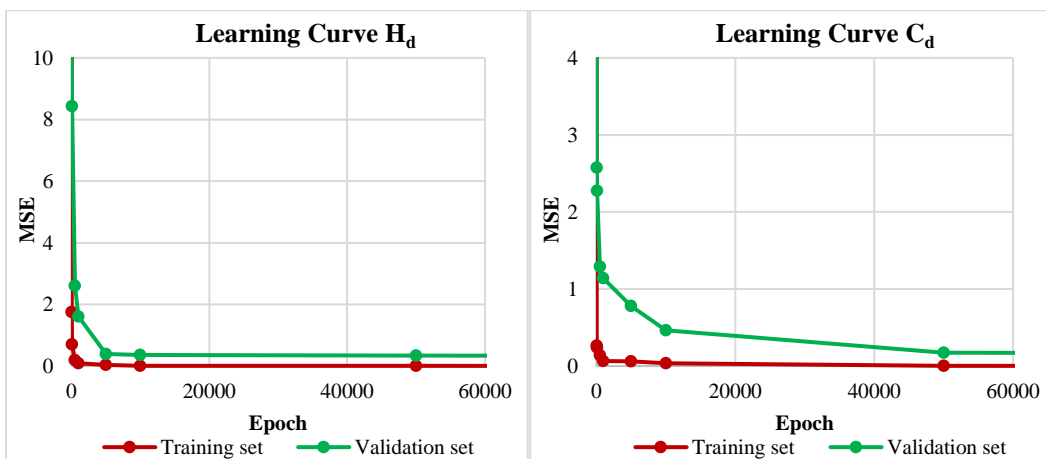


Fig. 31E. Learning curves of the predicted heating (a) and cooling (b) energy demands for the two layered Modular ANN with LM learning algorithm.

To guarantee the replicability of the previous results, Tables 8E and 9E also includes the numerical value of the target data calculated by dynamic simulations (TRNSYS) and that respectively predicted from the ANNs, while distinguishing the

H_d , C_d , and comprehensive energy demand (E_d) values for the training and validation set.

Table 8E

Target versus Predicted output for the validation set.

Training dataset											
Expected			Predicted								
TRNSYS			MLP ANN			Generalised ANN			Modular ANN		
H_d	C_d	E_d	H_d	C_d	E_d	H_d	C_d	E_d	H_d	C_d	E_d
2.35	31.56	33.91	2.31	31.58	33.89	2.35	31.55	33.90	2.33	31.58	33.91
0.70	32.99	33.69	0.72	32.99	33.71	0.70	32.99	33.69	0.67	33.03	33.70
8.90	21.22	30.12	8.89	21.24	30.13	8.91	21.24	30.14	8.87	21.24	30.11
4.68	31.52	36.20	4.70	31.53	36.23	4.69	31.54	36.23	4.65	31.57	36.22
7.82	26.98	34.80	7.82	26.99	34.81	7.84	27.00	34.84	7.80	27.03	34.83
3.05	44.90	47.95	3.10	44.87	47.97	3.06	44.86	47.93	3.04	44.94	47.98
8.54	26.41	34.95	8.55	26.40	34.96	8.54	26.40	34.94	8.54	26.43	34.97
11.66	15.73	27.39	11.65	15.69	27.35	11.67	15.76	27.43	11.66	15.75	27.41
20.34	16.02	36.36	20.31	15.99	36.30	20.34	16.04	36.38	20.31	16.03	36.35
15.83	35.70	51.53	15.83	35.70	51.52	15.83	35.73	51.56	15.83	35.70	51.53
20.86	34.19	55.05	20.87	34.19	55.06	20.86	34.20	55.06	20.84	34.19	55.03
17.54	26.66	44.20	17.54	26.66	44.20	17.54	26.66	44.20	17.51	26.66	44.17
10.54	39.72	50.26	10.55	39.73	50.27	10.54	39.74	50.28	10.53	39.72	50.25
2.71	32.77	35.48	2.69	32.79	35.48	2.72	32.80	35.52	2.73	32.79	35.51
52.08	0.00	52.08	52.07	0.01	52.08	52.09	0.01	52.09	52.04	0.00	52.04
20.90	16.63	37.53	20.97	16.62	37.59	20.92	16.68	37.61	20.91	16.60	37.50
2.98	31.05	34.03	3.00	31.06	34.06	2.99	31.07	34.06	3.01	31.07	34.08
14.85	16.73	31.58	14.86	16.66	31.52	14.86	16.75	31.61	14.82	16.71	31.53
4.35	28.56	32.91	4.30	28.55	32.85	4.36	28.57	32.93	4.39	28.58	32.97
13.80	31.72	45.52	13.82	31.71	45.53	13.79	31.74	45.53	13.86	31.71	45.57
4.09	31.48	35.57	4.10	31.43	35.53	4.08	31.49	35.57	4.16	31.43	35.59
2.01	47.17	49.18	1.99	47.14	49.13	2.01	47.14	49.15	2.07	47.10	49.17
4.16	23.66	27.82	4.16	23.68	27.84	4.16	23.67	27.83	4.22	23.60	27.81
4.10	29.01	33.11	4.09	29.04	33.13	4.11	29.03	33.14	4.16	28.96	33.12
22.08	13.84	35.92	22.10	13.88	35.98	22.08	13.85	35.93	22.08	13.79	35.88
13.86	24.24	38.10	13.88	24.25	38.13	13.87	24.24	38.11	13.84	24.23	38.07
11.34	18.24	29.58	11.35	18.19	29.54	11.35	18.26	29.61	11.28	18.29	29.57
33.32	0.00	33.32	33.33	6.14	39.48	33.32	6.17	39.49	33.26	6.20	39.46
16.27	14.85	31.12	16.26	14.82	31.08	16.27	14.88	31.15	16.24	14.91	31.14
12.88	20.17	33.05	12.88	20.16	33.04	12.89	20.20	33.09	12.79	20.24	33.03
9.90	15.15	25.05	9.90	15.15	25.05	9.91	15.18	25.09	9.82	15.23	25.05
13.33	39.22	52.55	13.35	39.21	52.56	13.33	39.27	52.60	13.31	39.26	52.57

Training dataset											
Expected			Predicted								
TRNSYS			MLP ANN			Generalised ANN			Modular ANN		
H_d	C_d	E_d	H_d	C_d	E_d	H_d	C_d	E_d	H_d	C_d	E_d
1.42	24.13	25.55	1.42	24.07	25.49	1.42	24.15	25.57	1.43	24.19	25.62
41.53	0.00	41.53	41.55	11.75	53.30	41.53	11.77	53.30	41.50	11.76	53.26
9.10	22.40	31.50	9.11	22.38	31.49	9.11	22.43	31.54	9.01	22.47	31.48
6.06	25.43	31.49	6.06	25.41	31.47	6.07	25.47	31.54	6.06	25.48	31.54
17.88	21.45	39.33	17.96	21.41	39.37	17.89	21.50	39.39	17.88	21.46	39.34
16.10	11.44	27.54	16.09	11.42	27.51	16.11	11.46	27.57	16.04	11.47	27.51
14.76	16.25	31.01	14.81	16.32	31.13	14.78	16.27	31.06	14.72	16.29	31.01
12.74	18.83	31.57	12.76	18.79	31.55	12.71	18.87	31.58	12.72	18.87	31.59
19.39	16.19	35.58	19.46	16.23	35.69	19.40	16.23	35.62	19.36	16.22	35.58
32.01	0.00	32.01	32.01	1.08	33.09	32.01	1.08	33.09	31.95	1.11	33.06
3.11	27.20	30.31	3.12	27.18	30.29	3.11	27.20	30.31	3.12	27.24	30.36
5.35	24.32	29.67	5.36	24.32	29.68	5.37	24.37	29.73	5.36	24.37	29.74
15.49	22.47	37.96	15.59	22.52	38.11	15.46	22.50	37.96	15.55	22.50	38.05
15.92	31.17	47.09	15.94	31.17	47.10	15.93	31.21	47.14	15.94	31.19	47.13
14.02	13.81	27.83	14.03	13.78	27.81	14.02	13.83	27.86	13.98	13.87	27.85
15.93	17.55	33.48	15.85	17.48	33.33	15.94	17.61	33.55	15.95	17.58	33.53
6.48	40.89	47.37	6.41	40.88	47.29	6.46	40.91	47.38	6.61	40.92	47.53
1.53	25.01	26.54	1.53	25.03	26.56	1.53	25.02	26.55	1.64	25.08	26.72
22.32	16.77	39.09	22.32	16.75	39.07	22.32	16.80	39.12	22.32	16.81	39.13
14.39	16.22	30.61	14.38	16.20	30.59	14.40	16.24	30.64	14.41	16.27	30.68
20.60	14.24	34.84	20.58	14.27	34.85	20.62	14.27	34.89	20.63	14.27	34.90
2.91	30.27	33.18	2.93	30.25	33.18	2.92	30.28	33.20	2.96	30.31	33.27
22.41	13.15	35.56	22.42	13.10	35.52	22.42	13.19	35.61	22.39	13.16	35.55
9.18	18.32	27.50	9.16	18.19	27.35	9.15	18.35	27.50	9.17	18.32	27.49
18.93	16.23	35.16	18.92	16.21	35.13	18.95	16.26	35.21	18.92	16.21	35.13
7.14	32.17	39.31	7.15	32.17	39.32	7.16	32.19	39.35	7.18	32.16	39.34
8.57	30.05	38.62	8.58	30.01	38.59	8.57	30.06	38.63	8.64	30.04	38.68
33.29	0.00	33.29	33.31	3.62	36.92	33.29	3.62	36.91	33.26	3.58	36.83
19.01	0.00	19.01	19.02	8.22	27.24	19.00	8.20	27.20	19.01	8.20	27.20
13.78	22.88	36.66	13.80	22.82	36.62	13.80	22.93	36.73	13.76	22.86	36.62
11.21	33.85	45.06	11.24	33.83	45.07	11.21	33.89	45.09	11.19	33.84	45.03
24.02	14.61	38.63	24.03	14.47	38.51	24.03	14.64	38.66	23.99	14.59	38.58
32.45	0.00	32.45	32.47	14.33	46.80	32.45	14.32	46.78	32.49	14.28	46.77
15.13	0.00	15.13	15.12	4.18	19.30	15.13	4.16	19.28	15.08	4.16	19.24
27.53	26.04	53.57	27.57	26.05	53.62	27.54	26.04	53.58	27.54	26.01	53.55
42.38	0.00	42.38	42.39	0.02	42.41	42.38	0.03	42.41	42.28	0.00	42.28
4.03	44.69	48.72	4.02	44.68	48.70	4.02	44.73	48.75	4.05	44.71	48.77
11.04	14.42	25.46	11.05	14.45	25.49	11.06	14.44	25.50	10.99	14.43	25.42

Training dataset											
Expected			Predicted								
TRNSYS			MLP ANN			Generalised ANN			Modular ANN		
<i>H_d</i>	<i>C_d</i>	<i>E_d</i>	<i>H_d</i>	<i>C_d</i>	<i>E_d</i>	<i>H_d</i>	<i>C_d</i>	<i>E_d</i>	<i>H_d</i>	<i>C_d</i>	<i>E_d</i>
35.45	0.00	35.45	35.49	0.62	36.11	35.45	0.67	36.12	35.36	0.63	35.99
19.55	0.00	19.55	19.57	18.52	38.08	19.55	18.49	38.04	19.58	18.49	38.07
44.58	0.00	44.58	44.60	-0.01	44.59	44.59	0.02	44.61	44.48	0.00	44.48
16.34	15.53	31.87	16.40	15.55	31.95	16.34	15.59	31.94	16.29	15.55	31.84
12.43	27.92	40.35	12.42	27.87	40.30	12.44	27.93	40.37	12.45	27.94	40.39
15.08	19.90	34.98	15.11	19.89	35.00	15.08	19.93	35.02	15.01	19.92	34.94
5.26	37.98	43.24	5.27	37.98	43.25	5.26	38.00	43.26	5.25	38.02	43.27
11.19	20.06	31.25	11.24	20.03	31.27	11.21	20.08	31.30	11.12	20.08	31.20
17.71	17.22	34.93	17.69	17.22	34.91	17.72	17.24	34.95	17.67	17.24	34.91
8.01	40.70	48.71	8.07	40.69	48.77	8.04	40.71	48.74	8.05	40.72	48.77
6.30	41.60	47.90	6.35	41.59	47.95	6.29	41.59	47.88	6.29	41.62	47.91
10.12	25.20	35.32	10.16	25.22	35.38	10.12	25.22	35.34	10.09	25.20	35.29
8.13	18.87	27.00	8.12	18.87	26.99	8.18	18.91	27.09	8.10	18.89	26.99
16.98	0.00	16.98	16.97	2.73	19.70	16.98	2.72	19.70	16.94	2.74	19.68
7.74	41.82	49.56	7.71	41.83	49.54	7.77	41.86	49.63	7.73	41.85	49.58
11.15	29.39	40.54	11.14	29.37	40.51	11.14	29.42	40.56	11.17	29.41	40.58
30.75	0.00	30.75	30.77	1.10	31.87	30.75	1.10	31.86	30.71	1.08	31.79
11.85	32.03	43.88	11.85	32.02	43.88	11.86	32.02	43.88	11.83	32.05	43.89
16.43	0.00	16.43	16.43	10.63	27.06	16.44	10.63	27.07	16.40	10.65	27.04
9.51	15.95	25.46	9.53	15.94	25.46	9.51	15.98	25.49	9.45	15.99	25.44
11.20	25.70	36.90	11.23	25.69	36.91	11.23	25.70	36.93	11.15	25.74	36.89
4.28	30.72	35.00	4.35	30.71	35.06	4.30	30.73	35.04	4.22	30.76	34.98
14.40	20.67	35.07	14.42	20.67	35.10	14.41	20.69	35.11	14.32	20.71	35.03
36.92	0.00	36.92	36.94	3.60	40.54	36.93	3.61	40.54	36.88	3.60	40.48
38.40	0.00	38.40	38.42	0.02	38.44	38.40	0.03	38.43	38.36	0.03	38.39
10.83	27.48	38.31	10.84	27.46	38.30	10.84	27.48	38.32	10.77	27.51	38.28
30.28	0.00	30.28	30.29	8.94	39.23	30.29	8.95	39.23	30.22	8.95	39.17
11.37	26.47	37.84	11.45	26.48	37.92	11.39	26.49	37.88	11.29	26.52	37.82
14.53	38.44	52.97	14.56	38.44	53.00	14.54	38.44	52.98	14.45	38.50	52.95
12.37	15.88	28.25	12.37	15.85	28.22	12.38	15.90	28.28	12.30	15.92	28.21
13.49	18.95	32.44	13.54	18.98	32.52	13.50	18.98	32.47	13.48	18.96	32.44
22.29	33.13	55.42	22.32	33.12	55.44	22.30	33.12	55.42	22.28	33.14	55.42
8.53	21.98	30.51	8.51	21.97	30.49	8.53	21.98	30.51	8.47	22.01	30.47
19.01	35.19	54.20	19.02	35.17	54.20	19.02	35.23	54.25	18.97	35.22	54.19
11.16	19.60	30.76	11.15	19.57	30.72	11.16	19.60	30.76	11.13	19.63	30.75
21.98	10.75	32.73	22.00	10.78	32.78	21.98	10.77	32.75	21.97	10.77	32.74
11.11	23.47	34.58	11.11	23.47	34.58	11.12	23.48	34.60	11.12	23.47	34.60
29.61	0.00	29.61	29.62	5.84	35.47	29.61	5.84	35.45	29.64	5.82	35.46

Training dataset											
Expected			Predicted								
TRNSYS			MLP ANN			Generalised ANN			Modular ANN		
H_d	C_d	E_d	H_d	C_d	E_d	H_d	C_d	E_d	H_d	C_d	E_d
15.35	17.42	32.77	15.39	17.44	32.83	15.36	17.42	32.78	15.36	17.43	32.79
18.43	37.15	55.58	18.46	37.11	55.57	18.45	37.16	55.61	18.45	37.15	55.60
1.85	33.10	34.95	1.81	33.11	34.92	1.85	33.10	34.95	1.79	33.16	34.95
7.54	28.24	35.78	7.57	28.27	35.84	7.54	28.23	35.77	7.48	28.30	35.78
22.11	0.00	22.11	22.12	17.83	39.94	22.12	17.86	39.98	22.09	17.88	39.97
11.94	24.89	36.83	11.97	24.90	36.86	11.96	24.91	36.87	11.96	24.88	36.84
11.44	24.67	36.11	11.38	24.57	35.95	11.49	24.67	36.17	11.40	24.68	36.07
9.03	31.62	40.65	9.07	31.59	40.66	9.03	31.63	40.66	8.96	31.65	40.61
11.08	37.30	48.38	11.08	37.27	48.35	11.09	37.30	48.39	11.00	37.34	48.34
17.78	21.49	39.27	17.79	21.52	39.32	17.79	21.49	39.27	17.73	21.50	39.23
13.17	16.66	29.83	13.13	16.61	29.74	13.18	16.67	29.85	13.14	16.64	29.78
37.13	0.00	37.13	37.15	2.18	39.33	37.14	2.21	39.34	37.14	2.15	39.29
15.73	26.05	41.78	15.75	26.03	41.78	15.74	26.02	41.76	15.66	26.07	41.73
1.75	25.84	27.59	1.74	25.80	27.54	1.75	25.82	27.57	1.67	25.90	27.57
19.21	11.43	30.64	19.24	11.42	30.66	19.22	11.44	30.67	19.19	11.39	30.58
14.44	17.37	31.81	14.45	17.36	31.81	14.45	17.36	31.81	14.43	17.37	31.80
18.02	26.54	44.56	18.00	26.51	44.51	18.02	26.54	44.56	18.00	26.57	44.57
9.92	19.53	29.45	9.95	19.54	29.50	9.92	19.57	29.49	9.91	19.54	29.45
4.01	41.89	45.90	4.05	41.88	45.93	4.02	41.89	45.92	3.97	41.94	45.91
13.07	38.34	51.41	13.11	38.34	51.44	13.06	38.31	51.37	13.04	38.37	51.42
12.57	19.06	31.63	12.66	19.07	31.72	12.56	19.07	31.64	12.61	19.06	31.67
4.01	30.54	34.55	3.97	30.52	34.49	4.00	30.55	34.55	4.00	30.59	34.59
1.60	24.94	26.54	1.61	24.97	26.58	1.60	24.92	26.53	1.58	24.98	26.56
1.36	47.28	48.64	1.37	47.30	48.67	1.36	47.29	48.65	1.34	47.33	48.68
14.27	18.47	32.74	14.30	18.51	32.81	14.31	18.50	32.81	14.30	18.49	32.79
11.36	38.47	49.83	11.35	38.46	49.80	11.37	38.50	49.87	11.35	38.54	49.89
22.06	27.86	49.92	22.08	27.83	49.91	22.07	27.88	49.95	22.09	27.88	49.97
13.10	18.87	31.97	13.10	18.91	32.00	13.09	18.90	31.99	13.16	18.87	32.02
2.43	29.08	31.51	2.45	29.06	31.52	2.43	29.08	31.52	2.44	29.14	31.58
43.29	0.00	43.29	43.29	1.78	45.07	43.30	1.77	45.07	43.35	1.73	45.08
26.88	31.97	58.85	26.92	31.98	58.90	26.89	31.98	58.86	26.94	31.96	58.90
6.89	27.44	34.33	6.93	27.42	34.34	6.88	27.46	34.34	6.94	27.44	34.38
5.56	43.55	49.11	5.56	43.54	49.10	5.57	43.56	49.12	5.59	43.58	49.16
3.64	24.14	27.78	3.63	24.16	27.79	3.64	24.14	27.78	3.67	24.15	27.83
20.31	20.77	41.08	20.24	20.77	41.02	20.32	20.75	41.08	20.31	20.79	41.10
18.39	17.57	35.96	18.35	17.54	35.88	18.40	17.56	35.96	18.38	17.62	35.99
7.67	29.88	37.55	7.68	29.84	37.52	7.68	29.90	37.57	7.64	29.95	37.60
26.39	32.59	58.98	27.21	31.80	59.01	26.52	31.91	58.42	26.37	32.63	59.01

Training dataset											
Expected			Predicted								
TRNSYS			MLP ANN			Generalised ANN			Modular ANN		
<i>H_d</i>	<i>C_d</i>	<i>E_d</i>	<i>H_d</i>	<i>C_d</i>	<i>E_d</i>	<i>H_d</i>	<i>C_d</i>	<i>E_d</i>	<i>H_d</i>	<i>C_d</i>	<i>E_d</i>
4.00	34.88	38.88	4.60	35.15	39.75	4.01	35.09	39.10	3.98	34.97	38.94
10.19	24.03	34.22	7.59	24.78	32.37	10.31	24.73	35.04	10.17	24.10	34.27
17.06	17.93	34.99	17.50	18.01	35.50	17.31	17.79	35.10	17.05	17.96	35.01
18.15	21.64	39.79	18.28	21.23	39.51	18.65	21.26	39.91	18.12	21.68	39.80
4.31	37.97	42.28	5.04	37.93	42.97	4.34	37.69	42.04	4.27	38.04	42.31
13.31	19.66	32.97	13.32	19.68	33.01	13.31	19.71	33.02	13.28	19.68	32.96
12.35	19.05	31.40	13.35	19.69	33.04	12.27	17.85	30.12	12.31	19.07	31.38
3.49	31.89	35.38	3.67	31.74	35.41	3.51	31.80	35.30	3.44	31.95	35.38
12.89	25.08	37.97	12.95	25.09	38.04	13.40	24.88	38.28	12.83	25.10	37.93
16.19	38.57	54.76	15.96	38.28	54.24	17.30	37.70	55.00	16.13	38.60	54.73
25.71	14.13	39.84	26.36	14.16	40.51	26.27	14.44	40.71	25.63	14.16	39.80
20.49	20.83	41.32	21.00	20.58	41.58	21.02	20.55	41.58	20.46	20.86	41.31
8.48	24.10	32.58	8.81	23.72	32.53	8.78	23.42	32.20	8.46	24.13	32.59
9.78	26.19	35.97	10.42	26.24	36.66	10.20	26.24	36.44	9.77	26.21	35.99
12.48	39.55	52.03	12.86	38.73	51.59	15.24	37.85	53.09	12.47	39.56	52.03
16.96	0.00	16.96	15.85	9.06	24.91	16.23	8.99	25.22	16.95	9.38	26.33
14.24	15.66	29.90	14.61	15.24	29.85	15.06	15.63	30.69	14.23	15.66	29.89
14.23	36.28	50.51	14.88	36.93	51.81	14.60	36.94	51.54	14.22	36.29	50.50
0.69	35.29	35.98	0.20	35.84	36.03	0.00	36.21	36.21	0.68	35.30	35.98
16.44	18.59	35.03	15.90	18.80	34.71	15.52	17.63	33.15	16.44	18.59	35.03

Table 9E

Target versus Predicted output for the validation set.

Validation set											
Expected			Predicted								
TRNSYS			MLP ANN			Generalised ANN			Modular ANN		
<i>H_d</i>	<i>C_d</i>	<i>E_d</i>	<i>H_d</i>	<i>C_d</i>	<i>E_d</i>	<i>H_d</i>	<i>C_d</i>	<i>E_d</i>	<i>H_d</i>	<i>C_d</i>	<i>E_d</i>
10.35	24.26	34.61	10.23	23.97	34.20	10.84	24.08	34.92	10.70	24.09	34.79
8.31	28.79	37.10	8.60	28.53	37.12	8.69	28.67	37.36	8.48	28.85	37.33
10.11	17.15	27.26	9.33	16.88	26.22	10.58	16.50	27.08	9.91	16.94	26.84
9.37	13.97	23.35	9.26	14.01	23.27	9.59	14.01	23.61	9.14	13.78	22.92
15.77	0.00	15.77	17.11	12.41	29.52	16.67	11.60	28.28	15.44	13.25	28.69
5.12	41.96	47.07	5.00	41.74	46.75	4.64	42.02	46.65	5.04	42.02	47.06
6.95	42.26	49.21	6.27	41.74	48.01	5.97	41.45	47.42	7.18	41.15	48.33
21.14	16.98	38.13	21.38	17.71	39.09	20.65	15.79	36.44	20.94	16.82	37.75
4.33	43.44	47.77	4.62	43.65	48.27	4.68	43.46	48.14	4.37	43.40	47.77
8.80	19.96	28.76	8.90	20.11	29.00	9.21	19.98	29.19	8.93	19.97	28.91

Validation set											
Expected			Predicted								
TRNSYS			MLP ANN			Generalised ANN			Modular ANN		
H_d	C_d	E_d	H_d	C_d	E_d	H_d	C_d	E_d	H_d	C_d	E_d
4.30	24.54	28.84	4.60	24.40	29.00	4.85	24.43	29.28	4.18	24.44	28.62
7.00	30.39	37.39	6.58	30.38	36.97	6.81	30.34	37.15	6.56	30.23	36.79
29.19	0.00	29.19	29.15	7.47	36.62	29.92	7.37	37.29	28.95	7.22	36.17
10.06	16.64	26.70	10.79	16.16	26.95	10.72	16.22	26.93	9.92	16.36	26.28
11.14	37.76	48.91	12.07	37.76	49.83	11.70	36.77	48.47	11.51	38.25	49.75
13.29	37.16	50.45	13.22	37.03	50.25	12.75	37.19	49.94	13.02	37.26	50.28
40.40	0.00	40.40	39.64	2.87	42.51	41.31	4.30	45.62	40.11	3.03	43.14
10.65	30.15	40.80	10.99	30.15	41.15	11.04	30.07	41.12	10.90	30.29	41.19
20.20	12.68	32.88	20.11	12.95	33.06	20.02	12.84	32.86	20.22	12.70	32.91
16.52	26.47	42.99	15.86	26.54	42.41	16.04	26.32	42.36	16.08	26.50	42.58
8.93	42.12	51.05	9.36	41.69	51.05	9.04	42.36	51.40	8.16	40.82	48.98
9.62	24.26	33.87	9.56	24.10	33.66	9.02	24.32	33.33	9.55	24.06	33.61
7.49	26.01	33.50	7.15	26.23	33.38	6.83	26.48	33.31	7.45	26.05	33.50
9.47	15.48	24.96	10.25	14.98	25.23	10.32	15.49	25.82	9.50	15.43	24.93
13.98	14.28	28.26	13.74	14.46	28.19	15.05	14.42	29.47	13.90	14.03	27.93
25.74	10.75	36.49	26.13	10.83	36.96	26.40	11.29	37.69	25.78	10.58	36.36
1.97	30.71	32.68	2.14	30.22	32.36	2.85	30.11	32.96	1.90	30.84	32.74
15.61	14.44	30.05	15.77	14.75	30.52	16.49	15.74	32.23	16.61	15.34	31.95
9.48	18.71	28.19	9.27	18.57	27.84	9.05	18.94	27.98	9.57	18.92	28.49

E.5.3.2 ANN Performance Analysis

Following the ASHRAE Guideline 14 [27], the criteria to validate and compare prediction model performances in the field of building energy efficiency are the NMBE and the CV-RMSE indices [57]. Smaller values of these two indices identify models that present a more reliable prediction ability. Table 10E reports the limit values and ranges of applicability for the criteria of both indices [27].

Table 10E

Criteria and error indices for the evaluation of the model.

Criteria	Index	ASHRAE
Monthly [%]	NMBE	± 5
	CV(RMSE)	15
Hourly [%]	NMBE	± 10
	CV(RMSE)	30
Recommendation	R ²	> 0.75

Based on the time step of the representative database, it was necessary to evaluate the performance of the ANN prediction model to determine the limit values for an annual period (Table 11E).

Table 11E

Annual Criteria for the evaluation of the model.

Performance Criteria	Index	ASHRAE
Annual [%]	NMBE	± 4.45
	CV-RMSE	± 13.36
Recommendation	R ²	> 0.75

In more detail, in *Section B.6*, the definitions of NMBE and CV-RMSE are reported. Applying the two indices at the data reported in Table 9E the following errors were obtained (Fig. 32E):

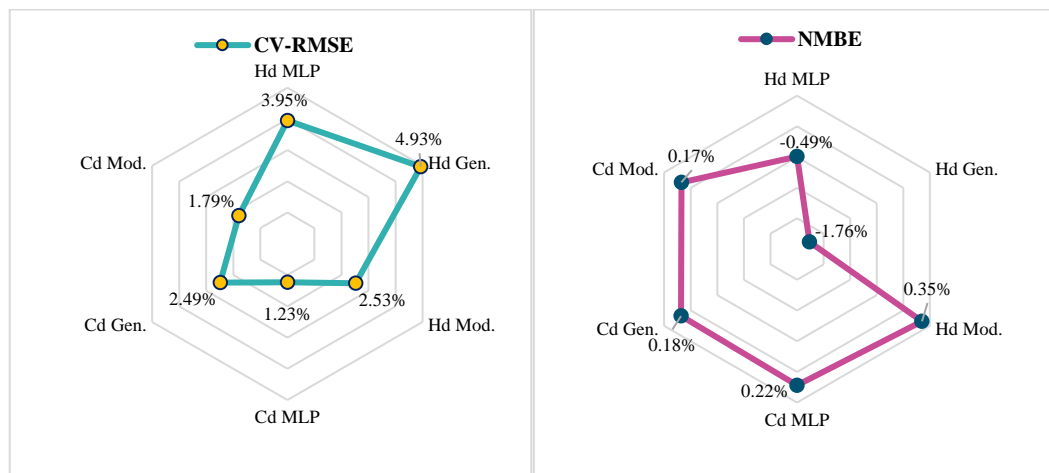


Fig. 32E. Performance analysis of the ANN models for the H_d/C_d evaluation for the Validation set.

For all three ANNs, all criteria are valid. Indeed, the NMBE is within the required applicability ranges, and CV-RMSE is lower than the specified limit values. This guarantees the validity of the model, and justifies the application of the ANN as an alternative model for solving a building energy balance.

E.5.4 Sensitivity Analysis

The selection of the explanatory variables of the phenomenon is a crucial step in the modelling of alternative prediction model, and trying to minimise their number makes it easier to find a solution. In the literature, in fact, there are several studies dedicated to the identification and reduction of the number of input variables, through various methods such as the use of Pearson and Spearman correlation coefficients that identify the strongest correlation between the building load and weather parameters, as applied in Gunay et al. [63] and Kapetanakis et al. [64], or the K-methods and clustering methods applied by Yan Ding et al. [65], which studied the accuracy of cooling load prediction models in office buildings influenced by input data. David Hsu [66] used K-means and cluster regression methods for an energy needs forecasting model. Similarly, in this case study, it was applied a Pearson correlation coefficient analysis (r) to identify the parameters that most influence the energy demands for heating and cooling of the studied building stock [58].

As indicated in the Eq. (14) of **Chapter C**, the Pearson correlation coefficient is defined as the ratio between the covariance of the two variables and the standard deviation of each. The coefficient r measures the linear correlation between two variables, assuming a value from 1, that represents a positive linear correlation and -1 indicates a total negative linear correlation, the value of 0 indicates that there is no linear correlation. After calculating the coefficient r for each parameter identified as an input in the previous ANNs, a sensitivity analysis was applied to identify the variables that most influence the building thermal balance. One of the most useful identification criterion for determining the most correlated values is represented by an empirical rule that, for a high value of input number (n), selects those variables for which the value of r is greater than $2/\sqrt{n}$ [67]. The following table (Table 12E) reports the values of R^2 and r for the input variables most-correlated with the two outputs, based on the r values and the criterion.

Table 12E

Determination and correlation coefficients of the most correlated and available input data.

Variables	Sensitivity Analysis			
	H_d		C_d	
	R^2	r	R^2	r
<i>HDD</i>	0.8444	0.919	--	--
<i>CDD</i>	--	--	0.41	0.64
<i>S/V</i>	0.6461	0.804	0.121	-0.348
<i>S_w</i>	0.5101	-0.735	0.014	0.118
<i>S_{op}</i>	0.6257	0.294	0.0864	-0.791

E.5.5 ANN and Input Selection

Considering the two best ANNs (the MLP and modular), and based on the sensitivity analysis, the two optimised ANNs were retrained for 10^6 epochs, considering a database with only 5 inputs (*HDD*, *CDD*, *S/V*, *S_w*, and *S_{op}*) and 2 outputs (H_d and C_d). The results of the two ANNs are collected in Table 13E, and Table 14E indicates the errors during the training and validation phases.

Table 13E

Post processing data of ANNs for the training dataset.

Training dataset										
Models	H_d					C_d				
	Min	Max	Mean	Median	StD	Min	Max	Mean	Median	StD
MLP ANN	0.000	2.225	-0.037	0.011	0.374	0.000	8.567	0.070	0.011	0.878
Modular ANN	0.000	0.051	0.012	0.011	0.015	0.000	0.084	0.016	0.011	0.020

Table 14E

Post processing data of ANNs for the validation dataset.

Validation dataset										
Models	H_d					C_d				
	Min	Max	Mean	Median	StD	Min	Max	Mean	Median	StD
MLP ANN	0.025	5.294	-0.249	-0.085	1.845	0.025	3.453	0.518	-0.009	1.060
Modular ANN	0.155	10.956	0.238	1.535	3.990	0.251	13.509	-0.234	1.535	5.400

Fig. 33E illustrates the differences between the MAE, MSE, RMSE, MAPE, CV-RMSE, and NMBE obtained from the MLP and modular ANNs trained with only 5 inputs, and those from the previous ANNs (Section E.5.3).

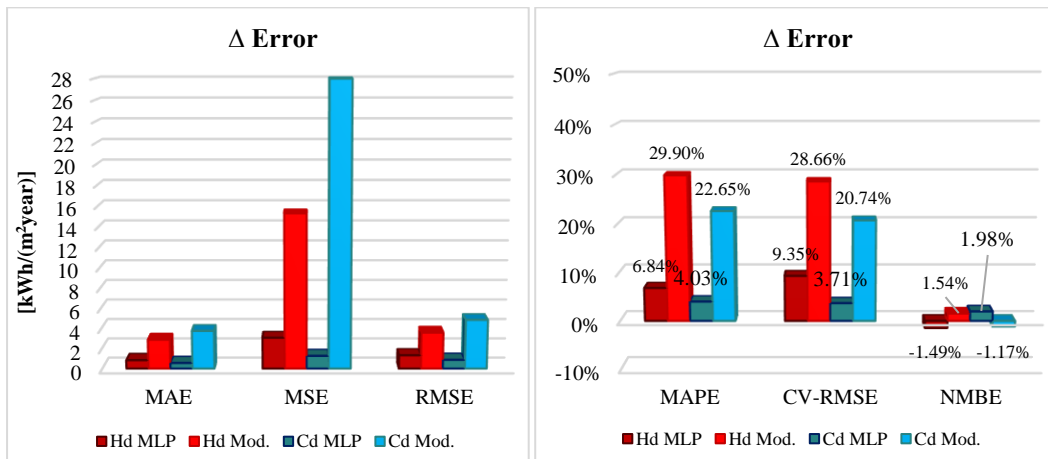


Fig. 33E. Error differences between Post and Pre sensitivity analysis for MLP and Modular ANNs.

Fig. 34E illustrates the R^2 values of the two ANNs before and after input reduction, and also displays the numerical difference (Δ).

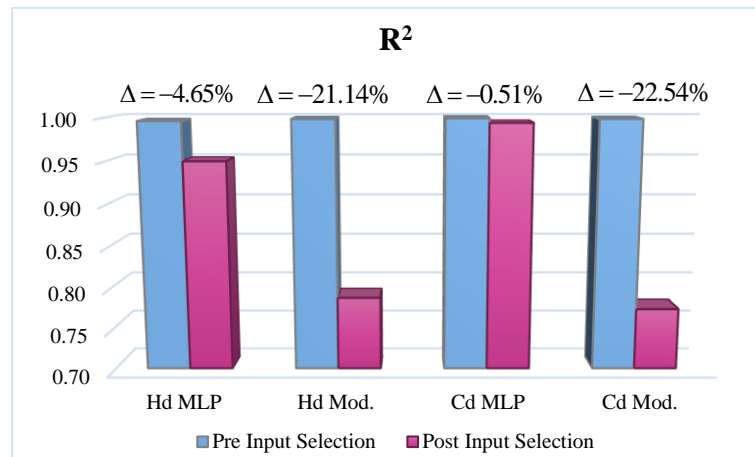


Fig. 34E. R^2 comparison between Post and Pre sensitivity analysis for MLP and Modular ANNs.

Although the reduction of input data allows for identification of a complex problem with few and well-known parameters and speeds up the evaluation phase, it causes a response with reduced quality. Indeed, in all cases, the errors between post- and

pre-sensitivity analysis increase for the two ANNs, whereas the R^2 value decreases; in particular, between the two networks, the modular ANN is characterised by the worst performance. Moreover, to validate the two new models, the performance analyses were carried out, but in this case, only the MLP ANN respected the selected criterion for all indices (Table 15E).

Table 15E

Performance analysis of the best two ANNs after the input reduction.

Performance Criteria	Index	ASHRAE	H_d	C_d	H_d	C_d
			MLP	MLP	Modular	Modular
Annual [%]	NMBE	± 4.45	-1.98	2.20	1.89	-0.99
	CV-RMSE	± 13.36	13.30	4.94	31.19	22.53
Recommendation	R^2	> 0.75	0.95	0.99	0.79	0.77

These considerations confirm that a sensitivity analysis applied to minimise the input data can be a good solution to simplify a complex problem such as a building energy balance, but its applicability must be followed by a careful performance evaluation and selection of a neural network configuration.

E.6 DISCUSSION

The thermal balance of a building is often influenced by a multitude of physical, environmental and human factors that sometimes influence each other. Consequently, the analysis of a building's energy performance requires substantial input data describing detailed constructions, environmental conditions, thermo-physical properties, building geometry, and control strategies. The evaluation of the thermal load for the winter conditioning of a building normally requires the adoption of complex and expensive dynamic simulation tools, almost always inaccessible to untrained and non-expert users. Moreover, these tools require a large amount of data, often not available with adequate precision. To make the preliminary assessment of the energy performance of several buildings belonging to a cluster easier and faster, it is more convenient to adopt an alternative approach to detailed dynamic simulations. In this context, it can be extremely advantageous to use neuro-computing, which, based on a large amount of experimental data, can

establish dependency relationships between input and output variables. The choice of this Black-Box method overcomes some of the limits shown by several papers, such as a long computational time or the need of an expert-user. It is necessary for the identification of a generic solution, able to interpret any condition and to accelerate the resolution with high reliability.

In the first part of this chapter, have exploited the power of ANNs to solve the thermal balance of non-residential building designed with high-performance in accordance with European energy standards. As explained in **Chapter B**, the results collected in *Annex 2* have been used. Based on this database, four ANNs, with different numbers of neurons and hidden layers were investigated: A1 (8 neurons) and A2 (30 neurons), B1 (400-120 neurons) and B2 (500-250 neurons). Analysing the data collected in Table 5E, it is possible to observe that the B architecture, in general, is characterised by the best results with the lowest MAPE; on the other hand, this configuration required a longer computational time than the A architecture. Further, the A1 topology is a good compromise between results and computational time. The achievement of these positive results ($R^2 > 95\%$) confirmed that the ANN application to the heat transfer problems in buildings is a valid and attractive alternative solution for thermal balance resolution.

In the second part, the ANN were used based on usage of a reliable building energy database representative of a non-residential building stock designed with high energy performance and located in the Italian peninsula. Owing to the development of a matrix of 19 input columns, 2 output columns, and 195 rows that identified all possible scenarios (*Annex 3*), several neural network configurations were trained. The best three static networks were the Multi-Layer Perceptron, Generalized and Modular artificial neural network. A careful statistical analysis permitted affirmation of the application of the ANN is an optimal alternative model for solving a traditional building energy balance, and for calculating a comprehensive energy demand. Indeed, analysing the results in all cases, the deviations for heating and cooling loads are approximately zero (kWh/(m² year)) for the training dataset, and are between ± 1.5 (kWh/(m² year)) for the validation set. These are very low deviation values with respect to the mean values of the heating energy demand of

approximately 15 (kWh/(m² year)) and cooling energy consumption of approximately 23 (kWh/(m² year)). In general, the analysis of the results displayed in Fig.26E, the best values are related to the modular ANN for the heating load and to the MLP ANN for the cooling evaluation. In detail, for the heating loads the MSE, MAE and RSME have values less than of 0.32 kWh/m² and a MAPE of 2.23 %, whereas for the cooling loads the MSE, MAE and RSME have values less than of 0.29 kWh/m² and a MAPE of 1.39 %. Furthermore, the validity of the model was ensured by a performance analysis that, according to the ASHRAE Guidelines, identified the range of the criteria to validate, and compared prediction models' performances in the field of building energy efficiency.

At the end, to simplify the problem, minimise the input data to train the neural networks, and provide an easier use phase, a sensitivity analysis based on the Pearson coefficient, which reduced the input numbers to only 5 variables, was applied. Although the reduction of input data allows for identification of a complex problem with few and/or well-known parameters and speeds up the evaluation phase, it could reduce the quality of the response. Indeed, in all cases, the errors between post- and pre-sensitivity analysis increase for the two networks, while the R² values decrease. In particular, between the two networks, as illustrated in Fig.33E the modular neural network is characterised by the worst performance. Moreover, performance analyses were carried out to validate the two new models, but only the MLP respected the selected criterion for all indices.

The application of ANNs allowed for achievement of the aim of the study: obtaining a simplified, flexible, and easy-to-use decision support tool that solves a complex problem such as building energy balance, thereby accelerating and assisting evaluation phases in energy planning. Evidently, the possibility of reducing the input data is important for simplifying and accelerating the use phase, but only if the quality of the response is higher and the performance analysis is positive. Therefore, by integrating and upgrading the building energy database, the proposed methodology could be replicated in any context and for any condition, offering a strong, versatile, and easy tool for private designers, municipalities, and public administrations that a non-expert user can use.

MY RELATED PUBLICATIONS

The research covered in **Chapter E** were published in the following international Journal:

1. Ciulla, G., **D'Amico, A.**, Brano, V. L., & Traverso, M. (2019). Application of optimized artificial intelligence algorithm to evaluate the heating energy demand of non-residential buildings at European level. *Energy*, 176, 380-391.

Furthermore, the following research is under review:

2. **D'Amico, A.**, Ciulla, G., Simplified and optimised forecasting tool of comprehensive building-stock thermal needs. Under review in *Energy* from 28th August 2019.

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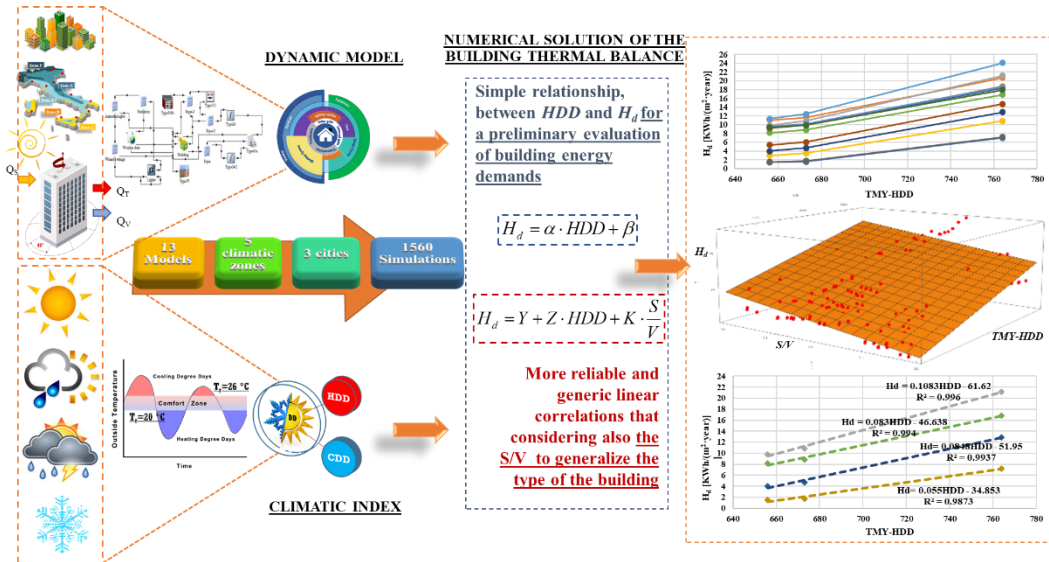
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CHAPTER F

THE IMPORTANCE OF THE CLIMATIC DATASET IN THE BUILDING ENERGY EVALUATION

THE IMPORTANCE OF THE CLIMATIC DATASET IN THE BUILDING ENERGY EVALUATION



ABSTRACT

Simultaneously of previously research, it was underlined as the weather is one of the main factors to consider when modelling a building energy predictive tool because it represents the most important boundary condition to affect the dynamic behaviour of the building. A deep discussion about this is reported in this chapter, in which is demonstrated that the assessment of building energy demand through any model based on the use of the degree day is correct only if the determination of the climate index is a function of the same weather data used to model the tool. This objective is pursued applying the MLR analysis that identifies the relationship between HDD and heating energy performance. In detail, it was used HDDs based on three climate data-sets, which develop different relationships and feedback. For the extraction of these correlations, the database built for the Italian climatic context is used. From the analysis of the results, it is clear that the relationships with higher determination coefficients (higher than 0.9) are those that are a function of the degree days calculated from the same climatic file used during the simulations on which the database is built. The proposed methodology, validated in this chapter for an Italian case study can be extended to any country and can be used to improve the reliability of any decision support tool based on climatic indexes.

NOMENCLATURE

<u>Acronyms</u>	
HVAC	Heating, Ventilating and Air-Conditioning
MHD	Mean Degree-Hours
TMY	Typical Meteorological Year
<u>Building Thermal Balance parameters</u>	
<i>CDD</i>	Cooling Degree Days [K day]
<i>dd</i>	Daily Degree Days [K day]
<i>DD</i>	Degree Days [K day]
<i>DD_m</i>	Monthly Degree Days [K day]
<i>H_d</i>	Heating energy demand [kWh/(m ² ·year)]
<i>HDD</i>	Heating Degree Days [K day]
<i>S/V</i>	shape factor [m ⁻¹]
<i>S_i</i>	Solar Irradiance [W/m ²]
<u>Climatic index parameters</u>	
<i>a, b</i>	Coefficients of linear regression related to climate information
<i>h</i>	Altitude [m]
<i>N</i>	Number of locations used
<i>N_g</i>	Number of days in a heating period
<i>N_m</i>	Number of days in the month
<i>T_i</i>	Average daily temperature [°C]
<i>T_r</i>	Reference indoor thermal comfort temperature [°C]
<i>T_s</i>	Second reference temperature [°C]
<i>θ_b</i>	Base temperature [°C]
<i>θ_{max}</i>	Maximum daily temperature [°C]
<i>θ_{min}</i>	Minimum daily temperature [°C]
<i>θ_o</i>	Outdoor temperature [°C]
<i>θ_{o,m}</i>	Monthly mean temperature [°C]
<i>θ₁</i>	<i>HDD</i> regression coefficient [kWh/(K·m ² ·year)]
<i>θ₂</i>	<i>S/V</i> regression coefficient [kWh/(m·year)]
<i>σ_θ</i>	Standard deviation of the variation in temperature throughout the month
<u>Performance parameters</u>	
<i>R²</i>	Determination coefficient

F.1 INTRODUCTION

To enable a reliable development of energy prediction model and detailed energy planning, it is necessary to understand the manner in which climate change affects the increase in atmospheric temperatures, and therefore, making the historic 20-year averages unreliable. In the future, the temperature increase will determine the setting of new energy budgets [1]; indeed, climate change is reshaping the energy performance of buildings and cities [2,3]. The variation in the energy performance of buildings in terms of space heating and cooling in the future (until 2030) was investigated by [4]. Outdoor temperature variations directly affect water resources, power generation, agriculture, construction, and, in particular, energy consumption for the cooling and heating of buildings [5]. As several works [6,7] have outlined, building energy consumption is considerably affected by these temperature changes. For example, in [8], the impact of climate warming on the Swiss building energy demand was investigated by means of the *DD* method. In [9], energy consumption for heating/cooling was analysed in different locations, demonstrating that *DD* affect the behaviour of building consumption against the standard degree. In [10], a new methodology was proposed for assessing energy demands for space heating in buildings on the city scale: a *DD* method was applied, coupled with the use of a dynamic urban meteorological model that computes a building energy budget day. In [11], it was demonstrated that the change in the urban climate affected the energy performance in the city of Rome, with a heating consumption reduction of up to 21% in residential buildings and 18% in office buildings, as well as an increase in cooling consumption of up to 74% in residential buildings and 53% in office buildings. In other studies, the authors assessed the impact of climate change on electricity consumption, which increases over time; in [12], it was determined that the electricity demand in Australia will increase by between 2.7% and 4.5% by 2050; in a review [13], the impact on cooling loads was found to be significant at approximately 13%. The European Union (EU) has always paid attention to environmental issues [14] and energy supply [15]. Since its formation, the EU has identified various measures [16,17] that, when implemented, will

achieve important standards for energy saving, greenhouse gas emission reduction [18], and renewable energy production [19]. In 2013, the EU took another step forward by defining the “2030 Framework for Climate and Energy Policies” [20]. The 2030 Framework outlines the importance of continuing along the path towards energy saving and energy efficiency, which member states have already initiated. The proposed targets that each member state must achieve are reducing emissions by 40% compared to 1990 levels and promoting the production of at least 27% renewable energy in the EU. In this context, the interventions necessary for achieving these energy targets affect the key economic sectors of individual member states, particularly industry, transportation and the civil sector. As previously seen, estimation of heat demands/loads is a complex task. However, in the civil sector, it is important to assess the contribution of all activities taking place within buildings in terms of energy consumption.

Taking into account these considerations and previous studies, the importance of the quality of climatic data in accurately evaluating the energy needs of a building cannot be underestimated. Indeed, a deep discussion, developed simultaneously with the previous works, underlined as the climatic parameters represent important boundary conditions for building design, affecting the transient behaviour of the building envelope during its useful life [21]. Among these parameters, the *DD* could be used to quantify energy demands.

In general, the *DD* value is considered as an index of the energy consumption of buildings, and represents an old but simple method used in Heating, Ventilating and Air-Conditioning (HVAC) industries to estimate the heating and/or cooling energy requirements [22]. Essentially, *DD* provides the summation of temperature differences over time, calculated between a fixed indoor reference temperature and the outdoor air temperature, whenever the latter is less/more (for heating/cooling requirements, respectively) than the former. The reference temperature for buildings is a known variable (base temperature), and corresponds to the outdoor temperature at which the heating/cooling systems do not need to run to maintain indoor comfort conditions.

In addition to the base temperature, the external temperature value is very important; not taking the variation of this value into account in the *DD* calculation makes it unreliable for use in the assessment of the building energy demand. For example, in London and Edinburgh from 1976 to 1995, the *DD* value decreased by approximately 10% [23]. It is conceivable that *HDD* may drop by 30% to 40% in the UK by the 2080s, owing to a constant increment in the outdoor temperature. In this context, it will be important to evaluate the impact of climate change on the estimation of *DD* and building energy demands. More recent works, for different countries, have been carried out: Romania [24], Turkey [25,26], Australia [27], Greece [28], China [29,30], Spain [31], Switzerland [8], Saudi Arabia [5,32], Morocco [33], and France [10]. Although the general direction of the temperature effect on energy use is similar for most studies, the relative change in the energy demand differs significantly according to the location, time period, and methodology used [34].

F.1.1 Contribution of the Work

It is widely recognised that the correct estimation and prediction of the building energy demand represents a crucial point to perform scenario analyses, which may determine the best energy policy for compliance with standards for new and existing buildings set by the EU [35] and other countries.

It must be emphasised that, if the *DD* index is not correctly calculated, determining the building energy performance as a function of *DD* may lead to imprecise evaluations. To link the building energy performance with the correct *DD* value, it is necessary to calculate *DD* based on the same TMY used for the building energy evaluation. Because the building energy requirements are strictly dependent on the external climate, it could be more convenient to provide a correlation that allows for the evaluation of the energy demand with a high level of accuracy and without excessive computational costs or user expertise, while knowing only the dependence of the *DD* values. However, the close correlation between *DD* and the

building energy requirement is valid only if the building energy assessment has been conducted, using the same updated database that led to the *DD* determination. Each city is characterised by a certain *DD* value, which is calculated based on individual laws and standards and on a specific climate dataset. For this reason, during analysis of the energy performance of a building, it is incorrect to link the results obtained from a generic building simulation tool with a defined *DD* value indicated in a law or standard. The correlation between the energy demand of a building and a *DD* value calculated using different standards or a specific climate file will produce different relationships and feedback. To demonstrate this, several simple correlations to evaluate H_d knowing only the *DD* value has been developed. This was achieved by taking three climate datasets for the same location and using them to calculate different *DD* values to represent three varying scenarios. For the extraction of these correlations, were used the data related to the Italian building energy database described in *Section B.7.3*. Owing to an in-depth analysis of the results, it was possible to identify a specific correlation for each case, in which the heating energy demand was a function of the *DD*, and its validity was evaluated using the respective correlation coefficient (R^2). Furthermore, a comparison of the relationships obtained from three different weather datasets underlines the fact the building energy demand assessment is dependent on the *DD* only if the climatic index is a function of the same weather data used during the simulations. This is demonstrated by the higher R^2 coefficients.

The proposed methodology, which is validated in this work for an Italian case study, can be extended to any country and/or climatic region, and can be used to improve the reliability of any energy building decision support tool based on the use of climatic indexes.

F.2 METHODOLOGY

This chapter describes a topic that with simultaneously with the previous research works has been dealt. In detail, as previously stated, the strong correlation between the energy performance of the building and the *DD* is founded if the same set of

meteorological data is used. Following definitions and descriptions of the well-known methods for determining the *DD* (Section F.3), considering the purpose of this work and based on the particular situation of the Italian building energy-efficiency laws and standards currently in force, it was decided to describe an Italian case study, representing a methodology that can also be extended to other contexts. Thanks to the data obtained from the TRNSYS dynamic simulations (Section B.7.3) [36], several correlations were constructed that are valid for buildings designed according to the energy requirements standards and laws in Italy.

An in-depth analysis of the Italian procedure for determining the energy performance of a building indicated that, owing to the obsolescence of the old Italian technical standards UNI 10349: 1994 [37] and DPR 412/93 [38] based on climatic data prior to 1994, and in the absence of the Cooling Degree Day (*CDD*) values, the new version of the standard, UNI 10349, published in 2016 [39], should be used. The standard UNI 10349-1: 2016 contains monthly average data calculated from test reference years, developed by the Italian Thermo-technical Committee for 110 Italian locations, and recalculates the *HDD* and *CDD* values. However, at present, UNI 10349: 2016 calculates the *HDD* and *CDD* values without changing the previously stated heating or cooling periods for all Italian cities, and without making any distinction between the climate zones. For this reason, the current evaluation of the energy performance of Italian buildings is based on the old *HDD* and does not consider the *CDD*. Therefore, for this work, only the heating load was analysed.

To evaluate the correct correlation between the thermal energy requirement obtained from the validated simulation and *DD*, the following questions must be asked: is it advisable to use the *HDD* value from the old standard, or is it preferable to use that of the new standard? Furthermore, if a specific climate file in a dynamic simulation that does not refer to either of the two standards has been used, are the correlations between the *HDD* values, dictated by law, and the energy requirements, obtained from a generic simulation, correct?

To answer these questions, in this work, the simulation data were used to explore whether a direct correlation of a generic *HDD* with the simulated H_d value,

obtained from a generic software tool, could lead to unrealistic consumption estimates. To demonstrate this, it was performed an MLR analysis between H_d and HDD , and then evaluated its reliability for 3 different scenarios:

- the HDD relating to the old Italian standard [37–39] (Section F.4.1);
- the HDD calculated based on the TMY (Section F.4.2); and
- the HDD relating to the new Italian standard (Section F.4.3).

Moreover, other correlations were developed by generalising the results, and considering the variability of the building energy performance within the climatic context and its shape. These relationships enable the simplification of the evaluation of energy performance in any initial energy planning phase.

The obtained results underline the importance of the selection of weather data in evaluating the heating energy demand of a building. Furthermore, the high degree of correlation of each issued relationship clearly proves that HDD is a suitable index for assessing the building energy performance if it is truly representative of the climatic boundary conditions (Section F.4.4).

The flow chart in Fig. 1F describes the proposed methodology for the evaluation of the heating energy demand of a building in detail, illustrating the procedure, scenario, and results.

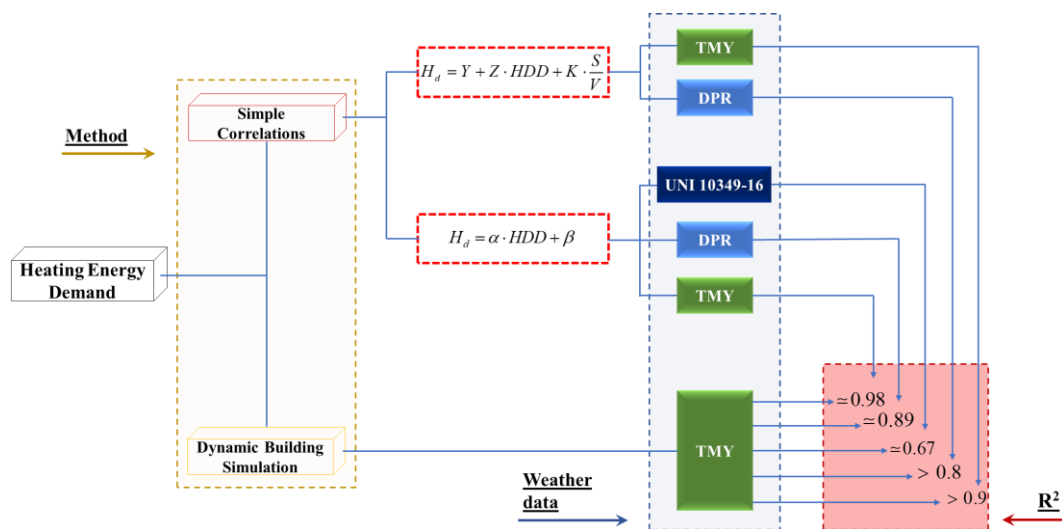


Fig. 1F. Flow chart on the determination of heating energy demand.

F.3 DEGREE DAYS DEFINITION

Generally, *DDs* for a location are defined as the sum of only the positive differences between the base temperature and the daily average outdoor temperature, extended to all days of a conventional twelve-month period. In the case of *HDD*, the differences between outdoor and base temperature are computed only when the outdoor temperature falls below the base temperature during the heating period. Conversely, in the case of *CDD*, the differences are calculated only when the outdoor temperature exceeds the base temperature during the cooling period.

In the literature, it is possible to find several ways of calculating the *DD* [1,31]:

- Mean Degree-Hours (MDH): calculated from the hourly temperature records (the Italian calculation method);
- Daily maximum and minimum temperatures: e.g. the UK Meteorological Office equations which use mean daily temperature; and
- Direct calculation of monthly *DD* from mean monthly temperature and the monthly standard deviation; e.g. Hitchin's formula.

The MDH is the most rigorous and most mathematically precise method of calculating *DD*, and is defined as the ratio of the sum of hourly temperature differences to 24. In this version, only positive differences are summed; in the case of *DD*, when the outdoor temperature exceeds the base temperature, the value of *DD* is null. Eq. (1) shows the general formula for *DD*:

$$\text{if } (\theta_b - \theta_{o,j}) > 0 \rightarrow DD = \frac{\sum_{j=1}^{24} (\theta_b - \theta_{o,j})}{24} \quad (1)$$

where

DD is the degree-days for one day;

θ_b is the base temperature; and

$\theta_{o,j}$ is the outdoor temperature in the j^{th} hour.

The UK Meteorological Office Equations are sometime referred to as the “McVicker” or the “British Gas” formulas. Since 1928, this definition has been the standard method for calculating DD in the UK as an approximation of the integral:

$$DD = \int (dd) dt = \int (\theta_b - \theta_o) dt \quad (2)$$

for daily dd using daily maximum and minimum outdoor temperatures. The formulas were developed to be computed with a simple manual calculation using only a single (maximum and minimum) value for each day. Different formulations for different cases are shown in Table 1F:

Table 1F

UK Meteorological Office equations for calculating daily heating degree-days.

Case	Condition	Daily heating degree-day
1	$\theta_{\max} < \theta_b$	$dd = \theta_b - \frac{(\theta_{\max} + \theta_{\min})}{2}$
2	$\theta_{\min} < \theta_b$ and $(\theta_{\max} - \theta_b) < (\theta_b - \theta_{\min})$	$dd = \frac{(\theta_b - \theta_{\min})}{2} - \frac{(\theta_{\max} - \theta_b)}{4}$
3	$\theta_{\max} > \theta_b$ and $(\theta_{\max} - \theta_b) > (\theta_b - \theta_{\min})$	$dd = \frac{(\theta_b - \theta_{\min})}{4}$
4	$\theta_{\min} \geq \theta_b$	$dd = 0$

The mean daily temperature method is used in the USA, as defined by ASHRAE [40], and in Germany [41], where dd is calculated from:

$$\begin{aligned} \text{if } \theta_{\max} < \theta_b &\rightarrow dd = \theta_b - \frac{(\theta_{\max} + \theta_{\min})}{2} \\ \text{if } \theta_{\min} \geq \theta_b &\rightarrow dd = \frac{(\theta_{\max} + \theta_{\min})}{2} - \theta_b \end{aligned} \quad (3)$$

The adoption of mean daily temperature permits a simple definition and calculation of *DD*. As a consequence, this definition applies the reasonable assumption that heating systems do not operate on days when the average outdoor temperatures exceed the base one.

Furthermore, many attempts to calculate degrees-days starting from reduced meteorological data there have been, for example, Thom [42,43] and Erbs [44] in the USA, based their work on the statistical analysis of truncated temperature distributions. Usually, these attempts are based on monthly mean temperature and on monthly standard deviation. Hitchin [45] proposed a relatively simple formula for *HDD* that has shown a good correlation with the UK climate. Hitchin's formula states:

$$DD_m = \frac{N_m (\theta_b - \bar{\theta}_{o,m})}{1 - e^{-k(\theta_b - \bar{\theta}_{o,m})}} \quad (4)$$

where

DD_m is the monthly degree-day value;

N_m is the number of days in the month;

$\bar{\theta}_{o,m}$ is the mean monthly temperature;

k is a location specific constant given by $2.5/\sigma_\theta$; and

σ_θ is the standard deviation of the variation in temperature throughout the month.

Furthermore, ASHRAE recommends the method in [44] to estimate monthly degree-days. There are also reports of individual energy managers adopting their own techniques based on the kind of weather data that is available to them [23].

However, it should be noted that Eq. (1) should always be the preferred option if suitable hourly data and adequate data processing tools are available.

F.3.1 Italian *DD*

In the evaluation of building energy requirements, in relation to meteorological conditions, the determination of *DD* is fundamental. Attention to energy saving and the subsequent release of the first relevant standards happened in 1974 after the first energy crisis.

Italy faced this problem by amending a law [46] and then updating art. 37 of the law [47], which for the first time stated the principle of modern energy saving concepts in terms of plant design and thermal insulation of buildings. This was the first time, the Italian *DDs* were tabulated in a decree [48]. For a given location and, a fixed reference indoor thermal comfort temperature T_r , the *DD* index is calculated according to:

$$DD = \sum_i (T_r - T_i) \quad (5)$$

where the sum is extended to all i days of the year in which the average external daily temperature T_i is lower than a second reference temperature T_s conventionally fixed, and T_r is the reference indoor thermal comfort temperature.

In order to calculate *DD*, for all Italian cities, it was necessary to have a reliable daily temperature measurement for a sufficiently long period (at least 7-10 years). This information was known only for some cities, and in [48] *DD* values only for 103 locations, where there were Italian Military Air Force weather stations, have been established. Then, employing a calculation method dictated by [48], it was possible to extend the calculation of *DD* to all areas of the Italian territory. In particular, the cities that do not fall in the list of 103 locations had a *DD* based on the following formula:

$$\text{if } \Delta h > 100m \rightarrow \Delta DD = \Delta h \frac{N_g}{100} \quad (6)$$

where

N_g is the number of days in the heating period of the reference location; and

Δh is the difference between the altitude of two compared cities.

The application of this procedure led to a qualitative estimation of DD which affects its own reliability. In fact, this procedure presents some problems such as:

- the limited number of weather stations (103 locations or only about 1.3% of Italian municipalities);
- the reference temperature $T_s = 12$ °C chosen based on the technical design of the buildings and climate of a northern country (Germany), which are not representative of Italian climatic conditions; and
- Eq. (6) which can be extended to the calculation of DD in all municipalities, but it is not always automatically applicable to all Italian regions.

The comparison of the DD value calculated employing 1970s data with the DD calculated with this procedure, led to deviations higher than 150%. In the 1980s, different methods of calculation were studied and analysed and a new procedure, currently in force, was adopted. In this case, reference data are based on a time series of 872 locations (10% of Italian municipalities).

It should be stressed that the calculation of DD must concern a fixed period of heating (or cooling). In the locations where there were weather stations, the DD was calculated using Eq. (5) in which the temperature T_r is equal to 20 °C. To define the heating period, it was assumed that it starts after 3 consecutive days of temperature $T_i < T_s = 12$ °C and ends when for 3 consecutive days the temperature $T_i > T_s = 12$ °C; the time extension of the heating period has a minimum of 90 days (from December 1st to February 28th). Because of the specificity of the buildings (non-residential), the total number of days in which the heating system can be active excluding weekends and holidays has been determined. For each simulated model, the heating system is considered turned on for 8 hours a day, from Monday to Friday, from 06.00 to 12.00 AM and from 3.00 to 5.00 PM. For other locations, a linear regression procedure was adopted:

$$DD(h) = a + b \cdot h \quad (7)$$

where

h is the altitude of the locations;

a and b are the coefficients of linear regression related to climate information of the territory by the following formulae:

$$\left\{ \begin{array}{l} a = \frac{\sum_i DD_i \cdot \sum_i h_i^2 - \sum_i DD_i \cdot \sum_i h_i}{\Delta} \\ b = \frac{N \cdot \sum_i h_i \cdot DD_i - \sum_i h_i \cdot DD_i}{\Delta} \\ \Delta = N \cdot \sum_i h_i^2 - \sum_i h_i \end{array} \right. \quad (8)$$

where

N is the number of used locations;

h_i is the altitude of the i^{th} location; and

DD_i is the Degrees Day of the i^{th} location.

The procedure described above has therefore led to the determination of DD for the Italian national territory [37,39]. In the last Italian standard, the HDD and CDD were calculated for all regional capital cities and for a heating period that can extend from 15th October to 14th April, and a cooling period that can extend from 15th April to 14th October. As this standard was recently issued, the Italian law decrees) have currently not been updated [38,49–51]. For this reason, this study takes into consideration only the data issued by the actual standard and the actual law decree.

F.4 ITALIAN CASE STUDY

As previously reported in *Section B.7.3*, according to the Italian national guidelines for building energy certification [52], the peninsula is characterised by 6 climatic zones, which theoretically have the same climate (zone A represents the hottest and zone F represents the coolest) [38]. To evaluate the building energy performance in the same city, correlating the energy demand with the climate context, it is necessary to have knowledge of the weather data and the correct *HDD*.

The annual heating demand obtained from the dynamic models was used to validate the simple correlations that determine the H_d value, knowing only the *HDD* value or, more generally, knowing the contemporary *HDD* and *S/V*.

As explained in Fig. 1F, simple correlations were developed using different weather data, and the results were compared to the simulated data, indicating the respective R^2 values.

Evidently, the three climate databases, determine three different types of *HDD* values for the same city, so the correlation degree will also vary. In detail:

- *HDD* from 412/93 and UNI 10349:1994 (*Section F.4.1*);
- *HDD* from TMY (*Section F.4.2*); and
- *HDD* from UNI 10349: 2016 (*Section F.4.3*).

The results, indicated by the high R^2 values underline the fact that correct evaluation of the building energy performance could be obtained with knowledge of only one or two well-known parameters, such as *HDD* and/or *S/V*, if the climate file used to determine the *HDD* is the same as that used for the energy evaluation.

F.4.1 Heating Demand and *HDD* from 412/93 DPR

Based on the current Italian law and UNI TS 11300-1, 2 [49,50], the cities simulated in the case study are characterised by the *HDD* and climatic zone indicated in Table 2F; furthermore, the results obtained from the dynamic simulations for each model, are presented in Table 3F.

Table 2F
Selected Italian cities and DPR 412/94 *HDD* values.

Italian climatic zones									
B		C		D		E		F	
Location	<i>HDD</i>	Location	<i>HDD</i>	Location	<i>HDD</i>	Location	<i>HDD</i>	Location	<i>HDD</i>
Messina	707	Cagliari	990	Genova	1435	Trieste	2102	Cuneo	3012
Palermo	751	Bari	1185	Firenze	1821	Torino	2617	Cortina	4433
Crotone	899	Termoli	1350	Forlì	2087	Bolzano	2791	Sestriere	5165

Table 3F
Thermal heating energy demand in each location and for different *S/V*.

Climatic Zone	Location	<i>HDD</i> DPR 412/93	<i>H_d</i> models [kWh/(m ² ·year)]												
			1	2	3	4	5	6	7	8	9	10	11	12	13
B	Messina	707	1.60	11.66	10.83	3.49	12.43	8.80	4.68	6.06	1.75	9.92	10.06	10.11	9.90
	Palermo	751	1.42	11.04	9.78	2.98	11.37	8.13	4.01	5.35	1.53	9.18	9.47	9.51	9.37
	Crotone	899	4.16	16.27	15.73	7.00	18.02	12.74	8.57	10.35	4.30	14.27	14.24	14.39	13.98
C	Cagliari	990	0.70	11.16	6.95	1.36	8.93	6.99	2.01	4.00	0.69	7.82	8.90	9.10	9.48
	Bari	1185	1.97	15.35	10.54	3.05	13.33	10.12	4.03	7.14	1.85	11.44	12.57	12.88	13.17
	Termoli	1350	4.35	18.93	15.83	6.48	19.01	13.78	8.01	11.15	4.28	15.49	15.93	16.44	16.34
D	Genova	1435	2.42	14.76	11.14	4.01	14.23	9.62	5.12	7.67	2.35	11.11	11.34	12.35	12.36
	Firenze	1821	2.90	17.06	12.48	4.33	16.19	11.20	5.56	9.03	2.71	12.89	13.30	14.39	14.44
	Forlì	2087	7.48	24.02	22.29	11.07	26.88	17.88	13.29	16.52	7.54	20.31	19.38	21.14	20.60
E	Trieste	2102	4.10	17.71	14.52	6.30	18.42	11.94	7.74	10.64	4.09	13.85	13.48	15.07	14.85
	Torino	2617	8.52	25.74	22.05	11.84	27.53	18.38	13.79	17.70	8.47	20.90	20.20	22.41	21.98
	Bolzano	2791	8.53	25.71	20.86	11.35	26.39	18.15	13.07	17.53	8.30	20.48	20.33	22.32	22.08
F	Cuneo	3012	3.64	19.21	11.20	4.31	15.92	11.19	5.26	10.19	3.11	13.10	14.02	15.61	16.10
	Cortina	4433	16.43	43.24	32.43	19.55	41.52	29.19	22.10	30.28	15.76	33.32	33.28	36.92	37.11
	Sestriere	5165	16.97	50.37	29.42	16.96	40.18	30.61	19.01	31.90	15.13	35.06	37.92	41.56	43.40

For each zone in the graphs from Figs. 2F to 6F, the *H_d* versus *HDD* of the 13 models are plotted.

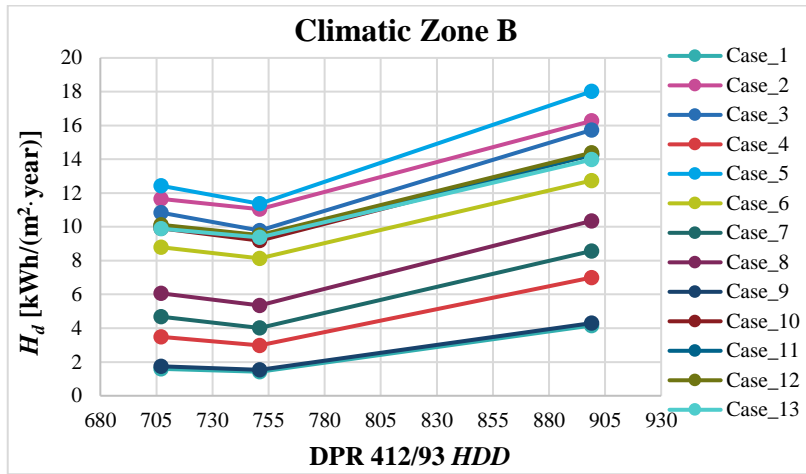


Fig. 2F. Heating demand versus 412/93 DPR *HDD* of climatic zone B.

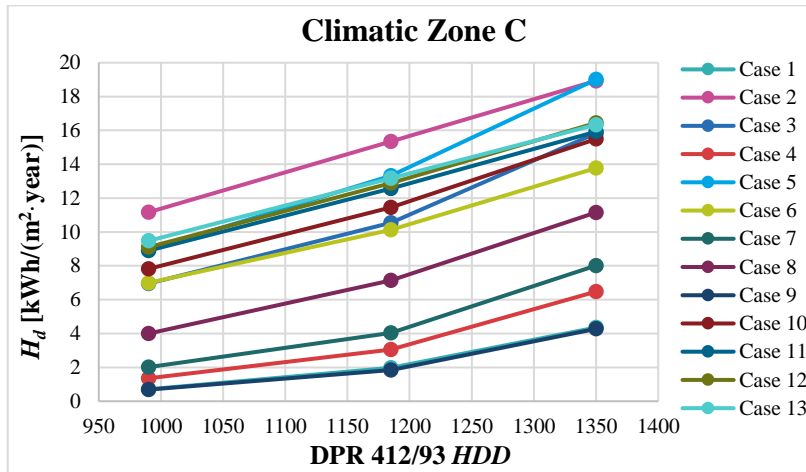


Fig. 3F. Heating demand versus 412/93 DPR *HDD* of climatic zone C.

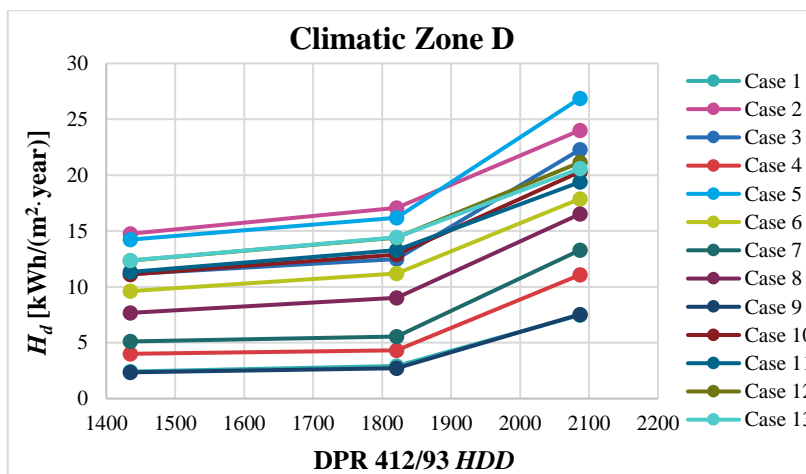


Fig. 4F. Heating demand versus 412/93 DPR *HDD* of climatic zone D.

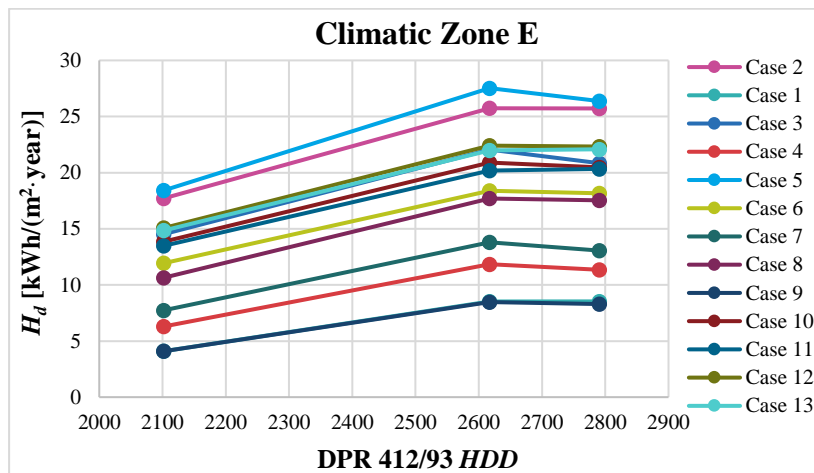


Fig. 5F. Heating demand versus 412/93 DPR HDD of climatic zone E.

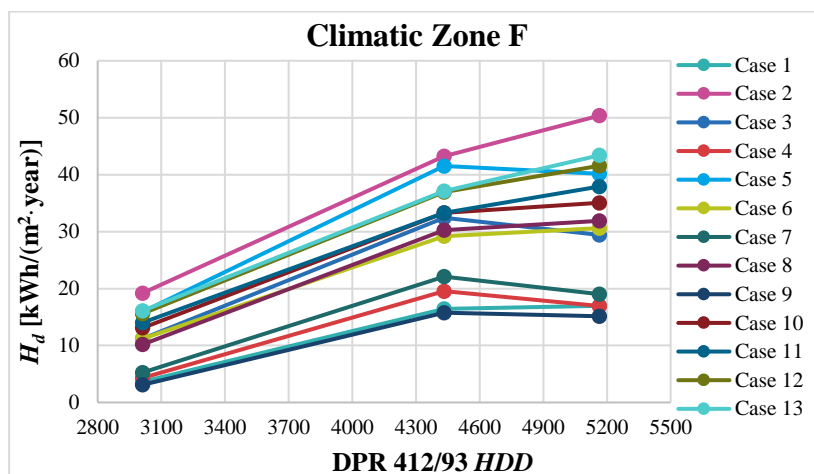


Fig. 6F. Heating demand versus 412/93 DPR HDD of climatic zone F.

In general, for the same boundary conditions, it is expected that increasing the *HDD* value will increase the thermal energy requirements in each case study. Analysing the data trend for each climatic zone, except for climatic zones C and D, where it is possible to observe a regular growing trend, the thermal behaviour differs in other climatic zones:

- in climatic zone B, the models are characterised by a lower H_d for the average *HDD*;

- in climatic zone E, the models are characterised by a higher H_d for the average HDD ; and
- in climatic zone F, certain models are characterised by a lower H_d for the average HDD .

It was hypothesised a linear relationship between H_d and HDD as follows:

$$H_d = \alpha \cdot HDD + \beta \quad (9)$$

where

α is a regression coefficient; and

β is a correction coefficient expressed in [kWh/(m² year)].

In Fig. 7F, it is possible to observe the respective correlation coefficients R^2 of several case studies of climatic zones B and D; all results for all relationships in each zone are collected in *Annex 4*.

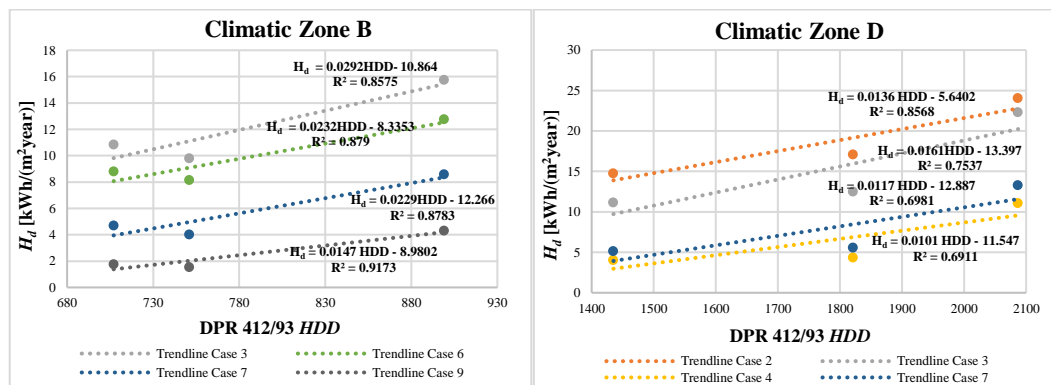


Fig. 7F. Trend line examples of H_d function of 412/93 DPR HDD in climatic zone B and D.

These results emphasise that it is important to establish a climatic index that is representative of the actual weather conditions considered in the simulation tool. Indeed, in this case, the climatic data implemented in the simulation tool differ with respect to the TMY used to determine the HDD , so the relationships between the heating demand obtained by the simulation tool and the HDD values dictated by the actual Italian laws are not really linked. For these reasons, to correlate the H_d

simulated data with the respective climatic context accurately, were recalculated the *HDD* values, considering the TMY used in the building simulation tools.

F.4.2 Heating Demand and *HDD* from TMY

TMY2 was used to develop the dynamic models in TRNSYS, considering actual monitored data recorded from 2000 to 2009. By applying the same procedure as in Section 3 (MDH), the *TMY-HDD* values for each location were calculated (Table 8F):

Table 8F

Selected Italian cities and *TMY-HDD* values.

Italian Climatic Zones									
B		C		D		E		F	
Location	<i>TMY-HDD</i>	Location	<i>TMY-HDD</i>	Location	<i>TMY-HDD</i>	Location	<i>TMY-HDD</i>	Location	<i>TMY-HDD</i>
Messina	673	Cagliari	1024	Genova	1417	Trieste	1760	Cuneo	2213
Palermo	656	Bari	764	Firenze	1598	Torino	2386	Cortina	4473
Crotone	1012	Termoli	1370	Forli	1953	Bolzano	2384	Sestriere	6804

Based on the distribution of the climatic zones presented in Table 18B, it is possible to observe that, using the new updated weather data:

- Crotone, originally belonging to climatic zone B, now falls back to climatic zone C;
- Bari, originally belonging to climatic zone C, now falls back to climatic zone B;
- Trieste, originally belonging to climatic zone E, now falls back to climatic zone D; and
- Cuneo, originally belonging to climatic zone F, now falls back to climatic zone E.

In general, it is possible to observe a generic reduction in *HDD* values, which is probably due to the general increase in average temperatures observed throughout

the Italian peninsula in recent years. To analyse the simulation results correctly, the cities listed in Table 9F were linked with new climatic zones; to consider an additional three cities in climatic zone F, another location, namely Stelvio, was added.

Table 9F

Selected Italian cities and *TMY-HDD* values.

Italian Climatic Zones									
B		C		D		E		F	
Location	<i>TMY-HDD</i>	Location	<i>TMY-HDD</i>	Location	<i>TMY-HDD</i>	Location	<i>TMY-HDD</i>	Location	<i>TMY-HDD</i>
Messina	673	Crotone	1012	Genova	1417	Cuneo	2213	Cortina	4473
Palermo	656	Cagliari	1024	Firenze	1598	Torino	2386	Stelvio	6339
Bari	764	Termoli	1370	Forli	1953	Bolzano	2384	Sestriere	6804

Changing the *HDD* value and climatic zone alters, the heating periods and consequently the limit transmittance values. Table 10F presents the results obtained from the new dynamic simulations for each model, for only those cities with a changed climatic zone.

Table 10F

Thermal heating energy demand in some cities and for different *S/V*.

Climatic Zone	Location	<i>TMY-HDD</i>	<i>H_d</i> [kWh/m ² year]												
			1	2	3	4	5	6	7	8	9	10	11	12	13
B	Bari	764	7.00	20.68	21.18	10.88	24.05	16.82	12.88	14.75	7.21	18.72	18.32	18.61	17.92
C	Crotone	1012	0.70	11.06	6.85	1.31	8.79	6.81	1.97	4.12	0.66	7.77	8.85	9.03	9.40
E	Cuneo	2213	5.14	21.69	15.33	6.78	20.36	14.03	8.14	12.81	4.73	16.11	16.57	18.28	18.40
	Cortina	4473	16.43	43.27	32.43	19.55	41.52	29.36	22.10	30.28	15.76	33.32	33.28	36.92	37.12
F	Stelvio	6339	17.86	50.32	32.67	19.27	43.24	31.74	21.77	33.11	16.40	36.26	37.96	41.85	43.22
	Sestriere	6804	16.97	52.08	29.60	16.96	40.37	30.75	19.01	31.99	15.13	35.44	38.40	42.38	44.58

By plotting *H_d* versus new *HDD* indexes, it was possible to observe the following trends for each climatic zone (Figs. 8F to 14F):

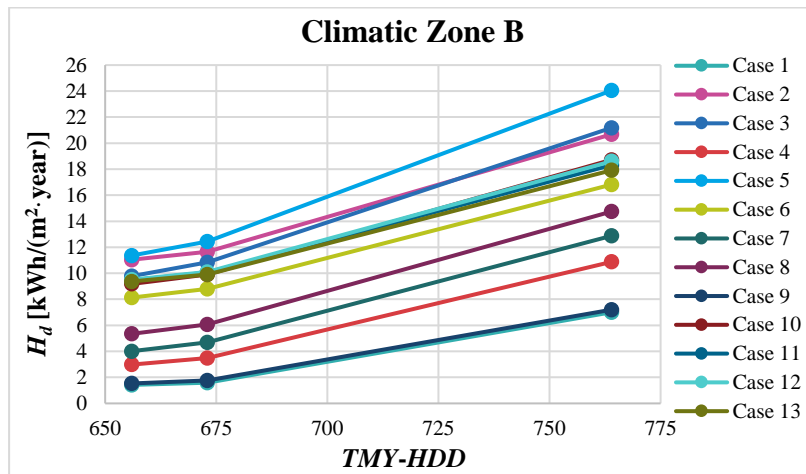


Fig. 8F. Heating demand versus TMY-HDD of climatic zone B.

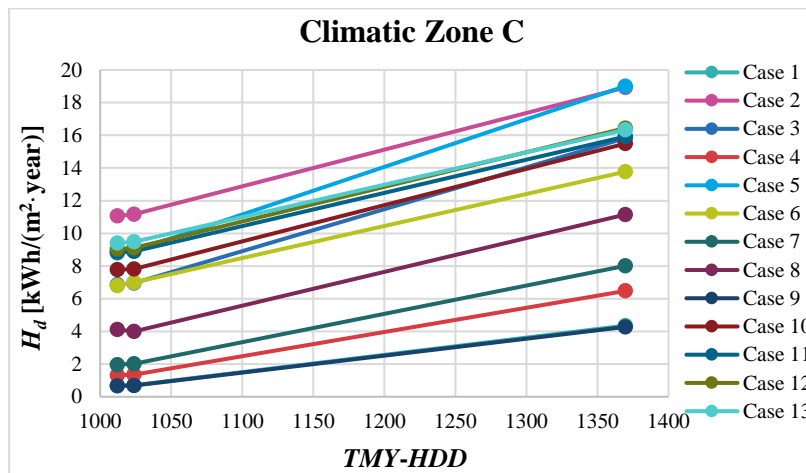


Fig. 9F. Heating demand versus TMY-HDD of climatic zone C.

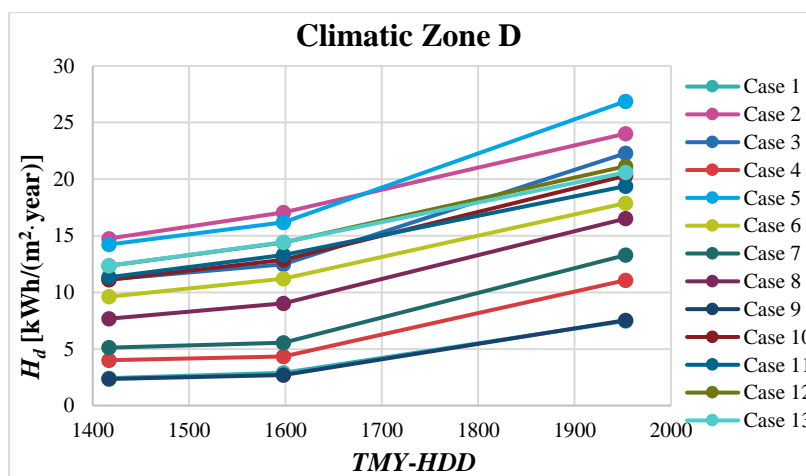


Fig. 10F. Heating demand versus TMY-HDD of climatic zone D.

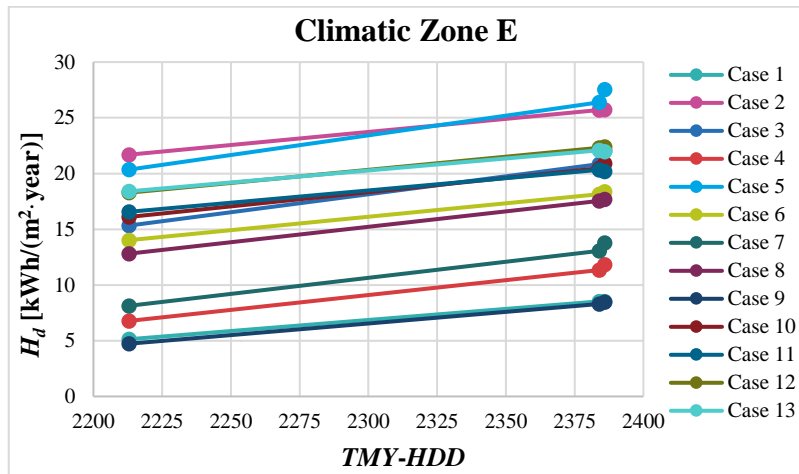


Fig. 11F. Heating demand versus *TMY-HDD* of climatic zone E.

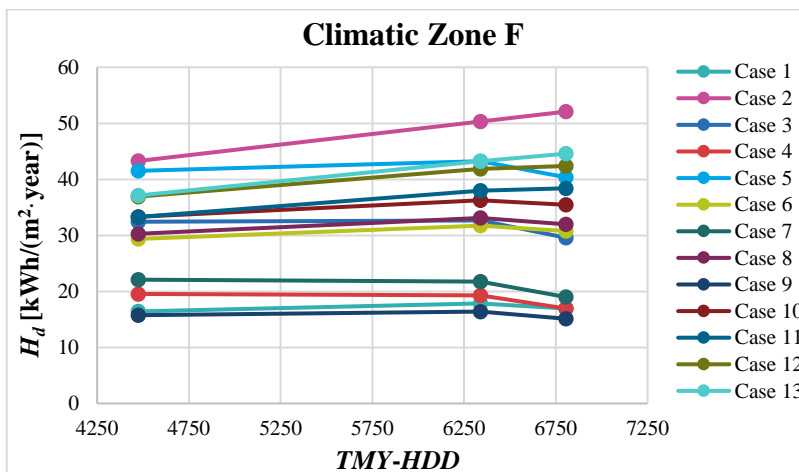


Fig. 12F. Heating demand versus *TMY-HDD* of climatic zone F.

From the results, a more regular trend could be observed in each climatic zone with respect to the previous results (Figs. 2F to 6F). Moreover, in this case, it was possible to determine linear correlations between the H_d and HDD values with higher correlation coefficients, R^2 (Fig. 13F).

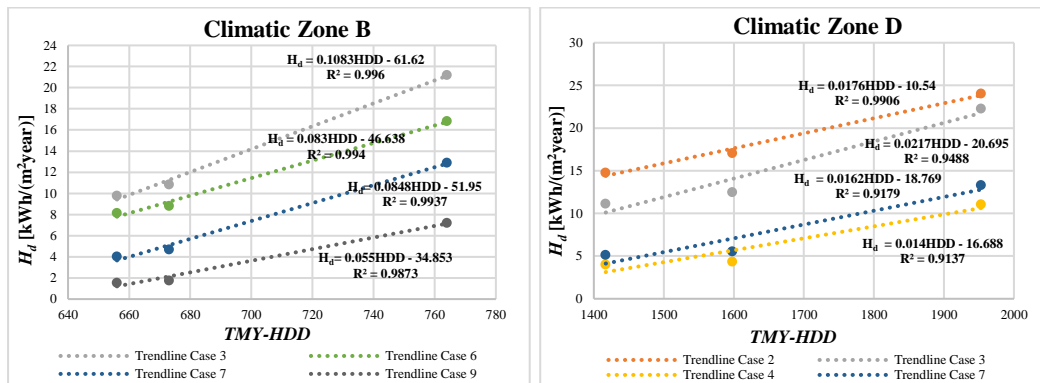


Fig. 13F. Trend line examples of H_d function of $TMY-HDD$ in climatic zone B and D.

In Fig. 13F, several trend-lines relating to the data from climatic zones B and D are illustrated. In these cases, it is possible to observe higher R^2 values with respect to Fig. 7F (all results are collected in Annex 5).

In contrast to the general trend, the H_d value was lower in relation to the maximum HDD value only in climatic zone F and for $S/V < 0.4$. These results confirmed the fact that the evaluation of the heating energy demand as a function of only a climatic parameter does NOT completely explain the building thermal balance. Indeed, by analysing the climatic data such as the temperature and solar irradiance relating to the locations belonging to climatic zone F, it is possible to observe the following graph (Fig. 14F):

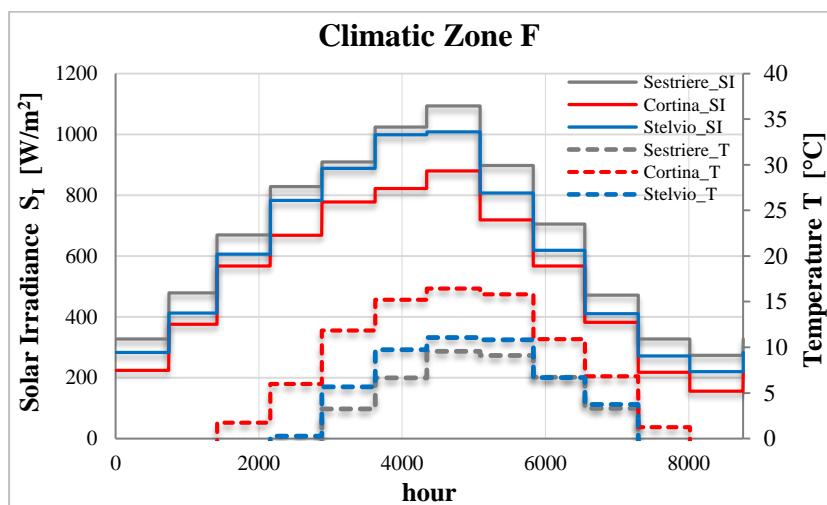


Fig. 14F. Climatic data of cities belonging in climatic zone F.

Although Cortina is characterised by the highest external average temperature, and thus, by a smaller HDD value than other cities, the H_d value is not always the smallest, because it is important to consider other boundary conditions such as the solar irradiance. Indeed, Cortina is characterised by a lower monthly solar irradiance than the other cities.

Furthermore, as indicated in Table 9F, it is possible to change the dataset, HDD values, and even climatic zone, as for Bari, Crotone and Cuneo. The change in the climatic zone determines the variation in the heating period and the thermal transmittance limit values.

Indeed, according to DPR412/93, Bari belongs in climatic zone C, while $TMY-HDD$ places it in climatic zone B (Fig. 15F). In this case, the change from a colder to a warmer climate class, determines a greater thermal energy demand, even though it reduces the operating heating period; contrary to common-sense expectations, this variation is attributable to the increase in the limit transmittance values, causing the building-plant system to be less thermo-insulated and resulting in greater thermal losses.

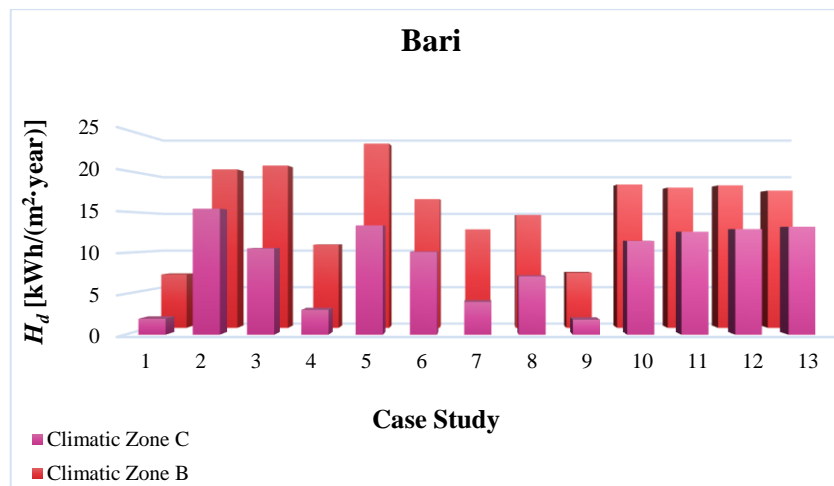


Fig. 15F. Comparison between H_d calculated in climatic zone B and H_d calculated in climatic zone C for Bari.

The same observation can be extended to the locations of Crotone (Fig. 16F) and Cuneo (Fig. 17F): the first location changes from a warmer (B) to a cooler (C)

climate class, while the second changes from a colder (F) to a warmer (E) climate class.

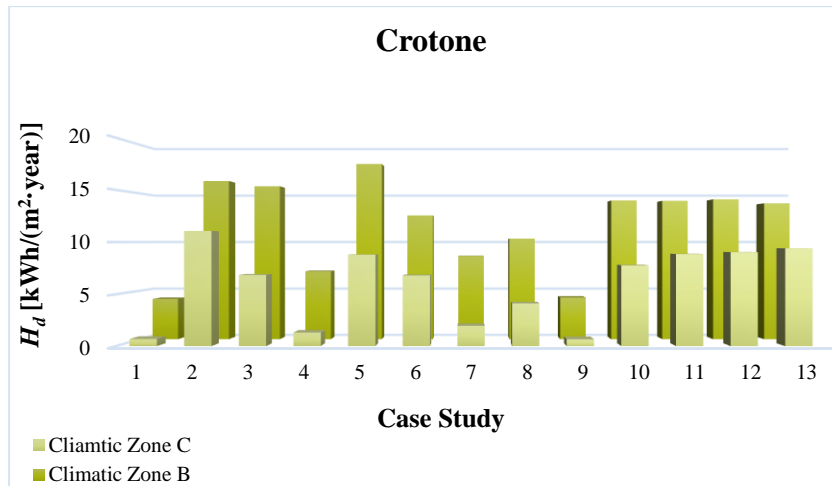


Fig. 16F. Comparison between H_d calculated in climatic zone B and H_d calculated in climatic zone C for Crotone.

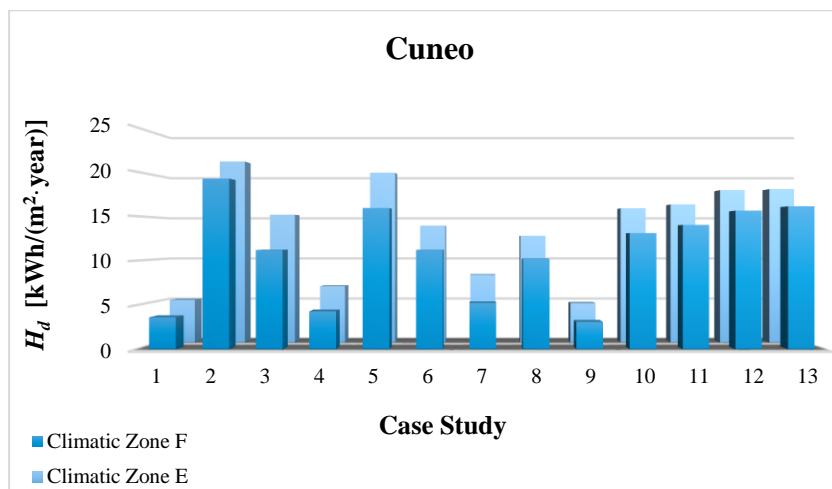


Fig. 17F. Comparison between H_d calculated in climatic zone B and H_d calculated in climatic zone C for Cuneo.

The evaluation of H_d linked to DPR412/93-HDD is completely different from the evaluation of the same H_d linked to the TMY-HDD used in the simulation tool, particularly in those locations where the calculation of HDD leads to a change in the climatic class and thermo-physical design limits.

F.4.3 Heating Demand and *HDD* from Italian Standard 10349: 2016

The new Italian technical standard [39] collects updated *HDD* values from all Italian regional capital cities. The procedure is based on the calculation defined in [53], and the range for the heating period is from October 15th to April 14th (the heating period of climatic zone E). In this work, three of the 15 selected cities are not included in UNI 10349-3: 2016, namely: Termoli, Cortina, and Sestriere. By applying the *HDD* procedure indicated by UNI 10349-1: 2016 and using the representative TMY, the *HDD* values for these three cities have been determined (Table 11F).

Table 11F

Selected Italian locations *10349: 2016-HDD*.

Location	<i>10349: 2016-HDD</i>
Palermo	1121
Messina	1262
Crotone	1264
Genova	1549
Termoli	1555
Cagliari	1584
Bari	1759
Firenze	1835
Trieste	1848
Forlì	2304
Bolzano	2346
Torino	2648
Cuneo	2919
Cortina	4015
Sestriere	4430

Unfortunately, in this case, the *HDD* values for all locations, were evaluated for the same heating period, making it impossible to identify the specific climatic zone for each city. Only the cities of Torino, Cuneo, and Bolzano are characterised by *HDD* values that continue to belong in climate zone E, according to DPR 412/93 ($2100 < HDD < 3000$, Table 2). For this reason, considering the H_d designed and simulated

in climate zone E and correlating these results with the 10349: 2016-*HDD* values, it is possible to obtain and evaluate the following results (Fig. 18F).

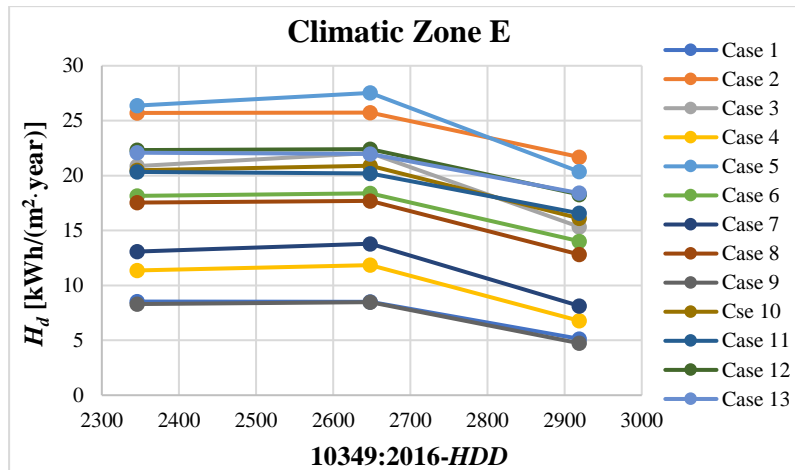


Fig. 18F. Heating demand versus 10349:2016 *HDD*.

In general, a decreasing trend of H_d can be observed, linked to an increase in the *HDD* value; these trends are unusual compared to case studies described previously, and are characterised by correlations with very low R^2 - values with the optimal value being 0.75 (*Annex 6*, Table 6.1). To conduct a generic comparison between these results and those demonstrated before (Fig. 11F), it is necessary for the *HDD* value to be calculated over the same heating period.

For this reason, based on the weather data of TMY2, generated by Meteonorm, the *HDD* values for the three aforementioned cities have been recalculated, considering the heating period dictated by the 10349: 2016 technical standard. This assessment led to the determination of the following *HDD* values:

- Torino *HDD*: 2483 [K day];
- Bolzano *HDD*: 2559 [K day]; and
- Cuneo *HDD*: 2347 [K day].

These data were correlated with the H_d values of the 13 simulated buildings, obtaining the following trends:

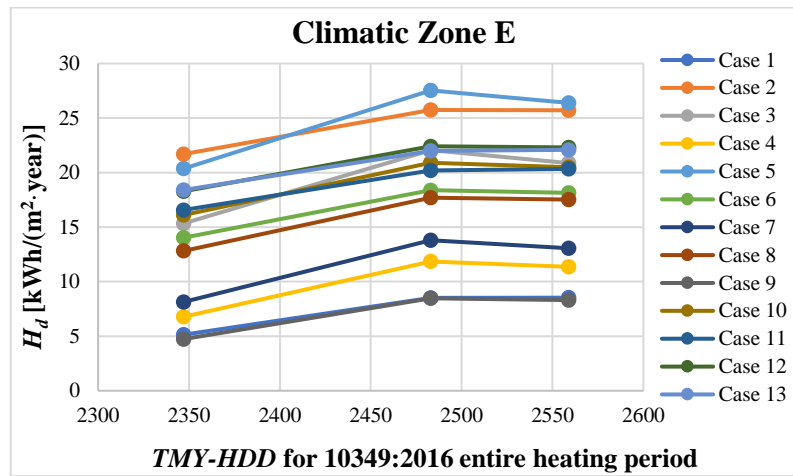


Fig. 19F. Heating demand versus *TMY-HDD* for 10349:2016.

In Fig. 19F, an improvement can be observed in the trend of the H_d value for the increasing *HDD* with respect to the trend illustrated in Fig. 18F. The correlations of H_d versus *TMY-HDD* calculated for the heating period from 15th October to 14th April are presented in Annex 6, Table 6.2.

However, despite the *HDD* calculation for the heating period provided by the new standard, using the TMY2 files and the trends shown in Fig. 19F, being superior those illustrated in Fig. 18F, these results are still far from those obtained in Fig. 11F.

F.4.4 Heating Demand Correlations

As demonstrated in [54], a more extensive calculation of H_d should be a function of:

$$H_d = f\left(HDD, \frac{S}{V}\right) \quad (10)$$

Indeed, to evaluate the heating energy demand, it is necessary to consider simultaneously the HDD and S/V an important factor that strongly influences heat loss, heat gain and the heated volume.

The results looking for some correlations in which H_d is a function simultaneously of the HDD and S/V parameters have been generalised [55]. In this research, more reliable linear relationships between H_d , HDD and S/V were developed with the following form:

$$H_d = Y + Z \cdot HDD + K \cdot \frac{S}{V} \quad (11)$$

For each climatic zone, applying the last squared method, the values of Y , Z and K were determined; the results of the fitting procedure are shown in Tables 12F and 13F, where for each climatic zone and for the entire Italian peninsula, the value of the three coefficients, the R^2 values and a graphic representation are provided.

In Table 13 the results related to the DPR 412/93 HDD are collected, while in Table 14 the results related to the $TMY-HDD$ are summarised.

Table 12F

H_d function of DPR 412/93 HDD and S/V.

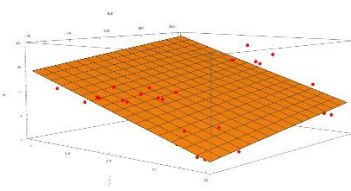
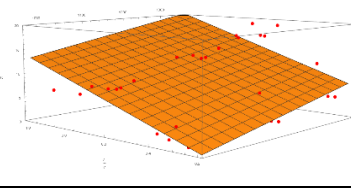
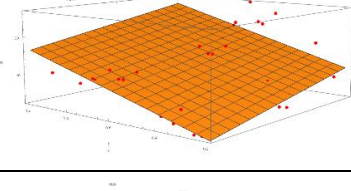
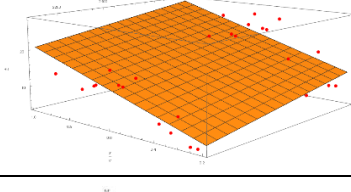
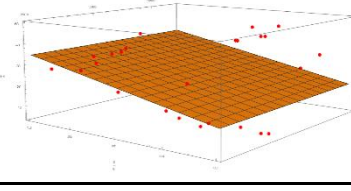
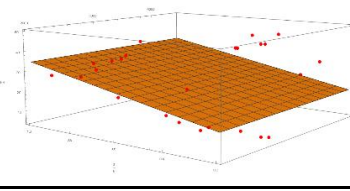
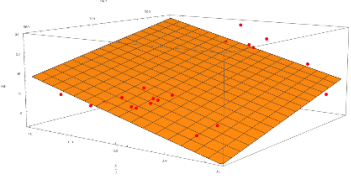
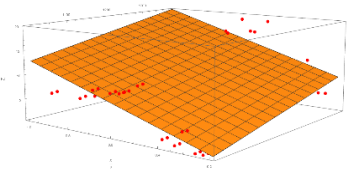
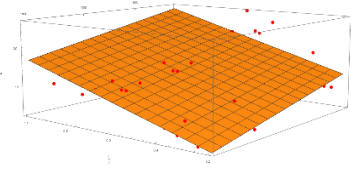
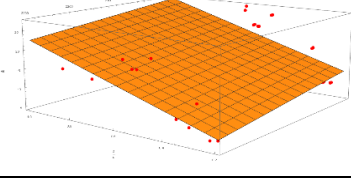
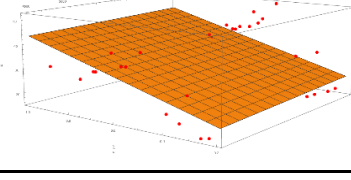
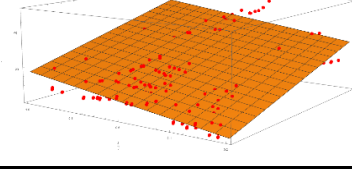
DPR 412/93-HDD			
Climatic zone	H_d equation form	H_d equation plan	R²
B	$H_d = -17.9785 + 0.0237916 HDD + 15.5132 S/V$		0.94
C	$H_d = -21.3214 + 0.0186898 HDD + 16.2852 S/V$		0.91
D	$H_d = -19.0741 + 0.0122947 HDD + 18.0579 S/V$		0.92
E	$H_d = -19.1646 + 0.0100572 HDD + 19.007 S/V$		0.94
F	$H_d = 10.1441 + 0.000455946 HDD + 23.7375 S/V$		0.81
Italian Peninsula	$H_d = -5.69106 + 0.00534053 HDD + 18.5202 S/V$		0.83

Table 13F

H_d function of *TMY-HDD* and *S/V*.

<i>TMY-HDD</i>			
Climatic zone	H_d equation form	H_d equation plan	R^2
B	$H_d = -57.9013 + 0.0853618 HDD + 16.402 SV$		0.95
C	$H_d = -21.568 + 0.0192865 HDD + 14.9309 SV$		0.91
D	$H_d = -24.251 + 0.0163489 HDD + 18.0579 SV$		0.93
E	$H_d = -55.0521 + 0.0263763 HDD + 19.6228 SV$		0.94
F	$H_d = 10.9852 + 0.000931086 HDD + 28.4968 SV$		0.93
Italian Peninsula	$H_d = -4.59104 + 0.00432513 HDD + 19.5021 SV$		0.90

It is possible to determine the H_d of a building with a single equation and with a high correlation degree just knowing *HDD* and *S/V*. In particular, for the entire

Italian peninsula, the correlation with *TMY-HDD* is characterised by an $R^2 = 0.9$ while the correlation determined by the *DPR 412/93- HDD* is characterised by an $R^2 = 0.83$.

F.4.5 Comparison

To provide an improved understanding the results obtained from each scenario, the equations and correlation values collected in the *Appendices* were compared. Table 14F displays the average R^2 values of the correlations for each zone, and the global average R^2 for each scenario. Evidently, as explained previously, only the values for climatic zone E are indicated for the *10349: 2016 HDD* scenario.

Table 14F
 Average and global R^2 correlation values for each climatic zone.

Average R^2	B	C	D	E	F	Global
<i>DPR 412/93 HDD</i>	0.889	0.978	0.784	0.916	0.896	0.893
<i>TMY-HDD</i>	0.993	1.000	0.960	0.994	0.911	0.972
<i>10349: 2016 HDD</i>	-	-	-	0.673	-	0.673

In all cases, the optimal results were related to the *TMY-HDD* scenario, demonstrating an R^2 value higher than 0.911. The same observations are valid for the results collected in *Section 4.4*, in which the correlations of H_d as a function of *HDD* and *S/V* are reported (Tables 12F and 13F).

Moreover, in this case, the optimal correlations were obtained for the *TMY-HDD* scenario in which the R^2 value was higher than the R^2 value relating to the *DPR 412/93 HDD* scenario for each climatic zone.

Furthermore, the final mathematical solution enables the identification of the building energy performance in any Italian city and for any building shape; its simple form and high reliability accelerate the building energy evaluation phase, and its use does not require expert user knowledge. This methodology for determining these correlations and the previous considerations regarding the importance of the selection of correct weather data for calculating the climatic index can be extended to any country, climatic zone, and building type.

F.5 DISCUSSION

The energy performance of a building is strictly dependent on the climatic conditions. For this reason, in the literature, it is possible to identify several studies that have attempted to determine the energy demand as a function of weather indexes. The *HDD* value for each considered location represents the most important climate severity index and can be used to evaluate the building energy performance. In general, a higher *HDD* value indicates a higher thermal energy demand for maintaining comfort conditions. It is important to emphasise that the results emerging from a building thermal balance are necessarily correlated to the employed weather data. The assessment of the heating energy demand of a building, by means of the *HDD*, is correct if the determination of the climate index is a function of the same weather data used during the energy balance analysis.

This chapter affirms that a direct correlation of a generic *DD* values with the simulated heating energy demand obtained from a generic software tool could lead to unrealistic consumption estimates. To demonstrate this, several simple correlations between the heating energy demand and the *HDD* were extrapolated, evaluating the reliability of these correlations for three different scenarios. Based on the particular situation of the Italian building energy efficiency laws and standards currently in force, an Italian case study was analysed.

Following a review of the Degree Days extrapolation methods used globally, an in-depth analysis of the Italian procedure was carried out. Owing to the obsolescence of the old technical standard [37,38], based on climatic data collected before 1994, recent legislation [39] was enacted; this latest version updates the climatic data and recalculates the *HDD* values only for all regional capital cities of Italy. However, [38] remains current, and determines the climatic zone and heating period of the entire Italian peninsula. The *HDD* values indicated in [38] and [39] differ: in the former, the heating period is a function of the climatic zone, while in the latter, it is the same for the entire Italian peninsula. If users were to evaluate the energy performance of a building by means of simulation software such as TRNSYS,

where the climate file differs from the weather data employed to deploy the law, the resulting evaluations would not be related to the *HDD* indicated by the norm. To achieve the aim of this study, it was evaluated the correlation degree between the heating energy demand and *HDD* by simulating the heating energy demand of 13 building models, located in 15 Italian cities. As expected, not only do different *HDD* values induce variations, but so does a change in the pertaining climatic zone and the transmittance limits dictated by law for the building envelope design. In this way, were identified correlations between the heating energy demand versus the *DD* dictated by the current law (DPR 412/93-*HDD*), versus the *DD* calculated with the Mean Degree Hours method based on the same climatic file used in the simulation tool (*TMY-HDD*), and finally versus the *DD* dictated by the new standard (10349: 2016-*HDD*). All results are presented in *Appendices A, B, and C*. A comparison of these results demonstrates that the optimal correlations are those relating to *TMY-HDD*, indicating that the correct evaluation of a building energy balance can only depend on a climatic index if the thermal needs and *HDD* are calculated using the same weather data file. Indeed, the evaluation of the energy performance of a building by means of the correlation with an *HDD* value dictated by a technical standard exhibits inferior correlation coefficient values; the simulated data from any software are based on a typical meteorological year, which is not the same as that used by the technical standard.

The same considerations are valid for the correlations proposed in *Section 4.4*, in which the heating energy demand is simultaneously a function of the building climatic context and shape factor. This final mathematical solution enables the identification of the building energy performance in any Italian city and for any shape of any building; its simple form and high reliability accelerates the building energy evaluation phase and its use does not require long computational time or expert users.

The presented methodology for the determination of these correlations and the previous considerations regarding the importance of the selection of correct weather data for the calculation of the climatic index can be extended to any country, climatic zone, and building type. Therefore, this work has highlighted critical issues

in the field of energy performance assessment of buildings based on the use of climate indexes, and demonstrates the manner in which these can be overcome by means of the correct selection of climate files for their definition. The correct determination of these indexes, in relation to building energy requirements, can lead to the development of simplified alternative methods, such as the correlations proposed herein, which, owing to their high degree of reliability, can simplify the energy diagnosis phases and the selections of high-efficiency designs.

MY RELATED PUBLICATIONS

The research covered in **Chapter F** was published in the following Journal and Conference:

1. **D’Amico, A.**, Ciulla, G., Panno, D., & Ferrari, S. (2019). Building energy demand assessment through heating degree days: The importance of a climatic dataset. *Applied energy*, 242, 1285-1306.
2. **D’Amico A.**, Ciulla G., Lo Brano V., Panno D., Ferrari S. Heating Energy Demand of non-Residential Buildings using Updated Degree Days in Italy. Conference on Sustainable Development of Energy, Water and Environment System, Palermo 30-4.10.2018. D’Amico A. was the speaker of the oral presentation.

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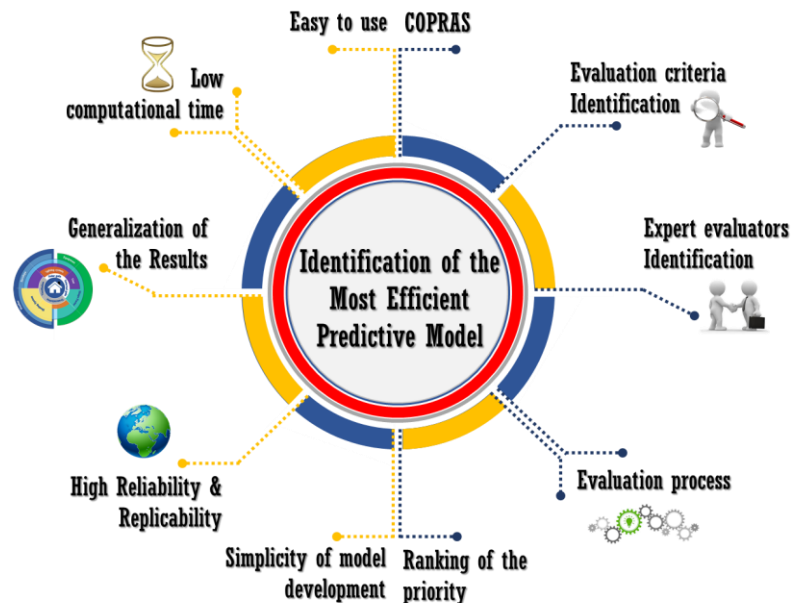
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MULTIPLE CRITERIA ASSESSMENT FOR BUILDING ENERGY PERFORMANCE PREDICTION



ABSTRACT

As previously explained, in this research work the research of models able to predict the heating and cooling consumption from the first design and energy planning phase was conducted aiming to identify actions for improving building sustainability. Use of traditional tools tends to encounter difficulties relevant to the amount of data required, implementation of the models, computational costs and inability to generalize the output. Therefore, this thesis focused on the research and development of alternative resolution models previously explained: Multiple Linear Regression Model, Buckingham Model and Artificial Neural Network. As each proposed model is characterised by different strengths and weaknesses, a simple comparison of these does not permit the choice of the most convenient to use and is not clear and simple the identification of the most efficient. For this reason, to accomplish this, it was decided to apply a Multiple Criteria Assessment, with the Complex Proportional Assessment Method. The analysis contemplates the evaluation of each model based on four phases and the involvement of a team of ten experts in the field of a building's thermal balance resolution and the development of predictive models. Such a procedure revealed ranking of the models in each phase, overall assessment for the entire evaluation process, selection of the most efficient model in terms of evaluated criteria. This first application could represent an incentive for future multi-criteria analyses involving a growing number of alternative models. Therefore, it could identify which of these models is best suited for the current purpose.

NOMENCLATURE

<u>Acronyms</u>	
ANN	Artificial Neural Network.
BM	Buckingham Model.
COPRAS	Complex Proportional Assessment.
INVAR	Degree of Project Utility and Investment Value Assessments.
MCA	Multiple Criteria Analysis.
MCDM	Multiple Criteria Decision-Making.
MLR	Multiple Linear Regression.
NZEB	Nearly Zero Energy Buildings.
<u>MCA parameters</u>	
a_j	j^{th} alternative.
E_j	Overall efficiency index of the j^{th} alternative.
m	Number of attributes.
M	Decision-making matrix.
M	Weighted normalised decision-making matrix.
n	Number of alternatives.
N_j	Utility degree of the j^{th} alternative.
P	Decision-making matrix for evaluation of the phases.
P	Weighted normalised decision-making matrix for evaluation of the phases.
q_i	Significance (weight) of the i^{th} criterion.
Q_j	Efficiency index of compared alternatives.
R	Number of experts.
S	Total square deviation.
S_{+j}	Sum of maximizing attributes.
S_{-j}	Sum of minimizing attributes.
$S_{\text{-min}}$	Minimal sum of minimizing attributes.
T_k	Index of reiterated ranks.
U_j	Overall utility degree of the j^{th} alternative.
w_i	Significance of the i^{th} evaluation phase.
W	Concordance coefficient.
V	Degree of freedom.
x_{ij}	Attribute value of the j^{th} alternative.
x_{ij}	Weighted normalised attribute value of the j^{th} alternative.
y_{ij}	Q_j value of the j^{th} alternative.
y_{ij}	Weighted normalised attribute value of the j^{th} alternative, evaluation of phases.
A	Level of significance.
χ^2	Significance of the concordance coefficient.
χ_{tbl}^2	Critical tabular value of χ^2 .

G.1 INTRODUCTION

The aim of this chapter is to identify, among the Black-Box approaches herein investigated, which is the most efficient to determine the building energy performance, considering also the objective of the evaluation, emphasizing one of the involved phases in the developing/using process of an alternative model. As deeply previously explained, these models are mainly used to deduce a prediction model from a relevant database. They do not require any information about physical phenomena but, rather, by a function deduced solely by means of interconnected sample data, which describe the behaviour of a specific system [1].

The building thermal balance was examined employing three different, alternative models, that are:

- Identification of some simple correlations by the MLR model using certain parameters that are well-known in every energy diagnosis [2–4];
- Definition of some dimensionless numbers that synthetically describe the relationships between the main characteristic parameters of thermal balance by applying the BM [5];
- Application of the ANN model [6–8] to determine the thermal needs of a building.

As explained in previous chapters, each model can be used to solve thermal building balance by knowing merely a few parameters representative of the problem along with strengths and weaknesses underlined for each approach.

To compare the accuracy of the three models, in the following figures are showed the trend of the predicted H_d by each model versus the target H_d ; in general, it is reported the H_d predicted by the best solution identified for each model.

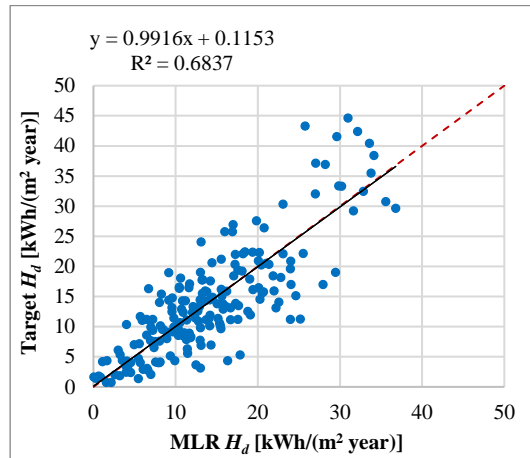


Fig. 1G. Trend of predicted H_d by MLR model versus the target H_d .

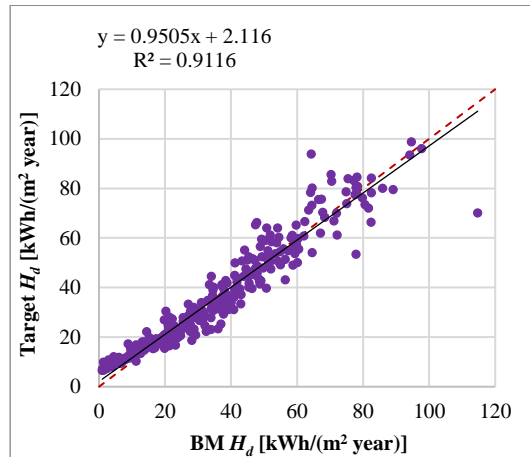


Fig. 2G. Trend of predicted H_d by BM model versus the target H_d .

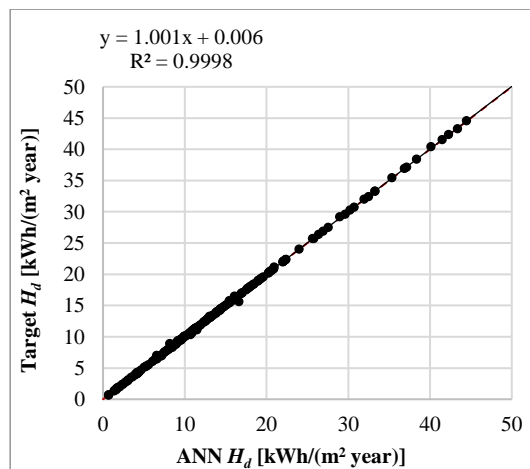


Fig. 3G. Trend of predicted H_d by ANN model versus the target H_d .

As is indicated from Fig. 1G to Fig. 3G, each trend is characterized by different R^2 values, underlining as the best solution is represented by the ANN model. This consideration is confirmed also from the calculation of MAPE and RMSE indexes, collected in Table 1G.

Table 1G

Comparison of the error indexes calculated for the three explored models.

Model/Error	MAPE	RMSE
	[%]	[kWh/m ² year]
MLR	0.498	5.822
BM	0.247	6.672
ANN	0.007	0.129

Regarding the other two models, it is more difficult to identify the more accurate model, because the indexes values are similar. From the point of view of R^2 , calculated by means the linear regression between predicted and target value, the discrepancy between the MLR and BM models, is justified by the use of a non-linear regression method applied in BM, which better approximate the complex problem of the building thermal balance.

In any case, the comparison of only the statistical indexes does not allow an adequate identification of the best model, as the efforts that were necessary for their implementation from the initial data collection phase to the use of the proposed instrument are not considered.

Nonetheless, some questions may be asked: Which of these models can be identified as promising the most efficient solution? Is it possible to compare the performance of these models? Is it possible to choose the most efficient model based on some specific phase in the evaluation, since several steps and phases should be considered when assessing the thermal needs of a building?

To attempt to answer these questions, it was decided to compare the three alternative models by applying Multi Criteria Analysis (MCA), a sub-discipline of operations research that explicitly evaluates multiple criteria in decision-making. It is a useful decision support tool to apply to many complex decisions by choosing among several alternatives.

The idea was born thanks to the scientific collaboration with the VGTU University of Vilnius, Lithuanian, in the person of Prof. A. Kaklauskas and Prof. L. Tupénaitė, for years experts in the field of multi-criteria analysis. In this work, for the first time, a multi-criteria procedure to determine the most efficient alternative model among some resolution procedures of a building's energy balance has been applied. This application has required extra effort in defining the criteria thanks to the collaboration with a team of experts.

To apply the MCA, it was necessary at the first to identify the salient phases of the procedure for the calculations to explain the most sensitive criteria for acquiring conscious, truthful answers that only a pool of experts in the field can provide. In the following, a detailed description of the application of the Multiple Criteria Complex Proportional Evaluation (COPRAS) method [9,10] for identifying the most efficient tool to evaluate building thermal needs has been illustrated.

G.1.1 Contribution of the Work

As previously underlined, the expertise needed to analyse the energy performance of any building is often lacking among public administration users; thus, traditional assessment tools are often difficult or unusable. The reasons making such tools difficult to use include having sufficient knowledge about the physics of a phenomenon, the need for auxiliary knowledge in the software technology field, the complicated data collection phase necessary to implement a large number of parameters in the development phase of a simulation model and in its calibration phase and the difficult interpretation of the results. All these features involve a great deal of time and cost for the pertinent computations. Although a dynamic simulation provides highly accurate results, its applicability cannot be generalised, indeed a single implemented model corresponds to a specific output. With the idea to overcome these limitations, during the PhD research period different models for resolving the building's energy balance in a non-traditional way have been identified and developed, thereby providing a decision support tool that is able to simplify and, at the same time, accelerate the energy planning phase, that even users

who are not highly qualified are able to employ such a tool. After identifying three possible alternative solutions, characterised by a high degree of reliability, easy and fast to use, it was considered important to evaluate whether among these it was possible to identify the most efficient model, the one that best answers the problem of energy balance. To answer at this problem, it was decided to apply an objective procedure that comparing all phases that represents a building energy balance evaluation and all features of each model, identify a solution: the MCA.

The added value of this work is due to the first application of an MCA to identify the more appropriate numerical method to assess the building energy performance or to choose the best predictive model for a specific energy evaluation phase. In detail, the entire thermal balance evaluation process was divided in four main phases: Pre-processing, Implementation, Post-processing and Use. For each phase and in relation of the alternative models considered, several criteria were examined and a team of experts, in respect to the evaluation of the model, evaluated the significance of each criterion. Furthermore, each alternative model according to each evaluation criterion has been assessed. Obviously, the validity of the work correlates to the reliability of the attributes provided by experts. To assure a high level of reliability, it was selected a team of 10 highly qualified experts, working in the field of energy balance solution of buildings and on the development of prediction and/or forecasting tools and models. These experts identified the most efficient model to determine the energy performance of a generic building in terms of simplicity, user-friendliness, reliability and other criteria.

The active contribution of many researchers in the sector and the high interest aroused by the need to improve the energy planning phases and, therefore, the modelling of prediction tools to reduce energy consumption and its interconnected environmental impacts will make it possible in the future to extend an MCA analysis to an even greater number of tools or models for predicting the energy performance of a building. Then, following an appropriately multi-criteria approach, it was possible to identify which of these is the most suitable with the current purpose.

G.2 METHODOLOGY

To better understand the structure of the work and to facilitate the reading of this chapter, the main steps involved are illustrated in this section. Fig. 4G displays a detailed flow chart of the entire procedure.

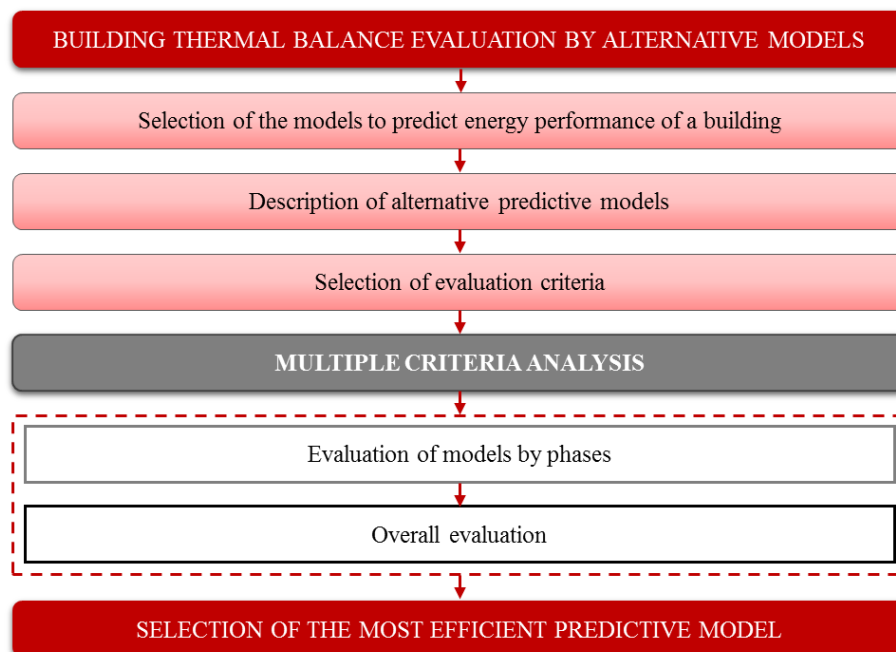


Fig.4G. Main steps flow chart to determine the most efficient predictive model.

In the following, after a brief description of the MCA, the COPRAS procedure is detailed explained. In detail, in *Section G.3.2*, the application of the multicriteria assessment at the entire evaluation procedure and for specific main phases (Pre-processing, Development, Post-processing and Use) it was applied to identify the most efficient model. As indicated in *Section G.3*, based on an analysis of the three models, the pertinent literature and additional consultations with experts, several criteria to evaluate each alternative model for each phase has been identified. Ten international experts in the field of evaluating building thermal balance and developing predictive tools conducted a survey to determine the significances and attribute values of the criteria. The application the COPRAS multi-criteria assessment method determined the priority of the alternative models within each

phase. The use of the obtained results conducted to an overall evaluation of these models along with the priority ranking and selection of the most efficient alternative.

In summary, the work proposes a methodology for a multi-criteria evaluation of alternative models used to estimate the energy performance of a building. It permits analysing these models within the four phases making. Thereby the overall evaluation becomes integrated and it selects the most efficient model in terms of simplicity, user-friendliness, reliability and other criteria.

G.3 MULTIPLE CRITERIA ANALYSIS

Multiple Criteria Decision-Making (MCDM) provides a set of methods that allows the aggregation of several evaluation criteria in order to choose, rank, sort or describe a set of alternatives. It also deals with the study of the activity of a decision to a well-identified decision maker (i.e., individual, firm, organization, etc.). Its principal objective is to provide a decision maker with tools enabling him/her to advance the resolution of a decision problem, where several, often conflicting, multiple criteria must be taken into consideration.

The MCDM had extraordinary use in recent decades; its role in different application areas has increased significantly as new methods are developed and old methods, improved. This spread is due to the versatility of MCDM methods and their applicability to different situations for evaluating relative advantages and disadvantages of alternatives [11]. The MCDM problems can be solved by many available methods. From 2000 to the present, MCDM methods have been especially considered, used and compared in literature [12]. The work in [13] presents a panorama of decision making methods and summarizes the most important results. A detailed review of more than 90 papers appears in [14] to analyse the applicability of various methods while, in [15], the authors consider major principles of methods based on quantitative measurements. In general, it is possible to find the following methods: Simple Additive Weighting (SAW), PROMETHEE II, compromise

programming (CP), ELECTRE II, Analytic Hierarchy Process (AHP), Technique for Order of Preference by Similarity to Idea Solution (TOPSIS), etc.

The basis for several methods used for energy planning decisions consists of employing weighted averages, priority setting and their combinations. For example, in [16], the authors introduce a comprehensive approach based on data envelopment analysis to provide a ranking of alternatives. Meanwhile, in [17], the application of MCDM was for selecting a renewable energy project according to the Spanish Government's renewable energy plan. The authors of [18] evaluated the multiplicity of energy efficiency and consumption reduction measures with the integration of renewable energy sources for planning and renovation of residential buildings by means of MCDM. In the field of building energy performance, the authors of [9] developed computer-based assessment methodology of integrated buildings based on a multiple-criteria approach. The selection of an efficient model for solving the thermal energy balance of a building is a multidisciplinary problem, which requires a multiple criteria approach. Therefore, have chosen the MCDM method COPRAS to solve the problem of research. The method is presented next.

G.3.1 COPRAS Method

The COPRAS method, developed by [12], was used to evaluate the three developed models and achieve the aim of the research. Scientific research worldwide has widely applying the COPRAS method and comparing it with other methods many times, e.g., in [7,9,10] and scientific studies revealed that the COPRAS method is reliable [19–21]. This method assumes direct and proportional dependence of the efficiency and priority of investigated alternatives on a system of criteria. The system of criteria is determined *a priori*; based on this system, a team of experts identify the significances and attribute values for each criterion. The interested parties, taking their goals and the existing capabilities into consideration, can check and correct all the information.

The stages that describe the application of the COPRAS method to determine the efficiency and priority of alternatives are the following:

Stage 1. Developing the initial decision-making matrix M .

A fundamental step for applying the COPRAS methodology consists of the implementation of a decision-making matrix by a team of experts who are highly qualified in the study of the problem under investigation. A consistent but not excessive number of opinions must be collected to ensure a fair robustness and accuracy of the evaluation of alternatives. An optimum would include a team of 7 to 10 experts. The decision-making matrix consists of several criteria for evaluating the alternatives to be examined in the rows and the alternatives in the columns (Eq. (1)). All experts evaluate each alternative in respect to specific criteria by scores. Finally, a matrix is developed, where each element x_{ij} is the average value of all scores assigned by the experts for a specific attribute value of an alternative (in this case, the predictive model).

$$M = \begin{matrix} & a_1 & a_2 & \dots & a_n \\ \begin{matrix} x_1 \\ x_2 \\ \dots \\ x_m \end{matrix} & \left[\begin{matrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \dots & \dots & \dots & \dots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{matrix} \right] & ; & i = \overline{1, m} ; & j = \overline{1, n} . \end{matrix} \quad (1)$$

Where

a_i is the j^{th} alternative;

x_i is the i^{th} criterion;

n is the number of the considered alternatives;

m is the number of assessed performance criteria; and

x_{ij} is the attribute value of the j^{th} alternative.

Stage 2. Determining the significances of criteria q_i by experts.

The significances of criteria, determined by a weight calculation, express the importance of the criteria. Using the expert ranking method, each expert scores each criterion based on its importance. Then, the sums of the scores are calculated, and each significance is determined by Eq. (2). The sum of the significances must equal 1:

$$q_i = \frac{s_i}{\sum_{i=1}^m s_i} \quad (2)$$

where: s_i – sum of estimations (scores) of the i^{th} criterion by the experts.

The coefficient of concordance (agreement) of the opinions by respondents can express the reliability of the evaluation by describing the extent of the proximity of individual views. In cases with reiterated ranks for the same parameters, as in this case, the coefficient of concordance is expressed by Eq. (3) [22]:

$$W = \frac{12S}{r^2(m^3 - m) - r \sum_{k=1}^r T_k}; W \in [0;1]. \quad (3)$$

where

S is the total square deviation of the rankings of each attribute;

T_k – the sum of reiterated ranks;

r – the number of experts; and

m – the number of evaluation criteria.

However, the W value is stochastic; therefore, the significance of the concordance coefficient has to be calculated as follows [23]:

$$\chi_{\alpha,\nu}^2 = W \cdot r \cdot (m-1) = \frac{12S}{r \cdot m \cdot (m+1) - \frac{1}{m-1} \sum_{k=1}^r T_k} \quad (4)$$

If $\chi_{\alpha,\nu}^2 > \chi_{tbl}^2$ then, the concordance coefficient is significant at α level (in this case $\alpha = 0.05$), where $\nu = n - 1$ degree of freedom, and the opinions of the experts are consistent. Otherwise, when $\chi_{\alpha,\nu}^2 < \chi_{tbl}^2$ is obtained, the opinions of experts are not in agreement.

Stage 3. Calculating the weighted, normalised, decision-making matrix M .

Now the assessment of each attribute value is in terms of criteria significances and, additionally, in terms of the dimensionless values obtained (Eq. (5)). In other words, the value of the significance q_i of an investigated criterion is proportionally distributed among all alternative versions a_j according to their values x_{ij} :

$$x_{ij} = \frac{x_{ij} \cdot q_i}{\sum_{j=1}^n x_{ij}}; \quad i = \overline{1, m}; \quad j = \overline{1, n}. \quad (5)$$

where

n is the number of alternatives;

m – the number of criteria;

x_{ij} – the attribute value of the j^{th} alternative; and

q_i – the significance (weight) of the i^{th} criterion.

The sum of the dimensionless weighted index values x_{ij} of each criterion is always equal to the significance q_i of this attribute:

$$q_i = \sum_{j=1}^n x_{ij}; \quad i = \overline{1, m}; \quad j = \overline{1, n}. \quad (6)$$

These dimensionless, weighted, index values x_{ij} represent the components of the matrix M (Eq. (7)).

$$M = \begin{matrix} & a_1 & a_2 & \dots & a_n \\ \begin{matrix} x_1 \\ x_2 \\ \dots \\ x_m \end{matrix} & \left[\begin{matrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \dots & \dots & \dots & \dots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{matrix} \right] & ; & i = \overline{1, m}; & j = \overline{1, n}. \end{matrix} \quad (7)$$

Stage 4. Calculating the sums of weighted, normalised indexes.

For each alternative, the sums that take into account all x_{ij} values for minimizing criteria¹ (S_{-j}) and all x_{ij} values for maximizing criteria² (S_{+j}) are calculated. The following equations calculate the sums describing the j^{th} alternative:

$$S_{+j} = \sum_{i=1}^m x_{+ij}; \quad S_{-j} = \sum_{i=1}^m x_{-ij}; \quad i = \overline{1, m}; \quad j = \overline{1, n}. \quad (8)$$

The consideration here is that the evaluation of each alternative is better the greater is the S_{+j} value and poorer the lower is the S_{-j} value.

¹ Lower values are preferred.

² Higher values are preferred.

Stage 5. Determining the efficiency degree of compared alternatives (Q_j).

The determination of the relative efficiency Q_j of the j^{th} alternative is according to the next equation:

$$Q_j = S_{+j} + \frac{S_{-\min} \cdot \sum_{j=1}^n S_{-j}}{S_{-j} \cdot \sum_{j=1}^n \frac{S_{-\min}}{S_{-j}}}; \quad j = \overline{1, n}. \quad (9)$$

where $S_{-\min}$ is the minimum value among the S_{-j} values calculated for each alternative.

Stage 6. Determining the priority order of alternatives.

The greater is the Q_j , the higher is the efficiency of an alternative. To visually assess efficiency of the alternative, the utility degree N_j can be calculated [24]. The degree of utility is determined by comparing the assessed alternative with the most efficient one (Eq. (10)).

$$N_j = \frac{Q_j}{Q_{\max}} \cdot 100\% \quad (10)$$

where Q_{\max} is the maximum value among the Q_j calculated for each alternative.

Stage 7. Assessing the results.

To achieve the aim of the research, repeat the first seven stages as many times as the number of the phases characterizing the entire evaluation process of thermal balance. This case calls for an assessment of four phases for each model; Pre-processing, Implementation, Post-processing and Use. The primary results allow evaluating the priority of the models within each single phase. To determine the

overall priority of the alternatives and to identify the most efficient predictive tool, it is necessary to apply a multi-criteria analysis by the following steps.

Stage 8. Ranking the thermal balance evaluation phases by experts.

The expert team is involved in this step to establish the ranks of the thermal balance evaluation phases.

Stage 9. Determining the significance of the application phase of each model.

The same as in the case of determining criteria significances, the significance of each phase is calculated as follows (Eq. (11)):

$$w_i = \frac{p_i}{\sum_{i=1}^m p_i} \quad (11)$$

where p_i is the sum of the ranks by experts for the i^{th} phase.

The coefficient of concordance expresses the reliability of the evaluation, the same way as previously discussed in Stage 2.

Stage 10. Developing the decision-making matrix P for an overall assessment of the predictive models.

This new decision-making matrix contains efficiency degrees of compared alternatives (Q_j) previously determined for each phase (in the rows) by the corresponding alternatives (in the columns) (Eq. (12)).

$$P = \begin{matrix} & a_1 & a_2 & \dots & a_n \\ \begin{matrix} y_1 \\ y_2 \\ \dots \\ y_m \end{matrix} & \left[\begin{matrix} y_{11} & y_{12} & \dots & y_{1n} \\ y_{21} & y_{22} & \dots & y_{2n} \\ \dots & \dots & \dots & \dots \\ y_{m1} & y_{m2} & \dots & y_{mn} \end{matrix} \right] & ; & i = \overline{1, m} ; j = \overline{1, n} . \end{matrix} \quad (12)$$

Where

a_j is the j^{th} alternative;

y_i – the i^{th} phase;

n – the number of the considered alternatives;

m – the number of phases; and

y_{ij} – the Q_j value of the j^{th} alternative.

Stage 11. Calculating the weighted, normalised, decision-making matrix P .

This procedure requires calculating the weighted, normalised, decision-making matrix (Eq. (13)):

$$y_{ij} = \frac{y_{ij} \cdot w_i}{\sum_{j=1}^n y_{ij}} ; \quad i = \overline{1, m} ; j = \overline{1, n} . \quad (13)$$

where w_i is the significance of the i^{th} phase.

Stage 12. Determining the integrated efficiency index E_j of alternatives under comparison.

In this case, all the thermal balance evaluation phases are maximized; consequently, E_j is equal to the sum of all weighted, normalised, indices for the j^{th} alternative from the P matrix (Eq. (14)):

$$E_j = \sum_{i=1}^m y_{+ij} ; \quad i = \overline{1, m} ; j = \overline{1, n} . \quad (14)$$

Stage 13. Determining the utility degree (U_j) and ranking the alternatives.

The same procedure as illustrated in Stage 6 applies to this stage as well.

Application of the COPRAS method, as explained in this section, allows comparing and ranking different alternatives to solve any problem characterised by several phases.

G.3.2 Application of the Methodology

As previously explained, the aim of the work is to compare and identify the most efficient alternative model for an evaluation of building energy performance.

Three models, MLR, BM and ANN, which belong to the Black-Box category, were compared to simplify, speed up and help in the choice of the most efficient examined tool.

To analyse each model, an evaluation of each phase of its application, from data collection for its implementation and to its development, testing and use, applying the COPRAS Method, has been done.

The application of this methodology requires selecting several criteria and assigning significances that explain their importance to evaluate predictive models regarding building energy performance. As explained in *Section G.3.1*, the basis of the calculation of significances consisted of the careful evaluations by ten international experts working in the field of building thermal balance evaluation and development of predictive models by means of a questionnaire survey and additional discussions.

The entire evaluation process involved the analysis of four principal phases characterised by different criteria, which are listed as follows:

- Pre-Processing phase:
 1. Knowledge of the physical phenomenon (Building Thermal Balance);
 2. Knowledge of other complementary aspects;
 3. Data collection necessary for the development of the model; and
 4. Data analysis of the collected data to implement the model.

- Implementation phase:
 1. Model implementation;
 2. Simulation phase to develop the model;
 3. Computational time during the model implementation; and
 4. Model calibration.
- Post-Processing phase:
 1. Data extraction;
 2. Analysis of results;
 3. Accuracy of results;
 4. Use phase; and
 5. User Skills.
- Computational time during the use phase:
 1. Availability of a generalised model;
 2. Sensitivity analysis;
 3. Input data required; and
 4. Output data obtained.

The COPRAS method was applied for the entire evaluation process following the procedure illustrated in the previous section; the evaluation of each single phase is illustrated in Fig. 5G. In this way it was evaluated the efficiency of three alternative predictive models in each phase and selected the most efficient model in terms of all assessment criteria.

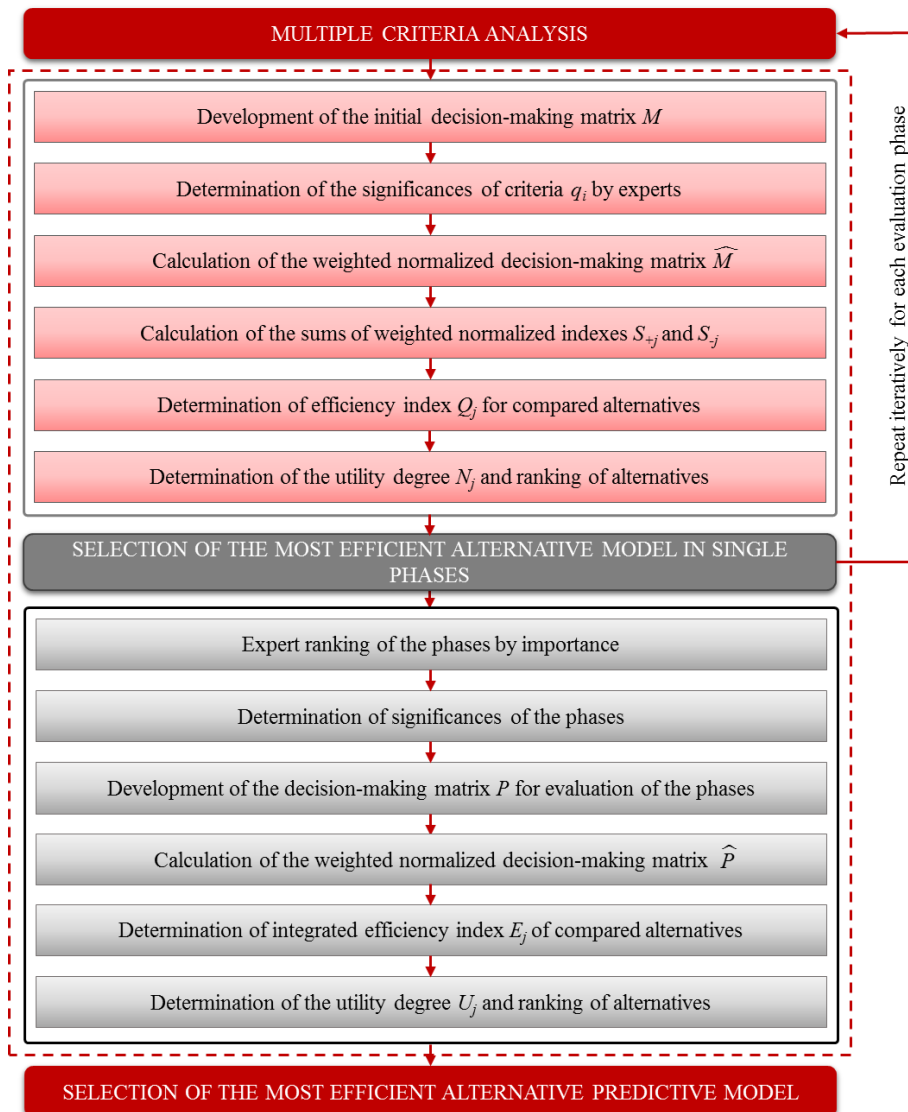


Fig. 5G. COPRAS method for this work, flow chart.

In this case, the generic, decision-making matrix M is composed of 3 columns representing the 3 alternative models (MLR, BM and ANN) and of several rows representing the evaluation criteria (Stage 1). It was necessary to develop four matrices from M_1 to M_4 in detail, one for each single phase.

$$\begin{matrix}
 & \begin{matrix} MLR & BM & ANN \end{matrix} \\
 \begin{matrix} a \\ b \\ c \\ d \end{matrix} & \begin{bmatrix} 2.8 & 3.8 & 2.6 \\ 2.8 & 4 & 4.5 \\ 3.2 & 4 & 3.9 \\ 3.7 & 4.1 & 4.5 \end{bmatrix}
 \end{matrix} ;
 \begin{matrix}
 & \begin{matrix} MLR & BM & ANN \end{matrix} \\
 \begin{matrix} e \\ f \\ g \\ h \end{matrix} & \begin{bmatrix} 2.9 & 4 & 4.4 \\ 2.6 & 3.6 & 3.7 \\ 2.8 & 3.9 & 4.2 \\ 3.9 & 4.5 & 4.2 \end{bmatrix}
 \end{matrix} ; \\
 \\
 \begin{matrix}
 & \begin{matrix} MLR & BM & ANN \end{matrix} \\
 \begin{matrix} i \\ j \\ k \end{matrix} & \begin{bmatrix} 2.5 & 3.7 & 2.7 \\ 2.3 & 3.6 & 3.3 \\ 2.6 & 3.5 & 4.6 \end{bmatrix}
 \end{matrix} ;
 \begin{matrix}
 & \begin{matrix} MLR & BM & ANN \end{matrix} \\
 \begin{matrix} l \\ m \\ n \\ o \\ p \\ q \end{matrix} & \begin{bmatrix} 2.2 & 4.2 & 1.2 \\ 1.9 & 3.8 & 1.1 \\ 3.5 & 3.5 & 4.9 \\ 1 & 1 & 4.3 \\ 1.9 & 3.5 & 3.3 \\ 2.5 & 3 & 4.2 \end{bmatrix}
 \end{matrix} .
 \end{matrix}$$

Based on the indications described in Table 2G to Table 5G, a team of experts assigned a detailed score from 1 to 5. For each matrix, each x_{ij} value was obtained by averaging the scores assigned by all experts.

Table 2G

Description of criteria and their values for evaluation of models in Phase 1 (Pre-processing).

Phase	Criterion	Max/Min	Description
1	a.	–	Knowledge degree about the building thermal balance from the theoretical and mathematical point of view, needed to develop each model (1 – lowest degree of knowledge required to 5 – highest degree of knowledge required)
	b.	–	Complementary knowledge required to develop each model (1 – lowest degree of knowledge required to 5 – highest degree of knowledge required)
	c.	–	Complexity degree to collect the data to implement each model (1 – lowest complexity degree to 5 – highest complexity degree)
	d.	–	Complexity of data analysis to implement each model (e.g. need of a preliminary input selection analysis, quality of the data and outlier’s detection) (1 – lowest complexity degree to 5 – highest complexity degree)

Table 3G

Description of criteria and their values for evaluation of models in Phase 2 (Implementation).

Phase	Criterion	Max/Min	Description
2	e.	-	Complexity degree to implement a complete model (1 – lowest complexity degree to 5 – highest complexity degree)
	f.	-	Complexity degree to develop and manage a simulation model (1 – lowest complexity degree to 5 – highest complexity degree)
	g.	-	Computational time to implement a detailed model (1 – lowest computational time required to 5 – highest computational time required)
	h.	-	Importance of the calibration phase to validate a model (1 – lowest importance to 5 – highest importance)

Table 4G

Description of criteria and their values for evaluation of models in Phase 3 (Post-processing).

Phase	Criterion	Max/Min	Description
3	i.	-	Complexity degree to extract the data from the tool/model (1 – lowest complexity degree to 5 – highest complexity degree)
	j.	-	Complexity degree to analyse the data output and results (1 – lowest complexity degree to 5 – highest complexity degree)
	k.	+	Accuracy of the results from each model (1 – lowest accuracy to 5 – highest accuracy)

Table 5G

Description of criteria and their values for evaluation of models in Phase 4 (Use).

Phase	Criterion	Max/Min	Description
4	l.	-	Expertise of the user required to use the model (1 – lowest expertise required to 5 – highest expertise required)
	m.	-	Computational time to simulate a model and obtain results (1 – lowest computational time required to 5 – highest computational time required)
	n.	+	Ability to provide a generalised response for any building in any boundary condition and configuration (1 – lowest generalization ability to 5 – highest generalization ability)
	o.	+	Capacity to perform a sensitivity analysis of the data. (1 – lowest capacity to 5 – highest capacity)
	p.	-	Extent of input data necessary to develop a reliable model (1 – lowest extent of inputs to 5 – highest extent of inputs)
	q.	+	Ability to provide multiple outputs (1 – lowest ability to 5 – highest ability)

The symbol (+/-) in the second column of the previous tables specifies that a higher/lower value of the criterion is better.

As explained in the Stage 2 (*Section G.3.1*), it was necessary to obtain an evaluation from experts to assign the significances to all evaluation criteria. Each expert

assigned a detailed score expressing the significance of each criterion based on the scale provided in Table 6G. Each expert assigned a score from 1 to 5 to each criterion, where 1 is the most insignificant criterion and 5 is the most significant criterion.

Table 6G

Scale to evaluate significances of criteria.

Score	Importance	Explanation
1	Very low	The criterion has a very low significance for evaluating a building energy performance predictive model
2	Low	The criterion has a low significance for evaluating a building energy performance predictive model
3	Middle	The criterion has a middle significance for evaluating a building energy performance predictive model
4	High	The criterion has a high significance for evaluating a building energy performance predictive model
5	Very High	The criterion has a very high significance for evaluating a building energy performance predictive model

The calculated significance q_i of each criterion for each phase appear in Table 7G to Table 10G. To clarify the evaluation, each criterion is described; whereas, the last two columns in these tables indicate the sum of all scores assigned by the expert for each criterion and a calculated significance as indicated in Eq. (2), respectively.

Table 7G

Significances of the criteria in Phase 1(Pre-processing).

Phase	Criterion	Description	Sum	Significance
1	a.	Knowledge degree of the building thermal balance from the theoretical and mathematical point of view to apply a model	40	0.27
	b.	Knowledge of software/tool language, standards and laws, mathematical algorithms, design and comfort conditions, etc. to apply a model	32	0.21
	c.	Amount of input data necessary to develop a model: thermophysical features, weather and boundary conditions, geometric characteristics, intended use, etc.	44	0.30
	d.	Importance of the quality of data collected to implement each model (e.g., need of a preliminary input selection analysis, quality of the data and outlier's detection)	33	0.22
$W = 0.29; \chi^2 = 8.7$			149	1

Table 8G

Significances of the criteria in Phase 2 (Implementation).

Phase	Criterion	Description	Sum	Significance
2	e.	Development of the simulation model, application of a calculation procedure and development of mathematical or intelligent algorithms	47	0.30
	f.	Simulation phase necessary to develop the model (complexity to identify and solve possible errors)	37	0.24
	g.	Required time to perform a simulation or a group of simulations, to develop an algorithm or to train an ANN model	36	0.23
	h.	Importance of the calibration phase to validate a model	37	0.24
$W = 0.27; \chi^2 = 8.1$			157	1

Table 9G

Significances of the criteria in Phase 3 (Post-processing).

Phase	Criterion	Description	Sum	Significance
3	i.	Simplicity of data extraction	33	0.31
	j.	Simplicity of the explanation of the simulation results	29	0.28
	k.	Reliability of the model after a deep statistical analysis	41	0.40
$W = 0.48; \chi^2 = 9.56$			103	1

Table 10G

Significances of the criteria in Phase 4 (Use).

Phase	Criterion	Description	Sum	Significance
4	l.	Knowledge degree required by the user	42	0.19
	m.	Computational time during the use phase	37	0.17
	n.	Capacity to generalize the results for different building and boundary conditions	37	0.17
	o.	Capacity to perform a sensitivity analysis of the data	36	0.16
	p.	Amount of input data required for the analysis	34	0.15
	q.	Amount of output data obtained from the model	38	0.17
$W = 0.38; \chi^2 = 11.4$			224	1

Calculated concordance coefficients W and their significances χ^2 in each phase affirm that the opinions of experts are consistent; therefore, the determined significances can be used in a further analysis.

Following the procedure indicated in Stage 3 (*Section G.3.1*), it was possible to develop the weighted, normalised matrices M for each phase. The results are as follows:

$$\begin{array}{c}
 \begin{array}{ccc}
 & MLR & BM & ANN \\
 a & \left[\begin{array}{ccc} 0.08 & 0.11 & 0.08 \\ 0.05 & 0.08 & 0.09 \\ 0.09 & 0.11 & 0.10 \\ 0.07 & 0.07 & 0.08 \end{array} \right] \\
 b \\
 c \\
 d
 \end{array} \\
 M_1 =
 \end{array}
 ;
 \begin{array}{c}
 \begin{array}{ccc}
 & MLR & BM & ANN \\
 e & \left[\begin{array}{ccc} 0.08 & 0.11 & 0.12 \\ 0.06 & 0.09 & 0.09 \\ 0.06 & 0.08 & 0.09 \\ 0.07 & 0.08 & 0.08 \end{array} \right] \\
 f \\
 g \\
 h
 \end{array} \\
 M_2 =
 \end{array}
 ;
 \begin{array}{c}
 \begin{array}{ccc}
 & MLR & BM & ANN \\
 i & \left[\begin{array}{ccc} 0.09 & 0.13 & 0.10 \\ 0.07 & 0.11 & 0.10 \\ 0.10 & 0.13 & 0.17 \end{array} \right] \\
 j \\
 k
 \end{array} \\
 M_3 =
 \end{array}
 ;
 \begin{array}{c}
 \begin{array}{ccc}
 & MLR & BM & ANN \\
 l & \left[\begin{array}{ccc} 0.05 & 0.10 & 0.03 \\ 0.05 & 0.09 & 0.03 \\ 0.05 & 0.05 & 0.07 \\ 0.03 & 0.03 & 0.11 \\ 0.03 & 0.06 & 0.06 \\ 0.04 & 0.05 & 0.07 \end{array} \right] \\
 m \\
 n \\
 o \\
 p \\
 q
 \end{array} \\
 M_4 =
 \end{array}
 .
 \end{array}$$

Subsequently the sums of weighted, normalised indices were calculated, and the efficiency of compared alternatives Q_j were determined by applying the equations indicated in Stages 4 and 5 from *Section G.3.1*. The results for each phase appear in Table 11G.

Table 11G

Sums of weighted normalised indices and efficiency indexes Q_j for each phase.

Phase		Alternatives		
		MLR	BM	ANN
1	S_{+j}	0	0	0
	S_{-j}	0.29	0.37	0.35
	Q_j	0.38	0.30	0.32
2	S_{+j}	0	0	0
	S_{-j}	0.27	0.36	0.37
	Q_j	0.41	0.30	0.29
3	S_{+j}	0.10	0.13	0.17
	S_{-j}	0.16	0.24	0.20
	Q_j	0.34	0.29	0.37
4	S_{+j}	0.12	0.13	0.25
	S_{-j}	0.13	0.26	0.11
	Q_j	0.31	0.22	0.47

The priority order of the models in each phase was determined (Fig. 6G) according to Stage 6 of the COPRAS procedure (Section G.3.1). The results revealed (Stage 7) that the MLR performs the most efficiently in the first two phases (Pre-processing and Implementation), whereas, in the other two phases (Post-processing and Use), the MLR is the second preference. In contrast, the ANN is the most efficient model in terms of the last two phases; instead, the BM is characterised as the intermediate preference.

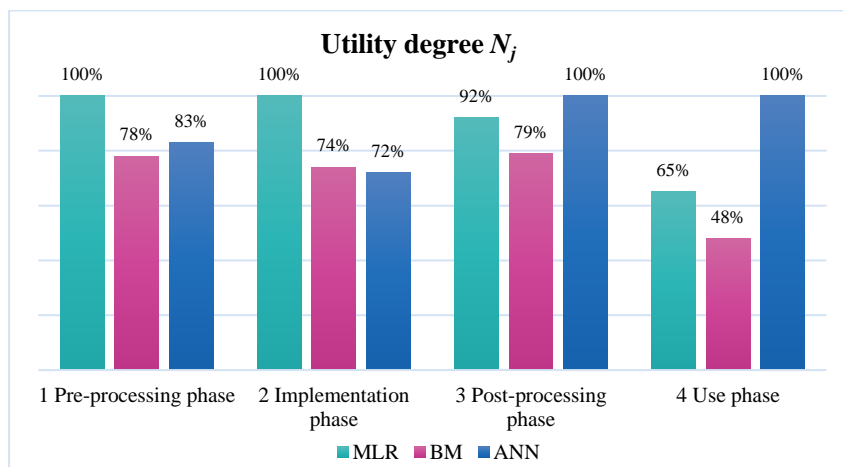


Fig. 6G. N_j values of the alternative predictive models in each phase.

To provide a solution that takes into account all phases included in the evaluation of the energy performance process, it was requested the experts to rank the four phases (Stage 8, *Section G.3.1*) by scoring them from 1 to 4 according to their importance. The sum of the scores assigned to each phase along with the w_i values calculated according to Eq. (11) (Stage 9) appear in Table 12G.

Table 12G

Significance of each phase.

Phase	Description	Significance
1	Pre-processing phase	0.15
2	Implementation phase	0.24
3	Post-processing phase	0.27
4	Use phase	0.34
$W = 0.37; \chi^2 = 11.16$		1

Matrix P was developed by taking Q_j values of Table 11G for an overall assessment of alternative models (Stage 10, *Section G.3.1*):

$$P = \begin{matrix} & \begin{matrix} MLR & BM & ANN \end{matrix} \\ \begin{matrix} 1 \\ 2 \\ 3 \\ 4 \end{matrix} & \begin{bmatrix} 0.38 & 0.30 & 0.32 \\ 0.41 & 0.30 & 0.29 \\ 0.34 & 0.29 & 0.37 \\ 0.31 & 0.22 & 0.47 \end{bmatrix} \end{matrix}$$

Significances of the phases, indicated in Table 12G, were used to develop the new, weighted, normalised, decision-making matrix P where all components are obtained by applying Eq. (13):

$$P = \begin{matrix} & \begin{matrix} MLR & BM & ANN \end{matrix} \\ \begin{matrix} 1 \\ 2 \\ 3 \\ 4 \end{matrix} & \begin{bmatrix} 0.06 & 0.04 & 0.05 \\ 0.10 & 0.07 & 0.07 \\ 0.09 & 0.08 & 0.10 \\ 0.10 & 0.08 & 0.16 \end{bmatrix} \end{matrix}$$

Finally, the E_j values (Stage 12) and the U_j values (Stage 13) were obtained, thereby allowing the determination of the priorities of the assessed models considering all phases and distinguishing the most efficient one. The final calculation results appear in Table 13G.

Table 13G

Efficiency (E_j) and utility (U_j) degrees of the alternative models

Overall evaluation			
	MLR	BM	ANN
E_j	0.35	0.27	0.38
U_j	93%	72%	100%

From the results and the calculated U_j values, it is possible to affirm that the most efficient model among the three analysed Black-Box tools used to solve the thermal balance of a building is the ANN model followed by the MLR and, finally, by the BM.

G.4 RESULTS

The MCA applied in this research determined the ranks of the models in each energy performance evaluation phase and also provided the ranks for the entire evaluation procedure. The detailed analysis of the results obtained for each phase (Fig. 6G) shows that the MLR model has the priority for the Pre-processing and Implementation Phases. These trends are justified by a lesser knowledge of the physical phenomenon and a complementary knowledge (criteria a and b) required in the first phase and by the simplest model implementation, simulation and lowest computational time (criteria e, f and g). On the other hand, among the BM and

ANN, the ANN has a higher priority only in the first phase but with a low difference in both cases. The most efficient alternative model for the third phase is the ANN. The data extraction and the analysis of results (criteria i and j) are indeed very simple, and the accuracy of the obtained results is highest (criterion k). Then the MLR model follows with a utility degree equal to 92%. At last, there is the BM with a utility degree equal to 79%. Similar observations are valid for the fourth phase, where the ANN has a utility degree equal to 100%. This is because it is characterised by very low values linked to user skills, computational time and required input data (criteria l, m and p). Indeed, after implementation of the ANN in a software tool, a non-expert user can also resolve the thermal balance of a building immediately by knowing only a few parameters. Moreover, the characteristics of the ANN are higher generalization availability, the possibility to provide a sensitivity analysis and the capability to issue several outputs (criteria n, o and q). Indeed, it is also possible to solve a condition that has not been previously implemented in the learning database.

Fig. 7G displays the utility degree N_j of each model according to each phase.

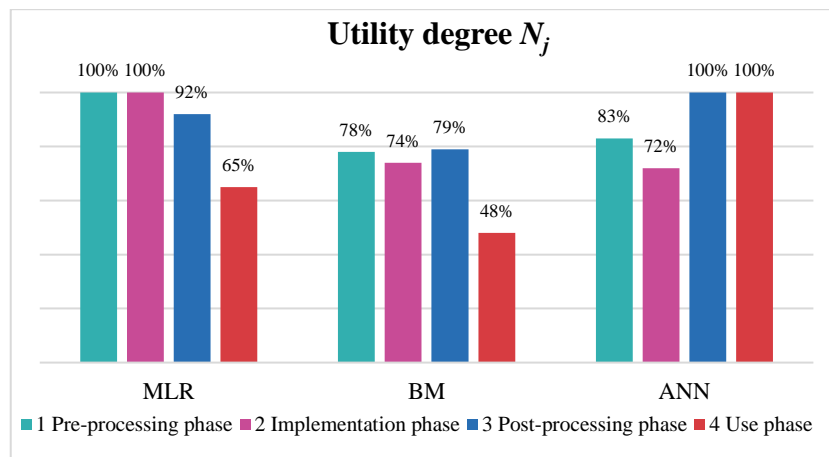


Fig. 7G. Utility degree trends of each phase in each model.

Finally, considering the entire energy performance evaluation procedure that takes all four phases, the MCA permitted comparing the performance of the three selected models and classifying them from the most to the least efficient one. In this case,

the utility degree $U_3 = 100\%$ for the ANN model, $U_1 = 93\%$ for the MLR model and $U_2 = 72\%$ for the BM (Fig. 8G).

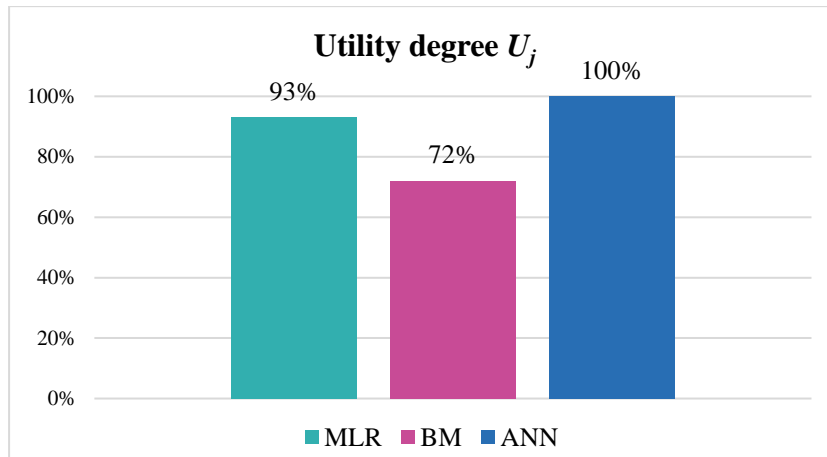


Fig. 8G. Comprehensive utility degree of each model.

G.5 DISCUSSION

The research of alternative and faster solutions to solve complex problems is one of the major issues addressed by the scientific community. In the field of evaluating the energy performances of buildings, the identification of a simpler, faster and economical model from the computational point of view with highly reliable results, which do not require an expert user is desirable. This allows accelerating the preliminary design and energy diagnosis and, thereby, assisting a legislator or public administrator in a more targeted energy planning action. The literature in the field proposes several alternative methods; however, the choice and identification of the most suitable model is still a critical point. Based on this observation, this thesis proposes a methodology to identify the most efficient alternative model for resolving the energy balance of a building.

The results obtained in previous works provided the basis to apply for the first time the multicriteria analysis for comparing three alternative models belonging to the Black-Box category: MLR, BM and ANN. Generally, the application of this kind of analysis covers many complex decisions when choosing among several alternatives.

To achieve the aim of this research, it was necessary to identify the salient phases of the calculation procedure for the building energy balance and determine the most important criteria. The team of international experts was involved in assessing the significances of criteria and alternative models.

The entire process for the assessment of the building energy performance divided into the Pre-processing, Implementation, Post-Processing and Use Phases.

The application of the COPRAS Method by an iterative procedure was to determine the priority of the alternative models in each phase. The use of these results was to perform an overall multiple criteria assessment of the alternative models and, finally, to identify the most efficient one.

The application of this MCA method determined a ranking for the entire building energy balance evaluation process as well as for each phase separately. Some criteria have higher importance with respect to others in a specific phase.

Considering that the entire evaluation procedure takes into account all four phases and their significances, the multicriteria analysis of three selected models revealed the most efficient one as the ANN model and the worst performing one as the Buckingham Model.

This methodology is a first application able to represent a replicable procedure for a larger number of alternative models. It represents a model to compare and to identify, in an objective way, the most efficient solution to use in the assessment of a building energy balance. Moreover, the MCA, specifically the INVAR method, can be used to improve the alternative models under consideration. These can constitute the tasks for future research.

MY RELATED PUBLICATIONS

The research covered in **Chapter G** and the scientific collaboration with the VGTU of Vilnius, Lithuania from 23th April to 24th May 2019, permitted the development of the following paper under review:

1. **D'Amico, A.**, Ciulla, G., Tupenatitè, L., Kauklauskas, A. Multiple Criteria Assessment of Methods for Forecasting Building Energy Performance. Under review in Energy from 29th September 2019.

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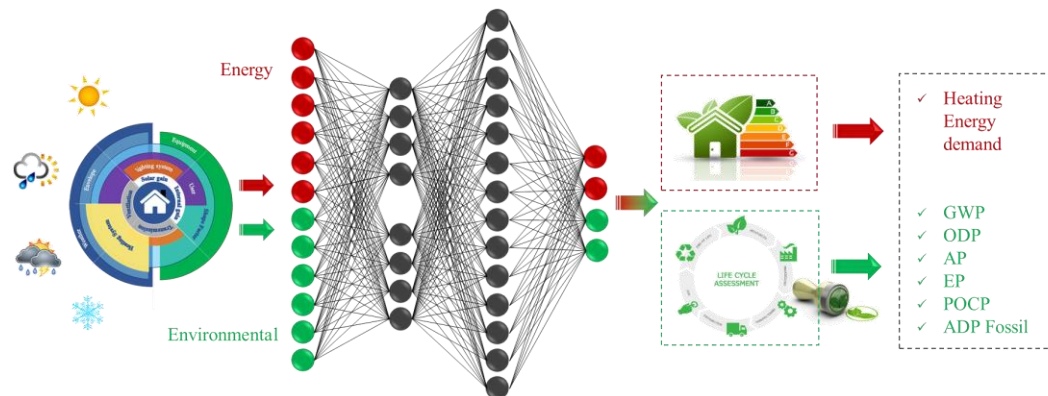
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CHAPTER H

ANN TO ASSESS ENERGY AND ENVIRONMENTAL PERFORMANCE OF BUILDINGS

ANN TO ASSESS ENERGY AND ENVIRONMENTAL PERFORMANCE OF BUILDINGS



ABSTRACT

Based on the results obtained and explained in **Chapter F**, it was decided to apply the most efficient alternative predictive tool, to solve a comprehensive building performance assessment that simultaneously considers the energy and environmental impacts. To achieve this objective, a building's life cycle is necessary. To date, the resolution of this complex problem is entrusted to numerous software and calculation algorithms that are often complex to use. They involve long diagnosis phases and are characterised by the lack of a common language. Despite the efforts by the scientific community in the building sector, there is no simple and reliable tool that simultaneously solves the energy and environmental balance of buildings. Among the goals that this research work has fixed, it was addressed this challenge by proposing the application of the ANN. Due to the demonstrated high reliability of learning algorithms in the resolution of complex and non-linear problems, it was possible to simultaneously solve two different but strongly dependent aspects after a deep training phase. The implemented database to train the neural network, characterised by several building models simulated in different climatic conditions (Italian building energy database), collects 29 inputs (13 energy data and 16 environmental data) and provides 7 outputs, 1 for heating energy demand and 6 of the most used indicators in life cycle assessment of buildings. A statistical analysis of the results confirmed that the proposed model is appropriate to achieve the goal of the study. The best artificial neural network for each output presented low RMSE, MAE lower than 5%, and R^2 close to 1. The excellent results confirmed that this methodology can be extended in any context and to any condition (other countries and building stocks). The possibility to use an instrument to predict a building's performance in its design and planning phase, represent an important result to support decision-making processes toward more sustainable choices.

NOMENCLATURE

Acronyms

AF	Activation Function
ANN	Artificial Neural Network
BIM	Building Information Modelling
BP	Back-propagation algorithm
BPS	Building Performance Simulation
EC	Energy Carrier
EI	Environmental Impact
EPD	Environmental Product Declaration
GD	Gradient Descendent algorithm
HL	Hidden Layer
LCA	Life Cycle Assessment
MLP	Multi-Layer perceptron

Error and performance parameters

MAPE	Mean Absolute Percentage Error [%]
MSE	Mean Squared Error
RMSE	Root Mean Square Error
R ²	Determination coefficient
StD	Standard Deviation

Other parameters

C_T	Total thermal capacity [kWh/(m ³ ·K)]
EI_{EC}	Environmental Impact of the energy carrier
EI_{glazed}	Environmental Impact of the glazed surface
EI_{global}	Global Environmental Impact of the building
EI_{opaque}	Environmental Impact of the opaque surface
h	Operating heating hour [h]
H_d^*	Annual heating energy demand [kWh/year]
HDD	Heating Degree Days [K day]
M_i	Mass of opaque layer [kg]
Q_G	Internal gains [kWh/year]
Q_S	solar gains [kWh/year]
S_H	Heat surface [m ²]
S_{op}	Opaque surface [m ²]
S_w	Surface of the glazed component [m ²]
S/V	Shape factor [m ⁻¹]
U_o	Overall U-value [W/(m ² ·K)]
U_{op}	Opaque thermal transmittance [W/(m ² ·K)]
U_w	Glazed thermal transmittance [W/(m ² ·K)]
v	Wind speed [m/s]
a	Momentum
η	Learning rate

Outputs of the model

ADP _{Fossil}	Abiotic Depletion Potential-Fossil [MJ]
AP	Acidification Potential kg [SO ₂ eq]
EP	Eutrophication Potential kg [PO ₄ ³⁻ eq]
GWP	Global Warming Potential [kg CO ₂ eq]
H_d	Heating energy demand [kWh/(m ² ·year)]
ODP	Ozone Depletion Potential [kg CFC11 eq]
POCP	Photochemical Ozone Creation Potential [kg C ₂ H ₄ eq]

H.1 INTRODUCTION

Energy transition to a low-carbon economy is one of the European Commission priorities. This transition should be in line with the Paris Climate Agreement and with the goals of climate action and sustainable production and consumption (12 and 13th SDGs, 2012) concerning environmental pollution, waste, management, and reduction of raw materials and natural resources. Moreover, Europe's economic dependence on fossil fuels and on non-European resources increases the need for meticulous assessments regarding future energy consumption, raw material demand, and environmental impacts. In this context the building sector is essential and presents a significant potential. Indeed, as explained previous, this sector is responsible for 25% to 30% of all waste generated in the EU [2]. For these reasons the building sector should be designed, constructed, used, and rebuilt considering all mentioned priority areas.

The idea to investigate a model the simultaneously solve the energy and environmental balance of a building is based on the research period carried out from September 2018 to March 2019, at University of Aachen, thanks to the scientific collaboration with Prof. Marzia Traverso, Full Professor for Sustainability in Civil Engineering and Head of the Institute of Sustainability in Civil Engineering at RWTH Aachen University.

H.1.1 State of the art Review

From an energy consumption perspective, there have been significant efforts to improve the efficiency of buildings and reduce energy consumption through the development of various energy saving policies worldwide. As widely discussed above, extensive efforts have been made to develop different BPS tools based on as many numerical approaches able to solve the building thermal balance. Indeed, as explained in **Chapter B** although the BPS are more precise than simplified procedures based on a stationary approach [3], contrariwise are characterised by the lack of a common language, excessive computational costs and high complexity;

furthermore, is always necessary to be a skilled user to implement, solve, evaluate the results, and correct any possible mistakes during their application [4,5].

From the environmental point of view, the most appropriate scientific method to measure the environmental impacts of the entire building's life (raw material supply, manufacture of construction products, construction process, usage, demolition, and/or recycling) is the Life Cycle Assessment (LCA) [6–8]. LCA aims to assess the environmental impacts of a product along its life cycle according to the [6,9], and for buildings according to the [10]. Several studies describe the LCA of a building from a theoretical point of view, whereas other papers used this methodology in analytical manner and through case studies [11–15]. LCA has been implemented in residential, commercial, and office buildings for at least two decades [16,17]. Several databases and software programs, such as GaBi[®] and Simapro[®], were developed to support LCA implementation in the building sector. Moreover, a type III ecolabel scheme, the Environmental Product Declaration (EPD) [18], was developed and widely applied to assess buildings and their components. In this context, the first developed database based on LCA results from EPD of building materials was the Ökobaudat. The Ökobaudat platform is a standardised database for environmental evaluations of buildings provided by the Federal Ministry of the Interior, Building and Community [19]. However, although LCA is standardised by the ISO 14040/44 (2006), its implementation in the building sector still presents several challenges. Recently, several researchers are working on the development of a comprehensive life cycle energy analysis tool. For example, in [20] is described a framework which considers energy requirements at the building and city scales. This framework has been implemented through the development of a software tool which analyses the life cycle energy demand of buildings. In [21] is presented a computational tool to help practitioners in the design of material-efficient structures for multi-storey buildings frames. In all cases, not only the energy consumption of the building is considered, but also embodied energy, and energy within the LCA phases [22].

Based on these considerations and on the difficulties that characterise the energy performance analysis of buildings, a comprehensive energy and environmental

building assessment is difficult to implement. To analyse the energy and environmental performance of buildings, certification schemes such as LEED, DGNB, etc. have been developed. All of them include a sustainability assessment in their evaluation, but not all are based on a life cycle approach. Another possibility is the inclusion of LCA data on the Building Information Modelling (BIM). This solution facilitates the application of LCA in the building sector [23] during the preliminary design phase [24,25], and it provides data required to evaluate the energy needs and environmental impacts of a building during its entire useful life [23,26]. There are several works regarding the power of BIM [27,28], whereas others underline the aims and potential of green BIM in the building sector [29,30]. However, there is a growing concern regarding BIM and LCA integration due to its high complexity [31]. In the construction sector, the implementation of a BIM tools requires evolved technologies to support sustainable construction and decision-making processes [30,32]. Furthermore, the lack of a harmonised methodology for BIM hinders the development of comprehensive building analyses from several points of view. No tool or methodology with low computational time is available for non-expert users [33]. This situation can influence energy planning, slowing down the preliminary assessment of the energy and environmental performance of a building stock. Therefore, a model and tool that allow for a comprehensive assessment of environmental and energy performance with user-friendly interface, low computational cost, and high level of accuracy without losing meaningful parameters should be developed to represent the complex reality. It would be necessary a study aims to issue an alternative method to support the decision-making process during the planning and designing of high energy performance buildings [34] and also mindful to environmental aspects; the method should provide an simultaneously estimation of the environmental and energy performances of a building's life cycle. Previous researches, such as [21] and [35], attempted to develop such method. However, significant lots efforts are still needed to meet this ambitious target.

A solution for this complex problem can be developed based on the use of artificial intelligence algorithms. As known from the **Chapter E**, these algorithms exploit the correlation between large amounts of data to identify functional connections between input and output, which would be difficult or impossible in some other way [36]. Known as one of the most popular AIs and as the widely applied to solve complex problems in different fields [37], and based on the results obtained in **Chapter G**, the ANN it was choose to achieve the aim of this work. It was underlined as ANNs have become a successful approach to solve problems in different areas such as robotics, power systems, optimization, and manufacturing [38] of complex domains such as image processing [39,40], industrial problems [41], and forecasting [42,43].

In particular, as found in the literature, ANNs have also been developed to determine the life cycle environmental impacts based on the energy inputs required for particular food processes. In [44], ANN was applied for the production of black tea, green tea, and oolong tea in Iran. In [45], it described the forecast for energy output and environmental impacts of paddy production. In [46] are applied ANNs to determine the environmental emissions from lentil cultivation; while in [47] are used ANNs to estimate the missing data for an LCA of electronic products. The first approach combining ANN and LCA for the building sector is described by [48], who includes only an economic analysis. As determined by [35], the possibilities of ANN applications to solve comprehensive building performance are endless. To better understand the readability of this research idea, in Table 1H are collected the papers that assess the energy and environmental performance of building, distinguished in the following key finding:

- Building LCA: samples of papers that evaluate the environmental aspects of the building construction through the LCA application;
- LCA and BIM: samples of papers that evaluate the environmental and energy aspects of the building construction through the simultaneously LCA and BIM application;

- ANN and Building: samples of papers that solve the building energy balance with the ANN application; and
- ANN and LCA: samples of papers that evaluate the environmental and energy aspects of the building construction through the simultaneously LCA and ANN application.

For each paper is indicated the key finding, the authors and year of publication, and a brief description of the main objectives:

Table 1H

Key finding of papers to evaluate the energy and environmental building performance.

Key finding	Reference	Main objective
<i>Building LCA</i>	[14]	Proposes the LCA as a tool for the eco-friendly building design.
	[15]	A review on embodied energy use in buildings, indicating research gaps and major strategies to reduce embodied energy.
	[12]	An overview of the current situation of Life cycle assessment (LCA) in the construction industry.
	[22]	An overview to identify key parameters affecting REE calculations in order to streamline the embodied energy calculation.
	[16]	Part of a research project aiming for the development of a performance-based approach for sustainable design, focusing on the efficient use of natural resources over the lifetime of buildings.
	[7]	Results of a detailed LCA study of a low-energy consumption building, complying with the "Passive House" standard, located in Italy, according to European ISO 14040 and 14044.
	[13]	Development of the Building Life Cycle Carbon Emissions Assessment Program (BEGAS 2.0) to support Korea's GBI certification system.
	[8]	A bottom-up approach to spatially model building stocks and quantify their embodied environmental requirements; each building's geometry is modelled and used to derive a bill of quantities
	[20]	A framework which takes into account energy requirements at the building scale, the embodied and operational energy of the building and its refurbishment, implemented through the development of a software tool which allows the rapid analysis of the life cycle energy demand of buildings at different scales.
	[21]	A computational tool that aims to help practitioners to design material-efficient structures for buildings based on an optimization framework.
<i>LCA and BIM</i>	[23]	A review to explore the application of LCA to the various areas in the buildings sector: the embodied energy and the building certification systems.
	[26]	Description of the integration of LCA and BIM to create synergies to develop a tool for attaining higher efficiency and sustainable construction.
	[27]	A book to the subject of sustainable design and of the use of building information models (BIMs). The first two chapters introduce both sustainable (or "green") design and BIM.

Key finding	Reference	Main objective
ANN and Building	[28]	Description of the integration of BIM with LCA, and presents the outcome of this integration in evaluating environmental impacts of building materials in the construction sector.
	[30]	An overview and comparison of 84 green BIM papers.
	[31]	An overview regarding LCA, BIM, and data exchange standards that could facilitate integrating; it is proposed a prototype, developed and validated, where a level 2 LCA tool is linked to a BIM model.
	[36]	The use of ANNs to predict the demand for thermal energy linked to the winter acclimatization of non-residential building at European level.
	[42]	A method for energy consumption forecasting in public buildings, to achieve energy savings, and to improve the energy efficiency, without affecting the comfort and wellness.
ANN and LCA in Building	[43]	A new one-hour-ahead load forecasting method using the correction of similar day data; the forecasted load power is obtained by adding a correction to the selected similar day data.
	[47]	A survey of the current Environment Impact Assessment (EIA) methodologies; an ANN approach is developed to estimate the missing data.
	[48]	An ANN model to estimate operating and maintenance costs of existing buildings; an Office Block, Penllergaer Business Park.
	[35]	A brief review of the current status of machine learning and neural network applications in structural and civil engineering, highlighting their potential use in research concerning sustainability related decisions concerned with building structures and structural materials.

H.1.2 Contribution of the Work

Based on the previous considerations, this research proposes a methodology to support decision makers during the planning and design phases of a building. The model can provide a valid estimation of the energy and environmental performance of a building along its life cycle. It can analyse different scenarios and identify the most sustainable one already in the strategic phase. Moreover, this tool can be used by non-experts on LCA and/or energy performance calculation, which is often the case in the administrations or stakeholders. The use of ANN to solve this complex problem can represent a valid and attractive alternative. However, also in this case a large and reliable dataset of actual and accurate building designs is needed. Starting from the validated energy database described in **Chapter B, Section B.7.3**, the model was improved and developed by adding other case studies and adding environmental impacts related to the construction material and energy carrier. In this manner, it was possible to develop a representative database where certain data

identifying building conditions as inputs, creating a certain data output that described the energy and environmental performances. This database, to train several ANNs to provide 1 energy output and 6 environmental outputs, has been used. For each building it is possible to have immediately knowledge on the heating energy demand and the values of representative environmental impacts [49,50] such as:

- Global Warming Potential (GWP);
- Ozone Depletion Potential (ODP);
- Acidification Potential (AP);
- Eutrophication Potential (EP);
- Photochemical Ozone Creation Potential (POCP); and
- Abiotic Depletion Potential-Fossil (ADP_{Fossil}).

The values of those indicators were acquired from the Environmental Product Declaration (EPD) relative to the materials already inserted in the database (*Annex 7*). In this chapter, the results of the best ANN solutions are presented; these networks are characterised by high R^2 , high MAPE, and low RMSE. The results confirmed that the use of ANN is a reliable approach to simultaneously solve the energy and environmental aspects of a building.

H.2 METHODOLOGY

To reach the study's objective, the research can be divided in two main areas: the energy balance solution and the LCA of a building. The application of the main theoretical concepts and numerical solutions of these areas will enable a building analysis which simultaneously provides an energy and an environmental response. Fig. 1H represents the work's schema, where the main tasks are identified. The first step was characterized by the implementation of a reliable energy and environmental building database; the two actions of this task are:

1. Implementation of a building energy database to determine the heating energy requirements (*Section B.7.3*);
2. Identification and selection of LCA results of building components, to introduce them into the database.

The second task contemplates the application of an ANN to simultaneously identify the energy and environmental performances of a generic building. Finally, these results will be used to develop a decision support tool which allows, non-expert users to quickly and easily identify energy and environmental building performances.

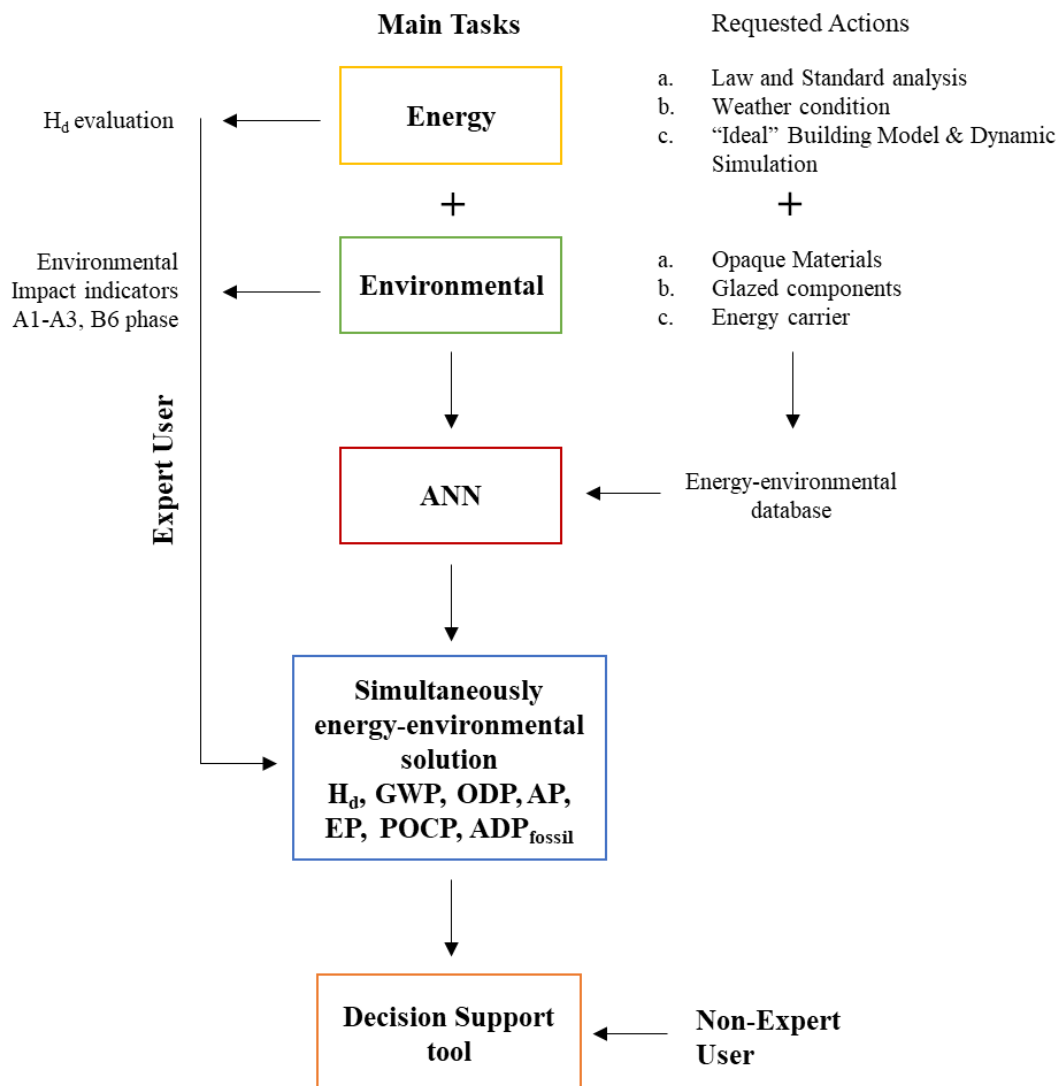


Fig. 1H. Flowchart of the main tasks.

H.2.1 Building Energy Database to Determine Heating Energy Requirements

As indicated in **Chapter E**, to apply the ANN approach, it is necessary to implement a suitable database that represents the analysed problem in any general form or condition. However, European country autonomously legislate the field of energy efficiency according to their own heating or cooling needs. Each country is characterised by a different existing real estate asset and varied transmittance limit values for the envelope and efficiency limit and type of systems. For this reason, it was decided to use the representative database for typical high energy performance non-residential building stocks located in the Italian context and described in detail in **Chapter B** (*Annex 3*).

H.2.2 Life Cycle Assessment of Buildings to Identify Environmental Impact Indicators

In this phase the aim is to identify and gather information on the environmental impacts of building components along their life cycle, and estimate the environmental profile of a generic Italian building. The environmental impacts of building models and their components are analysed and inserted in the database to select certain indicators for the environmental profile estimation of a building. In this initial work, it was decided to collect data with the use of the EPD according to the [51] considering from A1 to A3 and B6 phases to determine the following environmental indexes:

- **GWP:** contribution of a product to climate change; it measures the greenhouse gas emissions into the air over 100 years. The contribution to climate change by each greenhouse gas is compared to the CO₂ contribution. Hence, the indicator unit is kg of CO₂ per kg of emission;
- **ODP:** effect of an emitted gas in the reduction of the ozone layer that protects the earth from harmful UV-radiation. Each chemical effect is compared to CFC-11, and the unit used is kg of CFC-11 per kg of emission;

- AP: contribution to the acidification potential of each emitted air pollutant, such as SO₂ or NO_x. The AP unit is kg of SO₂;
- EP: indicates the levels of macronutrients, such as N and P, in the environment, and measures the contribution of each emission. The unit is kg of (PO₄²⁻) equivalents per kg of emission;
- POCP: contribution to photochemical ozone formation of each substance emitted into the air. The unit is kg of ethylene (C₂H₄) equivalents per kg of emission;
- ADP_{Fossil}: refers to the use of abiotic natural resources. It is a relative measure of the depletion by a reference element considering the impacts derived from the extraction of minerals and fossil fuels. In this study, antimony is used as a reference element, and the unit is kg of antimony (Sb) equivalents per kg of extracted mineral [52].

These indexes are very common in the literature and were used in an LCA study implemented with the CML database of Leiden University [53]. In this first work were considered only from A1 to A3 and B6 phases because the main goal was to train the ANN and prove that could simultaneously provide energy and environmental profile data under changing building scenarios.

H.2.3 Application of ANN to Simultaneously Identify the Energy and Environmental Performance of a Generic Building

As previously indicated, a wide range of scientifically validated tools are available internationally. However, to analyse several aspects of the same problem, multiple software programs may be needed. Based on the previous results, widely described in **Chapters E and G**, the exemplary database was used to identify, train and develop the optimal solutions and typologies of an ANN, which simultaneously represents and solves a traditional energy balance and LCA of a building.

H.3 CASE STUDY

To investigate the reliability of the ANN to simultaneously solve the energy-environmental balance of a building, it was necessary to train several ANNs topologies through the comprehensive building database. For this reason, starting from the representative and validated database of a Italian non-residential building described in **Chapter B**, were analysed the main environmental impacts of construction materials and energy carrier each model. Details are explained in the following.

H.3.1 Energy Assessment

From the energy point of view, it was used the Italian non-residential building stock energy database widely described in *Section B.7.3*. The dataset is constituted by 1560 dynamic simulations that consider an *Ideal Building* designed with high energy performance, according to the standard in force, for each climatic zone (five in total). As previously explained, for each climate zone three cities have been identified, each of which represents the coldest, warmest and mild condition. Every single model in each specific city has been simulated for thirteen shape factor and for eight orientations.

H.3.2 Environmental Assessment

According to ISO 14040 LCA is defined as the environmental profile of a product from cradle to grave (from extraction of raw materials to manufacture, usage, recycling, and/or end of life) [54]. The whole production process is analysed considering all inputs (raw materials and energy consumption) and their interactions [55]. LCA considers as environmental impacts all burdens caused by materials emitted into the air, soil, and water [56]. Based on [6], every LCA methodology consists of 4 stages: goal and scope definition, life cycle inventory analysis of materials or processes, life cycle impact assessment and interpretation of results. The data on the environmental performance of building components and

materials which are included in the ANN database were collected from LCAs in the literature (EPD) and the SimaPro[®] data. The ANN estimation of the environmental profile of different scenarios of a non-residential building in the design phase was done by changing shapes and geographical locations and consequently the thermophysical configurations of the buildings. For instance, changes in the location and climate zone, induce changes in the thickness of the insulation components. At this point the building LCA results related only to A1-A3 and B6 phases have been considered, and not the entire life cycle of buildings.

The functional unit is a generic non-residential building that changes position, shape, and characteristics within the Italian building stock in the database. To satisfy the heating energy demand 4 energy carrier scenarios have been supposed: electricity, natural gas, Liquid Propane Gas (LPG) and biogas. To represent the LCA profile of the materials, 6 well-known environmental indicators have been considered: GWP, ODP, AP, EP, POCP and ADP_{Fossil}.

First, based on the deep research and analysis of specific EPDs and on the selected construction materials for the *Ideal Building*, the environmental impacts of materials have been identified. Because perfect correspondence is difficult, have been selected materials that were similar to those chosen in the model (Table 2H).

Table 2H

Environmental impact indicators per kg of each construction material.

Materials	GWP	ODP	AP	EP	POCP	ADP _{Fossil}
	[kg CO ₂ eq]	[kg CFC11 eq]	[kg SO ₂ eq]	[kg PO ₄ ³⁻ eq]	[kg C ₂ H ₄ eq]	[MJ]
External plaster	2.60E-01	3.12E-07	1.58E-03	8.04E-04	2.59E-04	8.07E+00
Cement lime plaster	4.49E-01	3.05E-09	8.15E-04	1.52E-04	8.37E-05	4.59E+00
Rock wool	1.08E+00	4.41E-08	7.93E-03	3.78E-04	5.59E-04	1.80E+01
Tuff block	1.47E-01	2.54E-09	1.59E-04	2.28E-05	1.23E-05	1.09E+00
Internal plaster 1	1.20E-01	2.00E-08	4.80E-04	6.60E-05	4.40E-05	2.20E+00
Concrete brick	1.31E-01	9.26E-10	2.37E-04	2.27E-05	7.06E-05	8.19E-01
Concrete screed	1.06E-01	3.54E-09	3.96E-04	1.25E-04	1.79E-05	5.29E-01
Concrete slab	1.12E-01	2.55E-12	1.81E-04	2.88E-05	4.11E-06	5.80E-01
Internal plaster 2	1.20E-01	2.00E-08	4.80E-04	6.60E-05	4.40E-05	2.20E+00
Floor tile	1.04E+00	1.53E-10	2.71E-03	2.14E-03	2.19E-04	1.47E+01
Bitumen	6.33E-03	2.83E-09	2.54E-05	4.15E-06	6.72E-06	3.76E-01
Brick	1.53E-01	3.08E-08	5.12E-04	5.60E-05	1.56E-04	2.43E+00

Five types of windows were selected considering the thermal transmittance limit imposed by current legislation. For each climatic zone, a specific window characterised by diverse thermophysical characteristics has been considered. Using Simapro[®], a professional software that has several databases of life cycle impact assessment for different products and services, it was possible to identify and calculate the environmental impact indicators per square metre of glazed component (Table 3H).

Table 3H

Environmental impact indicators per m² of each glazed component.

Climatic Zone	GWP [kg CO ₂ eq]	ODP [kg CFC11 eq]	AP [kg SO ₂ eq]	EP [kg PO ₄ ³⁻ eq]	POCP [kg C ₂ H ₄ eq]	ADP_{Fossi} [MJ]
B	8.27E+01	7.32E-06	5.53E-01	1.90E-01	4.19E-02	9.31E+02
C	7.33E+01	6.67E-06	4.82E-01	1.56E-01	3.40E-02	8.38E+02
D	7.86E+01	7.03E-06	5.21E-01	1.75E-01	3.84E-02	8.90E+02
E	7.86E+01	7.03E-06	5.21E-01	1.75E-01	3.84E-02	8.90E+02
F	7.45E+01	6.75E-06	4.91E-01	1.60E-01	3.50E-02	8.50E+02

The environmental indicators for the single layer of a single model were calculated based on the mass of each single opaque layer and square metre of each glazed surface, the product between the value of the environmental indicator (Tables 2G and 3G), and single mass (Eq. (1)) or square metre (Eq. (2)):

$$EI_{opaque} = \sum_{i=1}^n (M_i \cdot EI_i) \quad (1)$$

$$EI_{glazed} = \sum_{j=1}^z (S_{w,j} \cdot EI_j) \quad (2)$$

where

M_i is the i^{th} mass of opaque layer [kg];

$S_{w,j}$ is the square metre of the j^{th} glazed component [m²]; and

$EI_{i/j}$ is the i^{th} or j^{th} Environmental Impact.

The mass values of the opaque layers and the square metre of the glazed surface were calculated for each model. A specific stratigraphy for the opaque surfaces was designed for each model and a specific window that respects the transmittance limit values for each climatic zone has been identified.

For a complete analysis, the impacts related to the thermal needs of the building must be considered. These impacts change with the energy carrier (EC) used to satisfy the heating energy demand. Therefore, 4 scenarios were investigated to obtain a significantly more heterogeneous and versatile database. The four scenarios are represented by: electricity, natural gas, LPG and biogas. Moreover, in this case, the environmental impacts of the energy carrier from Simapro[®] have been obtained (Table 4H).

Table 4H

Environmental impact indicators per kWh of each energy carrier considered to satisfy the heating energy demand.

Energy Carrier	GWP [kg CO ₂ eq]	ODP [kg CFC11 eq]	AP [kg SO ₂ eq]	EP [kg PO ₄ ³⁻ eq]	POCP [kg C ₂ H ₄ eq]	ADP _{Fossi} [MJ]
Electricity	4.16E-01	4.91E-08	2.10E-03	5.81E-04	8.65E-05	4.82E+00
Natural Gas	5.79E-02	2.45E-08	1.96E-04	1.99E-05	2.75E-05	4.13E+00
LPG	3.23E-02	2.33E-08	2.43E-04	3.12E-05	1.64E-05	1.86E+00
Biogas	7.97E-02	4.13E-09	2.16E-03	8.95E-04	2.76E-05	5.47E-01

For each energy carrier the respective environmental impact was calculated as (Eq. (3)):

$$EI_{EC} = \sum_{k=1}^m (H_d^* \cdot EI_{EC,k}) \quad (3)$$

where

H_d^* is the annual heating energy demand of the building [kWh/year]; and

$EI_{EC,k}$ is the environmental impact of the k^{th} energy carrier.

The sum of all indicators that compose the *Ideal Building* (Eq. (1), (2) and (3)) identify the global environmental indicator:

$$EI_{global} = EI_{opaque} + EI_{glazed} + EI_{EC} \quad (4)$$

In this manner, each building is characterised by 6 global environmental indicators. Table 5H illustrates the GWP indicators calculated for the electricity scenario, for the 13 models in 15 cities. In *Annex 7* are collected the results for all indexes.

Table 5H

GWP indicator of all 13 case studies calculated for electricity scenario.

Climatic Zone	Location	GWP [kg CO ₂ eq]												
		1	2	3	4	5	6	7	8	9	10	11	12	13
B	Messina	9.76	6.03	1.05	3.55	6.46	9.18	2.82	8.98	7.40	1.83	2.77	2.56	5.00
		E+05	E+06	E+06	E+05	E+05	E+05	E+05	E+05	E+05	E+05	E+06	E+06	E+06
	Palermo	9.50	5.76	9.71	3.36	6.01	8.62	2.66	8.51	7.16	1.72	2.64	2.43	4.78
		E+05	E+06	E+05	E+05	E+05	E+05	E+05	E+05	E+05	E+05	E+06	E+06	E+06
	Crotona	1.35	8.06	1.44	4.87	8.78	1.25	3.73	1.18	1.02	2.48	3.71	3.45	6.69
		E+06	E+06	E+06	E+05	E+05	E+06	E+05	E+06	E+06	E+06	E+06	E+06	E+06
C	Cagliari	8.67	5.84	7.52	2.78	4.85	7.72	2.23	7.74	6.38	1.52	2.52	2.36	4.85
		E+05	E+06	E+05	E+05	E+05	E+05	E+05	E+05	E+05	E+05	E+06	E+06	E+06
	Bari	1.05	7.68	1.03	3.42	6.68	1.03	2.70	9.83	7.65	2.07	3.35	3.15	6.38
		E+06	E+06	E+06	E+05	E+05	E+06	E+05	E+05	E+05	E+05	E+06	E+06	E+06
	Termoli	1.40	9.26	1.45	4.70	9.04	1.34	3.63	1.25	1.03	2.67	4.10	3.89	7.70
		E+06	E+06	E+06	E+05	E+05	E+06	E+05	E+06	E+06	E+06	E+06	E+06	E+06
D	Genova	1.22	7.63	1.12	4.10	7.28	1.03	3.21	1.10	9.03	2.09	3.18	3.14	6.25
		E+06	E+06	E+06	E+05	E+05	E+06	E+05	E+06	E+05	E+06	E+06	E+06	E+06
	Firenze	1.29	8.65	1.23	4.22	8.10	1.16	3.31	1.19	9.42	2.36	3.62	3.56	7.11
		E+06	E+06	E+06	E+05	E+05	E+06	E+05	E+06	E+05	E+06	E+06	E+06	E+06
	Forlì	1.96	1.17	1.99	6.75	1.25	1.72	5.12	1.69	1.47	3.47	4.99	4.97	9.67
		E+06	E+07	E+06	E+05	E+06	E+06	E+05	E+06	E+06	E+06	E+06	E+06	E+06
E	Trieste	1.39	8.79	1.36	4.77	8.90	1.20	3.66	1.24	1.04	2.45	3.59	3.64	7.15
		E+06	E+06	E+06	E+05	E+05	E+06	E+05	E+06	E+06	E+06	E+06	E+06	E+06
	Torino	2.04	1.23	1.95	6.85	1.27	1.73	5.08	1.71	1.52	3.51	5.10	5.16	1.01
		E+06	E+07	E+06	E+05	E+06	E+06	E+05	E+06	E+06	E+06	E+06	E+06	E+06
	Bolzano	2.04	1.23	1.86	6.66	1.22	1.72	4.91	1.70	1.50	3.45	5.13	5.15	1.02
		E+06	E+07	E+06	E+05	E+06	E+06	E+05	E+06	E+06	E+06	E+06	E+06	E+06
F	Cuneo	1.32	9.46	1.10	4.01	7.85	1.14	3.07	1.21	9.27	2.34	3.71	3.75	7.67
		E+06	E+06	E+06	E+05	E+05	E+06	E+05	E+06	E+05	E+06	E+06	E+06	E+06
	Cortina	3.20	2.00	2.76	9.72	1.85	2.63	7.01	2.55	2.32	5.37	8.04	8.18	1.64
		E+06	E+07	E+06	E+05	E+06	E+06	E+05	E+06	E+06	E+06	E+06	E+06	E+06
	Sestriere	3.28	2.32	2.53	8.75	1.79	2.75	6.29	2.66	2.25	5.63	9.08	9.15	1.90
		E+06	E+07	E+06	E+05	E+06	E+06	E+05	E+06	E+06	E+06	E+06	E+06	E+06

From Fig. 2H to Fig. 7H display the individual life cycle stages (A1-A3 and B6) and their contribution to environmental impacts over a 50-year building lifespan.

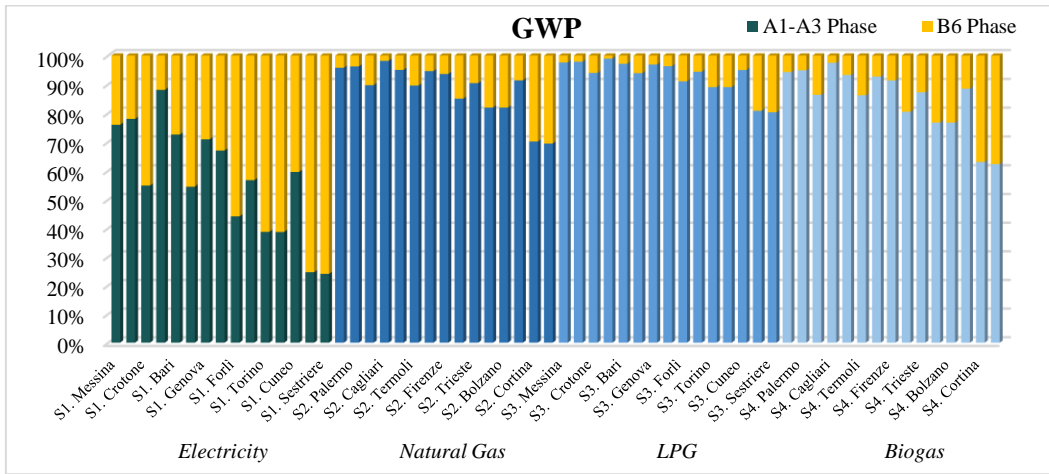


Fig. 2H. Life cycle stages (A1-A3 and B6) contribute to GWP indicator.

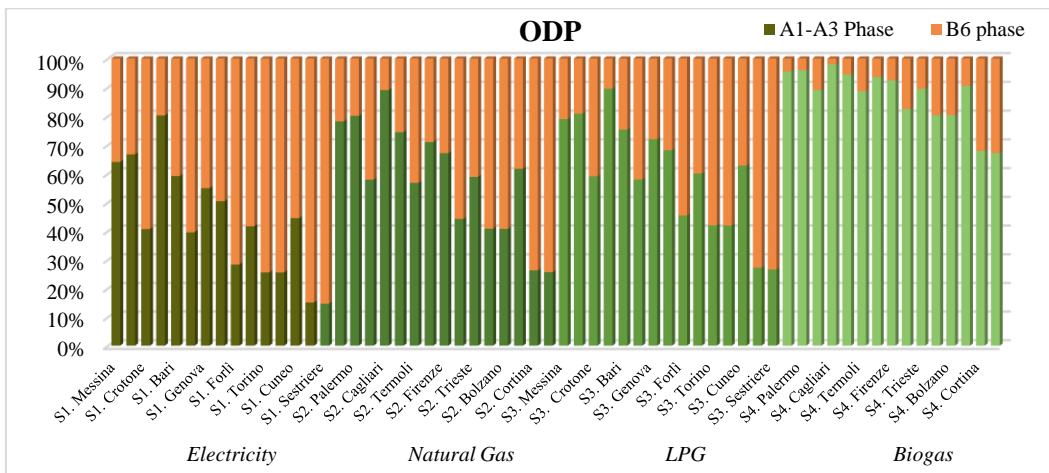


Fig. 3H. Life cycle stages (A1-A3 and B6) contribute to ODP indicator.

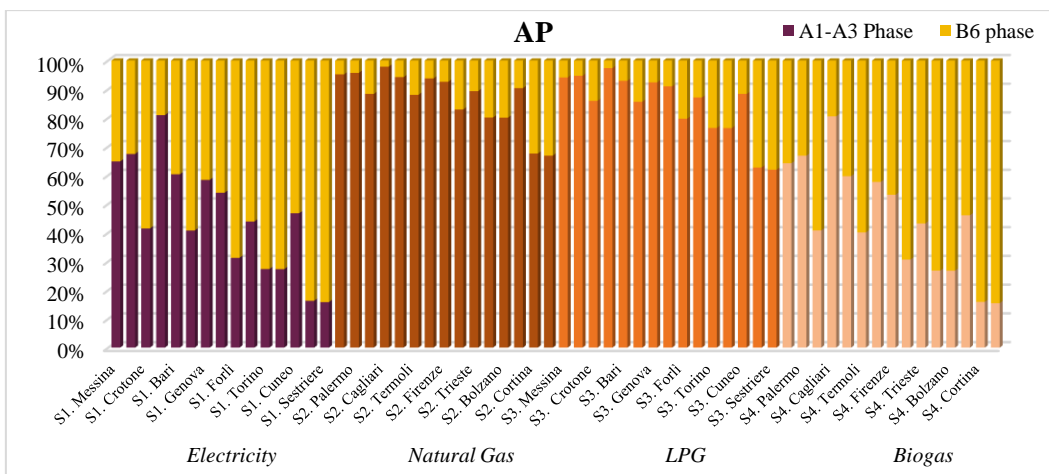


Fig. 4H. Life cycle stages (A1-A3 and B6) contribute to AP indicator.

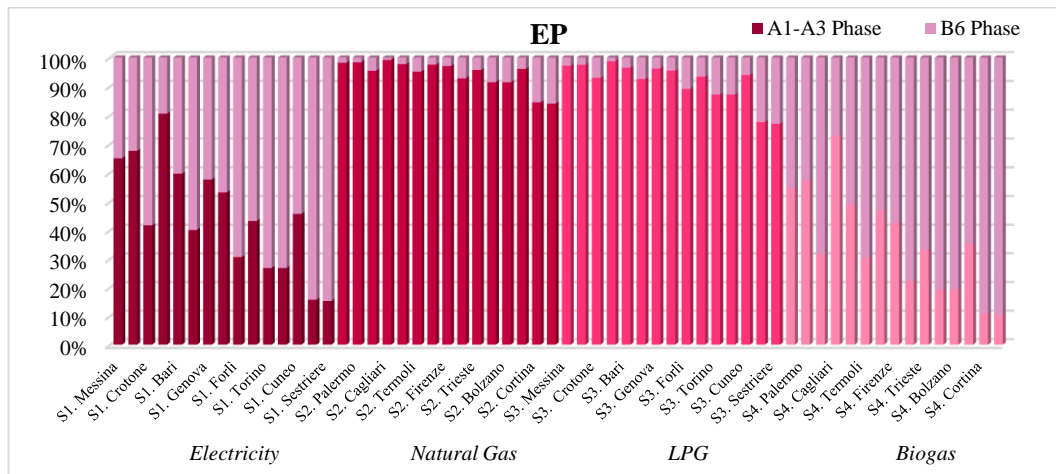


Fig. 5H. Life cycle stages (A1-A3 and B6) contribute to EP indicator.

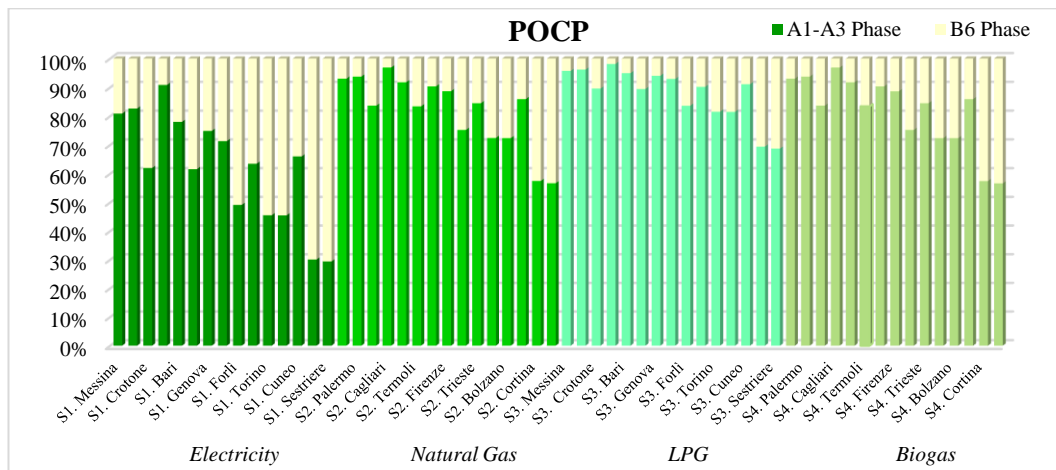


Fig. 6H. Life cycle stages (A1-A3 and B6) contribute to POCP indicator.

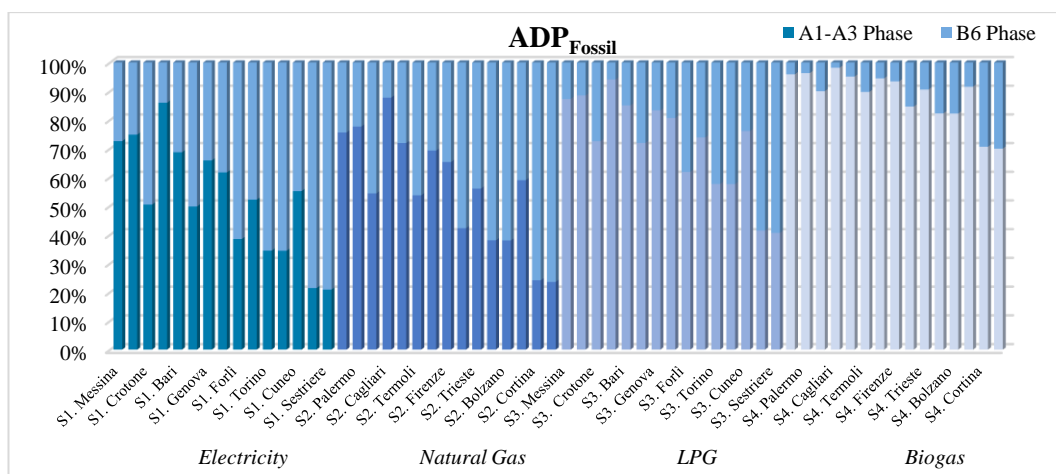


Fig. 7H. Life cycle stages (A1-A3 and B6) contribute to ADP_{Fossil} indicator.

In general, for all environmental impacts, except ODP and ADP_{Fossil} , the A1-A3 phases are higher than the B6 phase. Furthermore, the electricity scenario for all environmental indicators is characterised by a prevalent B6 phase.

H.3.3 Summary Database

The development of this approach allowed the implementation of an energy and environmental database. The database is composed by 36 columns and 780 rows for a total matrix composed of 28,080 cells. The columns are represented as follows:

1. Heating degree days [K day];
2. Shape factor [m^{-1}];
3. Heated surfaces [m^2];
4. Glazed surface [m^2];
5. Opaque losses surfaces [m^2];
6. Glazed surface transmittance [$\text{W}/(\text{m}^2 \text{K})$];
7. Opaque losses surface thermal transmittance [$\text{W}/(\text{m}^2 \text{K})$];
8. Overall thermal transmittance [$\text{W}/(\text{m}^2 \text{K})$];
9. Solar gains [kWh/year];
10. Heating operating hours [h];
11. Wind speed [m/s];
12. Thermal capacity [kWh/ $(\text{m}^3 \text{K})$];
13. Internal gains [kWh/year];
14. Electricity energy carrier;
15. Natural gas energy carrier;
16. LPG energy carrier;
17. Biogas energy carrier;

18. External plaster mass [kg];
19. Cement lime plaster mass [kg];
20. Rock wool mass [kg];
21. Tuff block mass [kg];
22. Internal plaster 1 mass [kg];
23. Concrete brick mass [kg];
24. Concrete screed mass [kg];
25. Concrete slab mass [kg];
26. Internal plaster 2 mass [kg];
27. Floor tile mass [kg];
28. Bitumen mass [kg];
29. Brick mass [kg];
30. Heating energy demand [kWh/(m² year)];
31. GWP [kg CO₂ eq];
32. ODP [kg CFC11 eq];
33. AP [kg SO₂ eq];
34. EP [kg PO₄⁻³ eq];
35. POCP [kg C₂H₄ eq]; and
36. ADP_{Fossil} [MJ].

In the rows, there are 13 building models located in three cities for 5 climatic zones, which were simulated for 4 energy carrier scenarios.

H.4 ANN APPLICATION

To obtain an optimal solution, the training process provides an iterative update of the synaptic connections (weights) after the presentation of all possible input/output pairs of the training database. The verse and intensity of the synaptic weights are guaranteed by minimizing the MSE between the provided output and the expected result. To model physical systems, a feed-forward BP-MLP structure is commonly applied [57].

In this study, several feed-forward BP neural networks with one input layer, one or more hidden layers, and a single layer of output neurons were evaluated and trained. To simultaneously solve the energy and environmental balance of a building through ANN, the appropriate input parameters of the model have been carefully selected. The performance of the ANN prediction was evaluated by comparing the network outputs with the target values. All networks were trained with 85% of the database, while the remaining 15% was used for validation. The criteria used to measure the network performance were RMSE, R^2 , and MAPE.

H.4.1 Input-Output Selection

Selection of appropriate input parameters for the ANN is essential for the model development. To ensure the suitability of this selection, a deep analysis of the relationship between description variables (inputs) and target variables (outputs) has been done. The analysis was based on the evaluation of traditional building energy balance and building environmental indicators, linked to the envelope and the energy carriers. Hence, it was possible to simultaneously identify strong correlations between energy and environmental inputs and output

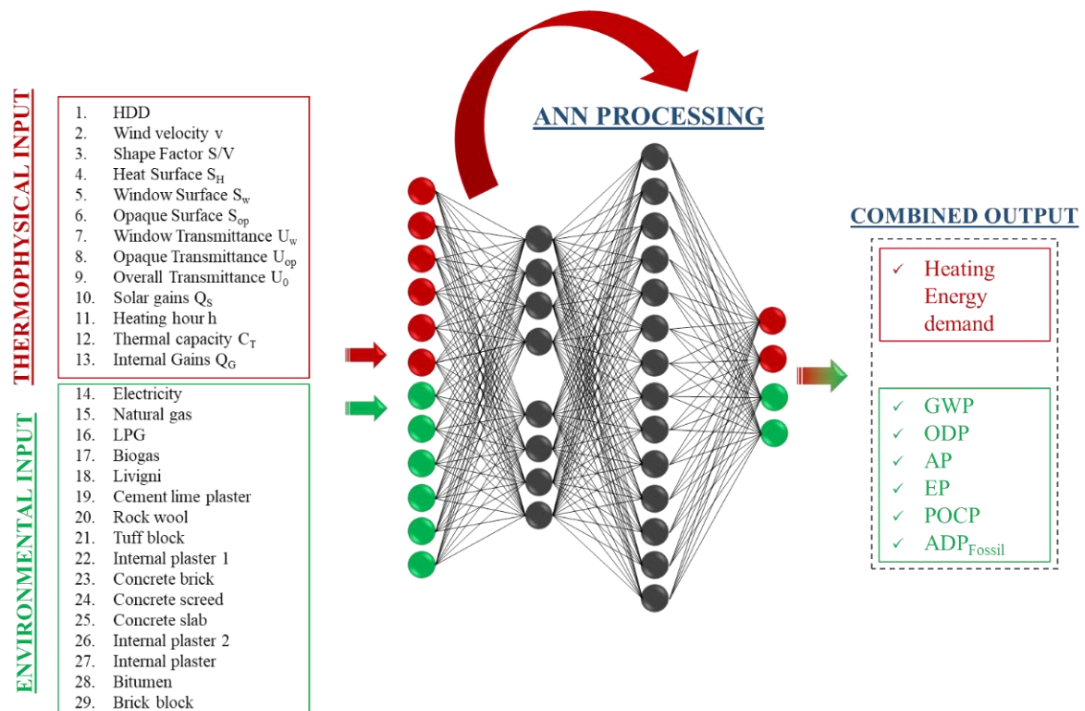


Fig. 8H. Input and output of the ANNs.

As indicated in Fig. 8H, 29 inputs and 7 outputs have been identified; among the input data, 13 are related to energy parameters and 16 to the environment; among the output data 1 is related to energy and 6 to the environment.

H.4.2 ANN Selection

Following the pre-processing phase, have been explored several topologies of ANNs by changing the number of neurons, hidden layers, activation functions, and all parameters of the learning process to minimize the MSE and to identify the optimal configuration. In this research, all configurations explored are characterised by two different activation functions: a tanh-sigmoid activation function for the hidden layers and a linear activation function for the output layer.

Also in this work it was used the Synapse environment, a component-based development created by Peltarion, for neural networks and adaptive systems [58]. To select the ANNs with the lowest MSE, have been chosen the three best configurations to compare the results by varying the complexity degree of the

network and the computational time. The main features (number of hidden layers and neurons) for each of them are summarized in Table 6H. To limit the poor generalization capacity, the training phase was interrupted before the overfitting phase. The training was stopped every time the error trend of the validation pattern and the training pattern began to diverge. Consequently, the epoch number for each ANN has been identified.

Table 6H

Main features of the ANNs design.

MLP Models	N° of HL	Signal path	N° of HL for each line	ANN Design				Epoch	α	η
				N° of Neurons		AF				
				1° HL	2° HL	Tanh-sigmoid	Linear			
ANN 1	2	Line 1	2	200	100	2	1	$8 \cdot 10^6$	0.7	0.1
			2	50	25	2	1			
ANN 2	2	Line 2	1	25	-	1	1	$1 \cdot 10^6$	0.7	0.1
		Line 3	1	50	-	1	1			
		Line 1	2	8	6	2	1			
ANN 3	4	Line 2	1	6	-	1	1	$8 \cdot 10^6$	0.7	0.1
		Line 3	1	8	-	1	1			
		Line 4	2	6	8	2	1			
		Line 5	-	-	-	-	1			
		Line 1	2	8	6	2	1			

The first “ANN 1” (Fig. 9H) is a linear feedforward MLP characterised by two hidden layers; the first with 200 neurons, and the second with 100 neurons.

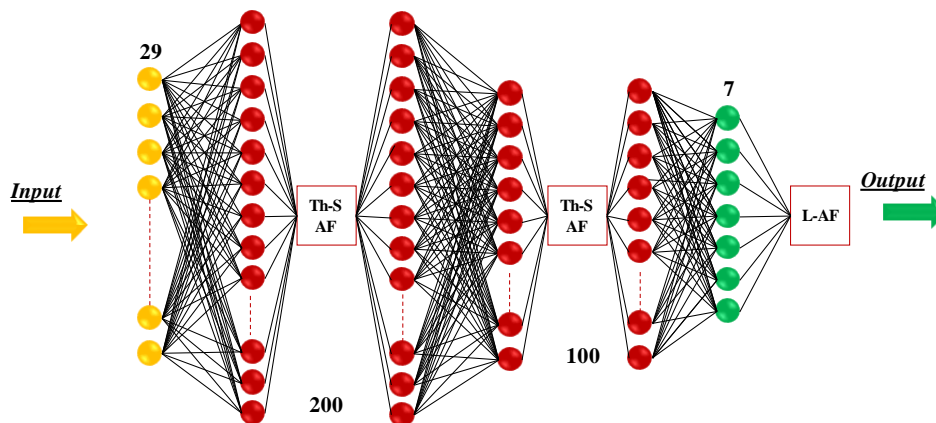


Fig. 9H. Design of the ANN 1.

The second “ANN 2” (Fig. 10H) is a feedforward MLP with two hidden layers (50 and 25 neurons in the first and second layers, respectively) differently connected to each other. Particularly, these connections allow the input signal to follow three different paths (Line 1-3):

- Line 1. The input signal starts from the input layer, passes through the two hidden layers and reaches the output neurons (longest path);
- Line 2. The input layer is directly connected to the second hidden layer (25 neurons) bypassing the first one. The input signal, starts from the input layer, passes through one hidden layer, and reaches the output neurons (shortest path);
- Line 3. The input layer is normally connected to the first hidden layer (50 neurons) which is directly connected with the output layer bypassing the second hidden layer. The input signal follows a short path.

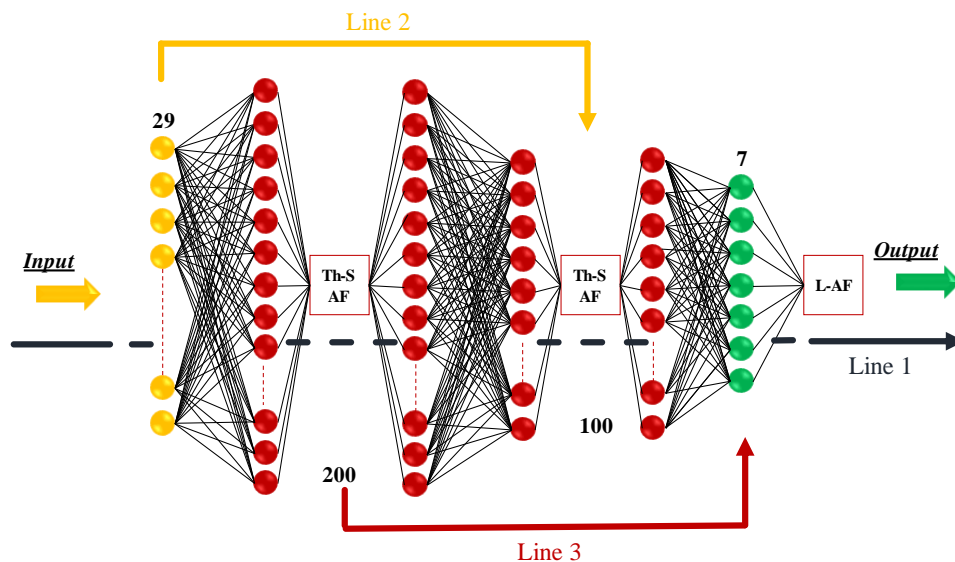


Fig. 10H. Design of the ANN 2.

The third “ANN 3” (Fig. 11H), is always a feedforward MLP, but there are 4 hidden layers: two with 8 neurons and two with 6 neurons. This ANN presents a higher complexity than the previously evaluated ones. The input signal follows 5 different

paths; the first 3 lines replicate the same path of Lines 1, 2, and 3 of ANN 2. The others two paths are as follows:

- Line 4. The input signal starts from the input layer and directly reaches the output neurons (shortest path);
- Line 5. The input layer is connected to the third hidden layer (6 neurons) passes through the fourth hidden layer (8 neurons) and is connected to the output layer. The input signal follows an alternative path compared to the previous one.

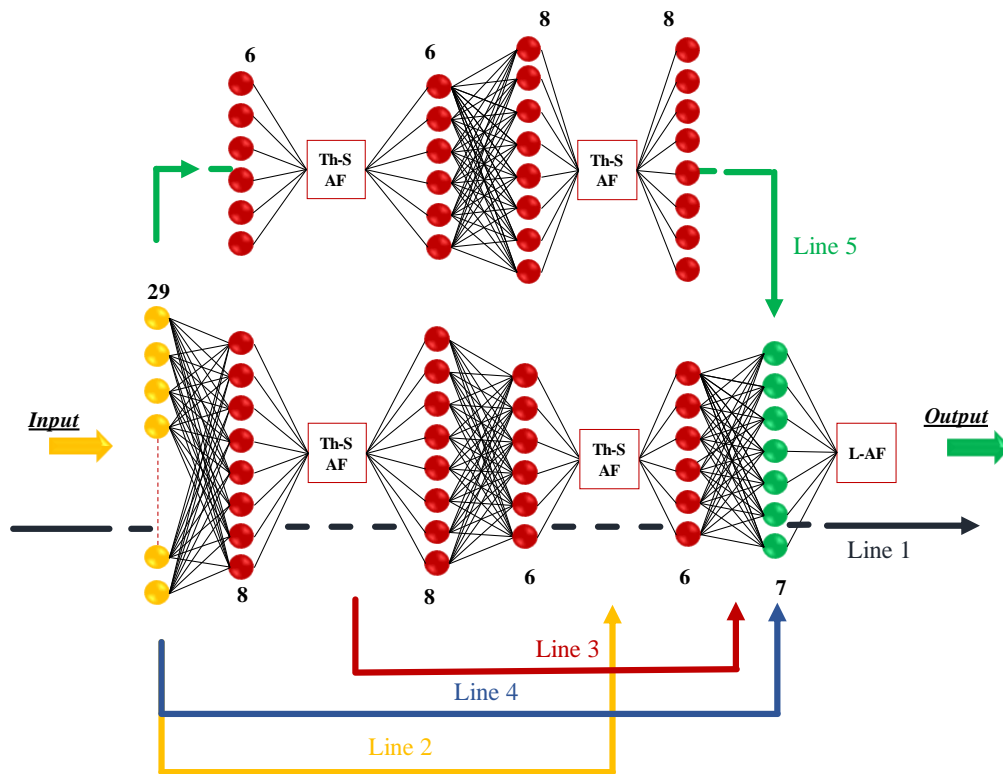


Fig. 11H. Design of the ANN 3.

H.5 RESULTS

Based on the comparison of the results from the three ANNs the optimal solution and the best network conditions that solve the complex energy and environmental building performance problem have been identified.

H.5.1 ANN Results

The post-processing phase is characterised by the results associated with the training phase (Table 7H) and the validation phase (Table 8H). In each phase and for each ANN, the data for Mean, Median, Standard Deviation (StD) and confidence range of each output have been collected.

Table 7H

Post processing data of ANNs for the training dataset.

		Training Set						
ANN Models	Results	H_d	GWP	ODP	AP	Ep	POCP	ADP_{Fossil}
		[kWh/(m ² ·year)]	[kg CO ₂ eq]	[kg CFC11 eq]	[kg SO ₂ eq]	[kg PO ₄ ³⁻ eq]	[kg C ₂ H ₄ eq]	[MJ]
ANN 1	Mean	-0.0097	1793.63	0.0002	5.96	1.22	0.3520	22570.42
	Median	-0.0090	-0.0090	-0.0090	-0.0090	-0.0090	-0.0090	-0.0090
	StD	0.0061	3397.67	0.0004	17.32	6.98	0.5401	45858.94
	Confidence Range (95%)	±0.0224	±7525.82	±0.0009	±35.87	±13.87	±1.26	±100117.40
ANN 2	Mean	0.0629	4557.28	0.0002	8.39	0.2608	0.7276	39024.21
	Median	0.0594	0.0594	0.0594	0.0594	0.0594	0.0594	0.0594
	StD	0.0782	15626.09	0.0019	78.24	31.11	2.77	196384.15
	Confidence Range (95%)	±0.1967	±31880.33	±0.0038	±154.12	±60.93	±5.62	±392146.9
ANN 3	Mean	-0.0217	11920.66	0.0005	-27.74	-21.06	0.9974	-54311.08
	Median	-0.0237	-0.0237	-0.0237	-0.0237	-0.0237	-0.0237	-0.0237
	StD	0.0752	32867.02	0.0043	175.61	72.42	5.0350	52341.09
	Confidence Range (95%)	±0.1533	±68478.63	±0.0085	±348.20	±147.71	±10.05	±1030621

Table 8H

Post processing data of ANNs for the validation dataset.

		Validation Set						
ANN Models	Results	H_d	GWP	ODP	AP	Ep	POCP	ADP _{Fossil}
		[kWh/(m ² ·year)]	[kg CO ₂ eq]	[kg CFC11 eq]	[kg SO ₂ eq]	[kg PO ₄ ³⁻ eq]	[kg C ₂ H ₄ eq]	[MJ]
ANN 1	Mean	-0.0110	2389.01	0.0008	3.54	-2.63	0.4387	868.81
	Median	-0.0150	-0.0150	-0.0150	-0.0150	-0.0150	-0.0150	-0.0150
	StD	0.1164	35432.40	0.0036	204.27	74.62	6.62	619265.44
	Confidence Range (95%)	±0.2280	±69307.16	±0.0072	±398.70	±145.73	±12.94	±1208541
ANN 2	Mean	0.0625	2734.19	0.0006	-10.60	-8.73	0.3938	9817.31
	Median	0.0557	0.0557	0.0557	0.0557	0.0557	0.0557	0.0557
	StD	0.1320	26795.77	0.0030	161.12	64.31	4.64	395709.99
	Confidence Range (95%)	±0.2820	±52567.69	±0.0060	±315.12	±126.68	±9.09	±772495.4
ANN 3	Mean	-0.0208	13507.18	-0.0002	-17.31	-16.10	0.7230	-154543.78
	Median	-0.0097	-0.0097	-0.0097	-0.0097	-0.0097	-0.0097	-0.0097
	StD	0.0953	39022.90	0.0057	242.13	101.79	5.85	799055.47
	Confidence Range (95%)	±0.1905	±80626.15	±0.0110	±473.75	±201.12	±11.51	±1588558

H.5.2 Comparison and Performance of the ANN

As previously mentioned, some of the most commonly used criteria were chosen to evaluate the performance of a model [46,59]: RMSE, MAPE, and R^2 , defined in Section A.4.

As indicated, the RMSE represents the square root of the quadratic mean of the difference between predicted and expected values. The MAPE evaluates the relative percentage deviation between the predicted and expected values; if it is smaller than 10% it is considered acceptable. The R^2 evaluates the accuracy of the model compared to the actual data points: higher is R^2 , more efficient is the model [46]; the best ANN is characterised by small MAPE and RMSE and high R^2 . Table 9H summarizes the RMSE data of the three ANNs; in general, the lowest values are related to ANN 2, expect for the H_d value.

Table 9H

Root Mean Square Error of the validation dataset.

ANN	H_d	GWP	ODP	AP	Ep	POCP	ADP _{Fossil}
	[kWh/(m ² ·year)]	[kg CO ₂ eq]	[kg CFC11 eq]	[kg SO ₂ eq]	[kg PO ₄ ³⁻ eq]	[kg C ₂ H ₄ eq]	[MJ]
ANN 1	0.12	35361.44	0.0037	203.42	74.35	6.60	616613.94
ANN 2	0.14	26820.74	0.0031	160.78	64.63	4.64	394137.58
ANN 3	0.10	41136.54	0.0056	241.71	102.62	5.87	810503.70

The following figures compare the MAPE (Fig. 12H) and R² (Fig. 13H) obtained from the three ANNs for each output.

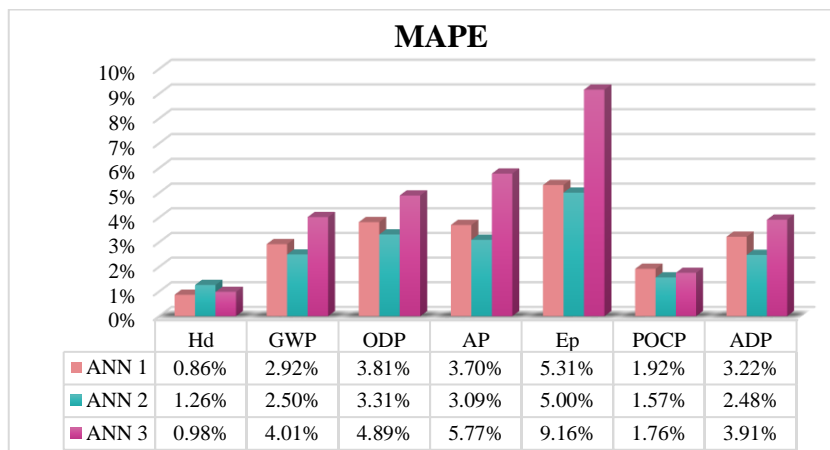


Fig. 12H. Mean Absolute Percentage Error of the validation dataset.

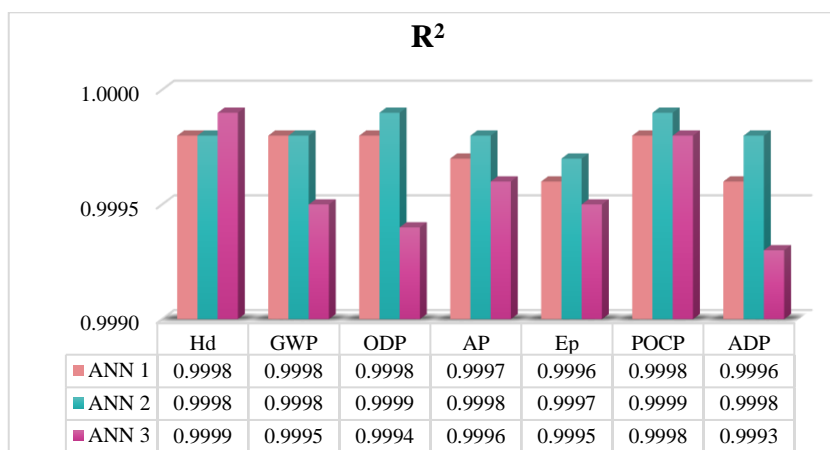


Fig. 13H. Determination coefficient of the validation dataset.

In this case, except for the H_d value, the smallest MAPE values for all outputs are related to ANN 2. The smallest MAPE for H_d was obtained from ANN 1. Regarding R^2 , the highest values are always related to ANN 2. Therefore, ANN 2 was selected as the optimal energy and environmental solution. It was considered the best compromise, since the high MAPE and RMSE related to H_d were irrelevant compared to the other values.

H.5.3 Best ANN

Considering the optimal solution (ANN 2), the frequency distribution trends of MSE for the training set between the expected and calculated output data are illustrated in the following figures. For examples, Fig. 14H illustrates the error frequency distribution between the predicted and expected H_d , and Fig. 15H the error frequency distribution of the predicted and expected GWP.

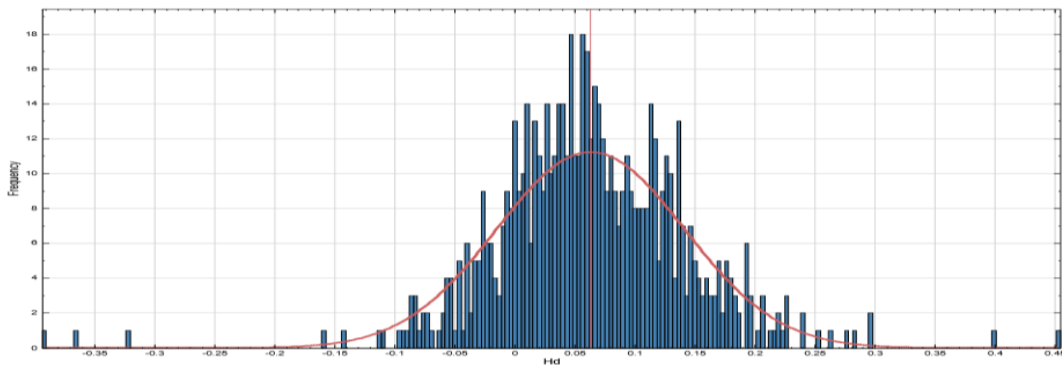


Fig. 14H. Error frequency distribution for the training set of the H_d .

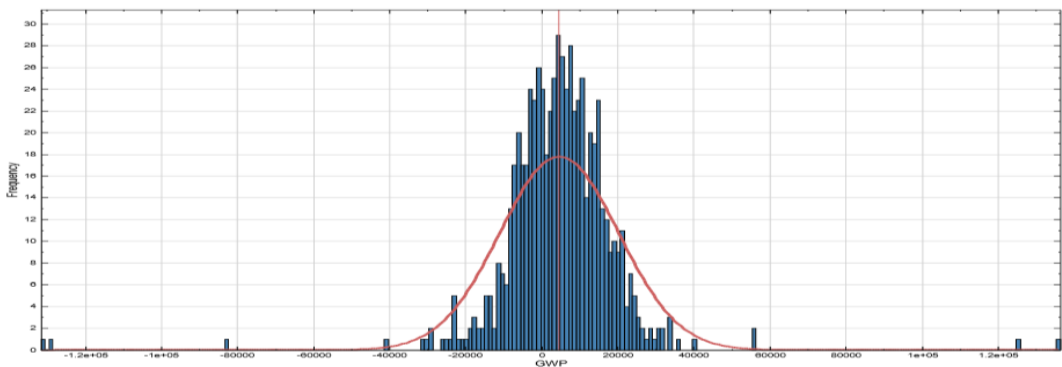


Fig. 15H. Error frequency distribution for the training set of the GWP.

The values of Mean, Median and StD, for each output, are collected in Table 7H; comparing these results with the average expected values, reported in Table 10H, it is possible to affirm that for all output indexes the difference between the Mean values and expected average values for training and validation sets are lower than 0.45%.

Table 10H

Average, maximum and minimum expected values of the entire dataset.

	<i>H_d</i>	GWP	ODP	AP	Ep	POCP	ADP _{Fossil}
	[kWh/(m ² year)]	[kg CO ₂ eq]	[kg CFC11 eq]	[kg SO ₂ eq]	[kg PO ₄ ³⁻ eq]	[kg C ₂ H ₄ eq]	[MJ]
Expected Average value	14.17	1.39E+06	0.18	8.65E+03	2.79E+03	3.53E+02	2.20E+07
Mean Training	0.0629	4557.28	0.0002	8.39	0.2608	0.7276	39024.21
Mean Validation	0.0625	2734.19	0.0006	-10.6	-8.73	0.3938	9817.31
Δ Mean Training	0.44%	0.33%	0.11%	0.10%	0.01%	0.21%	0.18%
Δ Mean Validation	0.44%	0.20%	0.34%	0.12%	0.31%	0.11%	0.04%

The analysis of the results underlined how, in a confidence range of 95%, the *H_d* trend has a margin error of approximately ±0.282 kWh/(m² year) for the validation dataset; similarly considerations are valid for the environmental indexes. For example, for a confidence range of 95%, the GWP indicator is characterized by a margin of error of approximately ±52567.69 kgCO₂eq.

A common and simple approach to evaluate and compare the performance of prediction models is the linear regression between expected and predicted values, and the comparison of intercept and slope parameters against the 1:1 line [60]. For this reason, from Fig. 16H to Fig. 19H, presents one graph for each output of the best ANN. R² and the comparison between the regression line (continued black line) and the 1:1 line (dashed red line) for the validation dataset are also displayed. The goodness of the ANN is emphasized not only by the scatter plots and high R² values, but also by the excellent intercept and slope values of the regression line calculated for all outputs.

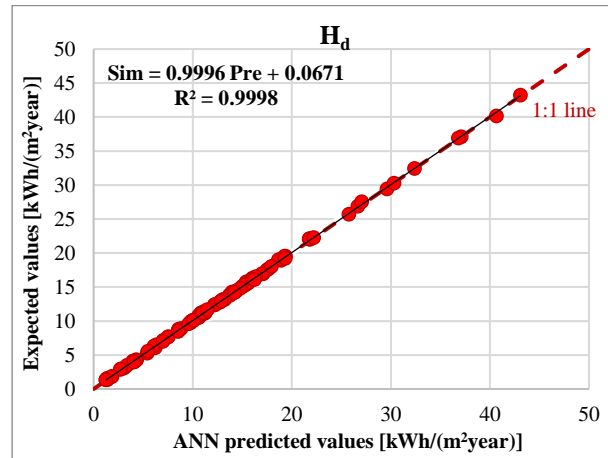


Fig. 16H. Regression between expected versus predicted H_d value.

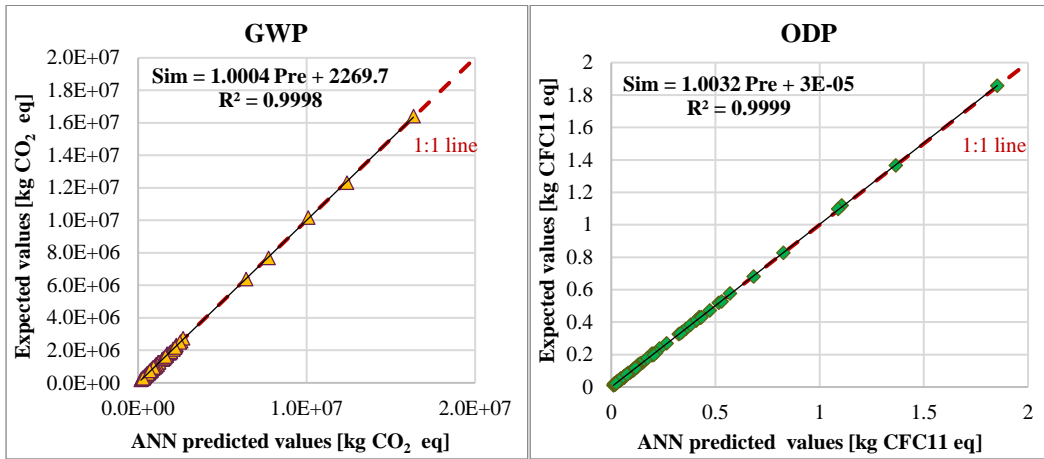


Fig. 17H. Regression between expected versus predicted GWP and ODP values.

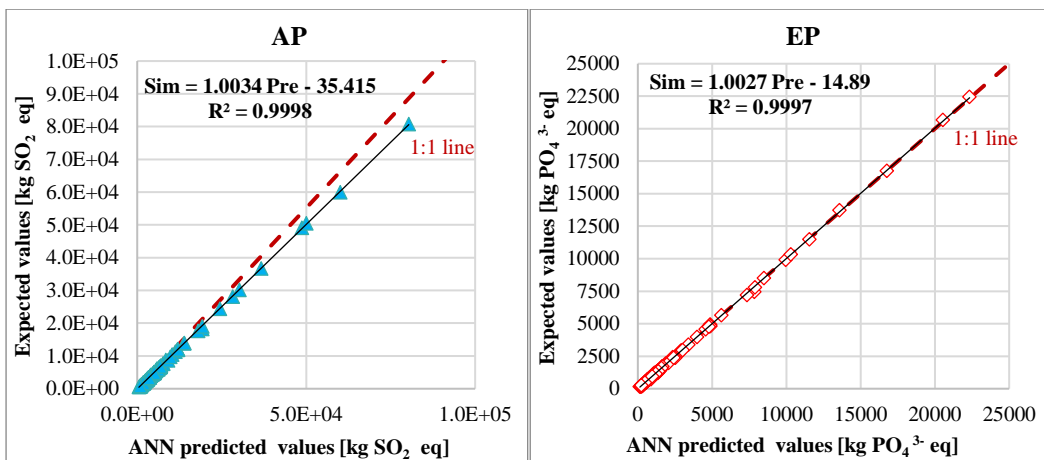


Fig. 18. Regression between expected versus predicted AP and EP values.

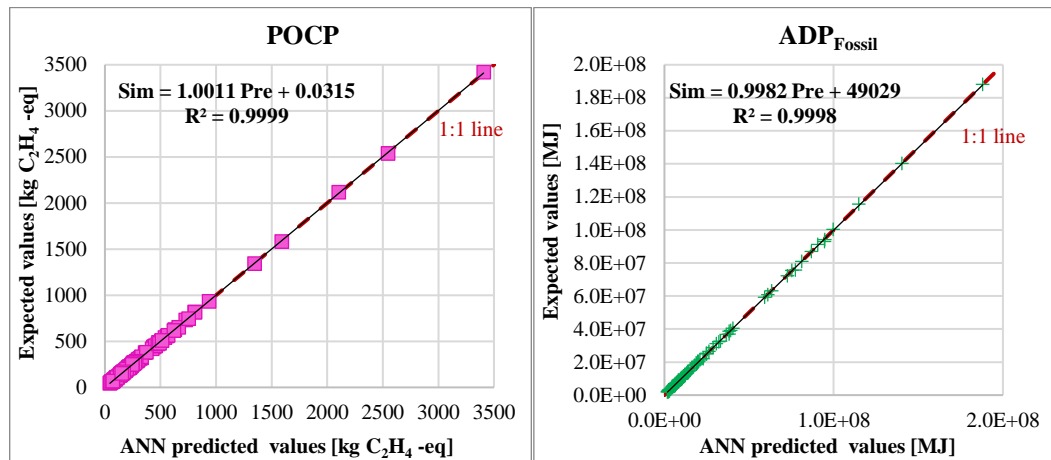


Fig. 19. Regression between expected versus predicted POCP and ADP_{Fossil} values.

The results for RMSE, MAPE, R^2 , and the intercept and slope of regression lines emphasise the potential of the proposed ANN model to predict the energy demand and environmental impacts of a building. Hence, it is demonstrated that, ANN is a reliable alternative to reach the goal of the work. ANN are advantageous due to their capability to overcome several typical limitations of traditional software, such as the collection of energy and environmental data, knowledge on the physical problem and the software language, long computational time, and necessity to calibrate the model. Furthermore, traditional tools issue a single solution for a specific condition, and cannot provide results generalization. In contrast, an ANN application, trained on a wide range of cases, can provide a reliable solution for any building under any condition. Another advantage is the possibility to have several outputs from the same ANN, so different problems of the same case study can be solved which would normally require multiple software tools and expert users. However, the validity of the neural network solution is strongly linked to the reliability of the database, which is generally difficult to implement, but reached acceptable levels in this work.

H.6 DISCUSSION

To correctly propose measures to save energy and reduce environmental impacts of a building such as the contribution to the greenhouse effect, a comprehensive energy and environmental assessment of the building's performance is necessary. Currently, the solution of this complex problem normally requires an interdisciplinary team, knowledge on specific software or algorithm, an expert user, collection of a large amount of data, and long computational time. The lack of a common language often complicates the interpretation of the results between these two areas that are significantly different but highly connected. Based on these observations, this work has allowed to develop a decision support tool that, quickly and reliably, determines the performance of buildings with minimum effort. Hence the application of the ANNs to simultaneously determine the energy demand and environmental impacts has been investigated. The neuro-computing approach established the relationships between input and output variables even when a problem is complex. In this chapter, the ANNs capacity to retrieve the energy and environmental performance of non-residential buildings designed with high-performance, according to Italian energy standards has been exploited. To apply this methodology, it was necessary to create a reliable database of training and validation data. For this reason, it was used the energy database described in **Chapter B**, representatives of the Italian building stock. Based on Environmental Product Declarations and Simapro©, 6 environmental indicators were calculated for each envelope surface (opaque and glazed) to measure their environmental impact. These indicators were: GWP, ODP, AP, EP, POCP and ADP-f. Furthermore, to evaluate the impacts related to the thermal needs of the building and how these impacts change according to the energy carrier used 4 scenarios of heating energy source, have been investigated: electricity, natural gas, liquid propane gas and biogas.

This large database, composed by 36 columns and 780 rows with a total of 28,080 records, was used to train the ANNs. Several topologies of Artificial Neural Networks were analysed and the best results were described in the *Section H.4.2*.

Following a deep statistical analysis and results comparison (*Sections H.5.1 and H.5.2*), the optimal solution was represented by ANN 2 (*Section H.5.3*). The good results and high degree of reliability emphasise the use of the ANN as an excellent alternative method to solve the complex problem of assessing building energy and environmental performances.

This work represents only the initial step in the research for an instrument that solves complex and different problems with a single informatics tool and a single language. The specific Italian case study enabled the understanding of a methodology that can be extended in any context and to any condition (other countries and building stocks). Future research should include the integration and implementation of a database with energy (cooling and electricity demand), environmental (considering all phases of an LCA), economic (costs and return time) and social aspects. It should provide a comprehensive building sustainability assessment. Furthermore, the implementation of the ANN algorithm in a software will enable the development of a suitable decision support tool. This tool should be, simple, reliable, and accessible for immediate use. The high reliability of the results should be assured even in a case of partial knowledge of the input data. The possibility to use an extremely consistent instrument to predict a building's performance before it is built, empowers decision-maker towards more sustainable choices upon analysing of reliable energy and environmental evaluations.

The presented results represent only the first step, in which is proposed an alternative procedure for determining the energy and environmental performance of a building. Obviously, given the complexity of the problem, at this moment the answer provided by the ANN is linked to the building typology, materials and energy vectors explored and implemented in the database. In the future, for a greater capacity for generalization it will be necessary to implement the database and its features also thanks to the contribution of other researchers.

MY RELATED PUBLICATIONS

The research covered in **Chapter H** and the scientific collaboration with the RWTH of Aachen, Germany from 01st September to 23rd March 2019, was published in the following Journal:

4. **D’Amico, A.**, Ciulla, G., Traverso, M., Brano, V. L., & Palumbo, E. (2019). Artificial Neural Networks to assess energy and environmental performance of buildings: An Italian case study. *Journal of Cleaner Production*, 239, 117993.

Other Information

This part of the research was object of a European Research Council (ERC) project prepared during my ERASMUS period in RWTH of Aachen, Germany. The project entitled “MISSION-B” was presented by the Aachen University, in the person of Prof. Marzia Traverso, with the collaboration of the University of Palermo in the person of Prof. Giuseppina Ciulla.

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RESEARCH CONCLUSION

In light of the greater efforts that the industrialized countries undertake to pursue in the field of a more efficient building system, through actions aimed at a more conscious use of the energy systems, an improvement of the thermophysical and environmental characteristics of the materials, at the most suitable design and retrofit actions choice, the preliminary energy planning phase becomes more important. Preventive knowledge, both in a residential and non-residential context, of the thermal energy consumption of a single building, construction type, and/or of a building district, allows to identify with greater precision the critical areas and conscious choices of the design and/or retrofit actions necessary to improve the energy and environmental sustainability of the building stock.

Based on these considerations, the need to provide public administrations, municipalities and/or institutions that deal with energy efficiency of buildings, reliable forecasts and right preliminary assessments, has led the scientific community to a growing interest in the investigation of calculation methods, procedures and new alternative tools capable to guarantee:

- the reliability of results;
- the generalization of the data;
- the high speed of outputs acquisition;
- the reduction of the computational costs and of the preliminary collection phase; and finally
- the replicability in other contexts on a global and/or local scale.

The resolution of the building's thermal balance for the determination of its performance is a complex problem that requires in-depth knowledge from the user both in the development of solution models phase, which, in the case of traditional methods, also in the use phase.

The main challenge of this thesis is precisely to research and develop alternative models that are able to overcome the limits of the traditional tools and procedures for calculating the energy needs of buildings. To achieve this aim, at the first it was necessary an in-depth analysis of the sector bibliography about the physical analysis of the thermal balance of a building, and the identification of the main solution methods available to date, emphasizing strengths and weaknesses of each of them. In detail, as explained in **Chapter A**, the limits shown by traditional methods or White Box (such as the detailed collecting building data, the evaluating the proper boundary conditions, the need for an expert user and the inability to generalize results), and the strengths of the Black Box methods (such as the ability to generalize the result, calculation speed and ease of use by a non-expert user) are the motivations that have led this research to investigate three different methods and the development of three alternative models.

The work out of these models, following a Black Box operation logic, requires the need for presence of a suitable and well-set database representative of a specific non-residential building stock. In this case, it was developed an ad hoc database, representative a high energy performance building stock; a detailed description of all the steps necessary for its implementation has been addressed in **Chapter B**, where, starting from the modelling and calibration of a real *Base Case* located in Sicily and through a parametric analysis in TRNSYS environment, it has been possible to develop 468 scenarios, whose characteristics were implemented in two generic databases: one applicable on a national scale, the other on an international scale. These databases represent the solid and reliable basis on which the developed alternative models have been implemented and, consequently, the necessary condition to achieve the purpose of the research.

The following chapters represent the heart of the research work carried out during the three years of PhD, presenting the three developed models applying the Multiple Linear Regression, Buckingham and Artificial Neural Network methods.

More in detail, the Multiple Linear Regression, discussed in **Chapter C**, permitted to determine linear relationships capable to assess the energy performance (heating, cooling and comprehensive energy needs) of a non-residential building to be in

accordance with European energy standards. Thereby, the knowledge of a group of only few well-known parameters allows the designer to avoid using simulation software, consequently accelerating the entire diagnosis process.

The second model, presented in **Chapter D**, is characterised by the application of the Buckingham theorem. In particular, this model, unlike the previous one, expects the application of a multiple non-linear regression which has not been directly applied to the main parameters that affect the thermal energy balance, but rather to a series of dimensionless coefficients appropriately calculated through dimensional analysis represented by the Buckingham theorem. The model allows the approximation of the thermal energy requirements using a single equation that is a function of only four well-known parameters and one dimensionless number. This approach represents a first and innovative application of the Buckingham theorem in the field of buildings thermos-physics.

In **Chapter E**, the application of Artificial Neural Networks has been discussed, which reproducing the human brain behaviour's mechanisms, is the one that best lends itself to the resolution of complex non-linear problems thanks to its high capacity to identify the relationships existing between a set of data through a learning process. After a brief description of the main characteristics and operating principles, the application of a genetic algorithm has allowed to optimize each single network explored and identify the best configuration by setting the number of neurons and hidden layers as well as the main factors that characterize the algorithm of learning. The developed model, unlike the previous ones requires the presence of a simple to use software, but is characterized by a higher speed response. Moreover, thanks to its flexibility, it is able to provide a reliable result even in the presence of partial input data, greatly increasing its applicability and generalization capacity. Also in this case, the complex problem of the building energy balance it was solve knowing only few and well-known parameters and not knowing anything about the physical phenomenon and the interactions between the building system and the boundary conditions.

To guarantee the goodness and reliability of the results presented by each of the three provided models, evaluating the main error indexes used by the sector

bibliography (e.g. R^2 , MAE, MAPE, MSE and RMSE), a performance analysis has been performed. Furthermore, to speed up the collection data and, consequently, to simplify the useful of the tools, an input selection and a sensitivity analysis have been carried out.

Simultaneously and transversally to the previous research, it was pointed out that weather is one of the main factors to consider when modeling a building's energy predictive tool because it represents one of the most important boundary conditions that influences the dynamic behavior. An in-depth discussion of this topic is reported in **Chapter F**, in which it is shown that the assessment of the energy demand of the building through any model based on the use of the Degree-Day is correct only if the determination of the climatic index is a function of the same time data used to model the building system.

The promising results showed by the each model, allow to present these models as simple and immediate tools able to solve a complex problem like the building energy balance solution, thereby accelerating and helping the energy planning phase on local, national, and international levels, presenting valid criteria that could be indicated in standards, laws and software in the field of the building energy performance. The comparison of the error indexes, calculated to evaluate the performance of each model, underlined how the ANN is characterized by the higher R^2 values and the lowest error indexes, while it is more difficulty to determine the more accurate model between the MLR and BM, which however are characterized by good statistical indices. Furthermore, just a numerical comparison it is not sufficient to identify the most efficient alternative model, because it is not considered the complexity of the model implementation phase, from the collection data to the development of the tool, the ease of use of the tool and the applicability field. Indeed, in general, each model can be used to solve thermal building balance by knowing merely a few parameters representative of the problem. Nonetheless, is it possible to choose the most efficient model while taking into account the quality of the result and the complexity of the evaluation process? To answer this question, it was necessary to apply a Multi-Criteria Analysis that involved a team of 10 experts in the field of the energy balance of buildings sector. All details and the

entire procedure are explained in **Chapter G**, in which is underlined the application of the COPRAS method, developed by the VGTU of the Vilnius University (Lithuania). This application allowed to determine as the most efficient model the ANN, pushing the research to investigate the possibility of being able to use this model for a more complete analysis that involved not only the energy aspects but also the environmental one. For this reason, thanks to the collaboration with the RWTH of Aachen University (Germany), the energy databases were extended adding the main environmental indicators, calculated for each analysed configuration considering materials, different energy carrier and energy needs. All main steps and results are collected in **Chapter H**. In this case, it was experimented the possibility to issue a single tool capable to solve a comprehensive energy and environmental building balance, not knowing the details of these phenomena but using only several parameters readily available from a diagnosis or technical data sheets.

Obviously, these types of approaches are not targeted to replace dynamic simulation software of a building. On the contrary, they represent an alternative decision support tool, easy to use, for a preliminary assessment of energy requirements related to European or to a specific country non-residential building stock. Therefore, the provided models could be useful in the field of energy planning at the urban, national and European scale. Indeed, this work tries to propose some alternative solutions, that in an immediately and simple way, solve the complex problem of the building thermal balance with a high reliable degree. Although it was possible to identify the most efficient model in the ANN model, all three models can be used in any first phase of the energy planning, helping the decision making to identify the best actions. More in detail, the models are three valid tools that can be used from different types of users. The MLR is the simplest model that could be used during the building energy evaluation when it is necessary to have an overall view with few information; in this case, for example, an energy manager would have from the early stages a rough estimate of the energy consumption that a particular building complex could have, knowing only two, maximum nine, fundamental parameters. While the dimensionless numbers are a good tool for the

planning of energy policies in a large-scale, for the drafting of guidelines that can help the legislator to identify a reliable and, in any case, simple to use criterion, to be proposed in laws and standards. At the end but not the least, the ANN model represents the absolute best solution, both from the point of view of the error indexes and from the application of the MCA. In fact, despite being characterized by a complex implementation phase which involves the presence of an expert user, the development of the model guarantees a tool that is simple, intuitive, immediate and with a very high degree of precision during use. This tool allows the evaluation of the energy performance of a building, in any boundary condition and situation, it does not require an expert user and provides the solution in real time. Furthermore, the great versatility of neural networks has allowed to investigate a solution that simultaneously take into account the environmental aspect. In this way, it was possible to provide a tool that gives an overall assessment of the thermal needs and the main environmental impacts without requiring the use of different software or separate calculation procedures.

CURRENT RESEARCH CONTRIBUTIONS

The research activity entitled “**ALTERNATIVE MODELS FOR BUILDING ENERGY PERFORMANCE ASSESSMENT**”, related to the PhD period carried out from 2016 to 2019 at the Department of Engineering of the University of Palermo has produced the following scientific works collected in Table 1 and Table 2. These works give robustness to the content of the thesis.

Table 1

Contributions of the thesis by means of international journals.

PUBLICATION IN INTERNATIONAL JOURNAL		
Related to	Info	Reference
CHAPTER B CHAPTER C	Title Authors Journal	Numerical assessment of heating energy demand for office buildings in Italy Ciulla, G., Lo Brano, V., & D’Amico, A. Energy Procedia, 101, 224-231 (2016).
CHAPTER A CHAPTER B CHAPTER C	Title Authors Journal	Modelling relationship among energy demand, climate and office building features: A cluster analysis at European level Ciulla, G., Lo Brano, V., & D’Amico, A. Applied energy, 183, 1021-1034 (2016).
CHAPTER B CHAPTER D	Title Authors Journal	Evaluation of building heating loads with dimensional analysis: Application of the Buckingham π theorem Ciulla, G., D’Amico, A., & Lo Brano, V. Energy and Buildings, 154, 479-490 (2017).
CHAPTER B CHAPTER F	Title Authors Journal	Building energy demand assessment through heating degree days: The importance of a climatic dataset D’Amico, A., Ciulla, G., Panno, D., & Ferrari, S. Applied energy, 242, 1285-1306 (2019).
CHAPTER A	Title Authors Journal	Results of a literature review on methods for estimating buildings energy demand at district level Ferrari, S., Zagarella, F., Caputo, P., & D’Amico, A. Energy, 175, 1130-1137 (2019).
CHAPTER E	Title Authors Journal	Application of optimized artificial intelligence algorithm to evaluate the heating energy demand of non-residential buildings at European level Ciulla, G., D’Amico, A., Lo Brano, V., & Traverso, M. Energy, 176, 380-391 (2019).
CHAPTER A CHAPTER B CHAPTER C	Title Authors Journal	Building energy performance forecasting: A multiple linear regression approach Ciulla, G., & D’Amico, A. Applied Energy, 253, 113500 (2019).
CHAPTER H	Title Authors Journal	Artificial Neural Networks to assess energy and environmental performance of buildings: An Italian case study D’Amico, A., Ciulla, G., Traverso, M., Lo Brano, V., & Palumbo, E. Journal of Cleaner Production, 239, 117993 (2019).
CHAPTER E	Title Authors Journal	Simplified and optimised forecasting tool of comprehensive building-stock thermal needs D’Amico, A., Ciulla, G. <i>Under review in Energy from 28th August 2019</i>
CHAPTER G	Title Authors Journal	Multiple Criteria Assessment of Methods for Forecasting Building Energy Performance D’Amico, A., Ciulla, G., Tupenatitè, L., Kauklauskas, A. <i>Under review in Energy from 29th September 2019</i>

Table 2

Contributions of the thesis by means of international congress.

PUBLICATION IN PROCEEDING OF CONFERENCE		
Related to	Info	Reference
CHAPTER E	Title	ANN decision support tool for the prediction of the thermal energy performance of European top rated energy efficient non-residential buildings
	Authors	Ciulla G., D'Amico A., Lo Brano V., Beccali M.
	Journal	Conference on Sustainable Development of Energy, Water and Environment System, Dubrovnik 4.-8.10.2017. 0062
CHAPTER F	Title	Heating Energy Demand of non-Residential Buildings using Updated Degree Days in Italy
	Authors	D'Amico A., Ciulla G., Lo Brano V., Panno D., Ferrari S.
	Journal	Conference on Sustainable Development of Energy, Water and Environment System, Palermo 30-4.10.2018.

OTHER RESEARCH AND ACTIVITIES

In addition, the PhD research period also included the deepening of some issues related to the integration and use of renewable energy sources in building, to their installation and analysis of energy performance [1-4]. In particular, as witnessed by some scientific papers, during the PhD course there was a collaboration for the installation and for a preliminary energy and environmental analysis of the Dish-Stirling system [5], the analysis of the performance of solar collectors [6] and of wind turbines [7,8].

Furthermore, during the first year of doctorate course, I attended the school of Technical-Physics in Sorrento from 19 to 23 June 2017, while during the second and third year, I attended the following course:

- Ingegneria del suono e della luce, Prof. Vincenzo Franzitta, 26/01/2018;
- Sistemi a propulsione elettrica e ibrida, Prof. Vincenzo Di Dio, 14/02/2018;
- Assessment methodologies of sustainable building, Prof. Marzia Traverso, 13/03/2019; and
- Sustainability Strategies in Politics and Companies, Prof. Marzia Traverso, 13/03/2019.

How indicated in the annual PhD reports, during the three years I also attended several conferences and training seminaries. In particular, during the Conference on Sustainable Development of Energy, Water and Environment System, SDEWES Palermo, 30 September - 4 October 2018, I presented as Speaker in an oral session the work “Heating Energy Demand of non-Residential Buildings using Updated Degree Days in Italy”.

OTHER RESEARCH WORKS

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- [8] Ciulla G., **D'Amico A.**, Di Dio V., Vazzana S., Lo Brano V., Cellura M. Modelling and Analysis of Real-World Wind Turbine Power Curves: An Application of Neural Network for Assessing Deviations from Nominal Curve. Conference on Sustainable Development of Energy, Water and Environment System, Rio De Janeiro 28.-31.01.2018.

ANNEX 1

Building energy Database of European context: 3 Building Models, 63 scenarios

Scenario	Country	City	<i>HDD</i>	<i>S/V</i>	<i>R_{w-op}</i>	<i>U_w</i>	<i>U_{op}</i>	<i>U_o</i>	<i>Q_s</i>	<i>v_s</i>	<i>h</i>	<i>H_d</i>
			[K day]	[m ⁻¹]		[W/(m ² K)]	[W/(m ² K)]	[W/(m ² K)]	[kWh/year]	[m/s]	[h]	[kWh/(m ² year)]
1	Belgium	Hubert	3190.72	0.24	0.64	1.4	0.57	0.7	142461	3.86	1512	13.89
2		Bruxelles	2239.30	0.24	0.64	1.4	0.57	0.7	98952	3.51	1152	11.41
3		Liegi	1975.16	0.24	0.64	1.4	0.57	0.7	58306	3.88	824	9.98
4	France	Bordeaux	1602.05	0.24	0.64	1.4	0.35	0.51	85215	3.42	888	8.84
5		Bourges	2226.74	0.24	0.64	1.4	0.35	0.51	97212	3.73	1064	12.83
6		Nice	1123.38	0.24	0.64	1.4	0.35	0.51	100475	3.94	800	3.52
7	Germany	Fichtelberg	4982.19	0.24	0.64	1.27	0.33	0.47	199483	6.63	1696	7.00
8		Frankfurt	2829.51	0.24	0.64	1.27	0.33	0.47	107326	2.34	1240	4.87
9		Hof	3425.53	0.24	0.64	1.27	0.33	0.47	129977	2.65	1328	5.10
10	Italy	Palermo	662.65	0.24	0.61	2.76	0.42	0.76	46836	3.73	712	0.16
11		Venezia	2077.81	0.24	0.61	2.76	0.42	0.76	50600	2.50	808	11.38
12		Sestriere	5265.20	0.24	0.61	2.76	0.42	0.76	172959	5.83	1608	23.08
13	Spain	Seville	702.80	0.24	0.61	2.76	0.57	0.89	61592	4.05	488	0.49
14		Madrid	1615.32	0.24	0.61	2.76	0.57	0.89	80830	4.10	888	2.04
15		Salamanca	2379.29	0.24	0.61	2.76	0.57	0.89	136409	3.29	1240	2.40
16	Sweden	Lund	3202.40	0.24	0.48	1.27	0.15	0.29	87037	6.39	1240	4.03
17		Umea	5299.05	0.24	0.48	1.27	0.15	0.29	145460	3.32	1696	5.70
18		Kiruna	6986.21	0.24	0.48	1.27	0.15	0.29	159517	2.68	1784	6.96
19	U. Kingdom	Camborne	2026.30	0.24	0.64	1.4	0.24	0.41	103282	5.38	1088	9.99
20		Birmingham	2773.73	0.24	0.64	1.4	0.24	0.41	101237	4.32	1336	13.59
21		Aviemore	3483.33	0.24	0.64	1.4	0.24	0.41	124287	3.55	1512	16.01
22	Belgium	Hubert	3190.72	0.5	0.64	1.4	0.59	0.62	88165	3.86	1512	21.97
23		Bruxelles	2239.30	0.5	0.64	1.4	0.59	0.62	61553	3.51	1152	17.33
24		Liegi	1975.16	0.5	0.64	1.4	0.59	0.62	36399	3.88	824	13.30
25	France	Bordeaux	1602.05	0.5	0.64	1.4	0.32	0.37	53166	3.42	888	19.31
26		Bourges	2226.74	0.5	0.64	1.4	0.32	0.37	60375	3.73	1064	22.90
27		Nice	1123.38	0.5	0.64	1.4	0.32	0.37	62744	3.94	800	16.15
28	Germany	Fichtelberg	4982.19	0.5	0.64	1.27	0.35	0.39	123414	6.63	1696	11.15
29		Frankfurt	2829.51	0.5	0.64	1.27	0.35	0.39	66638	2.34	1240	8.46
30		Hof	3425.53	0.5	0.64	1.27	0.35	0.39	80538	2.65	1328	9.01
31	Italy	Palermo	662.65	0.5	0.61	2.76	0.41	0.51	29210	3.73	712	4.30
32		Venezia	2077.81	0.5	0.61	2.76	0.41	0.51	31554	2.50	808	11.37

Scenario	Country	City	<i>HDD</i>	<i>S/V</i>	<i>R_{w-op}</i>	<i>U_w</i>	<i>U_{op}</i>	<i>U_o</i>	<i>Q_s</i>	<i>v_s</i>	<i>h</i>	<i>H_d</i>
			[K day]	[m ⁻¹]		[W/(m ² K)]	[W/(m ² K)]	[W/(m ² K)]	[kWh/year]	[m/s]	[h]	[kWh/(m ² year)]
33		Sestriere	5265.20	0.5	0.61	2.76	0.41	0.51	107230	5.83	1608	19.21
34	Spain	Seville	702.80	0.5	0.61	2.76	0.56	0.66	38465	4.05	488	2.34
35		Madrid	1615.32	0.5	0.61	2.76	0.56	0.66	50423	4.10	888	3.46
36		Salamanca	2379.29	0.5	0.61	2.76	0.56	0.66	84603	3.29	1240	4.65
37	Sweden	Lund	3202.40	0.5	0.48	1.27	0.15	0.19	53986	6.39	1240	8.07
38		Umea	5299.05	0.5	0.48	1.27	0.15	0.19	90142	3.32	1696	10.06
39		Kiruna	6986.21	0.5	0.48	1.27	0.15	0.19	98542	2.68	1784	11.40
40	U. Kingdom	Camborne	2026.30	0.5	0.64	1.4	0.21	0.26	64078	5.38	1088	21.08
41		Birmingham	2773.73	0.5	0.64	1.4	0.21	0.26	62866	4.32	1336	24.84
42		Aviemore	3483.33	0.5	0.64	1.4	0.21	0.26	77265	3.55	1512	27.78
43	Belgium	Hubert	3190.72	0.9	0.64	1.4	0.58	0.67	49234	3.86	1512	83.94
44		Bruxelles	2239.30	0.9	0.64	1.4	0.58	0.67	34678	3.51	1152	65.50
45		Liegi	1975.16	0.9	0.64	1.4	0.58	0.67	20632	3.88	824	60.08
46	France	Bordeaux	1602.05	0.9	0.64	1.4	0.34	0.46	30100	3.42	888	29.46
47		Bourges	2226.74	0.9	0.64	1.4	0.34	0.46	33918	3.73	1064	43.08
48		Nice	1123.38	0.9	0.64	1.4	0.34	0.46	35579	3.94	800	15.19
49	Germany	Fichtelberg	4982.19	0.9	0.64	1.27	0.33	0.44	68866	6.63	1696	46.42
50		Frankfurt	2829.51	0.9	0.64	1.27	0.33	0.44	37418	2.34	1240	35.29
51		Hof	3425.53	0.9	0.64	1.27	0.33	0.44	45063	2.65	1328	36.79
52	Italy	Palermo	662.65	0.9	0.61	2.76	0.41	0.68	16411	3.73	712	4.87
53		Venezia	2077.81	0.9	0.61	2.76	0.41	0.68	17725	2.50	808	37.62
54		Sestriere	5265.20	0.9	0.61	2.76	0.41	0.68	59644	5.83	1608	69.37
55	Spain	Seville	702.80	0.9	0.61	2.76	0.56	0.81	21720	4.05	488	9.05
56		Madrid	1615.32	0.9	0.61	2.76	0.56	0.81	28418	4.10	888	17.36
57		Salamanca	2379.29	0.9	0.61	2.76	0.56	0.81	47208	3.29	1240	21.19
58	Sweden	Lund	3202.40	0.9	0.48	1.27	0.15	0.26	30340	6.39	1240	25.56
59		Umea	5299.05	0.9	0.48	1.27	0.15	0.26	50577	3.32	1696	39.16
60		Kiruna	6986.21	0.9	0.48	1.27	0.15	0.26	54987	2.68	1784	46.99
61	U. Kingdom	Camborne	2026.30	0.9	0.64	1.4	0.22	0.36	35926	5.38	1088	32.48
62		Birmingham	2773.73	0.9	0.64	1.4	0.22	0.36	35302	4.32	1336	48.53
63		Aviemore	3483.33	0.9	0.64	1.4	0.22	0.36	43469	3.55	1512	59.39

ANNEX 2

Building energy Database of European context: 13 Building Models, 273 scenarios

Scenario	Model	Country	City	<i>HDD</i>	<i>S/V</i>	<i>S_w</i>	<i>S_{op}</i>	<i>U_w</i>	<i>U_{op}</i>	<i>U₀</i>	<i>Q_s</i>	<i>h</i>	<i>V_s</i>	<i>C_T</i>	<i>Q_G</i>	<i>H_d</i>
				[K day]	[m ⁻¹]	[m ²]	[m ²]	[W/(m ² K)]	[W/(m ² K)]	[W/(m ² K)]	[kWh/year]	[h]	[m/s]	[kWh/(m ³ K)]	[kWh/year]	[kWh/(m ² year)]
1			Hubert	3190.72	0.24	886.49	4910.04	1.40	0.57	0.70	142405.32	1512	3.86	0.0689	647566.44	27.06
2		Belgium	Bruxelles	2239.30	0.24	886.49	4910.04	1.40	0.57	0.70	98952.15	1152	3.51	0.0689	647566.44	18.49
3			Liegi	1975.16	0.24	886.49	4910.04	1.40	0.57	0.70	58305.43	824	3.88	0.0689	647566.44	19.82
4			Bordeaux	1602.05	0.24	886.49	4910.04	1.40	0.35	0.51	85216.14	888	3.42	0.0689	647566.44	6.30
5		France	Bourges	2226.74	0.24	886.49	4910.04	1.40	0.35	0.51	97213.03	1064	3.73	0.0689	647566.44	12.66
6			Nice	1123.38	0.24	886.49	4910.04	1.40	0.35	0.51	100475.92	800	3.94	0.0689	647566.44	0.99
7			Fichtelberg	4982.19	0.24	886.49	4910.04	1.27	0.33	0.47	199479.69	1696	6.63	0.0687	647566.44	27.85
8		Germany	Frankfurt	2829.51	0.24	886.49	4910.04	1.27	0.33	0.47	107324.70	1240	2.34	0.0687	647566.44	16.12
9			Hof	3425.53	0.24	886.49	4910.04	1.27	0.33	0.47	129823.17	1328	2.65	0.0687	647566.44	19.21
10			Palermo	662.65	0.24	860.68	4935.85	2.76	0.42	0.76	46838.08	712	3.73	0.0690	647566.44	1.33
11	A	Italy	Venezia	2077.81	0.24	860.68	4935.85	2.76	0.42	0.76	50605.89	808	2.5	0.0690	647566.44	20.70
12			Sestriere	5265.20	0.24	860.68	4935.85	2.76	0.42	0.76	173001.52	1608	5.83	0.0690	647566.44	49.34
13			Seville	702.80	0.24	860.68	4935.85	2.76	0.57	0.89	61593.57	488	4.05	0.0691	647566.44	4.50
14		Spain	Madrid	1615.32	0.24	860.68	4935.85	2.76	0.57	0.89	80834.77	888	4.1	0.0691	647566.44	16.60
15			Salamanca	2379.29	0.24	860.68	4935.85	2.76	0.57	0.89	136416.48	1240	3.29	0.0691	647566.44	22.27
16			Lund	3202.40	0.24	736.75	5059.78	1.27	0.15	0.29	87036.12	1240	6.39	0.0689	647566.44	13.07
17		Sweden	Umea	5299.05	0.24	736.75	5059.78	1.27	0.15	0.29	145457.97	1696	3.32	0.0689	647566.44	30.74
18			Kiruna	6986.21	0.24	736.75	5059.78	1.27	0.15	0.29	159514.23	1784	2.68	0.0689	647566.44	50.76
19			Camborne	2026.30	0.24	886.49	4910.04	1.40	0.24	0.41	103283.27	1088	5.38	0.0688	647566.44	6.82
20		U. Kingdom	Birmingham	2773.73	0.24	886.49	4910.04	1.40	0.24	0.41	101237.42	1336	4.32	0.0688	647566.44	14.42
21			Aviemore	3483.33	0.24	886.49	4910.04	1.40	0.24	0.41	124287.77	1512	3.55	0.0688	647566.44	19.97
22			Hubert	3190.72	0.27	864.00	3990.00	1.40	0.57	0.72	137709.35	1512	3.86	0.0655	483948.36	28.79
23		Belgium	Bruxelles	2239.30	0.27	864.00	3990.00	1.40	0.57	0.72	96318.17	1152	3.51	0.0655	483948.36	19.65
24			Liegi	1975.16	0.27	864.00	3990.00	1.40	0.57	0.72	56129.52	824	3.88	0.0655	483948.36	21.24
25			Bordeaux	1602.05	0.27	864.00	3990.00	1.40	0.35	0.54	83281.29	888	3.42	0.0655	483948.36	6.84
26		France	Bourges	2226.74	0.27	864.00	3990.00	1.40	0.35	0.54	94422.93	1064	3.73	0.0655	483948.36	13.68
27	B		Nice	1123.38	0.27	864.00	3990.00	1.40	0.35	0.54	98316.47	800	3.94	0.0655	483948.36	1.08
28			Fichtelberg	4982.19	0.27	864.00	3990.00	1.27	0.32	0.49	192731.53	1696	6.63	0.0653	483948.36	28.68
29		Germany	Frankfurt	2829.51	0.27	864.00	3990.00	1.27	0.32	0.49	104203.28	1240	2.34	0.0653	483948.36	17.18
30			Hof	3425.53	0.27	864.00	3990.00	1.27	0.32	0.49	125843.80	1328	2.65	0.0653	483948.36	20.14
31			Palermo	662.65	0.27	838.80	4015.15	2.76	0.42	0.82	45567.40	712	3.73	0.0656	483948.36	1.46
32		Italy	Venezia	2077.81	0.27	838.80	4015.15	2.76	0.42	0.82	49223.84	808	2.5	0.0656	483948.36	21.91

Scenario	Model	Country	City	<i>HDD</i>	<i>S/V</i>	<i>S_w</i>	<i>S_{op}</i>	<i>U_w</i>	<i>U_{op}</i>	<i>U_o</i>	<i>Q_s</i>	<i>h</i>	<i>V_s</i>	<i>C_T</i>	<i>Q_G</i>	<i>H_d</i>
				[K day]	[m ⁻¹]	[m ²]	[m ²]	[W/(m ² K)]	[W/(m ² K)]	[W/(m ² K)]	[kWh/year]	[h]	[m/s]	[kWh/(m ³ K)]	[kWh/year]	[kWh/(m ² year)]
33			Sestriere	5265.20	0.27	838.80	4015.15	2.76	0.42	0.82	166952.85	1608	5.83	0.0656	483948.36	50.33
34			Seville	702.80	0.27	838.80	4015.15	2.76	0.57	0.95	60137.07	488	4.05	0.0657	483948.36	4.09
35		Spain	Madrid	1615.32	0.27	838.80	4015.15	2.76	0.57	0.95	78801.63	888	4.1	0.0657	483948.36	15.20
36			Salamanca	2379.29	0.27	838.80	4015.15	2.76	0.57	0.95	131942.12	1240	3.29	0.0657	483948.36	20.26
37			Lund	3202.40	0.27	718.10	4135.95	1.27	0.15	0.31	84537.90	1240	6.39	0.0658	483948.36	15.25
38		Sweden	Umea	5299.05	0.27	718.10	4135.95	1.27	0.15	0.31	141105.13	1696	3.32	0.0658	483948.36	34.57
39			Kiruna	6986.21	0.27	718.10	4135.95	1.27	0.15	0.31	154077.28	1784	2.68	0.0658	483948.36	56.42
40			Camborne	2026.30	0.27	864.00	3990.00	1.40	0.25	0.45	100163.96	1088	5.38	0.0655	483948.36	8.06
41		U. Kingdom	Birmingham	2773.73	0.27	864.00	3990.00	1.40	0.25	0.45	98301.46	1336	4.32	0.0655	483948.36	16.40
42			Aviemore	3483.33	0.27	864.00	3990.00	1.40	0.25	0.45	120861.49	1512	3.55	0.0655	483948.36	22.30
43			Hubert	3190.72	0.32	561.95	4078.05	1.40	0.58	0.68	90074.38	1512	3.86	0.0226	293940.19	51.37
44		Belgium	Bruxelles	2239.30	0.32	561.95	4078.05	1.40	0.58	0.68	62494.86	1152	3.51	0.0226	293940.19	37.13
45			Liegi	1975.16	0.32	561.95	4078.05	1.40	0.58	0.68	36794.77	824	3.88	0.0226	293940.19	37.37
46			Bordeaux	1602.05	0.32	561.95	4078.05	1.40	0.34	0.47	53784.63	888	3.42	0.0225	293940.19	15.73
47		France	Bourges	2226.74	0.32	561.95	4078.05	1.40	0.34	0.47	61418.03	1064	3.73	0.0225	293940.19	25.67
48			Nice	1123.38	0.32	561.95	4078.05	1.40	0.34	0.47	63403.18	800	3.94	0.0225	293940.19	6.02
49			Fichtelberg	4982.19	0.32	561.95	4078.05	1.27	0.33	0.45	126133.08	1696	6.63	0.0230	293940.19	51.06
50		Germany	Frankfurt	2829.51	0.32	561.95	4078.05	1.27	0.33	0.45	67809.48	1240	2.34	0.0230	293940.19	31.90
51			Hof	3425.53	0.32	561.95	4078.05	1.27	0.33	0.45	82156.65	1328	2.65	0.0230	293940.19	36.27
52			Palermo	662.65	0.32	545.60	4094.41	2.76	0.41	0.69	29550.93	712	3.73	0.0226	293940.19	5.23
53	C	Italy	Venezia	2077.81	0.32	545.60	4094.41	2.76	0.41	0.69	31929.21	808	2.5	0.0226	293940.19	35.86
54			Sestriere	5265.20	0.32	545.60	4094.41	2.76	0.41	0.69	109292.63	1608	5.83	0.0226	293940.19	78.19
55			Seville	702.80	0.32	545.60	4094.41	2.76	0.56	0.82	38862.61	488	4.05	0.0225	293940.19	10.90
56		Spain	Madrid	1615.32	0.32	545.60	4094.41	2.76	0.56	0.82	51015.45	888	4.1	0.0225	293940.19	27.77
57			Salamanca	2379.29	0.32	545.60	4094.41	2.76	0.56	0.82	86202.72	1240	3.29	0.0225	293940.19	36.60
58			Lund	3202.40	0.32	467.03	4172.97	1.27	0.15	0.26	55042.91	1240	6.39	0.0251	293940.19	28.15
59		Sweden	Umea	5299.05	0.32	467.03	4172.97	1.27	0.15	0.26	92008.00	1696	3.32	0.0251	293940.19	54.17
60			Kiruna	6986.21	0.32	467.03	4172.97	1.27	0.15	0.26	100968.12	1784	2.68	0.0251	293940.19	82.45
61			Camborne	2026.30	0.32	561.95	4078.05	1.40	0.23	0.37	65274.85	1088	5.38	0.0228	293940.19	16.83
62		U. Kingdom	Birmingham	2773.73	0.32	561.95	4078.05	1.40	0.23	0.37	63968.97	1336	4.32	0.0228	293940.19	28.80
63			Aviemore	3483.33	0.32	561.95	4078.05	1.40	0.23	0.37	78514.70	1512	3.55	0.0228	293940.19	37.75
64			Hubert	3190.72	0.35	474.15	1640.85	1.40	0.56	0.75	75515.55	1512	3.86	0.1841	165341.36	77.17
65		Belgium	Bruxelles	2239.30	0.35	474.15	1640.85	1.40	0.56	0.75	52087.07	1152	3.51	0.1841	483948.36	58.21
66			Liegi	1975.16	0.35	474.15	1640.85	1.40	0.56	0.75	30540.09	824	3.88	0.1841	483948.36	57.36
67			Bordeaux	1602.05	0.35	474.15	1640.85	1.40	0.37	0.60	44676.40	888	3.42	0.1841	483948.36	23.16
68	D	France	Bourges	2226.74	0.35	474.15	1640.85	1.40	0.37	0.60	51286.15	1064	3.73	0.1841	483948.36	36.10
69			Nice	1123.38	0.35	474.15	1640.85	1.40	0.37	0.60	52609.64	800	3.94	0.1841	483948.36	10.30
70			Fichtelberg	4982.19	0.35	474.15	1640.85	1.27	0.31	0.53	105787.67	1696	6.63	0.1839	483948.36	64.31
71		Germany	Frankfurt	2829.51	0.35	474.15	1640.85	1.27	0.31	0.53	56638.71	1240	2.34	0.1839	483948.36	44.15

Scenario	Model	Country	City	<i>HDD</i>	<i>S/V</i>	<i>S_w</i>	<i>S_{op}</i>	<i>U_w</i>	<i>U_{op}</i>	<i>U_o</i>	<i>Q_s</i>	<i>h</i>	<i>V_s</i>	<i>C_T</i>	<i>Q_G</i>	<i>H_d</i>
				[K day]	[m ⁻¹]	[m ²]	[m ²]	[W/(m ² K)]	[W/(m ² K)]	[W/(m ² K)]	[kWh/year]	[h]	[m/s]	[kWh/(m ³ K)]	[kWh/year]	[kWh/(m ² year)]
72			Hof	3425.53	0.35	474.15	1640.85	1.27	0.31	0.53	68782.51	1328	2.65	0.1839	483948.36	47.84
73			Palermo	662.65	0.35	460.34	1654.66	2.76	0.43	0.93	24271.69	712	3.73	0.1841	483948.36	2.89
74		Italy	Venezia	2077.81	0.35	460.34	1654.66	2.76	0.43	0.93	26225.68	808	2.5	0.1841	483948.36	31.02
75			Sestriere	5265.20	0.35	460.34	1654.66	2.76	0.43	0.93	90371.86	1608	5.83	0.1841	483948.36	64.60
76			Seville	702.80	0.35	460.34	1654.66	2.76	0.57	1.05	32245.07	488	4.05	0.1841	483948.36	25.54
77		Spain	Madrid	1615.32	0.35	460.34	1654.66	2.76	0.57	1.05	42384.31	888	4.1	0.1841	483948.36	54.46
78			Salamanca	2379.29	0.35	460.34	1654.66	2.76	0.57	1.05	72097.99	1240	3.29	0.1841	483948.36	70.31
79			Lund	3202.40	0.35	394.05	1720.95	1.27	0.15	0.36	46069.18	1240	6.39	0.1834	483948.36	34.02
80		Sweden	Umea	5299.05	0.35	394.05	1720.95	1.27	0.15	0.36	77087.83	1696	3.32	0.1834	483948.36	63.56
81			Kiruna	6986.21	0.35	394.05	1720.95	1.27	0.15	0.36	84898.29	1784	2.68	0.1834	483948.36	94.18
82			Camborne	2026.30	0.35	474.15	1640.85	1.40	0.26	0.52	54573.17	1088	5.38	0.1840	483948.36	22.41
83		U. Kingdom	Birmingham	2773.73	0.35	474.15	1640.85	1.40	0.26	0.52	53425.42	1336	4.32	0.1840	483948.36	36.97
84			Aviemore	3483.33	0.35	474.15	1640.85	1.40	0.26	0.52	65490.52	1512	3.55	0.1840	483948.36	47.44
85			Hubert	3190.72	0.40	327.80	1262.19	1.40	0.57	0.74	51710.84	1512	3.86	0.0557	103338.35	41.75
86		Belgium	Bruxelles	2239.30	0.40	327.80	1262.19	1.40	0.57	0.74	36033.53	1152	3.51	0.0557	459580.17	29.27
87			Liegi	1975.16	0.40	327.80	1262.19	1.40	0.57	0.74	21280.24	824	3.88	0.0557	459580.17	31.17
88			Bordeaux	1602.05	0.40	327.80	1262.19	1.40	0.36	0.58	31085.83	888	3.42	0.0584	459580.17	11.30
89		France	Bourges	2226.74	0.40	327.80	1262.19	1.40	0.36	0.58	35361.30	1064	3.73	0.0584	459580.17	21.03
90			Nice	1123.38	0.40	327.80	1262.19	1.40	0.36	0.58	36673.32	800	3.94	0.0584	459580.17	2.40
91			Fichtelberg	4982.19	0.40	327.80	1262.19	1.27	0.32	0.51	72378.42	1696	6.63	0.0569	459580.17	39.15
92		Germany	Frankfurt	2829.51	0.40	327.80	1262.19	1.27	0.32	0.51	39030.63	1240	2.34	0.0569	459580.17	25.54
93			Hof	3425.53	0.40	327.80	1262.19	1.27	0.32	0.51	47205.77	1328	2.65	0.0569	459580.17	28.71
94			Palermo	662.65	0.40	318.26	1271.74	2.76	0.42	0.89	16979.68	712	3.73	0.0585	459580.17	3.91
95		E Italy	Venezia	2077.81	0.40	318.26	1271.74	2.76	0.42	0.89	18342.81	808	2.5	0.0585	459580.17	35.31
96			Sestriere	5265.20	0.40	318.26	1271.74	2.76	0.42	0.89	62475.56	1608	5.83	0.0585	459580.17	72.16
97			Seville	702.80	0.40	318.26	1271.74	2.76	0.57	1.01	22418.78	488	4.05	0.0579	459580.17	10.78
98		Spain	Madrid	1615.32	0.40	318.26	1271.74	2.76	0.57	1.01	29400.82	888	4.1	0.0579	459580.17	31.53
99			Salamanca	2379.29	0.40	318.26	1271.74	2.76	0.57	1.01	49434.32	1240	3.29	0.0579	459580.17	41.13
100			Lund	3202.40	0.40	272.43	1317.57	1.27	0.15	0.34	31720.68	1240	6.39	0.0603	459580.17	23.93
101		Sweden	Umea	5299.05	0.40	272.43	1317.57	1.27	0.15	0.34	52980.46	1696	3.32	0.0603	459580.17	49.29
102			Kiruna	6986.21	0.40	272.43	1317.57	1.27	0.15	0.34	57983.02	1784	2.68	0.0603	459580.17	78.11
103			Camborne	2026.30	0.40	327.80	1262.19	1.40	0.26	0.49	37543.82	1088	5.38	0.0588	459580.17	13.54
104		U. Kingdom	Birmingham	2773.73	0.40	327.80	1262.19	1.40	0.26	0.49	36821.29	1336	4.32	0.0588	459580.17	25.67
105			Aviemore	3483.33	0.40	327.80	1262.19	1.40	0.26	0.49	45235.02	1512	3.55	0.0588	459580.17	33.96
106			Hubert	3190.72	0.50	546.83	11439.89	1.40	0.59	0.62	88163.50	1512	3.86	0.0822	486170.64	67.37
107		Belgium	Bruxelles	2239.30	0.50	546.83	11439.89	1.40	0.59	0.62	61552.66	1152	3.51	0.0822	293940.19	50.92
108		F	Liegi	1975.16	0.50	546.83	11439.89	1.40	0.59	0.62	36398.82	824	3.88	0.0822	293940.19	47.89
109			Bordeaux	1602.05	0.50	546.83	11439.89	1.40	0.32	0.37	53166.18	888	3.42	0.0823	293940.19	24.04
110		France	Bourges	2226.74	0.50	546.83	11439.89	1.40	0.32	0.37	60375.28	1064	3.73	0.0823	293940.19	34.59

Scenario	Model	Country	City	<i>HDD</i>	<i>S/V</i>	<i>S_w</i>	<i>S_{op}</i>	<i>U_w</i>	<i>U_{op}</i>	<i>U_o</i>	<i>Q_s</i>	<i>h</i>	<i>V_s</i>	<i>C_T</i>	<i>Q_G</i>	<i>H_d</i>
				[K day]	[m ⁻¹]	[m ²]	[m ²]	[W/(m ² K)]	[W/(m ² K)]	[W/(m ² K)]	[kWh/year]	[h]	[m/s]	[kWh/(m ³ K)]	[kWh/year]	[kWh/(m ² year)]
111			Nice	1123.38	0.50	546.83	11439.89	1.40	0.32	0.37	62744.88	800	3.94	0.0823	293940.19	14.14
112			Fichtelberg	4982.19	0.50	546.83	11439.89	1.27	0.35	0.39	123410.41	1696	6.63	0.0823	293940.19	80.59
113		Germany	Frankfurt	2829.51	0.50	546.83	11439.89	1.27	0.35	0.39	66637.40	1240	2.34	0.0823	293940.19	54.15
114			Hof	3425.53	0.50	546.83	11439.89	1.27	0.35	0.39	80536.11	1328	2.65	0.0823	293940.19	60.13
115			Palermo	662.65	0.50	530.91	11455.80	2.76	0.41	0.51	29213.65	712	3.73	0.0824	293940.19	10.94
116		Italy	Venezia	2077.81	0.50	530.91	11455.80	2.76	0.41	0.51	31562.32	808	2.5	0.0824	293940.19	42.65
117			Sestriere	5265.20	0.50	530.91	11455.80	2.76	0.41	0.51	107276.82	1608	5.83	0.0824	293940.19	89.16
118			Seville	702.80	0.50	530.91	11455.80	2.76	0.56	0.66	38468.23	488	4.05	0.0823	293940.19	22.89
119		Spain	Madrid	1615.32	0.50	530.91	11455.80	2.76	0.56	0.66	50428.66	888	4.1	0.0823	293940.19	45.40
120			Salamanca	2379.29	0.50	530.91	11455.80	2.76	0.56	0.66	84610.82	1240	3.29	0.0823	293940.19	60.32
121			Lund	3202.40	0.50	454.46	11532.26	1.27	0.15	0.19	53984.86	1240	6.39	0.0831	293940.19	32.48
122		Sweden	Umea	5299.05	0.50	454.46	11532.26	1.27	0.15	0.19	90139.54	1696	3.32	0.0831	293940.19	58.54
123			Kiruna	6986.21	0.50	454.46	11532.26	1.27	0.15	0.19	98539.00	1784	2.68	0.0831	293940.19	85.96
124			Camborne	2026.30	0.50	546.83	11439.89	1.40	0.21	0.26	64078.28	1088	5.38	0.0824	293940.19	34.97
125		U. Kingdom	Birmingham	2773.73	0.50	546.83	11439.89	1.40	0.21	0.26	62866.21	1336	4.32	0.0824	293940.19	48.48
126			Aviemore	3483.33	0.50	546.83	11439.89	1.40	0.21	0.26	77265.24	1512	3.55	0.0824	293940.19	59.34
127			Hubert	3190.72	0.56	468.30	10731.70	1.40	0.59	0.62	75404.14	1512	3.86	0.1055	459580.17	67.10
128		Belgium	Bruxelles	2239.30	0.56	468.30	10731.70	1.40	0.59	0.62	52621.79	1152	3.51	0.1055	459580.17	51.19
129			Liegi	1975.16	0.56	468.30	10731.70	1.40	0.59	0.62	31108.27	824	3.88	0.1055	459580.17	47.45
130			Bordeaux	1602.05	0.56	468.30	10731.70	1.40	0.32	0.36	45437.82	888	3.42	0.1056	459580.17	21.41
131		France	Bourges	2226.74	0.56	468.30	10731.70	1.40	0.32	0.36	51618.74	1064	3.73	0.1056	459580.17	30.84
132			Nice	1123.38	0.56	468.30	10731.70	1.40	0.32	0.36	53619.98	800	3.94	0.1056	459580.17	12.62
133			Fichtelberg	4982.19	0.56	468.30	10731.70	1.27	0.35	0.38	105506.82	1696	6.63	0.1056	459580.17	59.15
134		Germany	Frankfurt	2829.51	0.56	468.30	10731.70	1.27	0.35	0.38	56974.63	1240	2.34	0.1056	459580.17	38.84
135			Hof	3425.53	0.56	468.30	10731.70	1.27	0.35	0.38	68869.67	1328	2.65	0.1056	459580.17	43.36
136			Palermo	662.65	0.56	454.66	10745.34	2.76	0.41	0.50	24969.20	712	3.73	0.1056	459580.17	9.28
137		G Italy	Venezia	2077.81	0.56	454.66	10745.34	2.76	0.41	0.50	26976.68	808	2.5	0.1056	459580.17	37.41
138			Sestriere	5265.20	0.56	454.66	10745.34	2.76	0.41	0.50	91735.03	1608	5.83	0.1056	459580.17	78.31
139			Seville	702.80	0.56	454.66	10745.34	2.76	0.56	0.65	32881.01	488	4.05	0.1056	459580.17	16.92
140		Spain	Madrid	1615.32	0.56	454.66	10745.34	2.76	0.56	0.65	43108.19	888	4.1	0.1056	459580.17	33.49
141			Salamanca	2379.29	0.56	454.66	10745.34	2.76	0.56	0.65	72363.49	1240	3.29	0.1056	459580.17	44.48
142			Lund	3202.40	0.56	389.19	10810.81	1.27	0.15	0.19	46173.75	1240	6.39	0.1061	459580.17	27.69
143		Sweden	Umea	5299.05	0.56	389.19	10810.81	1.27	0.15	0.19	77103.06	1696	3.32	0.1061	459580.17	50.87
144			Kiruna	6986.21	0.56	389.19	10810.81	1.27	0.15	0.19	84310.40	1784	2.68	0.1061	459580.17	75.41
145			Camborne	2026.30	0.56	468.30	10731.70	1.40	0.20	0.25	54785.81	1088	5.38	0.1057	459580.17	20.24
146		U. Kingdom	Birmingham	2773.73	0.56	468.30	10731.70	1.40	0.20	0.25	53745.42	1336	4.32	0.1057	459580.17	30.43
147			Aviemore	3483.33	0.56	468.30	10731.70	1.40	0.20	0.25	66049.14	1512	3.55	0.1057	459580.17	38.66
148		H Belgium	Hubert	3190.72	0.58	312.20	5487.80	1.40	0.58	0.63	50077.18	1512	3.86	0.0902	836139.47	68.39
149			Bruxelles	2239.30	0.58	312.20	5487.80	1.40	0.58	0.63	34744.32	1152	3.51	0.0902	836139.47	52.06

Scenario	Model	Country	City	<i>HDD</i>	<i>S/V</i>	<i>S_w</i>	<i>S_{op}</i>	<i>U_w</i>	<i>U_{op}</i>	<i>U_o</i>	<i>Q_s</i>	<i>h</i>	<i>V_s</i>	<i>C_T</i>	<i>Q_G</i>	<i>H_d</i>
				[K day]	[m ⁻¹]	[m ²]	[m ²]	[W/(m ² K)]	[W/(m ² K)]	[W/(m ² K)]	[kWh/year]	[h]	[m/s]	[kWh/(m ³ K)]	[kWh/year]	[kWh/(m ² year)]
150			Liegi	1975.16	0.58	312.20	5487.80	1.40	0.58	0.63	20456.24	824	3.88	0.0902	836139.47	48.79
151			Bordeaux	1602.05	0.58	312.20	5487.80	1.40	0.32	0.38	29899.45	888	3.42	0.0902	836139.47	21.71
152		France	Bourges	2226.74	0.58	312.20	5487.80	1.40	0.32	0.38	34142.85	1064	3.73	0.0902	836139.47	31.56
153			Nice	1123.38	0.58	312.20	5487.80	1.40	0.32	0.38	35246.59	800	3.94	0.0902	836139.47	12.24
154			Fichtelberg	4982.19	0.58	312.20	5487.80	1.27	0.34	0.39	70119.92	1696	6.63	0.0901	836139.47	59.73
155		Germany	Frankfurt	2829.51	0.58	312.20	5487.80	1.27	0.34	0.39	37696.66	1240	2.34	0.0901	836139.47	39.50
156			Hof	3425.53	0.58	312.20	5487.80	1.27	0.34	0.39	45672.56	1328	2.65	0.0901	836139.47	43.86
157			Palermo	662.65	0.58	303.10	5496.89	2.76	0.41	0.53	16450.43	712	3.73	0.0902	836139.47	9.42
158		Italy	Venezia	2077.81	0.58	303.10	5496.89	2.76	0.41	0.53	17774.76	808	2.5	0.0902	836139.47	39.63
159			Sestriere	5265.20	0.58	303.10	5496.89	2.76	0.41	0.53	60842.73	1608	5.83	0.0902	836139.47	81.62
160			Seville	702.80	0.58	303.10	5496.89	2.76	0.56	0.68	21631.49	488	4.05	0.0898	836139.47	16.99
161		Spain	Madrid	1615.32	0.58	303.10	5496.89	2.76	0.56	0.68	28396.06	888	4.1	0.0898	836139.47	34.41
162			Salamanca	2379.29	0.58	303.10	5496.89	2.76	0.56	0.68	47981.78	1240	3.29	0.0898	836139.47	45.51
163			Lund	3202.40	0.58	259.46	5540.54	1.27	0.15	0.20	30616.95	1240	6.39	0.0906	836139.47	29.28
164		Sweden	Umea	5299.05	0.58	259.46	5540.54	1.27	0.15	0.20	51178.50	1696	3.32	0.0906	836139.47	53.83
165			Kiruna	6986.21	0.58	259.46	5540.54	1.27	0.15	0.20	56162.49	1784	2.68	0.0906	836139.47	79.77
166			Camborne	2026.30	0.58	312.20	5487.80	1.40	0.21	0.27	36283.38	1088	5.38	0.0902	836139.47	21.02
167		U. Kingdom	Birmingham	2773.73	0.58	312.20	5487.80	1.40	0.21	0.27	35557.47	1336	4.32	0.0902	836139.47	32.13
168			Aviemore	3483.33	0.58	312.20	5487.80	1.40	0.21	0.27	43642.91	1512	3.55	0.0902	836139.47	40.84
169			Hubert	3190.72	0.62	157.89	1246.70	1.40	0.58	0.67	25614.24	1512	3.86	0.0873	45928.15	64.11
170		Belgium	Bruxelles	2239.30	0.62	157.89	1246.70	1.40	0.58	0.67	17843.23	1152	3.51	0.0873	165341.36	48.86
171			Liegi	1975.16	0.62	157.89	1246.70	1.40	0.58	0.67	10535.21	824	3.88	0.0873	165341.36	46.56
172			Bordeaux	1602.05	0.62	157.89	1246.70	1.40	0.34	0.45	15003.49	888	3.42	0.0871	165341.36	21.37
173		France	Bourges	2226.74	0.62	157.89	1246.70	1.40	0.34	0.45	17103.57	1064	3.73	0.0871	165341.36	33.95
174			Nice	1123.38	0.62	157.89	1246.70	1.40	0.34	0.45	17692.71	800	3.94	0.0871	165341.36	8.81
175			Fichtelberg	4982.19	0.62	157.89	1246.70	1.27	0.33	0.44	35081.77	1696	6.63	0.0871	165341.36	70.47
176		Germany	Frankfurt	2829.51	0.62	157.89	1246.70	1.27	0.33	0.44	18881.05	1240	2.34	0.0871	165341.36	47.96
177			Hof	3425.53	0.62	157.89	1246.70	1.27	0.33	0.44	22857.90	1328	2.65	0.0871	165341.36	52.30
178			Palermo	662.65	0.62	153.29	1251.30	2.76	0.41	0.67	8210.59	712	3.73	0.0874	165341.36	11.30
179		Italy	Venezia	2077.81	0.62	153.29	1251.30	2.76	0.41	0.67	8870.57	808	2.5	0.0874	165341.36	54.94
180			Sestriere	5265.20	0.62	153.29	1251.30	2.76	0.41	0.67	30297.10	1608	5.83	0.0874	165341.36	107.36
181			Seville	702.80	0.62	153.29	1251.30	2.76	0.56	0.80	10823.27	488	4.05	0.0873	165341.36	24.98
182		Spain	Madrid	1615.32	0.62	153.29	1251.30	2.76	0.56	0.80	14201.76	888	4.1	0.0873	165341.36	54.96
183			Salamanca	2379.29	0.62	153.29	1251.30	2.76	0.56	0.80	23944.71	1240	3.29	0.0873	165341.36	71.99
184			Lund	3202.40	0.62	131.22	1273.37	1.27	0.15	0.25	15334.11	1240	6.39	0.0883	165341.36	43.01
185		Sweden	Umea	5299.05	0.62	131.22	1273.37	1.27	0.15	0.25	25622.80	1696	3.32	0.0883	165341.36	77.87
186			Kiruna	6986.21	0.62	131.22	1273.37	1.27	0.15	0.25	28084.58	1784	2.68	0.0883	165341.36	114.70
187			Camborne	2026.30	0.62	157.89	1246.70	1.40	0.22	0.36	18169.18	1088	5.38	0.0873	165341.36	29.10
188		U. Kingdom	Birmingham	2773.73	0.62	157.89	1246.70	1.40	0.22	0.36	17811.80	1336	4.32	0.0873	165341.36	46.40

Scenario	Model	Country	City	HDD	S/V	S _w	S _{op}	U _w	U _{op}	U _o	Q _s	h	V _s	C _T	Q _G	H _d
				[K day]	[m ⁻¹]	[m ²]	[m ²]	[W/(m ² K)]	[W/(m ² K)]	[W/(m ² K)]	[kWh/year]	[h]	[m/s]	[kWh/(m ³ K)]	[kWh/year]	[kWh/(m ² year)]
189			Aviemore	3483.33	0.62	157.89	1246.70	1.40	0.22	0.36	21870.71	1512	3.55	0.0873	165341.36	58.78
190			Hubert	3190.72	0.69	300.50	4069.51	1.40	0.58	0.64	48199.74	1512	3.86	0.1050	165468.5473	67.81
191		Belgium	Bruxelles	2239.30	0.69	300.50	4069.51	1.40	0.58	0.64	33813.31	1152	3.51	0.1050	165468.5473	51.48
192			Liegi	1975.16	0.69	300.50	4069.51	1.40	0.58	0.64	20062.11	824	3.88	0.1050	165468.5473	49.05
193			Bordeaux	1602.05	0.69	300.50	4069.51	1.40	0.32	0.40	29284.77	888	3.42	0.1050	165468.5473	20.43
194		France	Bourges	2226.74	0.69	300.50	4069.51	1.40	0.32	0.40	33115.12	1064	3.73	0.1050	165468.5473	30.49
195			Nice	1123.38	0.69	300.50	4069.51	1.40	0.32	0.40	34590.26	800	3.94	0.1050	165468.5473	10.54
196			Fichtelberg	4982.19	0.69	300.50	4069.51	1.27	0.34	0.41	67315.34	1696	6.63	0.1049	165468.5473	45.44
197		Germany	Frankfurt	2829.51	0.69	300.50	4069.51	1.27	0.34	0.41	36471.67	1240	2.34	0.1049	165468.5473	29.63
198			Hof	3425.53	0.69	300.50	4069.51	1.27	0.34	0.41	43993.70	1328	2.65	0.1049	165468.5473	33.00
199			Palermo	662.65	0.69	291.74	4078.26	2.76	0.41	0.56	16037.81	712	3.73	0.1052	165468.5473	9.07
200	L	Italy	Venezia	2077.81	0.69	291.74	4078.26	2.76	0.41	0.56	17324.91	808	2.5	0.1052	165468.5473	41.13
201			Sestriere	5265.20	0.69	291.74	4078.26	2.76	0.41	0.56	58565.63	1608	5.83	0.1052	165468.5473	82.51
202			Seville	702.80	0.69	291.74	4078.26	2.76	0.56	0.71	21168.09	488	4.05	0.1051	165468.5473	16.60
203		Spain	Madrid	1615.32	0.69	291.74	4078.26	2.76	0.56	0.71	27720.24	888	4.1	0.1051	165468.5473	34.57
204			Salamanca	2379.29	0.69	291.74	4078.26	2.76	0.56	0.71	46257.84	1240	3.29	0.1051	165468.5473	45.50
205			Lund	3202.40	0.69	249.73	4120.27	1.27	0.15	0.21	29626.50	1240	6.39	0.1062	165468.5473	27.62
206		Sweden	Umea	5299.05	0.69	249.73	4120.27	1.27	0.15	0.21	49424.71	1696	3.32	0.1062	165468.5473	51.88
207			Kiruna	6986.21	0.69	249.73	4120.27	1.27	0.15	0.21	53869.18	1784	2.68	0.1062	165468.5473	77.88
208			Camborne	2026.30	0.69	300.50	4069.51	1.40	0.21	0.29	35108.14	1088	5.38	0.1051	165468.5473	19.84
209		U. Kingdom	Birmingham	2773.73	0.69	300.50	4069.51	1.40	0.21	0.29	34473.58	1336	4.32	0.1051	165468.5473	31.47
210			Aviemore	3483.33	0.69	300.50	4069.51	1.40	0.21	0.29	42412.62	1512	3.55	0.1051	165468.5473	40.08
211			Hubert	3190.72	0.70	262.24	5809.76	1.40	0.59	0.62	42307.64	1512	3.86	0.1180	247754.8877	66.55
212		Belgium	Bruxelles	2239.30	0.70	262.24	5809.76	1.40	0.59	0.62	29280.96	1152	3.51	0.1180	247754.8877	51.19
213			Liegi	1975.16	0.70	262.24	5809.76	1.40	0.59	0.62	17209.35	824	3.88	0.1180	247754.8877	47.78
214			Bordeaux	1602.05	0.70	262.24	5809.76	1.40	0.32	0.36	25165.89	888	3.42	0.1179	247754.8877	20.18
215		France	Bourges	2226.74	0.70	262.24	5809.76	1.40	0.32	0.36	28801.20	1064	3.73	0.1179	247754.8877	29.25
216			Nice	1123.38	0.70	262.24	5809.76	1.40	0.32	0.36	29653.19	800	3.94	0.1179	247754.8877	11.64
217			Fichtelberg	4982.19	0.70	262.24	5809.76	1.27	0.35	0.39	59253.97	1696	6.63	0.1178	247754.8877	55.83
218		Germany	Frankfurt	2829.51	0.70	262.24	5809.76	1.27	0.35	0.39	31799.38	1240	2.34	0.1178	247754.8877	37.29
219	M		Hof	3425.53	0.70	262.24	5809.76	1.27	0.35	0.39	38566.03	1328	2.65	0.1178	247754.8877	41.18
220			Palermo	662.65	0.70	254.60	5817.39	2.76	0.41	0.50	13867.16	712	3.73	0.1181	247754.8877	9.29
221		Italy	Venezia	2077.81	0.70	254.60	5817.39	2.76	0.41	0.50	14984.87	808	2.5	0.1181	247754.8877	37.99
222			Sestriere	5265.20	0.70	254.60	5817.39	2.76	0.41	0.50	51438.65	1608	5.83	0.1181	247754.8877	77.61
223			Seville	702.80	0.70	254.60	5817.39	2.76	0.56	0.66	18203.49	488	4.05	0.1181	247754.8877	17.73
224		Spain	Madrid	1615.32	0.70	254.60	5817.39	2.76	0.56	0.66	23909.37	888	4.1	0.1181	247754.8877	34.70
225			Salamanca	2379.29	0.70	254.60	5817.39	2.76	0.56	0.66	40514.47	1240	3.29	0.1181	247754.8877	45.57
226			Lund	3202.40	0.70	217.95	5854.05	1.27	0.15	0.19	25798.72	1240	6.39	0.1188	247754.8877	22.53
227		Sweden	Umea	5299.05	0.70	217.95	5854.05	1.27	0.15	0.19	43144.10	1696	3.32	0.1188	247754.8877	43.03

Scenario	Model	Country	City	<i>HDD</i>	<i>S/V</i>	<i>S_w</i>	<i>S_{op}</i>	<i>U_w</i>	<i>U_{op}</i>	<i>U_o</i>	<i>Q_s</i>	<i>h</i>	<i>V_s</i>	<i>C_T</i>	<i>Q_G</i>	<i>H_d</i>
				[K day]	[m ⁻¹]	[m ²]	[m ²]	[W/(m ² K)]	[W/(m ² K)]	[W/(m ² K)]	[kWh/year]	[h]	[m/s]	[kWh/(m ³ K)]	[kWh/year]	[kWh/(m ² year)]
228			Kiruna	6986.21	0.70	217.95	5854.05	1.27	0.15	0.19	47418.60	1784	2.68	0.1188	247754.8877	64.63
229			Camborne	2026.30	0.70	262.24	5809.76	1.40	0.20	0.26	30623.91	1088	5.38	0.1181	247754.8877	17.28
230		U. Kingdom	Birmingham	2773.73	0.70	262.24	5809.76	1.40	0.20	0.26	29997.96	1336	4.32	0.1181	247754.8877	26.67
231			Aviemore	3483.33	0.70	262.24	5809.76	1.40	0.20	0.26	36799.84	1512	3.55	0.1181	247754.8877	34.15
232			Hubert	3190.72	0.76	160.29	2250.45	1.40	0.58	0.64	25052.33	1512	3.86	0.0439	91856.31	82.56
233		Belgium	Bruxelles	2239.30	0.76	160.29	2250.45	1.40	0.58	0.64	17415.15	1152	3.51	0.0439	103338.35	62.02
234			Liegi	1975.16	0.76	160.29	2250.45	1.40	0.58	0.64	10267.43	824	3.88	0.0439	103338.35	60.50
235			Bordeaux	1602.05	0.76	160.29	2250.45	1.40	0.32	0.40	15392.72	888	3.42	0.0438	103338.35	18.99
236		France	Bourges	2226.74	0.76	160.29	2250.45	1.40	0.32	0.40	17514.48	1064	3.73	0.0438	103338.35	28.31
237			Nice	1123.38	0.76	160.29	2250.45	1.40	0.32	0.40	18158.67	800	3.94	0.0438	103338.35	9.81
238			Fichtelberg	4982.19	0.76	160.29	2250.45	1.27	0.34	0.40	35856.31	1696	6.63	0.0436	103338.35	51.93
239		Germany	Frankfurt	2829.51	0.76	160.29	2250.45	1.27	0.34	0.40	19331.21	1240	2.34	0.0436	103338.35	35.02
240			Hof	3425.53	0.76	160.29	2250.45	1.27	0.34	0.40	23383.58	1328	2.65	0.0436	103338.35	38.37
241			Palermo	662.65	0.76	155.62	2255.12	2.76	0.41	0.56	8443.36	712	3.73	0.0400	103338.35	8.00
242	N	Italy	Venezia	2077.81	0.76	155.62	2255.12	2.76	0.41	0.56	9122.14	808	2.5	0.0400	103338.35	37.38
243			Sestriere	5265.20	0.76	155.62	2255.12	2.76	0.41	0.56	31082.33	1608	5.83	0.0400	103338.35	74.91
244			Seville	702.80	0.76	155.62	2255.10	2.76	0.56	0.71	11123.82	488	4.05	0.0439	103338.35	19.93
245		Spain	Madrid	1615.32	0.76	155.62	2255.10	2.76	0.56	0.71	14589.41	888	4.1	0.0439	103338.35	40.94
246			Salamanca	2379.29	0.76	155.62	2255.10	2.76	0.56	0.71	24539.61	1240	3.29	0.0439	103338.35	53.56
247			Lund	3202.40	0.76	133.21	2277.53	1.27	0.15	0.21	15694.60	1240	6.39	0.0443	103338.35	24.70
248		Sweden	Umea	5299.05	0.76	133.21	2277.53	1.27	0.15	0.21	26215.54	1696	3.32	0.0443	103338.35	47.21
249			Kiruna	6986.21	0.76	133.21	2277.53	1.27	0.15	0.21	28697.09	1784	2.68	0.0443	103338.35	71.21
250			Camborne	2026.30	0.76	160.29	2250.45	1.40	0.21	0.29	18595.79	1088	5.38	0.0436	103338.35	17.13
251		U. Kingdom	Birmingham	2773.73	0.76	160.29	2250.45	1.40	0.21	0.29	18236.84	1336	4.32	0.0436	103338.35	27.76
252			Aviemore	3483.33	0.76	160.29	2250.45	1.40	0.21	0.29	22402.92	1512	3.55	0.0436	103338.35	35.66
253			Hubert	3190.72	0.90	309.46	2363.37	1.40	0.58	0.67	49235.20	1512	3.86	0.1213	86337.58	75.08
254		Belgium	Bruxelles	2239.30	0.90	309.46	2363.37	1.40	0.58	0.67	34678.72	1152	3.51	0.1213	486170.64	56.47
255			Liegi	1975.16	0.90	309.46	2363.37	1.40	0.58	0.67	20632.76	824	3.88	0.1213	486170.64	27.06
256			Bordeaux	1602.05	0.90	309.46	2363.37	1.40	0.34	0.46	30101.08	888	3.42	0.1209	486170.64	20.96
257		France	Bourges	2226.74	0.90	309.46	2363.37	1.40	0.34	0.46	33918.55	1064	3.73	0.1209	486170.64	33.03
258			Nice	1123.38	0.90	309.46	2363.37	1.40	0.34	0.46	35579.37	800	3.94	0.1209	486170.64	8.88
259			Fichtelberg	4982.19	0.90	309.46	2363.37	1.27	0.33	0.44	68866.35	1696	6.63	0.1208	486170.64	59.81
260	O	Germany	Frankfurt	2829.51	0.90	309.46	2363.37	1.27	0.33	0.44	37418.60	1240	2.34	0.1208	486170.64	41.80
261			Hof	3425.53	0.90	309.46	2363.37	1.27	0.33	0.44	45062.92	1328	2.65	0.1208	486170.64	44.99
262			Palermo	662.65	0.90	300.45	2372.40	2.76	0.41	0.68	16412.41	712	3.73	0.1215	486170.64	9.66
263		Italy	Venezia	2077.81	0.90	300.45	2372.40	2.76	0.41	0.68	17726.97	808	2.5	0.1215	486170.64	49.75
264			Sestriere	5265.20	0.90	300.45	2372.40	2.76	0.41	0.68	59652.30	1608	5.83	0.1215	486170.64	94.63
265			Seville	702.80	0.90	300.45	2372.37	2.76	0.56	0.81	21721.46	488	4.05	0.1215	486170.64	21.12
266		Spain	Madrid	1615.32	0.90	300.45	2372.37	2.76	0.56	0.81	28419.94	888	4.1	0.1215	486170.64	47.76

Scenario	Model	Country	City	<i>HDD</i>	<i>S/V</i>	<i>S_w</i>	<i>S_{op}</i>	<i>U_w</i>	<i>U_{op}</i>	<i>U_o</i>	<i>Q_s</i>	<i>h</i>	<i>V_s</i>	<i>C_T</i>	<i>Q_G</i>	<i>H_d</i>
				[K day]	[m ⁻¹]	[m ²]	[m ²]	[W/(m ² K)]	[W/(m ² K)]	[W/(m ² K)]	[kWh/year]	[h]	[m/s]	[kWh/(m ³ K)]	[kWh/year]	[kWh/(m ² year)]
267			Salamanca	2379.29	0.90	300.45	2372.37	2.76	0.56	0.81	47210.66	1240	3.29	0.1215	486170.64	62.38
268			Lund	3202.40	0.90	257.18	2415.64	1.27	0.15	0.26	30339.97	1240	6.39	0.1233	486170.64	33.91
269		Sweden	Umea	5299.05	0.90	257.18	2415.64	1.27	0.15	0.26	50577.43	1696	3.32	0.1233	486170.64	64.52
270			Kiruna	6986.21	0.90	257.18	2415.64	1.27	0.15	0.26	54986.58	1784	2.68	0.1233	486170.64	97.71
271			Camborne	2026.30	0.90	309.46	2363.37	1.40	0.22	0.36	35927.08	1088	5.38	0.1211	486170.64	22.86
272		U. Kingdom	Birmingham	2773.73	0.90	309.46	2363.37	1.40	0.22	0.36	35303.04	1336	4.32	0.1211	486170.64	38.17
273			Aviemore	3483.33	0.90	309.46	2363.37	1.40	0.22	0.36	43469.76	1512	3.55	0.1211	486170.64	48.68

ANNEX 3

Building energy Database of Italian context: 13 Building Models, 195 scenarios

Scenario	Model	Climatic Zone	City	HDD	CDD	T	RH	v_s	I_h	S/V	H_s	S_w	S_{op}	U_w	U_{op}	U_o	$Q_{s,n}$	$Q_{s,c}$	h_n	h_c	C_T	Q_G	H_d	C_d
				[K day]	[K day]	[C°]	[%]	[m/s]	[W/m ²]	[m ⁻¹]	[m ²]	[m ²]	[m ²]	[m ²]	[W/(m ² ·K)]	[W/(m ² ·K)]	[W/(m ² ·K)]	[kWh/(m ² year)]	[kWh/(m ² year)]	[h]	[h]	[kWh/(m ² ·K)]	[kWh/year]	[kWh/(m ² year)]
1			Messina	707	260	19.13	76.38	2.83	683.39	0.24	7049.8	860.68	4935.85	2.76	0.42	0.77	6.18	14.72	704	1040	0.0560	647566.44	1.60	24.94
2		B	Palermo	751	309	19.01	68.46	3.73	727.99	0.24	7049.8	860.68	4935.85	2.76	0.42	0.77	6.64	15.62	704	1040	0.0560	647566.44	1.42	24.13
3			Crotone	899	255	18.02	64.32	4.64	685.83	0.24	7049.8	860.68	4935.85	2.76	0.42	0.77	6.29	14.99	704	1040	0.0560	647566.44	4.16	23.66
4			Cagliari	990	222	17.47	71.70	3.91	677.79	0.24	7049.8	860.68	4935.85	2.26	0.37	0.65	15.86	31.96	792	1040	0.0588	647566.44	0.70	32.99
5		C	Bari	1185	314	16.03	68.62	3.21	673.21	0.24	7049.8	860.68	4935.85	2.26	0.37	0.65	15.82	33.26	792	1040	0.0588	647566.44	1.97	30.71
6			Termoli	1350	155	15.81	70.67	3.08	582.46	0.24	7049.8	860.68	4935.85	2.26	0.37	0.65	13.37	29.64	792	1040	0.0588	647566.44	4.35	28.56
7			Genova	1435	115	16.19	68.45	3.48	565.03	0.24	7049.8	860.68	4935.85	1.76	0.31	0.53	14.28	26.29	960	1040	0.0671	647566.44	2.43	29.08
8	1	D	Firenze	1821	331	15.61	66.59	2.24	594.31	0.24	7049.8	860.68	4935.85	1.76	0.31	0.53	15.64	26.99	960	1040	0.0671	647566.44	2.91	30.27
9			Forlì	2087	108	14.19	70.39	1.70	537.14	0.24	7049.8	860.68	4935.85	1.76	0.31	0.53	12.26	25.25	960	1040	0.0671	647566.44	7.49	26.01
10			Trieste	2102	125	15.48	63.55	2.79	545.21	0.24	7049.8	860.68	4935.85	1.76	0.28	0.50	14.54	26.01	1056	1040	0.0582	647566.44	4.10	29.01
11		E	Torino	2617	166	12.72	68.78	1.75	534.88	0.24	7049.8	860.68	4935.85	1.76	0.28	0.50	16.03	24.55	1056	1040	0.0582	647566.44	8.53	21.98
12			Bolzano	2791	135	12.87	63.20	1.73	588.83	0.24	7049.8	860.68	4935.85	1.76	0.28	0.50	19.26	27.26	1056	1040	0.0582	647566.44	8.54	26.41
13			Cuneo	3012	80	12.71	63.90	2.11	605.80	0.24	7049.8	860.68	4935.85	1.40	0.26	0.43	42.49	29.73	1832	1040	0.0582	647566.44	3.64	24.14
14		F	Cortina	4433	0	6.33	69.93	0.56	530.68	0.24	7049.8	860.68	4935.85	1.40	0.26	0.43	41.55	26.79	1832	1040	0.0582	647566.44	16.43	10.63
15			Sestriere	5165	0	1.36	70.61	5.83	668.21	0.24	7049.8	860.68	4935.85	1.40	0.26	0.43	58.80	35.64	1832	1040	0.0582	647566.44	16.98	2.72
16			Messina	707	260	19.13	76.38	2.83	683.39	0.5	5292.7	530.91	11455.80	2.76	0.41	0.52	5.13	11.96	704	1040	0.0736	293940.19	11.66	15.73
17		B	Palermo	751	309	19.01	68.46	3.73	727.99	0.5	5292.7	530.91	11455.80	2.76	0.41	0.52	5.52	12.68	704	1040	0.0736	293940.19	11.04	14.42
18			Crotone	899	255	18.02	64.32	4.64	685.83	0.5	5292.7	530.91	11455.80	2.76	0.41	0.52	5.22	12.18	704	1040	0.0736	293940.19	16.27	14.85
19			Cagliari	990	222	17.47	71.70	3.91	677.79	0.5	5292.7	530.91	11455.80	2.26	0.37	0.45	13.19	25.99	792	1040	0.0764	293940.19	11.16	19.60
20		C	Bari	1185	314	16.03	68.62	3.21	673.21	0.5	5292.7	530.91	11455.80	2.26	0.37	0.45	13.18	27.07	792	1040	0.0764	293940.19	15.35	17.42
21			Termoli	1350	155	15.81	70.67	3.08	582.46	0.5	5292.7	530.91	11455.80	2.26	0.37	0.45	11.11	24.16	792	1040	0.0764	293940.19	18.93	16.23
22			Genova	1435	115	16.19	68.45	3.48	565.03	0.5	5292.7	530.91	11455.80	1.76	0.31	0.37	11.88	21.47	960	1040	0.0948	293940.19	14.76	16.25
23	2	D	Firenze	1821	331	15.61	66.59	2.24	594.31	0.5	5292.7	530.91	11455.80	1.76	0.31	0.37	13.03	22.04	960	1040	0.0948	293940.19	17.06	17.93
24			Forlì	2087	108	14.19	70.39	1.70	537.14	0.5	5292.7	530.91	11455.80	1.76	0.31	0.37	10.18	20.62	960	1040	0.0948	293940.19	24.02	14.61
25			Trieste	2102	125	15.48	63.55	2.79	545.21	0.5	5292.7	530.91	11455.80	1.76	0.27	0.34	12.10	21.25	1056	1040	0.0779	293940.19	17.71	17.22
26		E	Torino	2617	166	12.72	68.78	1.75	534.88	0.5	5292.7	530.91	11455.80	1.76	0.27	0.34	13.34	20.07	1056	1040	0.0779	293940.19	25.74	10.75
27			Bolzano	2791	135	12.87	63.20	1.73	588.83	0.5	5292.7	530.91	11455.80	1.76	0.27	0.34	16.06	22.27	1056	1040	0.0779	293940.19	25.71	14.13
28			Cuneo	3012	80	12.71	63.90	2.11	605.80	0.5	5292.7	530.91	11455.80	1.40	0.25	0.30	34.98	24.23	1832	1040	0.0780	293940.19	19.21	11.43
29		F	Cortina	4433	0	6.33	69.93	0.56	530.68	0.5	5292.7	530.91	11455.80	1.40	0.25	0.30	34.20	21.85	1832	1040	0.0780	293940.19	43.29	1.76
30			Sestriere	5165	0	1.36	70.61	5.83	668.21	0.5	5292.7	530.91	11455.80	1.40	0.25	0.30	48.41	29.03	1832	1040	0.0780	293940.19	52.08	0.00
31	3	B	Messina	707	260	19.13	76.38	2.83	683.39	0.9	939.9	300.45	2372.40	2.76	0.42	0.68	16.20	36.39	704	1040	0.1178	486170.64	10.83	27.48

Scenario	Model	Climatic Zone	City	HDD	CDD	T	RH	v_s	I_h	S/V	H_s	S_w	S_{op}	U_w	U_{op}	U_o	$Q_{s,H}$	$Q_{s,C}$	h_H	h_C	C_T	Q_G	H_d	C_d
				[K day]	[K day]	[C°]	[%]	[m/s]	[W/m²]	[m⁻¹]	[m²]	[m²]	[m²]	[W/(m²·K)]	[W/(m²·K)]	[W/(m²·K)]	[kWh/(m² year)]	[kWh/(m² year)]	[h]	[h]	[kWh/(m³·K)]	[kWh/year]	[kWh/(m² year)]	[kWh/(m² year)]
32			Palermo	751	309	19.01	68.46	3.73	727.99	0.9	939.9	300.45	2372.40	2.76	0.42	0.68	17.46	38.54	704	1040	0.1178	486170.64	9.78	26.19
33			Crotone	899	255	18.02	64.32	4.64	685.83	0.9	939.9	300.45	2372.40	2.76	0.42	0.68	16.50	37.05	704	1040	0.1178	486170.64	15.73	26.05
34			Cagliari	990	222	17.47	71.70	3.91	677.79	0.9	939.9	300.45	2372.40	2.26	0.37	0.58	41.65	78.92	792	1040	0.1216	486170.64	6.95	42.26
35		C	Bari	1185	314	16.03	68.62	3.21	673.21	0.9	939.9	300.45	2372.40	2.26	0.37	0.58	41.75	82.29	792	1040	0.1216	486170.64	10.54	39.72
36			Termoli	1350	155	15.81	70.67	3.08	582.46	0.9	939.9	300.45	2372.40	2.26	0.37	0.58	35.08	73.67	792	1040	0.1216	486170.64	15.83	35.70
37			Genova	1435	115	16.19	68.45	3.48	565.03	0.9	939.9	300.45	2372.40	1.76	0.31	0.47	37.36	65.32	960	1040	0.1491	486170.64	11.14	37.76
38		D	Firenze	1821	331	15.61	66.59	2.24	594.31	0.9	939.9	300.45	2372.40	1.76	0.31	0.47	41.00	67.02	960	1040	0.1491	486170.64	12.48	39.55
39			Forlì	2087	108	14.19	70.39	1.70	537.14	0.9	939.9	300.45	2372.40	1.76	0.31	0.47	31.91	62.77	960	1040	0.1491	486170.64	22.29	33.13
40			Trieste	2102	125	15.48	63.55	2.79	545.21	0.9	939.9	300.45	2372.40	1.76	0.27	0.44	38.03	64.71	1056	1040	0.1252	486170.64	14.53	38.44
41		E	Torino	2617	166	12.72	68.78	1.75	534.88	0.9	939.9	300.45	2372.40	1.76	0.27	0.44	41.99	61.20	1056	1040	0.1252	486170.64	22.06	27.86
42			Bolzano	2791	135	12.87	63.20	1.73	588.83	0.9	939.9	300.45	2372.40	1.76	0.27	0.44	50.65	67.78	1056	1040	0.1252	486170.64	20.86	34.19
43			Cuneo	3012	80	12.71	63.90	2.11	605.80	0.9	939.9	300.45	2372.40	1.40	0.26	0.38	109.68	74.57	1832	1040	0.1252	486170.64	11.21	33.85
44		F	Cortina	4433	0	6.33	69.93	0.56	530.68	0.9	939.9	300.45	2372.40	1.40	0.26	0.38	107.13	67.36	1832	1040	0.1252	486170.64	32.45	14.31
45			Sestriere	5165	0	1.36	70.61	5.83	668.21	0.9	939.9	300.45	2372.40	1.40	0.26	0.38	151.78	89.26	1832	1040	0.1252	486170.64	29.61	5.84
46			Messina	707	260	19.13	76.38	2.83	683.39	0.35	1800	460.34	1654.66	2.76	0.43	0.93	12.57	30.79	704	1040	0.0571	483948.36	3.49	31.89
47		B	Palermo	751	309	19.01	68.46	3.73	727.99	0.35	1800	460.34	1654.66	2.76	0.43	0.93	13.48	32.71	704	1040	0.0571	483948.36	2.98	31.05
48			Crotone	899	255	18.02	64.32	4.64	685.83	0.35	1800	460.34	1654.66	2.76	0.43	0.93	12.78	31.35	704	1040	0.0571	483948.36	7.00	30.39
49			Cagliari	990	222	17.47	71.70	3.91	677.79	0.35	1800	460.34	1654.66	2.26	0.37	0.78	32.06	66.63	792	1040	0.0596	483948.36	1.36	47.28
50		C	Bari	1185	314	16.03	68.62	3.21	673.21	0.35	1800	460.34	1654.66	2.26	0.37	0.78	31.92	69.26	792	1040	0.0596	483948.36	3.05	44.90
51			Termoli	1350	155	15.81	70.67	3.08	582.46	0.35	1800	460.34	1654.66	2.26	0.37	0.78	27.04	61.60	792	1040	0.0596	483948.36	6.48	40.89
52			Genova	1435	115	16.19	68.45	3.48	565.03	0.35	1800	460.34	1654.66	1.76	0.32	0.63	28.77	54.34	960	1040	0.0686	483948.36	4.01	41.89
53		D	Firenze	1821	331	15.61	66.59	2.24	594.31	0.35	1800	460.34	1654.66	1.76	0.32	0.63	31.48	55.80	960	1040	0.0686	483948.36	4.33	43.44
54			Forlì	2087	108	14.19	70.39	1.70	537.14	0.35	1800	460.34	1654.66	1.76	0.32	0.63	24.75	52.16	960	1040	0.0686	483948.36	11.08	37.30
55			Trieste	2102	125	15.48	63.55	2.79	545.21	0.35	1800	460.34	1654.66	1.76	0.28	0.60	29.31	53.71	1056	1040	0.0600	483948.36	6.30	41.60
56		E	Torino	2617	166	12.72	68.78	1.75	534.88	0.35	1800	460.34	1654.66	1.76	0.28	0.60	32.26	50.66	1056	1040	0.0600	483948.36	11.85	32.03
57			Bolzano	2791	135	12.87	63.20	1.73	588.83	0.35	1800	460.34	1654.66	1.76	0.28	0.60	38.70	56.30	1056	1040	0.0600	483948.36	11.36	38.47
58			Cuneo	3012	80	12.71	63.90	2.11	605.80	0.35	1800	460.34	1654.66	1.40	0.26	0.51	87.70	62.23	1832	1040	0.0599	483948.36	4.31	37.97
59		F	Cortina	4433	0	6.33	69.93	0.56	530.68	0.35	1800	460.34	1654.66	1.40	0.26	0.51	85.82	56.02	1832	1040	0.0599	483948.36	19.55	18.48
60			Sestriere	5165	0	1.36	70.61	5.83	668.21	0.35	1800	460.34	1654.66	1.40	0.26	0.51	121.36	74.64	1832	1040	0.0599	483948.36	16.96	9.37
61			Messina	707	260	19.13	76.38	2.83	683.39	0.62	500	153.29	1251.30	2.76	0.42	0.67	15.28	36.27	704	1040	0.1116	165341.36	12.43	27.92
62		B	Palermo	751	309	19.01	68.46	3.73	727.99	0.62	500	153.29	1251.30	2.76	0.42	0.67	16.42	38.48	704	1040	0.1116	165341.36	11.37	26.47
63			Crotone	899	255	18.02	64.32	4.64	685.83	0.62	500	153.29	1251.30	2.76	0.42	0.67	15.54	36.92	704	1040	0.1116	165341.36	18.02	26.54
64			Cagliari	990	222	17.47	71.70	3.91	677.79	0.62	500	153.29	1251.30	2.26	0.37	0.58	39.10	78.55	792	1040	0.0874	165341.36	8.93	42.12
65		C	Bari	1185	314	16.03	68.62	3.21	673.21	0.62	500	153.29	1251.30	2.26	0.37	0.58	39.03	81.74	792	1040	0.0874	165341.36	13.33	39.22
66			Termoli	1350	155	15.81	70.67	3.08	582.46	0.62	500	153.29	1251.30	2.26	0.37	0.58	32.96	72.87	792	1040	0.0874	165341.36	19.01	35.19
67			Genova	1435	115	16.19	68.45	3.48	565.03	0.62	500	153.29	1251.30	1.76	0.31	0.47	35.10	64.42	960	1040	0.1068	165341.36	14.23	36.28
68		D	Firenze	1821	331	15.61	66.59	2.24	594.31	0.62	500	153.29	1251.30	1.76	0.31	0.47	38.44	66.14	960	1040	0.1068	165341.36	16.19	38.57

Scenario	Model	Climatic Zone	City	HDD	CDD	T	RH	v_s	I_h	S/V	H_s	S_w	S_{op}	U_w	U_{op}	U_o	$Q_{s,H}$	$Q_{s,C}$	h_H	h_C	C_T	Q_G	H_d	C_d
				[K day]	[K day]	[C°]	[%]	[m/s]	[W/m ²]	[m ⁻¹]	[m ²]	[m ²]	[m ²]	[W/(m ² ·K)]	[W/(m ² ·K)]	[W/(m ² ·K)]	[kWh/(m ² year)]	[kWh/(m ² year)]	[h]	[h]	[kWh/(m ² ·K)]	[kWh/year]	[kWh/(m ² year)]	[kWh/(m ² year)]
69			Forlì	2087	108	14.19	70.39	1.70	537.14	0.62	500	153.29	1251.30	1.76	0.31	0.47	30.11	61.87	960	1040	0.1068	165341.36	26.88	31.97
70			Trieste	2102	125	15.48	63.55	2.79	545.21	0.62	500	153.29	1251.30	1.76	0.27	0.44	35.74	63.73	1056	1040	0.0900	165341.36	18.43	37.15
71		E	Torino	2617	166	12.72	68.78	1.75	534.88	0.62	500	153.29	1251.30	1.76	0.27	0.44	39.39	60.17	1056	1040	0.0900	165341.36	27.53	26.04
72			Bolzano	2791	135	12.87	63.20	1.73	588.83	0.62	500	153.29	1251.30	1.76	0.27	0.44	47.35	66.79	1056	1040	0.0900	165341.36	26.39	32.59
73			Cuneo	3012	80	12.71	63.90	2.11	605.80	0.62	500	153.29	1251.30	1.40	0.26	0.38	105.39	73.63	1832	1040	0.0900	165341.36	15.92	31.17
74		F	Cortina	4433	0	6.33	69.93	0.56	530.68	0.62	500	153.29	1251.30	1.40	0.26	0.38	103.06	66.36	1832	1040	0.0900	165341.36	41.53	11.76
75			Sestriere	5165	0	1.36	70.61	5.83	668.21	0.62	500	153.29	1251.30	1.40	0.26	0.38	145.84	88.25	1832	1040	0.0900	165341.36	40.40	2.65
76			Messina	707	260	19.13	76.38	2.83	683.39	0.76	1000	155.62	2255.12	2.76	0.41	0.56	7.85	18.48	704	1040	0.1101	103338.35	8.80	19.96
77		B	Palermo	751	309	19.01	68.46	3.73	727.99	0.76	1000	155.62	2255.12	2.76	0.41	0.56	8.44	19.60	704	1040	0.1101	103338.35	8.13	18.87
78			Crotone	899	255	18.02	64.32	4.64	685.83	0.76	1000	155.62	2255.12	2.76	0.41	0.56	7.99	18.81	704	1040	0.1101	103338.35	12.74	18.83
79			Cagliari	990	222	17.47	71.70	3.91	677.79	0.76	1000	155.62	2255.12	2.26	0.37	0.49	20.14	40.08	792	1040	0.1141	103338.35	6.89	27.44
80		C	Bari	1185	314	16.03	68.62	3.21	673.21	0.76	1000	155.62	2255.12	2.26	0.37	0.49	20.12	41.72	792	1040	0.1141	103338.35	10.12	25.20
81			Termoli	1350	155	15.81	70.67	3.08	582.46	0.76	1000	155.62	2255.12	2.26	0.37	0.49	16.97	37.22	792	1040	0.1141	103338.35	13.78	22.88
82			Genova	1435	115	16.19	68.45	3.48	565.03	0.76	1000	155.62	2255.12	1.76	0.31	0.40	18.11	32.99	960	1040	0.1405	103338.35	9.62	24.26
83	6	D	Firenze	1821	331	15.61	66.59	2.24	594.31	0.76	1000	155.62	2255.12	1.76	0.31	0.40	19.85	33.86	960	1040	0.1405	103338.35	11.20	25.70
84			Forlì	2087	108	14.19	70.39	1.70	537.14	0.76	1000	155.62	2255.12	1.76	0.31	0.40	15.53	31.69	960	1040	0.1405	103338.35	17.88	21.45
85			Trieste	2102	125	15.48	63.55	2.79	545.21	0.76	1000	155.62	2255.12	1.76	0.27	0.37	18.44	32.64	1056	1040	0.1165	103338.35	11.94	24.89
86		E	Torino	2617	166	12.72	68.78	1.75	534.88	0.76	1000	155.62	2255.12	1.76	0.27	0.37	20.33	30.83	1056	1040	0.1165	103338.35	18.39	17.57
87			Bolzano	2791	135	12.87	63.20	1.73	588.83	0.76	1000	155.62	2255.12	1.76	0.27	0.37	24.45	34.21	1056	1040	0.1165	103338.35	18.15	21.64
88			Cuneo	3012	80	12.71	63.90	2.11	605.80	0.76	1000	155.62	2255.12	1.40	0.25	0.33	53.85	37.46	1832	1040	0.1166	103338.35	11.19	20.06
89		F	Cortina	4433	0	6.33	69.93	0.56	530.68	0.76	1000	155.62	2255.12	1.40	0.25	0.33	52.65	33.78	1832	1040	0.1166	103338.35	29.19	7.33
90			Sestriere	5165	0	1.36	70.61	5.83	668.21	0.76	1000	155.62	2255.12	1.40	0.25	0.33	74.52	44.89	1832	1040	0.1166	103338.35	30.75	1.08
91			Messina	707	260	19.13	76.38	2.83	683.39	0.4	1125	318.26	1271.74	2.76	0.42	0.89	14.04	32.98	704	1040	0.0710	459580.17	4.68	31.52
92		B	Palermo	751	309	19.01	68.46	3.73	727.99	0.4	1125	318.26	1271.74	2.76	0.42	0.89	15.09	34.98	704	1040	0.0710	459580.17	4.01	30.54
93			Crotone	899	255	18.02	64.32	4.64	685.83	0.4	1125	318.26	1271.74	2.76	0.42	0.89	14.28	33.58	704	1040	0.0710	459580.17	8.57	30.05
94			Cagliari	990	222	17.47	71.70	3.91	677.79	0.4	1125	318.26	1271.74	2.26	0.37	0.75	35.91	71.37	792	1040	0.0744	459580.17	2.01	47.17
95		C	Bari	1185	314	16.03	68.62	3.21	673.21	0.4	1125	318.26	1271.74	2.26	0.37	0.75	35.88	74.30	792	1040	0.0744	459580.17	4.03	44.69
96			Termoli	1350	155	15.81	70.67	3.08	582.46	0.4	1125	318.26	1271.74	2.26	0.37	0.75	30.27	66.29	792	1040	0.0744	459580.17	8.01	40.70
97			Genova	1435	115	16.19	68.45	3.48	565.03	0.4	1125	318.26	1271.74	1.76	0.32	0.61	32.18	58.54	960	1040	0.0859	459580.17	5.12	41.96
98	7	D	Firenze	1821	331	15.61	66.59	2.24	594.31	0.4	1125	318.26	1271.74	1.76	0.32	0.61	35.26	60.09	960	1040	0.0859	459580.17	5.56	43.55
99			Forlì	2087	108	14.19	70.39	1.70	537.14	0.4	1125	318.26	1271.74	1.76	0.32	0.61	27.58	56.23	960	1040	0.0859	459580.17	13.29	37.16
100			Trieste	2102	125	15.48	63.55	2.79	545.21	0.4	1125	318.26	1271.74	1.76	0.28	0.58	32.77	57.93	1056	1040	0.0745	459580.17	7.74	41.82
101		E	Torino	2617	166	12.72	68.78	1.75	534.88	0.4	1125	318.26	1271.74	1.76	0.28	0.58	36.12	54.71	1056	1040	0.0745	459580.17	13.80	31.72
102			Bolzano	2791	135	12.87	63.20	1.73	588.83	0.4	1125	318.26	1271.74	1.76	0.28	0.58	43.45	60.70	1056	1040	0.0745	459580.17	13.07	38.34
103			Cuneo	3012	80	12.71	63.90	2.11	605.80	0.4	1125	318.26	1271.74	1.40	0.26	0.49	96.66	67.20	1832	1040	0.0745	459580.17	5.26	37.98
104		F	Cortina	4433	0	6.33	69.93	0.56	530.68	0.4	1125	318.26	1271.74	1.40	0.26	0.49	94.51	60.60	1832	1040	0.0745	459580.17	22.11	17.85
105			Sestriere	5165	0	1.36	70.61	5.83	668.21	0.4	1125	318.26	1271.74	1.40	0.26	0.49	133.77	80.53	1832	1040	0.0745	459580.17	19.01	8.21

Scenario	Model	Climatic Zone	City	HDD	CDD	T	RH	v_s	I_h	S/V	H_s	S_w	S_{op}	U_w	U_{op}	U_o	$Q_{s,H}$	$Q_{s,C}$	h_H	h_C	C_T	Q_G	H_d	C_d
				[K day]	[K day]	[C°]	[%]	[m/s]	[W/m²]	[m⁻¹]	[m²]	[m²]	[m²]	[W/(m²·K)]	[W/(m²·K)]	[W/(m²·K)]	[kWh/(m² year)]	[kWh/(m² year)]	[h]	[h]	[kWh/(m³·K)]	[kWh/year]	[kWh/(m² year)]	[kWh/(m² year)]
106			Messina	707	260	19.13	76.38	2.83	683.39	0.32	3200	545.6	4094.41	2.76	0.42	0.69	8.60	20.56	704	1040	0.0620	293940.19	6.06	25.43
107		B	Palermo	751	309	19.01	68.46	3.73	727.99	0.32	3200	545.6	4094.41	2.76	0.42	0.69	9.23	21.83	704	1040	0.0620	293940.19	5.35	24.32
108			Crotone	899	255	18.02	64.32	4.64	685.83	0.32	3200	545.6	4094.41	2.76	0.42	0.69	8.74	20.94	704	1040	0.0620	293940.19	10.35	24.26
109			Cagliari	990	222	17.47	71.70	3.91	677.79	0.32	3200	545.6	4094.41	2.26	0.37	0.59	22.03	44.62	792	1040	0.0647	293940.19	4.00	34.88
110		C	Bari	1185	314	16.03	68.62	3.21	673.21	0.32	3200	545.6	4094.41	2.26	0.37	0.59	21.97	46.42	792	1040	0.0647	293940.19	7.14	32.17
111			Termoli	1350	155	15.81	70.67	3.08	582.46	0.32	3200	545.6	4094.41	2.26	0.37	0.59	18.57	41.36	792	1040	0.0647	293940.19	11.15	29.39
112			Genova	1435	115	16.19	68.45	3.48	565.03	0.32	3200	545.6	4094.41	1.76	0.31	0.48	19.83	36.66	960	1040	0.0757	293940.19	7.67	29.88
113	8	D	Firenze	1821	331	15.61	66.59	2.24	594.31	0.32	3200	545.6	4094.41	1.76	0.31	0.48	21.72	37.64	960	1040	0.0757	293940.19	9.03	31.62
114			Forlì	2087	108	14.19	70.39	1.70	537.14	0.32	3200	545.6	4094.41	1.76	0.31	0.48	17.03	35.20	960	1040	0.0757	293940.19	16.52	26.47
115			Trieste	2102	125	15.48	63.55	2.79	545.21	0.32	3200	545.6	4094.41	1.76	0.27	0.45	20.20	36.26	1056	1040	0.0648	293940.19	10.65	30.15
116		E	Torino	2617	166	12.72	68.78	1.75	534.88	0.32	3200	545.6	4094.41	1.76	0.27	0.45	22.25	34.23	1056	1040	0.0648	293940.19	17.78	21.49
117			Bolzano	2791	135	12.87	63.20	1.73	588.83	0.32	3200	545.6	4094.41	1.76	0.27	0.45	26.73	38.00	1056	1040	0.0648	293940.19	17.54	26.66
118			Cuneo	3012	80	12.71	63.90	2.11	605.80	0.32	3200	545.6	4094.41	1.40	0.26	0.39	59.22	41.53	1832	1040	0.0648	293940.19	10.19	24.03
119		F	Cortina	4433	0	6.33	69.93	0.56	530.68	0.32	3200	545.6	4094.41	1.40	0.26	0.39	57.92	37.42	1832	1040	0.0648	293940.19	30.28	8.94
120			Sestriere	5165	0	1.36	70.61	5.83	668.21	0.32	3200	545.6	4094.41	1.40	0.26	0.39	81.95	49.79	1832	1040	0.0648	293940.19	32.01	1.08
121			Messina	707	260	19.13	76.38	2.83	683.39	0.27	5280	838.8	4015.15	2.76	0.42	0.83	8.02	18.55	704	1040	0.0531	483948.36	1.75	25.84
122		B	Palermo	751	309	19.01	68.46	3.73	727.99	0.27	5280	838.8	4015.15	2.76	0.42	0.83	8.63	19.67	704	1040	0.0531	483948.36	1.53	25.01
123			Crotone	899	255	18.02	64.32	4.64	685.83	0.27	5280	838.8	4015.15	2.76	0.42	0.83	8.16	18.89	704	1040	0.0531	483948.36	4.30	24.54
124			Cagliari	990	222	17.47	71.70	3.91	677.79	0.27	5280	838.8	4015.15	2.26	0.37	0.70	20.58	40.23	792	1040	0.0559	483948.36	0.69	35.29
125		C	Bari	1185	314	16.03	68.62	3.21	673.21	0.27	5280	838.8	4015.15	2.26	0.37	0.70	20.58	41.91	792	1040	0.0559	483948.36	1.85	33.10
126			Termoli	1350	155	15.81	70.67	3.08	582.46	0.27	5280	838.8	4015.15	2.26	0.37	0.70	17.34	37.43	792	1040	0.0559	483948.36	4.28	30.72
127			Genova	1435	115	16.19	68.45	3.48	565.03	0.27	5280	838.8	4015.15	1.76	0.31	0.56	18.48	33.17	960	1040	0.0646	483948.36	2.35	31.56
128	9	D	Firenze	1821	331	15.61	66.59	2.24	594.31	0.27	5280	838.8	4015.15	1.76	0.31	0.56	20.27	34.04	960	1040	0.0646	483948.36	2.71	32.77
129			Forlì	2087	108	14.19	70.39	1.70	537.14	0.27	5280	838.8	4015.15	1.76	0.31	0.56	15.82	31.86	960	1040	0.0646	483948.36	7.54	28.24
130			Trieste	2102	125	15.48	63.55	2.79	545.21	0.27	5280	838.8	4015.15	1.76	0.28	0.53	18.82	32.84	1056	1040	0.0556	483948.36	4.09	31.48
131		E	Torino	2617	166	12.72	68.78	1.75	534.88	0.27	5280	838.8	4015.15	1.76	0.28	0.53	20.76	31.03	1056	1040	0.0556	483948.36	8.48	24.10
132			Bolzano	2791	135	12.87	63.20	1.73	588.83	0.27	5280	838.8	4015.15	1.76	0.28	0.53	24.99	34.40	1056	1040	0.0556	483948.36	8.31	28.79
133			Cuneo	3012	80	12.71	63.90	2.11	605.80	0.27	5280	838.8	4015.15	1.40	0.26	0.46	54.75	37.77	1832	1040	0.0557	483948.36	3.11	27.20
134		F	Cortina	4433	0	6.33	69.93	0.56	530.68	0.27	5280	838.8	4015.15	1.40	0.26	0.46	53.51	34.08	1832	1040	0.0557	483948.36	15.77	12.49
135			Sestriere	5165	0	1.36	70.61	5.83	668.21	0.27	5280	838.8	4015.15	1.40	0.26	0.46	75.76	45.25	1832	1040	0.0557	483948.36	15.13	4.17
136			Messina	707	260	19.13	76.38	2.83	683.39	0.69	1800	291.74	4078.26	2.76	0.41	0.57	8.27	18.91	704	1040	0.1016	165468.547	9.92	19.53
137		B	Palermo	751	309	19.01	68.46	3.73	727.99	0.69	1800	291.74	4078.26	2.76	0.41	0.57	8.91	20.03	704	1040	0.1016	165468.547	9.18	18.32
138			Crotone	899	255	18.02	64.32	4.64	685.83	0.69	1800	291.74	4078.26	2.76	0.41	0.57	8.42	19.25	704	1040	0.1016	165468.547	14.27	18.47
139	10		Cagliari	990	222	17.47	71.70	3.91	677.79	0.69	1800	291.74	4078.26	2.26	0.37	0.49	21.28	41.05	792	1040	0.1051	165468.547	7.82	26.98
140		C	Bari	1185	314	16.03	68.62	3.21	673.21	0.69	1800	291.74	4078.26	2.26	0.37	0.49	21.30	42.78	792	1040	0.1051	165468.547	11.44	24.67
141			Termoli	1350	155	15.81	70.67	3.08	582.46	0.69	1800	291.74	4078.26	2.26	0.37	0.49	17.93	38.25	792	1040	0.1051	165468.547	15.49	22.47
142		D	Genova	1435	115	16.19	68.45	3.48	565.03	0.69	1800	291.74	4078.26	1.76	0.31	0.40	19.14	33.97	960	1040	0.1290	165468.547	11.11	23.47

Scenario	Model	Climatic Zone	City	HDD	CDD	T	RH	v_s	I_h	S/V	H_s	S_w	S_{op}	U_w	U_{op}	U_o	$Q_{s,H}$	$Q_{s,C}$	h_H	h_C	C_T	Q_G	H_d	C_d
				[K day]	[K day]	[C°]	[%]	[m/s]	[W/m²]	[m⁻¹]	[m²]	[m²]	[m²]	[m²]	[W/(m²·K)]	[W/(m²·K)]	[W/(m²·K)]	[kWh/(m² year)]	[kWh/(m² year)]	[h]	[h]	[kWh/(m³·K)]	[kWh/year]	[kWh/(m² year)]
143			Firenze	1821	331	15.61	66.59	2.24	594.31	0.69	1800	291.74	4078.26	1.76	0.31	0.40	20.99	34.86	960	1040	0.1290	165468.547	12.89	25.08
144			Forlì	2087	108	14.19	70.39	1.70	537.14	0.69	1800	291.74	4078.26	1.76	0.31	0.40	16.37	32.64	960	1040	0.1290	165468.547	20.31	20.77
145			Trieste	2102	125	15.48	63.55	2.79	545.21	0.69	1800	291.74	4078.26	1.76	0.27	0.37	19.48	33.64	1056	1040	0.1074	165468.547	13.86	24.24
146		E	Torino	2617	166	12.72	68.78	1.75	534.88	0.69	1800	291.74	4078.26	1.76	0.27	0.37	21.50	31.80	1056	1040	0.1074	165468.547	20.90	16.63
147			Bolzano	2791	135	12.87	63.20	1.73	588.83	0.69	1800	291.74	4078.26	1.76	0.27	0.37	25.91	35.24	1056	1040	0.1074	165468.547	20.49	20.83
148			Cuneo	3012	80	12.71	63.90	2.11	605.80	0.69	1800	291.74	4078.26	1.40	0.25	0.33	56.14	38.50	1832	1040	0.1075	165468.547	13.10	18.87
149		F	Cortina	4433	0	6.33	69.93	0.56	530.68	0.69	1800	291.74	4078.26	1.40	0.25	0.33	54.86	34.75	1832	1040	0.1075	165468.547	33.32	6.17
150			Sestriere	5165	0	1.36	70.61	5.83	668.21	0.69	1800	291.74	4078.26	1.40	0.25	0.33	77.69	46.10	1832	1040	0.1075	165468.547	35.45	0.65
151			Messina	707	260	19.13	76.38	2.83	683.39	0.70	2700.00	254.6	5817.39	2.76	0.41	0.51	4.78	11.56	704	1040	0.1141	247754.888	10.06	16.64
152		B	Palermo	751	309	19.01	68.46	3.73	727.99	0.70	2700.00	254.6	5817.39	2.76	0.41	0.51	5.14	12.27	704	1040	0.1141	247754.888	9.47	15.48
153			Crotone	899	255	18.02	64.32	4.64	685.83	0.70	2700.00	254.6	5817.39	2.76	0.41	0.51	4.86	11.77	704	1040	0.1141	247754.888	14.24	15.66
154			Cagliari	990	222	17.47	71.70	3.91	677.79	0.70	2700.00	254.6	5817.39	2.26	0.37	0.45	12.26	25.11	792	1040	0.1180	247754.888	8.90	21.22
155		C	Bari	1185	314	16.03	68.62	3.21	673.21	0.70	2700.00	254.6	5817.39	2.26	0.37	0.45	12.22	26.11	792	1040	0.1180	247754.888	12.57	19.06
156			Termoli	1350	155	15.81	70.67	3.08	582.46	0.70	2700.00	254.6	5817.39	2.26	0.37	0.45	10.34	23.25	792	1040	0.1180	247754.888	15.93	17.55
157			Genova	1435	115	16.19	68.45	3.48	565.03	0.70	2700.00	254.6	5817.39	1.76	0.31	0.37	11.06	20.63	960	1040	0.1437	247754.888	11.34	18.24
158	11	D	Firenze	1821	331	15.61	66.59	2.24	594.31	0.70	2700.00	254.6	5817.39	1.76	0.31	0.37	12.11	21.19	960	1040	0.1437	247754.888	13.31	19.66
159			Forlì	2087	108	14.19	70.39	1.70	537.14	0.70	2700.00	254.6	5817.39	1.76	0.31	0.37	9.51	19.81	960	1040	0.1437	247754.888	19.39	16.19
160			Trieste	2102	125	15.48	63.55	2.79	545.21	0.70	2700.00	254.6	5817.39	1.76	0.27	0.33	11.27	20.40	1056	1040	0.1200	247754.888	13.49	18.95
161		E	Torino	2617	166	12.72	68.78	1.75	534.88	0.70	2700.00	254.6	5817.39	1.76	0.27	0.33	12.41	19.25	1056	1040	0.1200	247754.888	20.20	12.68
162			Bolzano	2791	135	12.87	63.20	1.73	588.83	0.70	2700.00	254.6	5817.39	1.76	0.27	0.33	14.90	21.38	1056	1040	0.1200	247754.888	20.34	16.02
163			Cuneo	3012	80	12.71	63.90	2.11	605.80	0.70	2700.00	254.6	5817.39	1.40	0.25	0.30	32.99	23.25	1832	1040	0.1201	247754.888	14.02	13.81
164		F	Cortina	4433	0	6.33	69.93	0.56	530.68	0.70	2700.00	254.6	5817.39	1.40	0.25	0.30	32.27	20.94	1832	1040	0.1201	247754.888	33.29	3.60
165			Sestriere	5165	0	1.36	70.61	5.83	668.21	0.70	2700.00	254.6	5817.39	1.40	0.25	0.30	45.65	27.88	1832	1040	0.1201	247754.888	38.40	0.02
166			Messina	707	260	19.13	76.38	2.83	683.39	0.58	2500	303.1	5496.89	2.76	0.41	0.54	6.13	14.65	704	1040	0.0870	836139.47	10.11	17.15
167		B	Palermo	751	309	19.01	68.46	3.73	727.99	0.58	2500	303.1	5496.89	2.76	0.41	0.54	6.58	15.55	704	1040	0.0870	836139.47	9.51	15.95
168			Crotone	899	255	18.02	64.32	4.64	685.83	0.58	2500	303.1	5496.89	2.76	0.41	0.54	6.23	14.92	704	1040	0.0870	836139.47	14.39	16.22
169			Cagliari	990	222	17.47	71.70	3.91	677.79	0.58	2500	303.1	5496.89	2.26	0.37	0.47	15.70	31.80	792	1040	0.0902	836139.47	9.10	22.40
170		C	Bari	1185	314	16.03	68.62	3.21	673.21	0.58	2500	303.1	5496.89	2.26	0.37	0.47	15.66	33.09	792	1040	0.0902	836139.47	12.88	20.17
171			Termoli	1350	155	15.81	70.67	3.08	582.46	0.58	2500	303.1	5496.89	2.26	0.37	0.47	13.24	29.48	792	1040	0.0902	836139.47	16.44	18.59
172	12		Genova	1435	115	16.19	68.45	3.48	565.03	0.58	2500	303.1	5496.89	1.76	0.31	0.38	14.14	26.14	960	1040	0.1108	836139.47	12.35	19.05
173		D	Firenze	1821	331	15.61	66.59	2.24	594.31	0.58	2500	303.1	5496.89	1.76	0.31	0.38	15.48	26.84	960	1040	0.1108	836139.47	14.40	20.67
174			Forlì	2087	108	14.19	70.39	1.70	537.14	0.58	2500	303.1	5496.89	1.76	0.31	0.38	12.14	25.10	960	1040	0.1108	836139.47	21.14	16.98
175			Trieste	2102	125	15.48	63.55	2.79	545.21	0.58	2500	303.1	5496.89	1.76	0.27	0.35	14.40	25.85	1056	1040	0.0919	836139.47	15.08	19.90
176		E	Torino	2617	166	12.72	68.78	1.75	534.88	0.58	2500	303.1	5496.89	1.76	0.27	0.35	15.87	24.40	1056	1040	0.0919	836139.47	22.41	13.15
177			Bolzano	2791	135	12.87	63.20	1.73	588.83	0.58	2500	303.1	5496.89	1.76	0.27	0.35	19.06	27.09	1056	1040	0.0919	836139.47	22.32	16.77
178			Cuneo	3012	80	12.71	63.90	2.11	605.80	0.58	2500	303.1	5496.89	1.40	0.25	0.31	42.18	29.58	1832	1040	0.0920	836139.47	15.61	14.44
179		F	Cortina	4433	0	6.33	69.93	0.56	530.68	0.58	2500	303.1	5496.89	1.40	0.25	0.31	41.25	26.65	1832	1040	0.0920	836139.47	36.92	3.60

Scenario	Model	Climatic Zone	City	HDD	CDD	T	RH	v_s	I_h	S/V	H_s	S_w	S_{op}	U_w	U_{op}	U_o	$Q_{s,H}$	$Q_{s,C}$	h_H	h_C	C_T	Q_G	H_d	C_d
				[K day]	[K day]	[C°]	[%]	[m/s]	[W/m ²]	[m ⁻¹]	[m ²]	[m ²]	[m ²]	[W/(m ² ·K)]	[W/(m ² ·K)]	[W/(m ² ·K)]	[kWh/(m ² year)]	[kWh/(m ² year)]	[h]	[h]	[kWh/(m ³ ·K)]	[kWh/year]	[kWh/(m ² year)]	[kWh/(m ² year)]
180			Sestriere	5165	0	1.36	70.61	5.83	668.21	0.58	2500	303.1	5496.89	1.40	0.25	0.31	58.37	35.46	1832	1040	0.0920	836139.47	42.38	0.02
181			Messina	707	260	19.13	76.38	2.83	683.39	0.56	5000	454.66	10745.34	2.76	0.41	0.51	4.64	10.84	704	1040	0.0860	459580.17	9.90	15.15
182		B	Palermo	751	309	19.01	68.46	3.73	727.99	0.56	5000	454.66	10745.34	2.76	0.41	0.51	4.99	11.50	704	1040	0.0860	459580.17	9.37	13.97
183			Crotone	899	255	18.02	64.32	4.64	685.83	0.56	5000	454.66	10745.34	2.76	0.41	0.51	4.72	11.04	704	1040	0.0860	459580.17	13.98	14.28
184			Cagliari	990	222	17.47	71.70	3.91	677.79	0.56	5000	454.66	10745.34	2.26	0.37	0.44	11.93	23.56	792	1040	0.0892	459580.17	9.48	18.71
185		C	Bari	1185	314	16.03	68.62	3.21	673.21	0.56	5000	454.66	10745.34	2.26	0.37	0.44	11.92	24.53	792	1040	0.0892	459580.17	13.17	16.66
186			Termoli	1350	155	15.81	70.67	3.08	582.46	0.56	5000	454.66	10745.34	2.26	0.37	0.44	10.05	21.89	792	1040	0.0892	459580.17	16.34	15.53
187			Genova	1435	115	16.19	68.45	3.48	565.03	0.56	5000	454.66	10745.34	1.76	0.31	0.36	10.75	19.45	960	1040	0.1097	459580.17	12.37	15.88
188	13	D	Firenze	1821	331	15.61	66.59	2.24	594.31	0.56	5000	454.66	10745.34	1.76	0.31	0.36	11.78	19.96	960	1040	0.1097	459580.17	14.44	17.37
189			Forlì	2087	108	14.19	70.39	1.70	537.14	0.56	5000	454.66	10745.34	1.76	0.31	0.36	9.21	18.68	960	1040	0.1097	459580.17	20.60	14.24
190			Trieste	2102	125	15.48	63.55	2.79	545.21	0.56	5000	454.66	10745.34	1.76	0.27	0.33	10.94	19.25	1056	1040	0.0908	459580.17	14.85	16.73
191		E	Torino	2617	166	12.72	68.78	1.75	534.88	0.56	5000	454.66	10745.34	1.76	0.27	0.33	12.06	18.18	1056	1040	0.0908	459580.17	21.98	10.75
192			Bolzano	2791	135	12.87	63.20	1.73	588.83	0.56	5000	454.66	10745.34	1.76	0.27	0.33	14.52	20.17	1056	1040	0.0908	459580.17	22.08	13.84
193			Cuneo	3012	80	12.71	63.90	2.11	605.80	0.56	5000	454.66	10745.34	1.40	0.25	0.30	31.69	21.96	1832	1040	0.0909	459580.17	16.10	11.44
194		F	Cortina	4433	0	6.33	69.93	0.56	530.68	0.56	5000	454.66	10745.34	1.40	0.25	0.30	30.98	19.81	1832	1040	0.0909	459580.17	37.13	2.20
195			Sestriere	5165	0	1.36	70.61	5.83	668.21	0.56	5000	454.66	10745.34	1.40	0.25	0.30	43.85	26.31	1832	1040	0.0909	459580.17	44.58	0.00

ANNEX 4

Correlation H_d versus 412/93 DPR HDD

Table 4.1

Correlation H_d versus HDD for climatic zone B.

Climatic Zone B	City	Messina	Palermo	Crotone	H_d equation form	R ²
	HDD DPR 412/93	707	751	899		
	Case Study	H_d [kWh/(m ² year)]				
	1	1.60	1.42	4.16	$H_d = 0.0146 HDD - 9.1092$	0.925
	2	11.66	11.04	16.27	$H_d = 0.0269 HDD - 8.1140$	0.896
	3	10.83	9.78	15.73	$H_d = 0.0292 HDD - 10.864$	0.858
	4	3.49	2.98	7.00	$H_d = 0.0205 HDD - 11.632$	0.891
	5	12.43	11.37	18.02	$H_d = 0.0331 HDD - 12.090$	0.869
	6	8.80	8.13	12.74	$H_d = 0.0232 HDD - 8.3353$	0.879
	7	4.68	4.01	8.57	$H_d = 0.0229 HDD - 12.266$	0.878
	8	6.06	5.35	10.35	$H_d = 0.0253 HDD - 12.603$	0.881
	9	1.75	1.53	4.30	$H_d = 0.0147 HDD - 8.9802$	0.917
	10	9.92	9.18	14.27	$H_d = 0.0256 HDD - 9.0186$	0.879
	11	10.06	9.47	14.24	$H_d = 0.0245 HDD - 7.9533$	0.894
	12	10.11	9.51	14.39	$H_d = 0.0250 HDD - 8.2861$	0.892
	13	9.90	9.37	13.98	$H_d = 0.0238 HDD - 7.5828$	0.898

Table 4.2

Correlation H_d versus HDD for climatic zone C.

Climatic Zone C	City	Cagliari	Bari	Termoli	H_d equation form	R ²
	<i>HDD</i> DPR 412/93	990	1185	1350		
	Case Study	H_d [kWh/(m ² year)]				
	1	0.70	1.97	4.35	$H_d = 0.0100 HDD - 9.4443$	0.951
	2	11.16	15.35	18.93	$H_d = 0.0216 HDD - 10.195$	1.000
	3	6.95	10.54	15.83	$H_d = 0.0245 HDD - 17.646$	0.975
	4	1.36	3.05	6.48	$H_d = 0.0141 HDD - 12.897$	0.943
	5	8.93	13.33	19.01	$H_d = 0.0278 HDD - 18.961$	0.985
	6	6.99	10.12	13.78	$H_d = 0.0188 HDD - 11.742$	0.991
	7	2.01	4.03	8.01	$H_d = 0.0165 HDD - 14.674$	0.945
	8	4.00	7.14	11.15	$H_d = 0.0198 HDD - 15.788$	0.986
	9	0.69	1.85	4.28	$H_d = 0.0098 HDD - 9.3020$	0.939
	10	7.82	11.44	15.49	$H_d = 0.0212 HDD - 13.360$	0.994
	11	8.90	12.57	15.93	$H_d = 0.0195 HDD - 10.456$	1.000
	12	9.10	12.88	16.44	$H_d = 0.0204 HDD - 11.107$	0.999
	13	9.48	13.17	16.34	$H_d = 0.0191 HDD - 9.4003$	1.000

Table 4.3

Correlation H_d versus HDD for climatic zone D.

Climatic Zone D	City	Genova	Firenze	Forli	H_d equation form	R ²
	<i>HDD</i> DPR 412/93	1435	1821	2087		
	Case Study	H_d [kWh/(m ² year)]				
	1	2.42	2.90	7.48	$H_d = 0.0073 HDD - 8.7064$	0.733
	2	14.76	17.06	24.02	$H_d = 0.0136 HDD - 5.6402$	0.857
	3	11.14	12.48	22.29	$H_d = 0.0161 HDD - 13.397$	0.754
	4	4.01	4.33	11.07	$H_d = 0.0101 HDD - 11.547$	0.691
	5	14.23	16.19	26.88	$H_d = 0.0184 HDD - 13.623$	0.783
	6	9.62	11.20	17.88	$H_d = 0.0121 HDD - 8.5819$	0.812
	7	5.12	5.56	13.29	$H_d = 0.0117 HDD - 12.887$	0.698
	8	7.67	9.03	16.52	$H_d = 0.0128 HDD - 11.802$	0.781
	9	2.35	2.71	7.54	$H_d = 0.0075 HDD - 9.0765$	0.711
	10	11.11	12.89	20.31	$H_d = 0.0134 HDD - 9.1357$	0.814
	11	11.34	13.30	19.38	$H_d = 0.0118 HDD - 6.3819$	0.853
	12	12.35	14.39	21.14	$H_d = 0.0129 HDD - 7.0055$	0.844
	13	12.36	14.44	20.60	$H_d = 0.0121 HDD - 5.7605$	0.859

Table 4.4

Correlation H_d versus HDD for climatic zone E.

Climatic Zone E	City	Trieste	Torino	Bolzano	H_d equation form	R ²
	<i>HDD</i> DPR 412/93	2102	2617	2791		
	Case Study	H_d [kWh/(m ² year)]				
1	4.10	8.52	8.53	$H_d = 0.0069 HDD - 10.279$	0.942	
2	17.71	25.74	25.71	$H_d = 0.0125 HDD - 8.2802$	0.940	
3	14.52	22.05	20.86	$H_d = 0.0104 HDD - 6.9713$	0.853	
4	6.30	11.84	11.35	$H_d = 0.0081 HDD - 10.485$	0.898	
5	18.42	27.53	26.39	$H_d = 0.0130 HDD - 8.3171$	0.876	
6	11.94	18.38	18.15	$H_d = 0.0098 HDD - 8.4249$	0.925	
7	7.74	13.79	13.07	$H_d = 0.0087 HDD - 10.127$	0.879	
8	10.64	17.70	17.53	$H_d = 0.0108 HDD - 11.857$	0.931	
9	4.09	8.47	8.30	$H_d = 0.0067 HDD - 9.7049$	0.924	
10	13.85	20.90	20.48	$H_d = 0.0105 HDD - 7.9942$	0.914	
11	13.48	20.20	20.33	$H_d = 0.0106 HDD - 8.6540$	0.949	
12	15.07	22.41	22.32	$H_d = 0.0114 HDD - 8.5148$	0.936	
13	14.85	21.98	22.08	$H_d = 0.0113 HDD - 8.5729$	0.947	

Table 4.5

Correlation H_d versus HDD for climatic zone F.

Climatic Zone F	City	Cuneo	Cortina	Sestriere	H_d equation form	R ²
	<i>HDD</i> DPR 412/93	3012	4433	5165		
	Case Study	H_d [kWh/(m ² year)]				
1	3.64	16.43	16.97	$H_d = 0.0066 HDD - 15.291$	0.910	
2	19.21	43.24	50.37	$H_d = 0.0148 HDD - 24.610$	0.986	
3	11.20	32.43	29.42	$H_d = 0.0093 HDD - 14.916$	0.793	
4	4.31	19.55	16.96	$H_d = 0.0065 HDD - 13.855$	0.770	
5	15.92	41.52	40.18	$H_d = 0.0122 HDD - 18.685$	0.857	
6	11.19	29.19	30.61	$H_d = 0.0095 HDD - 16.326$	0.926	
7	5.26	22.10	19.01	$H_d = 0.0071 HDD - 14.512$	0.758	
8	10.19	30.28	31.90	$H_d = 0.0106 HDD - 20.578$	0.927	
9	3.11	15.76	15.13	$H_d = 0.0060 HDD - 14.039$	0.859	
10	13.10	33.32	35.06	$H_d = 0.0107 HDD - 18.024$	0.929	
11	14.02	33.28	37.92	$H_d = 0.0114 HDD - 19.657$	0.976	
12	15.61	36.92	41.56	$H_d = 0.0125 HDD - 20.980$	0.971	
13	16.10	37.11	43.40	$H_d = 0.0130 HDD - 22.284$	0.986	

ANNEX 5

Correlation H_d versus *TMY-HDD*

Table 5.1

Correlation H_d versus *HDD* for climatic zone B.

Climatic Zone B	City	Palermo	Messina	Bari	H_d equation form	R ²
	<i>HDD</i> Weather data	656	673	764		
	H_d [kWh/(m ² year)]					
1	1.42	1.60	7.00	$H_d = 0.1209 HDD - 68.384$	0.995	
2	11.04	11.66	20.68	$H_d = 0.0925 HDD - 50.083$	0.992	
3	9.78	10.83	21.18	$H_d = 0.1083 HDD - 61.620$	0.996	
4	2.98	3.49	10.88	$H_d = 0.0758 HDD - 47.103$	0.992	
5	11.37	12.43	24.05	$H_d = 0.1209 HDD - 68.384$	0.995	
6	8.13	8.80	16.82	$H_d = 0.0830 HDD - 46.638$	0.994	
7	4.01	4.68	12.88	$H_d = 0.0848 HDD - 51.950$	0.994	
8	5.35	6.06	14.75	$H_d = 0.0898 HDD - 53.965$	0.994	
9	1.53	1.75	7.21	$H_d = 0.0550 HDD - 34.853$	0.987	
10	9.18	9.92	18.72	$H_d = 0.0911 HDD - 50.983$	0.994	
11	9.47	10.06	18.32	$H_d = 0.0848 HDD - 46.581$	0.992	
12	9.51	10.11	18.61	$H_d = 0.0873 HDD - 48.153$	0.992	
13	9.37	9.90	17.92	$H_d = 0.0821 HDD - 44.892$	0.992	

Table 5.2

Correlation H_d versus HDD for climatic zone C.

Climatic Zone C	City	Crotone	Cagliari	Termoli	H_d equation form	R ²
	HDD Weather data	1012	1024	1370		
	Case Study	H_d [kWh/(m ² year)]				
1	0.70	0.70	4.35	$H_d = 0.0104 HDD - 9.8704$	0.999	
2	11.06	11.16	18.93	$H_d = 0.0222 HDD - 11.502$	1	
3	6.85	6.95	15.83	$H_d = 0.0254 HDD - 18.923$	1	
4	1.31	1.36	6.48	$H_d = 0.0146 HDD - 13.553$	1	
5	8.79	8.93	19.01	$H_d = 0.0289 HDD - 20.510$	1	
6	6.81	6.99	13.78	$H_d = 0.0196 HDD - 13.004$	1	
7	1.97	2.01	8.01	$H_d = 0.0171 HDD - 15.434$	1	
8	4.12	4.00	11.15	$H_d = 0.0201 HDD - 16.445$	0.998	
9	0.66	0.69	4.28	$H_d = 0.0102 HDD - 9.7363$	0.999	
10	7.77	7.82	15.49	$H_d = 0.0219 HDD - 14.467$	0.999	
11	8.85	8.90	15.93	$H_d = 0.0200 HDD - 11.518$	0.999	
12	9.03	9.10	16.44	$H_d = 0.0210 HDD - 12.266$	1	
13	9.40	9.48	16.34	$H_d = 0.0196 HDD - 10.530$	1	

Table 5.3

Correlation H_d versus HDD for climatic zone D.

Climatic Zone D	City	Genova	Firenze	Forli	H_d equation form	R ²
	HDD Weather data	1417	1598	1953		
	Case Study	H_d [kWh/(m ² year)]				
1	2.42	2.90	7.48	$H_d = 0.0099 HDD - 12.138$	0.938	
2	14.76	17.06	24.02	$H_d = 0.0176 HDD - 10.540$	0.991	
3	11.14	12.48	22.29	$H_d = 0.0217 HDD - 20.695$	0.949	
4	4.01	4.33	11.07	$H_d = 0.0140 HDD - 16.688$	0.914	
5	14.23	16.19	26.88	$H_d = 0.0245 HDD - 21.471$	0.963	
6	9.62	11.20	17.88	$H_d = 0.0159 HDD - 13.418$	0.976	
7	5.12	5.56	13.29	$H_d = 0.0162 HDD - 18.769$	0.918	
8	7.67	9.03	16.52	$H_d = 0.0171 HDD - 17.309$	0.962	
9	2.35	2.71	7.54	$H_d = 0.0102 HDD - 12.734$	0.925	
10	11.11	12.89	20.31	$H_d = 0.0177 HDD - 14.499$	0.976	
11	11.34	13.30	19.38	$H_d = 0.0153 HDD - 10.676$	0.990	
12	12.35	14.39	21.14	$H_d = 0.0168 HDD - 11.797$	0.987	
13	12.36	14.44	20.60	$H_d = 0.0156 HDD - 10.085$	0.991	

Table 5.4Correlation H_d versus HDD for climatic zone E.

Climatic Zone E	City	Torino	Cuneo	Bolzano	H_d equation form	R^2
	<i>HDD</i> Weather data	2386	2213	2384		
	Case Study	H_d [kWh/(m ² year)]				
1	8.52	5.14	8.53	$H_d = 0.0197 HDD - 38.453$	1	
2	25.74	21.69	25.71	$H_d = 0.0234 HDD - 30.172$	1	
3	22.05	15.33	20.86	$H_d = 0.0356 HDD - 63.545$	0.975	
4	11.84	6.78	11.35	$H_d = 0.0280 HDD - 55.298$	0.994	
5	27.53	20.36	26.39	$H_d = 0.0384 HDD - 64.712$	0.981	
6	18.38	14.03	18.15	$H_d = 0.0247 HDD - 40.586$	0.999	
7	13.79	8.14	13.07	$H_d = 0.0308 HDD - 60.080$	0.988	
8	17.70	12.81	17.53	$H_d = 0.0279 HDD - 48.964$	1	
9	8.47	4.73	8.30	$H_d = 0.0212 HDD - 42.288$	0.999	
10	20.90	16.11	20.48	$H_d = 0.0267 HDD - 42.902$	0.995	
11	20.20	16.57	20.33	$H_d = 0.0215 HDD - 30.979$	0.998	
12	22.41	18.28	22.32	$H_d = 0.0237 HDD - 34.207$	1	
13	21.98	18.40	22.08	$H_d = 0.0211 HDD - 28.290$	0.999	

Table 5.5Correlation H_d versus HDD for climatic zone F.

Climatic Zone F	City	Cortina	Stelvio	Sestriere	H_d equation form	R^2
	<i>HDD</i> Weather data	4473	6339	6804		
	Case Study	H_d [kWh/(m ² year)]				
1	16.43	17.86	16.97	No reliable correlation	-	
2	43.27	50.32	52.08	$H_d = 0.0038 HDD + 26.364$	1	
3	32.43	32.67	29.60	No reliable correlation	-	
4	19.55	19.27	16.96	No reliable correlation	-	
5	41.52	43.24	40.37	No reliable correlation	-	
6	29.36	31.74	30.75	$H_d = 0.0008 HDD + 25.983$	0.667	
7	22.10	21.77	19.01	No reliable correlation	-	
8	30.28	33.11	31.99	$H_d = 0.001 HDD + 26.164$	0.687	
9	15.76	16.40	15.13	No reliable correlation	-	
10	33.32	36.26	35.44	$H_d = 0.0011 HDD + 28.543$	0.799	
11	33.28	37.96	38.40	$H_d = 0.0023 HDD + 23.127$	0.987	
12	36.92	41.85	42.38	$H_d = 0.0024 HDD + 26.122$	0.990	
13	37.12	43.22	44.58	$H_d = 0.0032 HDD + 22.72$	1	

ANNEX 6

Correlation H_d versus HDD value dictated by UNI 10349-3:2016 and HDD value calculated using the weather data and considering the heating period dictated by the same technical standard

Table 6.1

Correlation H_d versus HDD dictated by the technical standard UNI 10349-3:2016.

Climatic Zone E	City	Torino	Cuneo	Bolzano	H_d equation form	R^2
	HDD UNI 2016	2648	2919	2346		
	Case Study	H_d [kWh/(m ² year)]				
	1	8.52	5.14	8.53	$H_d = -0.0058 HDD + 22.722$	0.725
	2	25.74	21.69	25.71	$H_d = -0.0069 HDD + 42.521$	0.717
	3	22.05	15.33	20.86	$H_d = -0.0094 HDD + 44.152$	0.563
	4	11.84	6.78	11.35	$H_d = -0.0078 HDD + 30.568$	0.641
	5	27.53	20.36	26.39	$H_d = -0.0103 HDD + 51.803$	0.582
	6	18.38	14.03	18.15	$H_d = -0.0071 HDD + 35.450$	0.679
	7	13.79	8.14	13.07	$H_d = -0.0084 HDD + 33.816$	0.611
	8	17.70	12.81	17.53	$H_d = -0.0081 HDD + 37.299$	0.696
	9	8.47	4.73	8.30	$H_d = -0.0061 HDD + 23.254$	0.686
	10	20.90	16.11	20.48	$H_d = -0.0075 HDD + 38.860$	0.650
11	20.20	16.57	20.33	$H_d = -0.0065 HDD + 36.063$	0.751	
12	22.41	18.28	22.32	$H_d = -0.0069 HDD + 39.204$	0.705	
13	21.98	18.40	22.08	$H_d = -0.0063 HDD + 37.463$	0.744	

Table 6.2

Correlation H_d versus HDD calculated using the weather data and considering a heating period from 15 October to 14 April.

Climatic Zone E	City	Torino	Cuneo	Bolzano	H_d equation form	R^2
	<i>HDD</i> Weather data	2483	2347	2559		
	Case Study	H_d [kWh/(m ² year)]				
1	8.52	5.14	8.53	$H_d = 0.0171 HDD - 34.608$	0.877	
2	25.74	21.69	25.71	$H_d = 0.0202 HDD - 25.435$	0.871	
3	22.05	15.33	20.86	$H_d = 0.0288 HDD - 51.520$	0.745	
4	11.84	6.78	11.35	$H_d = 0.0234 HDD - 47.709$	0.811	
5	27.53	20.36	26.39	$H_d = 0.0313 HDD - 52.366$	0.761	
6	18.38	14.03	18.15	$H_d = 0.0209 HDD - 34.742$	0.842	
7	13.79	8.14	13.07	$H_d = 0.0254 HDD - 50.960$	0.787	
8	17.70	12.81	17.53	$H_d = 0.0239 HDD - 42.772$	0.855	
9	8.47	4.73	8.30	$H_d = 0.0181 HDD - 37.381$	0.847	
10	20.90	16.11	20.48	$H_d = 0.0224 HDD - 35.916$	0.819	
11	20.20	16.57	20.33	$H_d = 0.0188 HDD - 27.310$	0.895	
12	22.41	18.28	22.32	$H_d = 0.0204 HDD - 29.144$	0.862	
13	21.98	18.40	22.08	$H_d = 0.0184 HDD - 24.546$	0.890	

ANNEX 7

Building Environmental Database of Italian context: 13 Building Models, 780 scenarios

Model	Climatic Zone	City	Energy Carrier	External plaster	Cement lime plaster	Rock wool	Tuff block	Internal plaster 1	Concrete brick	Concrete screed	Concrete slab	Internal plaster 2	Floor tile	Bitumen	Brick	GWP	ODP	AP	EP	POCP	ADP-fossil
				[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg CO ₂ -eq]	[kg CFC11-eq]	[kg SO ₂ -eq]
1	B	Messina	Electricity	48371.4	36278.6	16842.8	604642.6	22842.1	128914.8	868148.2	2051549.8	376277.8	74022.7	211493.3	446549.1	9.76E+05	7.70E-02	3.37E+03	9.36E+02	2.55E+02	9.93E+06
			Natural Gas	48371.4	36278.6	16842.8	604642.6	22842.1	128914.8	868148.2	2051549.8	376277.8	74022.7	211493.3	446549.1	7.74E+05	6.31E-02	2.29E+03	6.20E+02	2.22E+02	9.53E+06
			LPG	48371.4	36278.6	16842.8	604642.6	22842.1	128914.8	868148.2	2051549.8	376277.8	74022.7	211493.3	446549.1	7.60E+05	6.25E-02	2.32E+03	6.26E+02	2.16E+02	8.26E+06
			Biogas	48371.4	36278.6	16842.8	604642.6	22842.1	128914.8	868148.2	2051549.8	376277.8	74022.7	211493.3	446549.1	7.87E+05	5.17E-02	3.40E+03	1.11E+03	2.22E+02	7.52E+06
		Palermo	Electricity	48371.4	36278.6	16842.8	604642.6	22842.1	128914.8	868148.2	2051549.8	376277.8	74022.7	211493.3	446549.1	9.50E+05	7.40E-02	3.24E+03	9.00E+02	2.50E+02	9.63E+06
			Natural Gas	48371.4	36278.6	16842.8	604642.6	22842.1	128914.8	868148.2	2051549.8	376277.8	74022.7	211493.3	446549.1	7.71E+05	6.16E-02	2.28E+03	6.19E+02	2.20E+02	9.28E+06
			LPG	48371.4	36278.6	16842.8	604642.6	22842.1	128914.8	868148.2	2051549.8	376277.8	74022.7	211493.3	446549.1	7.58E+05	6.10E-02	2.30E+03	6.24E+02	2.15E+02	8.14E+06
			Biogas	48371.4	36278.6	16842.8	604642.6	22842.1	128914.8	868148.2	2051549.8	376277.8	74022.7	211493.3	446549.1	7.82E+05	5.14E-02	3.27E+03	1.06E+03	2.20E+02	7.48E+06
		Crotone	Electricity	48371.4	36278.6	16842.8	604642.6	22842.1	128914.8	868148.2	2051549.8	376277.8	74022.7	211493.3	446549.1	1.35E+06	1.21E-01	5.26E+03	1.46E+03	3.33E+02	1.43E+07
			Natural Gas	48371.4	36278.6	16842.8	604642.6	22842.1	128914.8	868148.2	2051549.8	376277.8	74022.7	211493.3	446549.1	8.26E+05	8.52E-02	2.47E+03	6.38E+02	2.47E+02	1.33E+07
			LPG	48371.4	36278.6	16842.8	604642.6	22842.1	128914.8	868148.2	2051549.8	376277.8	74022.7	211493.3	446549.1	7.89E+05	8.35E-02	2.54E+03	6.54E+02	2.31E+02	9.94E+06
			Biogas	48371.4	36278.6	16842.8	604642.6	22842.1	128914.8	868148.2	2051549.8	376277.8	74022.7	211493.3	446549.1	8.58E+05	5.54E-02	5.35E+03	1.92E+03	2.47E+02	8.01E+06
	C	Cagliari	Electricity	48159.4	36119.5	20112.7	601992.3	22741.9	257593.4	970713.0	2049895.9	376202.2	74022.7	211493.3	446549.1	8.67E+05	6.15E-02	2.74E+03	7.40E+02	2.34E+02	8.54E+06
			Natural Gas	48159.4	36119.5	20112.7	601992.3	22741.9	257593.4	970713.0	2049895.9	376202.2	74022.7	211493.3	446549.1	7.78E+05	5.54E-02	2.27E+03	6.01E+02	2.19E+02	8.36E+06
			LPG	48159.4	36119.5	20112.7	601992.3	22741.9	257593.4	970713.0	2049895.9	376202.2	74022.7	211493.3	446549.1	7.72E+05	5.51E-02	2.28E+03	6.04E+02	2.16E+02	7.80E+06
			Biogas	48159.4	36119.5	20112.7	601992.3	22741.9	257593.4	970713.0	2049895.9	376202.2	74022.7	211493.3	446549.1	7.84E+05	5.04E-02	2.75E+03	8.18E+02	2.19E+02	7.48E+06
		Bari	Electricity	48159.4	36119.5	20112.7	601992.3	22741.9	257593.4	970713.0	2049895.9	376202.2	74022.7	211493.3	446549.1	1.05E+06	8.33E-02	3.67E+03	9.98E+02	2.72E+02	1.07E+07
			Natural Gas	48159.4	36119.5	20112.7	601992.3	22741.9	257593.4	970713.0	2049895.9	376202.2	74022.7	211493.3	446549.1	8.04E+05	6.63E-02	2.35E+03	6.10E+02	2.32E+02	1.02E+07
			LPG	48159.4	36119.5	20112.7	601992.3	22741.9	257593.4	970713.0	2049895.9	376202.2	74022.7	211493.3	446549.1	7.87E+05	6.55E-02	2.39E+03	6.18E+02	2.24E+02	8.63E+06
			Biogas	48159.4	36119.5	20112.7	601992.3	22741.9	257593.4	970713.0	2049895.9	376202.2	74022.7	211493.3	446549.1	8.19E+05	5.22E-02	3.72E+03	1.22E+03	2.32E+02	7.72E+06
Termoli		Electricity	48159.4	36119.5	20112.7	601992.3	22741.9	257593.4	970713.0	2049895.9	376202.2	74022.7	211493.3	446549.1	1.40E+06	1.25E-01	5.44E+03	1.49E+03	3.45E+02	1.47E+07	
		Natural Gas	48159.4	36119.5	20112.7	601992.3	22741.9	257593.4	970713.0	2049895.9	376202.2	74022.7	211493.3	446549.1	8.53E+05	8.69E-02	2.52E+03	6.27E+02	2.55E+02	1.37E+07	
		LPG	48159.4	36119.5	20112.7	601992.3	22741.9	257593.4	970713.0	2049895.9	376202.2	74022.7	211493.3	446549.1	8.14E+05	8.51E-02	2.59E+03	6.44E+02	2.38E+02	1.02E+07	
		Biogas	48159.4	36119.5	20112.7	601992.3	22741.9	257593.4	970713.0	2049895.9	376202.2	74022.7	211493.3	446549.1	8.86E+05	5.57E-02	5.53E+03	1.97E+03	2.55E+02	8.18E+06	
D	Genova	Electricity	48159.4	48159.4	25632.2	702324.4	22741.9	128284.8	1349755.7	2484681.6	375874.6	74022.7	105746.6	446549.1	1.22E+06	9.30E-02	4.31E+03	1.17E+03	2.94E+02	1.21E+07	
		Natural Gas	48159.4	48159.4	25632.2	702324.4	22741.9	128284.8	1349755.7	2484681.6	375874.6	74022.7	105746.6	446549.1	9.16E+05	7.20E-02	2.68E+03	6.92E+02	2.44E+02	1.15E+07	
		LPG	48159.4	48159.4	25632.2	702324.4	22741.9	128284.8	1349755.7	2484681.6	375874.6	74022.7	105746.6	446549.1	8.94E+05	7.10E-02	2.72E+03	7.02E+02	2.34E+02	9.54E+06	
		Biogas	48159.4	48159.4	25632.2	702324.4	22741.9	128284.8	1349755.7	2484681.6	375874.6	74022.7	105746.6	446549.1	9.34E+05	5.46E-02	4.36E+03	1.44E+03	2.44E+02	8.42E+06	
	Firenze	Electricity	48159.4	48159.4	25632.2	702324.4	22741.9	128284.8	1349755.7	2484681.6	375874.6	74022.7	105746.6	446549.1	1.29E+06	1.01E-01	4.67E+03	1.27E+03	3.09E+02	1.29E+07	
		Natural Gas	48159.4	48159.4	25632.2	702324.4	22741.9	128284.8	1349755.7	2484681.6	375874.6	74022.7	105746.6	446549.1	9.25E+05	7.61E-02	2.72E+03	6.95E+02	2.48E+02	1.22E+07	

Model	Climatic Zone	City	Energy Carrier	External plaster	Cement lime plaster	Rock wool	Tuff block	Internal plaster 1	Concrete brick	Concrete screed	Concrete slab	Internal plaster 2	Floor tile	Bitumen	Brick	GWP	ODP	AP	EP	POCP	ADP-fossil	
				[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg CO ₂ -eq]	[kg CFC11-eq]	[kg SO ₂ -eq]	[kg PO ₄₃ -eq]
2	B	E	Forlì	LPG	48159.4	48159.4	25632.2	702324.4	22741.9	128284.8	1349755.7	2484681.6	375874.6	74022.7	105746.6	446549.1	8.99E+05	7.50E-02	2.77E+03	7.07E+02	2.37E+02	9.86E+06
				Biogas	48159.4	48159.4	25632.2	702324.4	22741.9	128284.8	1349755.7	2484681.6	375874.6	74022.7	105746.6	446549.1	9.48E+05	5.53E-02	4.73E+03	1.59E+03	2.48E+02	8.51E+06
			Trieste	Electricity	48159.4	48159.4	25632.2	702324.4	22741.9	128284.8	1349755.7	2484681.6	375874.6	74022.7	105746.6	446549.1	1.96E+06	1.80E-01	8.05E+03	2.21E+03	4.48E+02	2.07E+07
				Natural Gas	48159.4	48159.4	25632.2	702324.4	22741.9	128284.8	1349755.7	2484681.6	375874.6	74022.7	105746.6	446549.1	1.02E+06	1.16E-01	3.03E+03	7.27E+02	2.93E+02	1.88E+07
				LPG	48159.4	48159.4	25632.2	702324.4	22741.9	128284.8	1349755.7	2484681.6	375874.6	74022.7	105746.6	446549.1	9.51E+05	1.13E-01	3.16E+03	7.57E+02	2.63E+02	1.29E+07
				Biogas	48159.4	48159.4	25632.2	702324.4	22741.9	128284.8	1349755.7	2484681.6	375874.6	74022.7	105746.6	446549.1	1.08E+06	6.20E-02	8.21E+03	3.03E+03	2.93E+02	9.40E+06
			Torino	Electricity	48189.7	48189.7	29345.3	702766.1	22756.2	128166.6	1172755.2	1928950.6	375799.0	74022.7	105746.6	446549.1	1.39E+06	1.22E-01	5.41E+03	1.48E+03	3.42E+02	1.46E+07
				Natural Gas	48189.7	48189.7	29345.3	702766.1	22756.2	128166.6	1172755.2	1928950.6	375799.0	74022.7	105746.6	446549.1	8.73E+05	8.60E-02	2.66E+03	6.67E+02	2.57E+02	1.36E+07
		LPG		48189.7	48189.7	29345.3	702766.1	22756.2	128166.6	1172755.2	1928950.6	375799.0	74022.7	105746.6	446549.1	8.36E+05	8.43E-02	2.73E+03	6.83E+02	2.41E+02	1.03E+07	
		Biogas		48189.7	48189.7	29345.3	702766.1	22756.2	128166.6	1172755.2	1928950.6	375799.0	74022.7	105746.6	446549.1	9.04E+05	5.66E-02	5.50E+03	1.93E+03	2.57E+02	8.40E+06	
		Bolzano	Electricity	48189.7	48189.7	29345.3	702766.1	22756.2	128166.6	1172755.2	1928950.6	375799.0	74022.7	105746.6	446549.1	2.04E+06	1.98E-01	8.68E+03	2.38E+03	4.77E+02	2.21E+07	
			Natural Gas	48189.7	48189.7	29345.3	702766.1	22756.2	128166.6	1172755.2	1928950.6	375799.0	74022.7	105746.6	446549.1	9.63E+05	1.24E-01	2.96E+03	6.98E+02	3.00E+02	2.00E+07	
			LPG	48189.7	48189.7	29345.3	702766.1	22756.2	128166.6	1172755.2	1928950.6	375799.0	74022.7	105746.6	446549.1	8.86E+05	1.21E-01	3.11E+03	7.32E+02	2.66E+02	1.32E+07	
			Biogas	48189.7	48189.7	29345.3	702766.1	22756.2	128166.6	1172755.2	1928950.6	375799.0	74022.7	105746.6	446549.1	1.03E+06	6.30E-02	8.86E+03	3.33E+03	3.00E+02	9.25E+06	
		F	Cuneo	Electricity	48189.7	48189.7	29345.3	702766.1	22756.2	128166.6	1172755.2	1928950.6	375799.0	74022.7	105746.6	446549.1	2.04E+06	1.98E-01	8.69E+03	2.38E+03	4.77E+02	2.21E+07
				Natural Gas	48189.7	48189.7	29345.3	702766.1	22756.2	128166.6	1172755.2	1928950.6	375799.0	74022.7	105746.6	446549.1	9.63E+05	1.24E-01	2.97E+03	6.98E+02	3.00E+02	2.00E+07
				LPG	48189.7	48189.7	29345.3	702766.1	22756.2	128166.6	1172755.2	1928950.6	375799.0	74022.7	105746.6	446549.1	8.86E+05	1.21E-01	3.11E+03	7.32E+02	2.66E+02	1.32E+07
				Biogas	48189.7	48189.7	29345.3	702766.1	22756.2	128166.6	1172755.2	1928950.6	375799.0	74022.7	105746.6	446549.1	1.03E+06	6.30E-02	8.87E+03	3.33E+03	3.00E+02	9.25E+06
			Cortina	Electricity	48129.1	48129.1	31795.8	701882.7	22727.6	128087.9	1172251.2	1928068.5	375748.6	74022.7	105746.6	446549.1	3.20E+06	3.35E-01	1.45E+04	3.99E+03	7.16E+02	3.55E+07
				Natural Gas	48129.1	48129.1	31795.8	701882.7	22727.6	128087.9	1172251.2	1928068.5	375748.6	74022.7	105746.6	446549.1	1.12E+06	1.92E-01	3.50E+03	7.42E+02	3.75E+02	3.15E+07
LPG	48129.1			48129.1	31795.8	701882.7	22727.6	128087.9	1172251.2	1928068.5	375748.6	74022.7	105746.6	446549.1	9.75E+05	1.85E-01	3.78E+03	8.07E+02	3.10E+02	1.84E+07		
Biogas	48129.1			48129.1	31795.8	701882.7	22727.6	128087.9	1172251.2	1928068.5	375748.6	74022.7	105746.6	446549.1	1.25E+06	7.44E-02	1.49E+04	5.81E+03	3.75E+02	1.08E+07		
Sestriere	Electricity		48129.1	48129.1	31795.8	701882.7	22727.6	128087.9	1172251.2	1928068.5	375748.6	74022.7	105746.6	446549.1	3.28E+06	3.44E-01	1.49E+04	4.10E+03	7.33E+02	3.65E+07		
	Natural Gas		48129.1	48129.1	31795.8	701882.7	22727.6	128087.9	1172251.2	1928068.5	375748.6	74022.7	105746.6	446549.1	1.13E+06	1.97E-01	3.54E+03	7.46E+02	3.80E+02	3.23E+07		
	LPG		48129.1	48129.1	31795.8	701882.7	22727.6	128087.9	1172251.2	1928068.5	375748.6	74022.7	105746.6	446549.1	9.81E+05	1.90E-01	3.82E+03	8.13E+02	3.13E+02	1.87E+07		
	Biogas		48129.1	48129.1	31795.8	701882.7	22727.6	128087.9	1172251.2	1928068.5	375748.6	74022.7	105746.6	446549.1	1.26E+06	7.52E-02	1.53E+04	5.98E+03	3.80E+02	1.09E+07		
Messina	Electricity	26843.1	20132.3	23253.1	335538.3	12675.9	132312.5	1587750.0	2593325.0	314705.1	222285.0	635100.0	36650.2	6.03E+06	6.35E-01	2.84E+04	8.09E+03	1.24E+03	6.79E+07			
	Natural Gas	26843.1	20132.3	23253.1	335538.3	12675.9	132312.5	1587750.0	2593325.0	314705.1	222285.0	635100.0	36650.2	1.61E+06	3.31E-01	4.94E+03	1.16E+03	5.09E+02	5.93E+07			
	LPG	26843.1	20132.3	23253.1	335538.3	12675.9	132312.5	1587750.0	2593325.0	314705.1	222285.0	635100.0	36650.2	1.29E+06	3.17E-01	5.52E+03	1.30E+03	3.72E+02	3.13E+07			
	Biogas	26843.1	20132.3	23253.1	335538.3	12675.9	132312.5	1587750.0	2593325.0	314705.1	222285.0	635100.0	36650.2	1.88E+06	8.04E-02	2.92E+04	1.20E+04	5.10E+02	1.51E+07			
Palermo	Electricity	26843.1	20132.3	23253.1	335538.3	12675.9	132312.5	1587750.0	2593325.0	314705.1	222285.0	635100.0	36650.2	5.76E+06	6.03E-01	2.71E+04	7.71E+03	1.18E+03	6.47E+07			
	Natural Gas	26843.1	20132.3	23253.1	335538.3	12675.9	132312.5	1587750.0	2593325.0	314705.1	222285.0	635100.0	36650.2	1.57E+06	3.15E-01	4.81E+03	1.15E+03	4.91E+02	5.66E+07			

Model	Climatic Zone	City	Energy Carrier	External plaster	Cement lime plaster	Rock wool	Tuff block	Internal plaster 1	Concrete brick	Concrete screed	Concrete slab	Internal plaster 2	Floor tile	Bitumen	Brick	GWP	ODP	AP	EP	POCP	ADP-fossil
				[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg CO ₂ -eq]	[kg CFC11-eq]	[kg SO ₂ -eq]
C	Crotona	LPG	26843.1	20132.3	23253.1	335538.3	12675.9	132312.5	1587750.0	2593325.0	314705.1	222285.0	635100.0	36650.2	1.27E+06	3.02E-01	5.36E+03	1.28E+03	3.61E+02	3.01E+07	
		Biogas	26843.1	20132.3	23253.1	335538.3	12675.9	132312.5	1587750.0	2593325.0	314705.1	222285.0	635100.0	36650.2	1.82E+06	7.77E-02	2.78E+04	1.14E+04	4.92E+02	1.47E+07	
		Electricity	26843.1	20132.3	23253.1	335538.3	12675.9	132312.5	1587750.0	2593325.0	314705.1	222285.0	635100.0	36650.2	8.06E+06	8.75E-01	3.87E+04	1.09E+04	1.66E+03	9.14E+07	
		Natural Gas	26843.1	20132.3	23253.1	335538.3	12675.9	132312.5	1587750.0	2593325.0	314705.1	222285.0	635100.0	36650.2	1.89E+06	4.51E-01	5.89E+03	1.26E+03	6.44E+02	7.94E+07	
		LPG	26843.1	20132.3	23253.1	335538.3	12675.9	132312.5	1587750.0	2593325.0	314705.1	222285.0	635100.0	36650.2	1.45E+06	4.31E-01	6.70E+03	1.46E+03	4.52E+02	4.04E+07	
		Biogas	26843.1	20132.3	23253.1	335538.3	12675.9	132312.5	1587750.0	2593325.0	314705.1	222285.0	635100.0	36650.2	2.26E+06	1.01E-01	3.97E+04	1.63E+04	6.44E+02	1.78E+07	
	Cagliari	Electricity	26450.3	19837.7	27057.1	330629.0	12490.4	264625.0	1693600.0	2593325.0	314705.1	222285.0	635100.0	36650.2	5.84E+06	6.10E-01	2.74E+04	7.78E+03	1.20E+03	6.55E+07	
		Natural Gas	26450.3	19837.7	27057.1	330629.0	12490.4	264625.0	1693600.0	2593325.0	314705.1	222285.0	635100.0	36650.2	1.60E+06	3.19E-01	4.90E+03	1.15E+03	5.04E+02	5.73E+07	
		LPG	26450.3	19837.7	27057.1	330629.0	12490.4	264625.0	1693600.0	2593325.0	314705.1	222285.0	635100.0	36650.2	1.30E+06	3.05E-01	5.45E+03	1.29E+03	3.72E+02	3.05E+07	
		Biogas	26450.3	19837.7	27057.1	330629.0	12490.4	264625.0	1693600.0	2593325.0	314705.1	222285.0	635100.0	36650.2	1.86E+06	7.84E-02	2.81E+04	1.15E+04	5.04E+02	1.50E+07	
	Bari	Electricity	26450.3	19837.7	27057.1	330629.0	12490.4	264625.0	1693600.0	2593325.0	314705.1	222285.0	635100.0	36650.2	7.68E+06	8.27E-01	3.67E+04	1.04E+04	1.58E+03	8.69E+07	
		Natural Gas	26450.3	19837.7	27057.1	330629.0	12490.4	264625.0	1693600.0	2593325.0	314705.1	222285.0	635100.0	36650.2	1.86E+06	4.27E-01	5.77E+03	1.24E+03	6.26E+02	7.56E+07	
		LPG	26450.3	19837.7	27057.1	330629.0	12490.4	264625.0	1693600.0	2593325.0	314705.1	222285.0	635100.0	36650.2	1.44E+06	4.09E-01	6.53E+03	1.43E+03	4.45E+02	3.88E+07	
		Biogas	26450.3	19837.7	27057.1	330629.0	12490.4	264625.0	1693600.0	2593325.0	314705.1	222285.0	635100.0	36650.2	2.21E+06	9.67E-02	3.77E+04	1.55E+04	6.27E+02	1.74E+07	
	Termoli	Electricity	26450.3	19837.7	27057.1	330629.0	12490.4	264625.0	1693600.0	2593325.0	314705.1	222285.0	635100.0	36650.2	9.26E+06	1.01E+00	4.47E+04	1.26E+04	1.91E+03	1.05E+08	
		Natural Gas	26450.3	19837.7	27057.1	330629.0	12490.4	264625.0	1693600.0	2593325.0	314705.1	222285.0	635100.0	36650.2	2.08E+06	5.20E-01	6.51E+03	1.32E+03	7.30E+02	9.12E+07	
		LPG	26450.3	19837.7	27057.1	330629.0	12490.4	264625.0	1693600.0	2593325.0	314705.1	222285.0	635100.0	36650.2	1.57E+06	4.97E-01	7.45E+03	1.54E+03	5.07E+02	4.58E+07	
		Biogas	26450.3	19837.7	27057.1	330629.0	12490.4	264625.0	1693600.0	2593325.0	314705.1	222285.0	635100.0	36650.2	2.52E+06	1.12E-01	4.59E+04	1.89E+04	7.31E+02	1.95E+07	
	Genova	Electricity	26450.3	26450.3	35216.3	385733.8	12490.4	132312.5	2434550.0	3778845.0	314705.1	222285.0	317550.0	36650.2	7.63E+06	7.98E-01	3.60E+04	1.01E+04	1.54E+03	8.50E+07	
		Natural Gas	26450.3	26450.3	35216.3	385733.8	12490.4	132312.5	2434550.0	3778845.0	314705.1	222285.0	317550.0	36650.2	2.04E+06	4.14E-01	6.21E+03	1.37E+03	6.23E+02	7.41E+07	
LPG		26450.3	26450.3	35216.3	385733.8	12490.4	132312.5	2434550.0	3778845.0	314705.1	222285.0	317550.0	36650.2	1.64E+06	3.96E-01	6.94E+03	1.54E+03	4.49E+02	3.87E+07		
Biogas		26450.3	26450.3	35216.3	385733.8	12490.4	132312.5	2434550.0	3778845.0	314705.1	222285.0	317550.0	36650.2	2.38E+06	9.64E-02	3.69E+04	1.50E+04	6.24E+02	1.82E+07		
D	Firenze	Electricity	26450.3	26450.3	35216.3	385733.8	12490.4	132312.5	2434550.0	3778845.0	314705.1	222285.0	317550.0	36650.2	8.65E+06	9.18E-01	4.11E+04	1.15E+04	1.76E+03	9.67E+07	
		Natural Gas	26450.3	26450.3	35216.3	385733.8	12490.4	132312.5	2434550.0	3778845.0	314705.1	222285.0	317550.0	36650.2	2.18E+06	4.74E-01	6.69E+03	1.42E+03	6.90E+02	8.42E+07	
		LPG	26450.3	26450.3	35216.3	385733.8	12490.4	132312.5	2434550.0	3778845.0	314705.1	222285.0	317550.0	36650.2	1.72E+06	4.53E-01	7.54E+03	1.62E+03	4.89E+02	4.33E+07	
		Biogas	26450.3	26450.3	35216.3	385733.8	12490.4	132312.5	2434550.0	3778845.0	314705.1	222285.0	317550.0	36650.2	2.57E+06	1.06E-01	4.22E+04	1.72E+04	6.91E+02	1.95E+07	
Forlì	Electricity	26450.3	26450.3	35216.3	385733.8	12490.4	132312.5	2434550.0	3778845.0	314705.1	222285.0	317550.0	36650.2	1.17E+07	1.28E+00	5.66E+04	1.58E+04	2.39E+03	1.32E+08		
	Natural Gas	26450.3	26450.3	35216.3	385733.8	12490.4	132312.5	2434550.0	3778845.0	314705.1	222285.0	317550.0	36650.2	2.61E+06	6.54E-01	8.14E+03	1.56E+03	8.93E+02	1.15E+08		
	LPG	26450.3	26450.3	35216.3	385733.8	12490.4	132312.5	2434550.0	3778845.0	314705.1	222285.0	317550.0	36650.2	1.96E+06	6.25E-01	9.33E+03	1.85E+03	6.10E+02	5.70E+07		
	Biogas	26450.3	26450.3	35216.3	385733.8	12490.4	132312.5	2434550.0	3778845.0	314705.1	222285.0	317550.0	36650.2	3.16E+06	1.37E-01	5.81E+04	2.38E+04	8.94E+02	2.35E+07		
E	Trieste	Electricity	26506.4	26506.4	41902.6	386552.0	12516.9	132312.5	1905300.0	2963800.0	314705.1	222285.0	317550.0	36650.2	8.79E+06	9.50E-01	4.22E+04	1.19E+04	1.81E+03	9.94E+07	
		Natural Gas	26506.4	26506.4	41902.6	386552.0	12516.9	132312.5	1905300.0	2963800.0	314705.1	222285.0	317550.0	36650.2	2.08E+06	4.89E-01	6.52E+03	1.34E+03	7.00E+02	8.64E+07	
		LPG	26506.4	26506.4	41902.6	386552.0	12516.9	132312.5	1905300.0	2963800.0	314705.1	222285.0	317550.0	36650.2	1.60E+06	4.67E-01	7.40E+03	1.55E+03	4.91E+02	4.39E+07	
		Biogas	26506.4	26506.4	41902.6	386552.0	12516.9	132312.5	1905300.0	2963800.0	314705.1	222285.0	317550.0	36650.2	2.49E+06	1.08E-01	4.34E+04	1.78E+04	7.01E+02	1.93E+07	
	Torino	Electricity	26506.4	26506.4	41902.6	386552.0	12516.9	132312.5	1905300.0	2963800.0	314705.1	222285.0	317550.0	36650.2	1.23E+07	1.37E+00	6.01E+04	1.68E+04	2.54E+03	1.40E+08	
		Natural Gas	26506.4	26506.4	41902.6	386552.0	12516.9	132312.5	1905300.0	2963800.0	314705.1	222285.0	317550.0	36650.2	2.57E+06	6.97E-01	8.19E+03	1.51E+03	9.34E+02	1.21E+08	

Model	Climatic Zone	City	Energy Carrier	External plaster	Cement lime plaster	Rock wool	Tuff block	Internal plaster 1	Concrete brick	Concrete screed	Concrete slab	Internal plaster 2	Floor tile	Bitumen	Brick	GWP	ODP	AP	EP	POCP	ADP-fossil
				[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg CO ₂ -eq]	[kg CFC11-eq]	[kg SO ₂ -eq]
3	F	Bolzano	LPG	26506.4	26506.4	41902.6	386552.0	12516.9	132312.5	1905300.0	2963800.0	314705.1	222285.0	317550.0	36650.2	1.87E+06	6.66E-01	9.47E+03	1.82E+03	6.31E+02	5.97E+07
			Biogas	26506.4	26506.4	41902.6	386552.0	12516.9	132312.5	1905300.0	2963800.0	314705.1	222285.0	317550.0	36650.2	3.16E+06	1.43E-01	6.17E+04	2.54E+04	9.36E+02	2.39E+07
		Bolzano	Electricity	26506.4	26506.4	41902.6	386552.0	12516.9	132312.5	1905300.0	2963800.0	314705.1	222285.0	317550.0	36650.2	1.23E+07	1.37E+00	6.00E+04	1.68E+04	2.54E+03	1.40E+08
			Natural Gas	26506.4	26506.4	41902.6	386552.0	12516.9	132312.5	1905300.0	2963800.0	314705.1	222285.0	317550.0	36650.2	2.57E+06	6.96E-01	8.18E+03	1.51E+03	9.33E+02	1.21E+08
			LPG	26506.4	26506.4	41902.6	386552.0	12516.9	132312.5	1905300.0	2963800.0	314705.1	222285.0	317550.0	36650.2	1.87E+06	6.65E-01	9.46E+03	1.82E+03	6.30E+02	5.97E+07
			Biogas	26506.4	26506.4	41902.6	386552.0	12516.9	132312.5	1905300.0	2963800.0	314705.1	222285.0	317550.0	36650.2	3.16E+06	1.43E-01	6.16E+04	2.53E+04	9.35E+02	2.39E+07
		Cuneo	Electricity	26394.2	26394.2	45288.7	384915.6	12463.9	132312.5	1905300.0	2963800.0	314705.1	222285.0	317550.0	36650.2	9.46E+06	1.03E+00	4.56E+04	1.28E+04	1.94E+03	1.07E+08
			Natural Gas	26394.2	26394.2	45288.7	384915.6	12463.9	132312.5	1905300.0	2963800.0	314705.1	222285.0	317550.0	36650.2	2.17E+06	5.28E-01	6.84E+03	1.37E+03	7.44E+02	9.30E+07
			LPG	26394.2	26394.2	45288.7	384915.6	12463.9	132312.5	1905300.0	2963800.0	314705.1	222285.0	317550.0	36650.2	1.65E+06	5.05E-01	7.80E+03	1.60E+03	5.17E+02	4.69E+07
			Biogas	26394.2	26394.2	45288.7	384915.6	12463.9	132312.5	1905300.0	2963800.0	314705.1	222285.0	317550.0	36650.2	2.62E+06	1.14E-01	4.68E+04	1.92E+04	7.45E+02	2.02E+07
		Cortina	Electricity	26394.2	26394.2	45288.7	384915.6	12463.9	132312.5	1905300.0	2963800.0	314705.1	222285.0	317550.0	36650.2	2.00E+07	2.28E+00	9.90E+04	2.75E+04	4.14E+03	2.30E+08
			Natural Gas	26394.2	26394.2	45288.7	384915.6	12463.9	132312.5	1905300.0	2963800.0	314705.1	222285.0	317550.0	36650.2	3.64E+06	1.15E+00	1.18E+04	1.87E+03	1.44E+03	1.98E+08
	LPG		26394.2	26394.2	45288.7	384915.6	12463.9	132312.5	1905300.0	2963800.0	314705.1	222285.0	317550.0	36650.2	2.47E+06	1.10E+00	1.40E+04	2.39E+03	9.34E+02	9.42E+07	
	Biogas		26394.2	26394.2	45288.7	384915.6	12463.9	132312.5	1905300.0	2963800.0	314705.1	222285.0	317550.0	36650.2	4.64E+06	2.19E-01	1.02E+05	4.19E+04	1.45E+03	3.41E+07	
	Sestriere	Electricity	26394.2	26394.2	45288.7	384915.6	12463.9	132312.5	1905300.0	2963800.0	314705.1	222285.0	317550.0	36650.2	2.32E+07	2.65E+00	1.15E+05	3.19E+04	4.80E+03	2.66E+08	
		Natural Gas	26394.2	26394.2	45288.7	384915.6	12463.9	132312.5	1905300.0	2963800.0	314705.1	222285.0	317550.0	36650.2	4.08E+06	1.33E+00	1.33E+04	2.02E+03	1.65E+03	2.29E+08	
		LPG	26394.2	26394.2	45288.7	384915.6	12463.9	132312.5	1905300.0	2963800.0	314705.1	222285.0	317550.0	36650.2	2.72E+06	1.27E+00	1.58E+04	2.63E+03	1.06E+03	1.08E+08	
		Biogas	26394.2	26394.2	45288.7	384915.6	12463.9	132312.5	1905300.0	2963800.0	314705.1	222285.0	317550.0	36650.2	5.24E+06	2.50E-01	1.18E+05	4.87E+04	1.65E+03	3.82E+07	
	B	Messina	Electricity	14119.7	10589.8	4597.3	176496.6	6667.7	23498.0	281976.0	460560.8	71237.1	39476.6	112790.4	37203.2	1.05E+06	1.11E-01	4.91E+03	1.40E+03	2.25E+02	1.19E+07
			Natural Gas	14119.7	10589.8	4597.3	176496.6	6667.7	23498.0	281976.0	460560.8	71237.1	39476.6	112790.4	37203.2	3.24E+05	6.12E-02	1.03E+03	2.57E+02	1.05E+02	1.04E+07
			LPG	14119.7	10589.8	4597.3	176496.6	6667.7	23498.0	281976.0	460560.8	71237.1	39476.6	112790.4	37203.2	2.72E+05	5.88E-02	1.12E+03	2.80E+02	8.25E+01	5.83E+06
			Biogas	14119.7	10589.8	4597.3	176496.6	6667.7	23498.0	281976.0	460560.8	71237.1	39476.6	112790.4	37203.2	3.68E+05	1.97E-02	5.03E+03	2.04E+03	1.05E+02	3.15E+06
		Palermo	Electricity	14119.7	10589.8	4597.3	176496.6	6667.7	23498.0	281976.0	460560.8	71237.1	39476.6	112790.4	37203.2	9.71E+05	1.02E-01	4.49E+03	1.28E+03	2.08E+02	1.09E+07
			Natural Gas	14119.7	10589.8	4597.3	176496.6	6667.7	23498.0	281976.0	460560.8	71237.1	39476.6	112790.4	37203.2	3.12E+05	5.63E-02	9.89E+02	2.53E+02	9.97E+01	9.63E+06
LPG			14119.7	10589.8	4597.3	176496.6	6667.7	23498.0	281976.0	460560.8	71237.1	39476.6	112790.4	37203.2	2.65E+05	5.42E-02	1.08E+03	2.74E+02	7.92E+01	5.46E+06	
Biogas			14119.7	10589.8	4597.3	176496.6	6667.7	23498.0	281976.0	460560.8	71237.1	39476.6	112790.4	37203.2	3.52E+05	1.89E-02	4.60E+03	1.86E+03	9.98E+01	3.04E+06	
Crotone		Electricity	14119.7	10589.8	4597.3	176496.6	6667.7	23498.0	281976.0	460560.8	71237.1	39476.6	112790.4	37203.2	1.44E+06	1.56E-01	6.84E+03	1.93E+03	3.05E+02	1.63E+07	
		Natural Gas	14119.7	10589.8	4597.3	176496.6	6667.7	23498.0	281976.0	460560.8	71237.1	39476.6	112790.4	37203.2	3.77E+05	8.37E-02	1.21E+03	2.76E+02	1.31E+02	1.42E+07	
		LPG	14119.7	10589.8	4597.3	176496.6	6667.7	23498.0	281976.0	460560.8	71237.1	39476.6	112790.4	37203.2	3.01E+05	8.03E-02	1.35E+03	3.09E+02	9.76E+01	7.54E+06	
		Biogas	14119.7	10589.8	4597.3	176496.6	6667.7	23498.0	281976.0	460560.8	71237.1	39476.6	112790.4	37203.2	4.42E+05	2.35E-02	7.02E+03	2.86E+03	1.31E+02	3.66E+06	
C	Cagliari	Electricity	13803.5	10352.6	5374.3	172543.7	6518.3	46996.0	300774.4	460560.8	71237.1	39476.6	112790.4	37203.2	7.52E+05	7.53E-02	3.37E+03	9.68E+02	1.62E+02	8.35E+06	
		Natural Gas	13803.5	10352.6	5374.3	172543.7	6518.3	46996.0	300774.4	460560.8	71237.1	39476.6	112790.4	37203.2	2.84E+05	4.31E-02	8.81E+02	2.35E+02	8.50E+01	7.44E+06	
		LPG	13803.5	10352.6	5374.3	172543.7	6518.3	46996.0	300774.4	460560.8	71237.1	39476.6	112790.4	37203.2	2.50E+05	4.16E-02	9.43E+02	2.50E+02	7.04E+01	4.48E+06	
		Biogas	13803.5	10352.6	5374.3	172543.7	6518.3	46996.0	300774.4	460560.8	71237.1	39476.6	112790.4	37203.2	3.12E+05	1.65E-02	3.45E+03	1.38E+03	8.51E+01	2.76E+06	
	Bari	Electricity	13803.5	10352.6	5374.3	172543.7	6518.3	46996.0	300774.4	460560.8	71237.1	39476.6	112790.4	37203.2	1.03E+06	1.08E-01	4.79E+03	1.36E+03	2.20E+02	1.16E+07	
		Natural Gas	13803.5	10352.6	5374.3	172543.7	6518.3	46996.0	300774.4	460560.8	71237.1	39476.6	112790.4	37203.2	3.23E+05	5.96E-02	1.01E+03	2.49E+02	1.04E+02	1.02E+07	

Model	Climatic Zone	City	Energy Carrier	External plaster	Cement lime plaster	Rock wool	Tuff block	Internal plaster 1	Concrete brick	Concrete screed	Concrete slab	Internal plaster 2	Floor tile	Bitumen	Brick	GWP	ODP	AP	EP	POCP	ADP-fossil	
				[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg CO2 -eq]	[kg CFC11 -eq]	[kg SO2 -eq]	[kg PO43--eq]
D	Termoli		LPG	13803.5	10352.6	5374.3	172543.7	6518.3	46996.0	300774.4	460560.8	71237.1	39476.6	112790.4	37203.2	2.72E+05	5.73E-02	1.11E+03	2.71E+02	8.15E+01	5.73E+06	
			Biogas	13803.5	10352.6	5374.3	172543.7	6518.3	46996.0	300774.4	460560.8	71237.1	39476.6	112790.4	37203.2	3.66E+05	1.93E-02	4.91E+03	1.98E+03	1.04E+02	3.13E+06	
		Genova		Electricity	13803.5	10352.6	5374.3	172543.7	6518.3	46996.0	300774.4	460560.8	71237.1	39476.6	112790.4	37203.2	1.45E+06	1.57E-01	6.88E+03	1.94E+03	3.06E+02	1.64E+07
				Natural Gas	13803.5	10352.6	5374.3	172543.7	6518.3	46996.0	300774.4	460560.8	71237.1	39476.6	112790.4	37203.2	3.80E+05	8.39E-02	1.21E+03	2.69E+02	1.31E+02	1.43E+07
				LPG	13803.5	10352.6	5374.3	172543.7	6518.3	46996.0	300774.4	460560.8	71237.1	39476.6	112790.4	37203.2	3.04E+05	8.05E-02	1.35E+03	3.02E+02	9.78E+01	7.58E+06
				Biogas	13803.5	10352.6	5374.3	172543.7	6518.3	46996.0	300774.4	460560.8	71237.1	39476.6	112790.4	37203.2	4.45E+05	2.34E-02	7.05E+03	2.87E+03	1.31E+02	3.67E+06
	Firenze		Electricity	13803.5	13803.5	6899.2	201301.0	6518.3	23498.0	432363.2	671102.9	71237.1	39476.6	56395.2	37203.2	1.12E+06	1.14E-01	5.14E+03	1.45E+03	2.34E+02	1.24E+07	
			Natural Gas	13803.5	13803.5	6899.2	201301.0	6518.3	23498.0	432363.2	671102.9	71237.1	39476.6	56395.2	37203.2	3.73E+05	6.29E-02	1.15E+03	2.80E+02	1.11E+02	1.09E+07	
			LPG	13803.5	13803.5	6899.2	201301.0	6518.3	23498.0	432363.2	671102.9	71237.1	39476.6	56395.2	37203.2	3.19E+05	6.05E-02	1.25E+03	3.04E+02	8.73E+01	6.18E+06	
			Biogas	13803.5	13803.5	6899.2	201301.0	6518.3	23498.0	432363.2	671102.9	71237.1	39476.6	56395.2	37203.2	4.18E+05	2.03E-02	5.27E+03	2.11E+03	1.11E+02	3.43E+06	
	Forlì		Electricity	13803.5	13803.5	6899.2	201301.0	6518.3	23498.0	432363.2	671102.9	71237.1	39476.6	56395.2	37203.2	1.23E+06	1.27E-01	5.67E+03	1.60E+03	2.56E+02	1.36E+07	
			Natural Gas	13803.5	13803.5	6899.2	201301.0	6518.3	23498.0	432363.2	671102.9	71237.1	39476.6	56395.2	37203.2	3.87E+05	6.91E-02	1.20E+03	2.85E+02	1.18E+02	1.20E+07	
			LPG	13803.5	13803.5	6899.2	201301.0	6518.3	23498.0	432363.2	671102.9	71237.1	39476.6	56395.2	37203.2	3.27E+05	6.64E-02	1.31E+03	3.12E+02	9.15E+01	6.65E+06	
			Biogas	13803.5	13803.5	6899.2	201301.0	6518.3	23498.0	432363.2	671102.9	71237.1	39476.6	56395.2	37203.2	4.38E+05	2.14E-02	5.81E+03	2.34E+03	1.18E+02	3.57E+06	
	E	Trieste		Electricity	13848.7	13848.7	8203.5	201959.8	6539.7	23498.0	338371.2	526355.2	71237.1	39476.6	56395.2	37203.2	1.36E+06	1.45E-01	6.42E+03	1.81E+03	2.88E+02	1.53E+07
				Natural Gas	13848.7	13848.7	8203.5	201959.8	6539.7	23498.0	338371.2	526355.2	71237.1	39476.6	56395.2	37203.2	3.85E+05	7.82E-02	1.22E+03	2.78E+02	1.27E+02	1.34E+07
				LPG	13848.7	13848.7	8203.5	201959.8	6539.7	23498.0	338371.2	526355.2	71237.1	39476.6	56395.2	37203.2	3.15E+05	7.51E-02	1.35E+03	3.08E+02	9.62E+01	7.26E+06
				Biogas	13848.7	13848.7	8203.5	201959.8	6539.7	23498.0	338371.2	526355.2	71237.1	39476.6	56395.2	37203.2	4.44E+05	2.27E-02	6.59E+03	2.67E+03	1.27E+02	3.67E+06
		Torino		Electricity	13848.7	13848.7	8203.5	201959.8	6539.7	23498.0	338371.2	526355.2	71237.1	39476.6	56395.2	37203.2	1.95E+06	2.15E-01	9.40E+03	2.63E+03	4.10E+02	2.22E+07
				Natural Gas	13848.7	13848.7	8203.5	201959.8	6539.7	23498.0	338371.2	526355.2	71237.1	39476.6	56395.2	37203.2	4.67E+05	1.13E-01	1.50E+03	3.06E+02	1.66E+02	1.93E+07
LPG				13848.7	13848.7	8203.5	201959.8	6539.7	23498.0	338371.2	526355.2	71237.1	39476.6	56395.2	37203.2	3.61E+05	1.08E-01	1.69E+03	3.53E+02	1.19E+02	9.89E+06	
Biogas				13848.7	13848.7	8203.5	201959.8	6539.7	23498.0	338371.2	526355.2	71237.1	39476.6	56395.2	37203.2	5.57E+05	2.85E-02	9.64E+03	3.93E+03	1.66E+02	4.44E+06	
Bolzano			Electricity	13848.7	13848.7	8203.5	201959.8	6539.7	23498.0	338371.2	526355.2	71237.1	39476.6	56395.2	37203.2	1.86E+06	2.04E-01	8.92E+03	2.50E+03	3.91E+02	2.11E+07	
			Natural Gas	13848.7	13848.7	8203.5	201959.8	6539.7	23498.0	338371.2	526355.2	71237.1	39476.6	56395.2	37203.2	4.54E+05	1.07E-01	1.46E+03	3.01E+02	1.59E+02	1.84E+07	
			LPG	13848.7	13848.7	8203.5	201959.8	6539.7	23498.0	338371.2	526355.2	71237.1	39476.6	56395.2	37203.2	3.53E+05	1.03E-01	1.64E+03	3.46E+02	1.16E+02	9.47E+06	
			Biogas	13848.7	13848.7	8203.5	201959.8	6539.7	23498.0	338371.2	526355.2	71237.1	39476.6	56395.2	37203.2	5.39E+05	2.76E-02	9.16E+03	3.73E+03	1.60E+02	4.32E+06	
F	Cuneo		Electricity	13758.3	13758.3	8874.5	200642.1	6497.0	23498.0	338371.2	526355.2	71237.1	39476.6	56395.2	37203.2	1.10E+06	1.15E-01	5.11E+03	1.44E+03	2.33E+02	1.23E+07	
			Natural Gas	13758.3	13758.3	8874.5	200642.1	6497.0	23498.0	338371.2	526355.2	71237.1	39476.6	56395.2	37203.2	3.48E+05	6.29E-02	1.10E+03	2.61E+02	1.09E+02	1.09E+07	
			LPG	13758.3	13758.3	8874.5	200642.1	6497.0	23498.0	338371.2	526355.2	71237.1	39476.6	56395.2	37203.2	2.94E+05	6.05E-02	1.19E+03	2.85E+02	8.53E+01	6.09E+06	
			Biogas	13758.3	13758.3	8874.5	200642.1	6497.0	23498.0	338371.2	526355.2	71237.1	39476.6	56395.2	37203.2	3.94E+05	2.00E-02	5.23E+03	2.10E+03	1.09E+02	3.33E+06	
	Cortina		Electricity	13758.3	13758.3	8874.5	200642.1	6497.0	23498.0	338371.2	526355.2	71237.1	39476.6	56395.2	37203.2	2.76E+06	3.11E-01	1.35E+04	3.76E+03	5.78E+02	3.16E+07	
			Natural Gas	13758.3	13758.3	8874.5	200642.1	6497.0	23498.0	338371.2	526355.2	71237.1	39476.6	56395.2	37203.2	5.79E+05	1.60E-01	1.88E+03	3.40E+02	2.19E+02	2.73E+07	

Model	Climatic Zone	City	Energy Carrier	External plaster	Cement lime plaster	Rock wool	Tuff block	Internal plaster 1	Concrete brick	Concrete screed	Concrete slab	Internal plaster 2	Floor tile	Bitumen	Brick	GWP	ODP	AP	EP	POCP	ADP-fossil
				[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg CO ₂ -eq]	[kg CFC11-eq]	[kg SO ₂ -eq]
4	B	Sestriere	LPG	13758.3	13758.3	8874.5	200642.1	6497.0	23498.0	338371.2	526355.2	71237.1	39476.6	56395.2	37203.2	4.23E+05	1.53E-01	2.17E+03	4.09E+02	1.51E+02	1.35E+07
			Biogas	13758.3	13758.3	8874.5	200642.1	6497.0	23498.0	338371.2	526355.2	71237.1	39476.6	56395.2	37203.2	7.12E+05	3.65E-02	1.39E+04	5.68E+03	2.19E+02	5.51E+06
			Electricity	13758.3	13758.3	8874.5	200642.1	6497.0	23498.0	338371.2	526355.2	71237.1	39476.6	56395.2	37203.2	2.53E+06	2.83E-01	1.23E+04	3.43E+03	5.29E+02	2.88E+07
			Natural Gas	13758.3	13758.3	8874.5	200642.1	6497.0	23498.0	338371.2	526355.2	71237.1	39476.6	56395.2	37203.2	5.46E+05	1.47E-01	1.77E+03	3.29E+02	2.03E+02	2.50E+07
		LPG	13758.3	13758.3	8874.5	200642.1	6497.0	23498.0	338371.2	526355.2	71237.1	39476.6	56395.2	37203.2	4.05E+05	1.40E-01	2.03E+03	3.92E+02	1.41E+02	1.25E+07	
		Biogas	13758.3	13758.3	8874.5	200642.1	6497.0	23498.0	338371.2	526355.2	71237.1	39476.6	56395.2	37203.2	6.67E+05	3.42E-02	1.26E+04	5.17E+03	2.03E+02	5.20E+06	
		Messina	Electricity	25871.7	19403.8	4837.4	323396.3	12217.2	31260.0	215040.0	500640.0	59405.8	18900.0	54000.0	42798.7	3.55E+05	3.16E-02	1.35E+03	3.92E+02	8.39E+01	3.67E+06
			Natural Gas	25871.7	19403.8	4837.4	323396.3	12217.2	31260.0	215040.0	500640.0	59405.8	18900.0	54000.0	42798.7	2.43E+05	2.39E-02	7.55E+02	2.16E+02	6.54E+01	3.45E+06
			LPG	25871.7	19403.8	4837.4	323396.3	12217.2	31260.0	215040.0	500640.0	59405.8	18900.0	54000.0	42798.7	2.35E+05	2.36E-02	7.69E+02	2.20E+02	6.19E+01	2.74E+06
			Biogas	25871.7	19403.8	4837.4	323396.3	12217.2	31260.0	215040.0	500640.0	59405.8	18900.0	54000.0	42798.7	2.50E+05	1.75E-02	1.37E+03	4.91E+02	6.54E+01	2.33E+06
		Palermo	Electricity	25871.7	19403.8	4837.4	323396.3	12217.2	31260.0	215040.0	500640.0	59405.8	18900.0	54000.0	42798.7	3.36E+05	2.94E-02	1.26E+03	3.66E+02	7.99E+01	3.45E+06
			Natural Gas	25871.7	19403.8	4837.4	323396.3	12217.2	31260.0	215040.0	500640.0	59405.8	18900.0	54000.0	42798.7	2.40E+05	2.28E-02	7.46E+02	2.15E+02	6.41E+01	3.26E+06
	LPG		25871.7	19403.8	4837.4	323396.3	12217.2	31260.0	215040.0	500640.0	59405.8	18900.0	54000.0	42798.7	2.33E+05	2.25E-02	7.58E+02	2.18E+02	6.11E+01	2.66E+06	
	Biogas		25871.7	19403.8	4837.4	323396.3	12217.2	31260.0	215040.0	500640.0	59405.8	18900.0	54000.0	42798.7	2.46E+05	1.73E-02	1.27E+03	4.50E+02	6.41E+01	2.30E+06	
	Crotona	Electricity	25871.7	19403.8	4837.4	323396.3	12217.2	31260.0	215040.0	500640.0	59405.8	18900.0	54000.0	42798.7	4.87E+05	4.71E-02	2.02E+03	5.76E+02	1.11E+02	5.19E+06	
		Natural Gas	25871.7	19403.8	4837.4	323396.3	12217.2	31260.0	215040.0	500640.0	59405.8	18900.0	54000.0	42798.7	2.61E+05	3.16E-02	8.17E+02	2.23E+02	7.41E+01	4.76E+06	
		LPG	25871.7	19403.8	4837.4	323396.3	12217.2	31260.0	215040.0	500640.0	59405.8	18900.0	54000.0	42798.7	2.45E+05	3.09E-02	8.46E+02	2.30E+02	6.70E+01	3.33E+06	
		Biogas	25871.7	19403.8	4837.4	323396.3	12217.2	31260.0	215040.0	500640.0	59405.8	18900.0	54000.0	42798.7	2.75E+05	1.88E-02	2.05E+03	7.74E+02	7.41E+01	2.50E+06	
	Cagliari	Electricity	25758.3	19318.7	5801.7	321978.8	12163.6	62340.0	239616.0	499380.0	59348.2	18900.0	54000.0	42798.7	2.78E+05	2.20E-02	9.40E+02	2.69E+02	6.68E+01	2.75E+06	
		Natural Gas	25758.3	19318.7	5801.7	321978.8	12163.6	62340.0	239616.0	499380.0	59348.2	18900.0	54000.0	42798.7	2.35E+05	1.90E-02	7.08E+02	2.01E+02	5.96E+01	2.67E+06	
		LPG	25758.3	19318.7	5801.7	321978.8	12163.6	62340.0	239616.0	499380.0	59348.2	18900.0	54000.0	42798.7	2.32E+05	1.89E-02	7.14E+02	2.02E+02	5.82E+01	2.39E+06	
		Biogas	25758.3	19318.7	5801.7	321978.8	12163.6	62340.0	239616.0	499380.0	59348.2	18900.0	54000.0	42798.7	2.37E+05	1.66E-02	9.48E+02	3.08E+02	5.96E+01	2.23E+06	
	Bari	Electricity	25758.3	19318.7	5801.7	321978.8	12163.6	62340.0	239616.0	499380.0	59348.2	18900.0	54000.0	42798.7	3.42E+05	2.95E-02	1.26E+03	3.58E+02	8.00E+01	3.49E+06	
		Natural Gas	25758.3	19318.7	5801.7	321978.8	12163.6	62340.0	239616.0	499380.0	59348.2	18900.0	54000.0	42798.7	2.44E+05	2.28E-02	7.38E+02	2.04E+02	6.38E+01	3.30E+06	
		LPG	25758.3	19318.7	5801.7	321978.8	12163.6	62340.0	239616.0	499380.0	59348.2	18900.0	54000.0	42798.7	2.37E+05	2.24E-02	7.51E+02	2.07E+02	6.07E+01	2.68E+06	
		Biogas	25758.3	19318.7	5801.7	321978.8	12163.6	62340.0	239616.0	499380.0	59348.2	18900.0	54000.0	42798.7	2.50E+05	1.72E-02	1.28E+03	4.44E+02	6.38E+01	2.32E+06	
	Termoli	Electricity	25758.3	19318.7	5801.7	321978.8	12163.6	62340.0	239616.0	499380.0	59348.2	18900.0	54000.0	42798.7	4.70E+05	4.47E-02	1.91E+03	5.37E+02	1.07E+02	4.98E+06	
		Natural Gas	25758.3	19318.7	5801.7	321978.8	12163.6	62340.0	239616.0	499380.0	59348.2	18900.0	54000.0	42798.7	2.61E+05	3.03E-02	7.99E+02	2.10E+02	7.23E+01	4.57E+06	
LPG		25758.3	19318.7	5801.7	321978.8	12163.6	62340.0	239616.0	499380.0	59348.2	18900.0	54000.0	42798.7	2.47E+05	2.96E-02	8.26E+02	2.17E+02	6.58E+01	3.25E+06		
Biogas		25758.3	19318.7	5801.7	321978.8	12163.6	62340.0	239616.0	499380.0	59348.2	18900.0	54000.0	42798.7	2.74E+05	1.85E-02	1.94E+03	7.20E+02	7.23E+01	2.48E+06		
D	Genova	Electricity	25758.3	25758.3	7237.5	375641.9	12163.6	30780.0	331992.0	605656.8	59098.6	18900.0	27000.0	42798.7	4.10E+05	3.44E-02	1.53E+03	4.33E+02	9.11E+01	4.12E+06	
		Natural Gas	25758.3	25758.3	7237.5	375641.9	12163.6	30780.0	331992.0	605656.8	59098.6	18900.0	27000.0	42798.7	2.81E+05	2.55E-02	8.46E+02	2.31E+02	6.98E+01	3.87E+06	
		LPG	25758.3	25758.3	7237.5	375641.9	12163.6	30780.0	331992.0	605656.8	59098.6	18900.0	27000.0	42798.7	2.72E+05	2.51E-02	8.63E+02	2.35E+02	6.58E+01	3.05E+06	
		Biogas	25758.3	25758.3	7237.5	375641.9	12163.6	30780.0	331992.0	605656.8	59098.6	18900.0	27000.0	42798.7	2.89E+05	1.81E-02	1.55E+03	5.47E+02	6.99E+01	2.57E+06	
Firenze	Electricity	25758.3	25758.3	7237.5	375641.9	12163.6	30780.0	331992.0	605656.8	59098.6	18900.0	27000.0	42798.7	4.22E+05	3.58E-02	1.59E+03	4.50E+02	9.36E+01	4.26E+06		
	Natural Gas	25758.3	25758.3	7237.5	375641.9	12163.6	30780.0	331992.0	605656.8	59098.6	18900.0	27000.0	42798.7	2.82E+05	2.62E-02	8.52E+02	2.31E+02	7.06E+01	3.99E+06		

Model	Climatic Zone	City	Energy Carrier	External plaster	Cement lime plaster	Rock wool	Tuff block	Internal plaster 1	Concrete brick	Concrete screed	Concrete slab	Internal plaster 2	Floor tile	Bitumen	Brick	GWP	ODP	AP	EP	POCP	ADP-fossil
				[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg CO2 -eq]	[kg CFC11 -eq]	[kg SO2 -eq]
5	B	Forlì	LPG	25758.3	25758.3	7237.5	375641.9	12163.6	30780.0	331992.0	605656.8	59098.6	18900.0	27000.0	42798.7	2.72E+05	2.57E-02	8.70E+02	2.36E+02	6.63E+01	3.10E+06
			Biogas	25758.3	25758.3	7237.5	375641.9	12163.6	30780.0	331992.0	605656.8	59098.6	18900.0	27000.0	42798.7	2.91E+05	1.83E-02	1.62E+03	5.72E+02	7.07E+01	2.59E+06
			Electricity	25758.3	25758.3	7237.5	375641.9	12163.6	30780.0	331992.0	605656.8	59098.6	18900.0	27000.0	42798.7	6.75E+05	6.56E-02	2.87E+03	8.02E+02	1.46E+02	7.18E+06
			Natural Gas	25758.3	25758.3	7237.5	375641.9	12163.6	30780.0	331992.0	605656.8	59098.6	18900.0	27000.0	42798.7	3.18E+05	4.10E-02	9.71E+02	2.43E+02	8.74E+01	6.49E+06
		Trieste	LPG	25758.3	25758.3	7237.5	375641.9	12163.6	30780.0	331992.0	605656.8	59098.6	18900.0	27000.0	42798.7	2.92E+05	3.99E-02	1.02E+03	2.55E+02	7.62E+01	4.23E+06
			Biogas	25758.3	25758.3	7237.5	375641.9	12163.6	30780.0	331992.0	605656.8	59098.6	18900.0	27000.0	42798.7	3.39E+05	2.08E-02	2.93E+03	1.12E+03	8.74E+01	2.92E+06
			Electricity	25774.5	25774.5	8322.2	375878.2	12171.3	30690.0	286416.0	469728.0	59041.0	18900.0	27000.0	42798.7	4.77E+05	4.44E-02	1.93E+03	5.44E+02	1.08E+02	5.03E+06
			Natural Gas	25774.5	25774.5	8322.2	375878.2	12171.3	30690.0	286416.0	469728.0	59041.0	18900.0	27000.0	42798.7	2.74E+05	3.04E-02	8.52E+02	2.26E+02	7.48E+01	4.63E+06
		Torino	LPG	25774.5	25774.5	8322.2	375878.2	12171.3	30690.0	286416.0	469728.0	59041.0	18900.0	27000.0	42798.7	2.59E+05	2.98E-02	8.79E+02	2.32E+02	6.84E+01	3.35E+06
			Biogas	25774.5	25774.5	8322.2	375878.2	12171.3	30690.0	286416.0	469728.0	59041.0	18900.0	27000.0	42798.7	2.86E+05	1.89E-02	1.97E+03	7.22E+02	7.48E+01	2.60E+06
			Electricity	25774.5	25774.5	8322.2	375878.2	12171.3	30690.0	286416.0	469728.0	59041.0	18900.0	27000.0	42798.7	6.85E+05	6.89E-02	2.98E+03	8.33E+02	1.51E+02	7.44E+06
			Natural Gas	25774.5	25774.5	8322.2	375878.2	12171.3	30690.0	286416.0	469728.0	59041.0	18900.0	27000.0	42798.7	3.03E+05	4.26E-02	9.50E+02	2.36E+02	8.85E+01	6.69E+06
		Bolzano	LPG	25774.5	25774.5	8322.2	375878.2	12171.3	30690.0	286416.0	469728.0	59041.0	18900.0	27000.0	42798.7	2.75E+05	4.14E-02	1.00E+03	2.48E+02	7.66E+01	4.28E+06
			Biogas	25774.5	25774.5	8322.2	375878.2	12171.3	30690.0	286416.0	469728.0	59041.0	18900.0	27000.0	42798.7	3.26E+05	2.09E-02	3.04E+03	1.17E+03	8.85E+01	2.88E+06
			Electricity	25774.5	25774.5	8322.2	375878.2	12171.3	30690.0	286416.0	469728.0	59041.0	18900.0	27000.0	42798.7	6.66E+05	6.67E-02	2.89E+03	8.08E+02	1.48E+02	7.22E+06
			Natural Gas	25774.5	25774.5	8322.2	375878.2	12171.3	30690.0	286416.0	469728.0	59041.0	18900.0	27000.0	42798.7	3.00E+05	4.15E-02	9.42E+02	2.35E+02	8.73E+01	6.51E+06
		Cuneo	LPG	25774.5	25774.5	8322.2	375878.2	12171.3	30690.0	286416.0	469728.0	59041.0	18900.0	27000.0	42798.7	2.74E+05	4.04E-02	9.90E+02	2.46E+02	7.59E+01	4.20E+06
			Biogas	25774.5	25774.5	8322.2	375878.2	12171.3	30690.0	286416.0	469728.0	59041.0	18900.0	27000.0	42798.7	3.22E+05	2.08E-02	2.95E+03	1.13E+03	8.73E+01	2.85E+06
			Electricity	25742.1	25742.1	9028.0	375405.7	12156.0	30630.0	286032.0	469056.0	59002.6	18900.0	27000.0	42798.7	4.01E+05	3.55E-02	1.55E+03	4.33E+02	9.15E+01	4.16E+06
			Natural Gas	25742.1	25742.1	9028.0	375405.7	12156.0	30630.0	286032.0	469056.0	59002.6	18900.0	27000.0	42798.7	2.62E+05	2.59E-02	8.08E+02	2.15E+02	6.86E+01	3.89E+06
Cortina	LPG	25742.1	25742.1	9028.0	375405.7	12156.0	30630.0	286032.0	469056.0	59002.6	18900.0	27000.0	42798.7	2.52E+05	2.55E-02	8.27E+02	2.20E+02	6.43E+01	3.01E+06		
	Biogas	25742.1	25742.1	9028.0	375405.7	12156.0	30630.0	286032.0	469056.0	59002.6	18900.0	27000.0	42798.7	2.71E+05	1.80E-02	1.57E+03	5.55E+02	6.87E+01	2.50E+06		
	Electricity	25742.1	25742.1	9028.0	375405.7	12156.0	30630.0	286032.0	469056.0	59002.6	18900.0	27000.0	42798.7	9.72E+05	1.03E-01	4.43E+03	1.23E+03	2.10E+02	1.08E+07		
	Natural Gas	25742.1	25742.1	9028.0	375405.7	12156.0	30630.0	286032.0	469056.0	59002.6	18900.0	27000.0	42798.7	3.41E+05	5.95E-02	1.08E+03	2.43E+02	1.06E+02	9.55E+06		
Sestriere	LPG	25742.1	25742.1	9028.0	375405.7	12156.0	30630.0	286032.0	469056.0	59002.6	18900.0	27000.0	42798.7	2.96E+05	5.75E-02	1.16E+03	2.63E+02	8.68E+01	5.56E+06		
	Biogas	25742.1	25742.1	9028.0	375405.7	12156.0	30630.0	286032.0	469056.0	59002.6	18900.0	27000.0	42798.7	3.80E+05	2.37E-02	4.53E+03	1.78E+03	1.06E+02	3.25E+06		
	Electricity	25742.1	25742.1	9028.0	375405.7	12156.0	30630.0	286032.0	469056.0	59002.6	18900.0	27000.0	42798.7	8.75E+05	9.13E-02	3.94E+03	1.09E+03	1.90E+02	9.65E+06		
	Natural Gas	25742.1	25742.1	9028.0	375405.7	12156.0	30630.0	286032.0	469056.0	59002.6	18900.0	27000.0	42798.7	3.28E+05	5.38E-02	1.03E+03	2.38E+02	1.00E+02	8.59E+06		
Messina	LPG	25742.1	25742.1	9028.0	375405.7	12156.0	30630.0	286032.0	469056.0	59002.6	18900.0	27000.0	42798.7	2.89E+05	5.20E-02	1.10E+03	2.55E+02	8.30E+01	5.13E+06		
	Biogas	25742.1	25742.1	9028.0	375405.7	12156.0	30630.0	286032.0	469056.0	59002.6	18900.0	27000.0	42798.7	3.61E+05	2.27E-02	4.03E+03	1.57E+03	1.00E+02	3.12E+06		
	Electricity	3874.9	2906.2	3244.0	48436.5	1829.8	24170.0	196680.0	408380.0	50165.8	21000.0	60000.0	29393.9	6.46E+05	6.64E-02	2.99E+03	8.44E+02	1.36E+02	7.17E+06		
	Natural Gas	3874.9	2906.2	3244.0	48436.5	1829.8	24170.0	196680.0	408380.0	50165.8	21000.0	60000.0	29393.9	2.00E+05	3.58E-02	6.26E+02	1.47E+02	6.31E+01	6.31E+06		
Palermo	LPG	3874.9	2906.2	3244.0	48436.5	1829.8	24170.0	196680.0	408380.0	50165.8	21000.0	60000.0	29393.9	1.69E+05	3.44E-02	6.85E+02	1.61E+02	4.92E+01	3.49E+06		
	Biogas	3874.9	2906.2	3244.0	48436.5	1829.8	24170.0	196680.0	408380.0	50165.8	21000.0	60000.0	29393.9	2.28E+05	1.06E-02	3.07E+03	1.23E+03	6.31E+01	1.86E+06		
			Electricity	3874.9	2906.2	3244.0	48436.5	1829.8	24170.0	196680.0	408380.0	50165.8	21000.0	60000.0	29393.9	6.01E+05	6.12E-02	2.77E+03	7.82E+02	1.27E+02	6.66E+06
				Natural Gas	3874.9	2906.2	3244.0	48436.5	1829.8	24170.0	196680.0	408380.0	50165.8	21000.0	60000.0	29393.9	1.94E+05	3.32E-02	6.06E+02	1.45E+02	6.02E+01

Model	Climatic Zone	City	Energy Carrier	External plaster	Cement lime plaster	Rock wool	Tuff block	Internal plaster 1	Concrete brick	Concrete screed	Concrete slab	Internal plaster 2	Floor tile	Bitumen	Brick	GWP	ODP	AP	EP	POCP	ADP-fossil
				[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg CO ₂ -eq]	[kg CFC11-eq]	[kg SO ₂ -eq]
C	Crotone		LPG	3874.9	2906.2	3244.0	48436.5	1829.8	24170.0	196680.0	408380.0	50165.8	21000.0	60000.0	29393.9	1.65E+05	3.19E-02	6.59E+02	1.58E+02	4.75E+01	3.29E+06
			Biogas	3874.9	2906.2	3244.0	48436.5	1829.8	24170.0	196680.0	408380.0	50165.8	21000.0	60000.0	29393.9	2.19E+05	1.01E-02	2.84E+03	1.14E+03	6.02E+01	1.80E+06
			Electricity	3874.9	2906.2	3244.0	48436.5	1829.8	24170.0	196680.0	408380.0	50165.8	21000.0	60000.0	29393.9	8.78E+05	9.39E-02	4.17E+03	1.17E+03	1.85E+02	9.87E+06
			Natural Gas	3874.9	2906.2	3244.0	48436.5	1829.8	24170.0	196680.0	408380.0	50165.8	21000.0	60000.0	29393.9	2.33E+05	4.95E-02	7.36E+02	1.58E+02	7.85E+01	8.61E+06
			LPG	3874.9	2906.2	3244.0	48436.5	1829.8	24170.0	196680.0	408380.0	50165.8	21000.0	60000.0	29393.9	1.87E+05	4.75E-02	8.21E+02	1.78E+02	5.84E+01	4.53E+06
			Biogas	3874.9	2906.2	3244.0	48436.5	1829.8	24170.0	196680.0	408380.0	50165.8	21000.0	60000.0	29393.9	2.72E+05	1.29E-02	4.28E+03	1.74E+03	7.86E+01	2.16E+06
	Cagliari	Electricity	7636.4	5727.3	2877.3	95455.5	3606.1	25000.0	160000.0	245000.0	42697.0	21000.0	60000.0	29393.9	4.85E+05	5.02E-02	2.21E+03	6.30E+02	1.05E+02	5.43E+06	
		Natural Gas	7636.4	5727.3	2877.3	95455.5	3606.1	25000.0	160000.0	245000.0	42697.0	21000.0	60000.0	29393.9	1.65E+05	2.82E-02	5.13E+02	1.29E+02	5.23E+01	4.81E+06	
		LPG	7636.4	5727.3	2877.3	95455.5	3606.1	25000.0	160000.0	245000.0	42697.0	21000.0	60000.0	29393.9	1.42E+05	2.72E-02	5.55E+02	1.39E+02	4.24E+01	2.79E+06	
		Biogas	7636.4	5727.3	2877.3	95455.5	3606.1	25000.0	160000.0	245000.0	42697.0	21000.0	60000.0	29393.9	1.84E+05	1.01E-02	2.27E+03	9.11E+02	5.23E+01	1.61E+06	
	Bari	Electricity	7636.4	5727.3	2877.3	95455.5	3606.1	25000.0	160000.0	245000.0	42697.0	21000.0	60000.0	29393.9	6.68E+05	7.18E-02	3.14E+03	8.85E+02	1.43E+02	7.55E+06	
		Natural Gas	7636.4	5727.3	2877.3	95455.5	3606.1	25000.0	160000.0	245000.0	42697.0	21000.0	60000.0	29393.9	1.90E+05	3.90E-02	5.99E+02	1.38E+02	6.44E+01	6.63E+06	
		LPG	7636.4	5727.3	2877.3	95455.5	3606.1	25000.0	160000.0	245000.0	42697.0	21000.0	60000.0	29393.9	1.56E+05	3.75E-02	6.62E+02	1.53E+02	4.96E+01	3.60E+06	
		Biogas	7636.4	5727.3	2877.3	95455.5	3606.1	25000.0	160000.0	245000.0	42697.0	21000.0	60000.0	29393.9	2.19E+05	1.19E-02	3.22E+03	1.30E+03	6.45E+01	1.85E+06	
	Termoli	Electricity	7636.4	5727.3	2877.3	95455.5	3606.1	25000.0	160000.0	245000.0	42697.0	21000.0	60000.0	29393.9	9.04E+05	9.97E-02	4.33E+03	1.22E+03	1.92E+02	1.03E+07	
		Natural Gas	7636.4	5727.3	2877.3	95455.5	3606.1	25000.0	160000.0	245000.0	42697.0	21000.0	60000.0	29393.9	2.23E+05	5.29E-02	7.11E+02	1.49E+02	8.01E+01	8.97E+06	
		LPG	7636.4	5727.3	2877.3	95455.5	3606.1	25000.0	160000.0	245000.0	42697.0	21000.0	60000.0	29393.9	1.74E+05	5.07E-02	8.00E+02	1.71E+02	5.89E+01	4.66E+06	
		Biogas	7636.4	5727.3	2877.3	95455.5	3606.1	25000.0	160000.0	245000.0	42697.0	21000.0	60000.0	29393.9	2.65E+05	1.42E-02	4.45E+03	1.81E+03	8.02E+01	2.16E+06	
	Genova	Electricity	7636.4	7636.4	3690.9	111364.7	3606.1	12500.0	230000.0	357000.0	42697.0	21000.0	30000.0	29393.9	7.28E+05	7.65E-02	3.39E+03	9.53E+02	1.53E+02	8.12E+06	
		Natural Gas	7636.4	7636.4	3690.9	111364.7	3606.1	12500.0	230000.0	357000.0	42697.0	21000.0	30000.0	29393.9	2.19E+05	4.15E-02	6.78E+02	1.55E+02	6.90E+01	7.13E+06	
		LPG	7636.4	7636.4	3690.9	111364.7	3606.1	12500.0	230000.0	357000.0	42697.0	21000.0	30000.0	29393.9	1.82E+05	3.99E-02	7.45E+02	1.71E+02	5.32E+01	3.90E+06	
		Biogas	7636.4	7636.4	3690.9	111364.7	3606.1	12500.0	230000.0	357000.0	42697.0	21000.0	30000.0	29393.9	2.50E+05	1.25E-02	3.47E+03	1.40E+03	6.91E+01	2.03E+06	
	D	Firenze	Electricity	7636.4	7636.4	3690.9	111364.7	3606.1	12500.0	230000.0	357000.0	42697.0	21000.0	30000.0	29393.9	8.10E+05	8.61E-02	3.80E+03	1.07E+03	1.70E+02	9.06E+06
			Natural Gas	7636.4	7636.4	3690.9	111364.7	3606.1	12500.0	230000.0	357000.0	42697.0	21000.0	30000.0	29393.9	2.30E+05	4.63E-02	7.17E+02	1.59E+02	7.44E+01	7.94E+06
LPG			7636.4	7636.4	3690.9	111364.7	3606.1	12500.0	230000.0	357000.0	42697.0	21000.0	30000.0	29393.9	1.88E+05	4.44E-02	7.93E+02	1.78E+02	5.64E+01	4.27E+06	
Biogas			7636.4	7636.4	3690.9	111364.7	3606.1	12500.0	230000.0	357000.0	42697.0	21000.0	30000.0	29393.9	2.65E+05	1.34E-02	3.90E+03	1.58E+03	7.45E+01	2.14E+06	
Forlì	Electricity	7636.4	7636.4	3690.9	111364.7	3606.1	12500.0	230000.0	357000.0	42697.0	21000.0	30000.0	29393.9	1.25E+06	1.39E-01	6.05E+03	1.69E+03	2.62E+02	1.42E+07		
	Natural Gas	7636.4	7636.4	3690.9	111364.7	3606.1	12500.0	230000.0	357000.0	42697.0	21000.0	30000.0	29393.9	2.92E+05	7.24E-02	9.26E+02	1.81E+02	1.04E+02	1.23E+07		
	LPG	7636.4	7636.4	3690.9	111364.7	3606.1	12500.0	230000.0	357000.0	42697.0	21000.0	30000.0	29393.9	2.23E+05	6.94E-02	1.05E+03	2.11E+02	7.39E+01	6.26E+06		
	Biogas	7636.4	7636.4	3690.9	111364.7	3606.1	12500.0	230000.0	357000.0	42697.0	21000.0	30000.0	29393.9	3.50E+05	1.78E-02	6.21E+03	2.53E+03	1.04E+02	2.72E+06		
E	Trieste	Electricity	7652.6	7652.6	4387.7	111601.0	3613.7	12500.0	180000.0	280000.0	42697.0	21000.0	30000.0	29393.9	8.90E+05	9.69E-02	4.24E+03	1.19E+03	1.88E+02	1.01E+07	
		Natural Gas	7652.6	7652.6	4387.7	111601.0	3613.7	12500.0	180000.0	280000.0	42697.0	21000.0	30000.0	29393.9	2.30E+05	5.16E-02	7.32E+02	1.56E+02	7.97E+01	8.80E+06	
		LPG	7652.6	7652.6	4387.7	111601.0	3613.7	12500.0	180000.0	280000.0	42697.0	21000.0	30000.0	29393.9	1.82E+05	4.95E-02	8.19E+02	1.76E+02	5.92E+01	4.62E+06	
		Biogas	7652.6	7652.6	4387.7	111601.0	3613.7	12500.0	180000.0	280000.0	42697.0	21000.0	30000.0	29393.9	2.70E+05	1.41E-02	4.35E+03	1.77E+03	7.98E+01	2.20E+06	
	Torino	Electricity	7652.6	7652.6	4387.7	111601.0	3613.7	12500.0	180000.0	280000.0	42697.0	21000.0	30000.0	29393.9	1.27E+06	1.42E-01	6.15E+03	1.72E+03	2.67E+02	1.45E+07	
		Natural Gas	7652.6	7652.6	4387.7	111601.0	3613.7	12500.0	180000.0	280000.0	42697.0	21000.0	30000.0	29393.9	2.82E+05	7.39E-02	9.11E+02	1.74E+02	1.05E+02	1.26E+07	

Model	Climatic Zone	City	Energy Carrier	External plaster	Cement lime plaster	Rock wool	Tuff block	Internal plaster 1	Concrete brick	Concrete screed	Concrete slab	Internal plaster 2	Floor tile	Bitumen	Brick	GWP	ODP	AP	EP	POCP	ADP-fossil
				[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg CO ₂ -eq]	[kg CFC11-eq]	[kg SO ₂ -eq]
6	F	Bolzano	LPG	7652.6	7652.6	4387.7	111601.0	3613.7	12500.0	180000.0	280000.0	42697.0	21000.0	30000.0	29393.9	2.12E+05	7.07E-02	1.04E+03	2.05E+02	7.41E+01	6.32E+06
			Biogas	7652.6	7652.6	4387.7	111601.0	3613.7	12500.0	180000.0	280000.0	42697.0	21000.0	30000.0	29393.9	3.42E+05	1.79E-02	6.32E+03	2.58E+03	1.05E+02	2.70E+06
			Electricity	7652.6	7652.6	4387.7	111601.0	3613.7	12500.0	180000.0	280000.0	42697.0	21000.0	30000.0	29393.9	1.22E+06	1.36E-01	5.91E+03	1.65E+03	2.57E+02	1.39E+07
			Natural Gas	7652.6	7652.6	4387.7	111601.0	3613.7	12500.0	180000.0	280000.0	42697.0	21000.0	30000.0	29393.9	2.76E+05	7.11E-02	8.89E+02	1.71E+02	1.02E+02	1.21E+07
		LPG	7652.6	7652.6	4387.7	111601.0	3613.7	12500.0	180000.0	280000.0	42697.0	21000.0	30000.0	29393.9	2.08E+05	6.81E-02	1.01E+03	2.01E+02	7.23E+01	6.11E+06	
		Biogas	7652.6	7652.6	4387.7	111601.0	3613.7	12500.0	180000.0	280000.0	42697.0	21000.0	30000.0	29393.9	3.33E+05	1.74E-02	6.07E+03	2.48E+03	1.02E+02	2.64E+06	
		Cuneo	Electricity	7620.2	7620.2	4748.5	111128.5	3598.4	12500.0	180000.0	280000.0	42697.0	21000.0	30000.0	29393.9	7.85E+05	8.46E-02	3.71E+03	1.04E+03	1.66E+02	8.87E+06
			Natural Gas	7620.2	7620.2	4748.5	111128.5	3598.4	12500.0	180000.0	280000.0	42697.0	21000.0	30000.0	29393.9	2.15E+05	4.54E-02	6.81E+02	1.48E+02	7.25E+01	7.76E+06
			LPG	7620.2	7620.2	4748.5	111128.5	3598.4	12500.0	180000.0	280000.0	42697.0	21000.0	30000.0	29393.9	1.74E+05	4.36E-02	7.56E+02	1.66E+02	5.48E+01	4.16E+06
			Biogas	7620.2	7620.2	4748.5	111128.5	3598.4	12500.0	180000.0	280000.0	42697.0	21000.0	30000.0	29393.9	2.50E+05	1.31E-02	3.81E+03	1.54E+03	7.26E+01	2.07E+06
		Cortina	Electricity	7620.2	7620.2	4748.5	111128.5	3598.4	12500.0	180000.0	280000.0	42697.0	21000.0	30000.0	29393.9	1.85E+06	2.10E-01	9.09E+03	2.53E+03	3.88E+02	2.12E+07
			Natural Gas	7620.2	7620.2	4748.5	111128.5	3598.4	12500.0	180000.0	280000.0	42697.0	21000.0	30000.0	29393.9	3.63E+05	1.08E-01	1.18E+03	1.99E+02	1.43E+02	1.83E+07
	LPG		7620.2	7620.2	4748.5	111128.5	3598.4	12500.0	180000.0	280000.0	42697.0	21000.0	30000.0	29393.9	2.57E+05	1.03E-01	1.38E+03	2.46E+02	9.67E+01	8.92E+06	
	Biogas		7620.2	7620.2	4748.5	111128.5	3598.4	12500.0	180000.0	280000.0	42697.0	21000.0	30000.0	29393.9	4.54E+05	2.36E-02	9.34E+03	3.83E+03	1.43E+02	3.46E+06	
	Sestriere	Electricity	7620.2	7620.2	4748.5	111128.5	3598.4	12500.0	180000.0	280000.0	42697.0	21000.0	30000.0	29393.9	1.79E+06	2.04E-01	8.81E+03	2.45E+03	3.76E+02	2.06E+07	
		Natural Gas	7620.2	7620.2	4748.5	111128.5	3598.4	12500.0	180000.0	280000.0	42697.0	21000.0	30000.0	29393.9	3.55E+05	1.05E-01	1.16E+03	1.97E+02	1.39E+02	1.78E+07	
		LPG	7620.2	7620.2	4748.5	111128.5	3598.4	12500.0	180000.0	280000.0	42697.0	21000.0	30000.0	29393.9	2.52E+05	1.00E-01	1.35E+03	2.42E+02	9.45E+01	8.67E+06	
		Biogas	7620.2	7620.2	4748.5	111128.5	3598.4	12500.0	180000.0	280000.0	42697.0	21000.0	30000.0	29393.9	4.43E+05	2.31E-02	9.05E+03	3.71E+03	1.40E+02	3.39E+06	
	B	Messina	Electricity	7313.6	5485.2	4505.7	91419.9	3453.6	25000.0	300000.0	490000.0	74325.1	42000.0	120000.0	36650.2	9.18E+05	9.44E-02	4.24E+03	1.21E+03	1.93E+02	1.03E+07
			Natural Gas	7313.6	5485.2	4505.7	91419.9	3453.6	25000.0	300000.0	490000.0	74325.1	42000.0	120000.0	36650.2	2.87E+05	5.11E-02	8.84E+02	2.25E+02	8.93E+01	9.06E+06
			LPG	7313.6	5485.2	4505.7	91419.9	3453.6	25000.0	300000.0	490000.0	74325.1	42000.0	120000.0	36650.2	2.42E+05	4.90E-02	9.67E+02	2.45E+02	6.97E+01	5.07E+06
			Biogas	7313.6	5485.2	4505.7	91419.9	3453.6	25000.0	300000.0	490000.0	74325.1	42000.0	120000.0	36650.2	3.26E+05	1.53E-02	4.34E+03	1.77E+03	8.94E+01	2.76E+06
		Palermo	Electricity	7313.6	5485.2	4505.7	91419.9	3453.6	25000.0	300000.0	490000.0	74325.1	42000.0	120000.0	36650.2	8.62E+05	8.78E-02	3.96E+03	1.13E+03	1.82E+02	9.64E+06
			Natural Gas	7313.6	5485.2	4505.7	91419.9	3453.6	25000.0	300000.0	490000.0	74325.1	42000.0	120000.0	36650.2	2.79E+05	4.78E-02	8.58E+02	2.22E+02	8.56E+01	8.51E+06
LPG			7313.6	5485.2	4505.7	91419.9	3453.6	25000.0	300000.0	490000.0	74325.1	42000.0	120000.0	36650.2	2.38E+05	4.59E-02	9.34E+02	2.40E+02	6.75E+01	4.82E+06	
Biogas			7313.6	5485.2	4505.7	91419.9	3453.6	25000.0	300000.0	490000.0	74325.1	42000.0	120000.0	36650.2	3.15E+05	1.47E-02	4.05E+03	1.65E+03	8.57E+01	2.69E+06	
Crotona		Electricity	7313.6	5485.2	4505.7	91419.9	3453.6	25000.0	300000.0	490000.0	74325.1	42000.0	120000.0	36650.2	1.25E+06	1.33E-01	5.89E+03	1.67E+03	2.61E+02	1.41E+07	
		Natural Gas	7313.6	5485.2	4505.7	91419.9	3453.6	25000.0	300000.0	490000.0	74325.1	42000.0	120000.0	36650.2	3.33E+05	7.03E-02	1.04E+03	2.40E+02	1.11E+02	1.23E+07	
		LPG	7313.6	5485.2	4505.7	91419.9	3453.6	25000.0	300000.0	490000.0	74325.1	42000.0	120000.0	36650.2	2.68E+05	6.74E-02	1.16E+03	2.69E+02	8.26E+01	6.54E+06	
		Biogas	7313.6	5485.2	4505.7	91419.9	3453.6	25000.0	300000.0	490000.0	74325.1	42000.0	120000.0	36650.2	3.88E+05	1.85E-02	6.04E+03	2.47E+03	1.11E+02	3.19E+06	
C	Cagliari	Electricity	7149.8	5362.3	5246.9	89372.4	3376.3	50000.0	320000.0	490000.0	74325.1	42000.0	120000.0	36650.2	7.72E+05	7.66E-02	3.49E+03	1.00E+03	1.63E+02	8.57E+06	
		Natural Gas	7149.8	5362.3	5246.9	89372.4	3376.3	50000.0	320000.0	490000.0	74325.1	42000.0	120000.0	36650.2	2.71E+05	4.22E-02	8.21E+02	2.15E+02	8.06E+01	7.60E+06	
		LPG	7149.8	5362.3	5246.9	89372.4	3376.3	50000.0	320000.0	490000.0	74325.1	42000.0	120000.0	36650.2	2.35E+05	4.06E-02	8.87E+02	2.31E+02	6.50E+01	4.43E+06	
		Biogas	7149.8	5362.3	5246.9	89372.4	3376.3	50000.0	320000.0	490000.0	74325.1	42000.0	120000.0	36650.2	3.01E+05	1.37E-02	3.57E+03	1.44E+03	8.06E+01	2.59E+06	
	Bari	Electricity	7149.8	5362.3	5246.9	89372.4	3376.3	50000.0	320000.0	490000.0	74325.1	42000.0	120000.0	36650.2	1.03E+06	1.07E-01	4.80E+03	1.36E+03	2.17E+02	1.16E+07	
		Natural Gas	7149.8	5362.3	5246.9	89372.4	3376.3	50000.0	320000.0	490000.0	74325.1	42000.0	120000.0	36650.2	3.07E+05	5.74E-02	9.44E+02	2.28E+02	9.78E+01	1.02E+07	

Model	Climatic Zone	City	Energy Carrier	External plaster	Cement lime plaster	Rock wool	Tuff block	Internal plaster 1	Concrete brick	Concrete screed	Concrete slab	Internal plaster 2	Floor tile	Bitumen	Brick	GWP	ODP	AP	EP	POCP	ADP-fossil
				[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg CO2 -eq]	[kg CFC11-eq]	[kg SO2 -eq]
D	Termoli		LPG	7149.8	5362.3	5246.9	89372.4	3376.3	50000.0	320000.0	490000.0	74325.1	42000.0	120000.0	36650.2	2.55E+05	5.51E-02	1.04E+03	2.51E+02	7.52E+01	5.59E+06
			Biogas	7149.8	5362.3	5246.9	89372.4	3376.3	50000.0	320000.0	490000.0	74325.1	42000.0	120000.0	36650.2	3.51E+05	1.63E-02	4.92E+03	2.00E+03	9.79E+01	2.93E+06
			Electricity	7149.8	5362.3	5246.9	89372.4	3376.3	50000.0	320000.0	490000.0	74325.1	42000.0	120000.0	36650.2	1.34E+06	1.43E-01	6.34E+03	1.79E+03	2.80E+02	1.51E+07
			Natural Gas	7149.8	5362.3	5246.9	89372.4	3376.3	50000.0	320000.0	490000.0	74325.1	42000.0	120000.0	36650.2	3.49E+05	7.53E-02	1.09E+03	2.42E+02	1.18E+02	1.32E+07
			LPG	7149.8	5362.3	5246.9	89372.4	3376.3	50000.0	320000.0	490000.0	74325.1	42000.0	120000.0	36650.2	2.79E+05	7.22E-02	1.22E+03	2.73E+02	8.72E+01	6.95E+06
			Biogas	7149.8	5362.3	5246.9	89372.4	3376.3	50000.0	320000.0	490000.0	74325.1	42000.0	120000.0	36650.2	4.09E+05	1.93E-02	6.50E+03	2.65E+03	1.18E+02	3.33E+06
		Genova	Electricity	7149.8	7149.8	6806.4	104267.8	3376.3	25000.0	460000.0	714000.0	74325.1	42000.0	60000.0	36650.2	1.03E+06	1.03E-01	4.70E+03	1.33E+03	2.12E+02	1.13E+07
			Natural Gas	7149.8	7149.8	6806.4	104267.8	3376.3	25000.0	460000.0	714000.0	74325.1	42000.0	60000.0	36650.2	3.43E+05	5.55E-02	1.03E+03	2.53E+02	9.81E+01	9.98E+06
			LPG	7149.8	7149.8	6806.4	104267.8	3376.3	25000.0	460000.0	714000.0	74325.1	42000.0	60000.0	36650.2	2.94E+05	5.33E-02	1.13E+03	2.75E+02	7.67E+01	5.62E+06
			Biogas	7149.8	7149.8	6806.4	104267.8	3376.3	25000.0	460000.0	714000.0	74325.1	42000.0	60000.0	36650.2	3.85E+05	1.64E-02	4.81E+03	1.94E+03	9.82E+01	3.10E+06
			Electricity	7149.8	7149.8	6806.4	104267.8	3376.3	25000.0	460000.0	714000.0	74325.1	42000.0	60000.0	36650.2	1.16E+06	1.18E-01	5.36E+03	1.51E+03	2.39E+02	1.28E+07
			Natural Gas	7149.8	7149.8	6806.4	104267.8	3376.3	25000.0	460000.0	714000.0	74325.1	42000.0	60000.0	36650.2	3.61E+05	6.32E-02	1.10E+03	2.59E+02	1.07E+02	1.13E+07
	Firenze	LPG	7149.8	7149.8	6806.4	104267.8	3376.3	25000.0	460000.0	714000.0	74325.1	42000.0	60000.0	36650.2	3.04E+05	6.06E-02	1.20E+03	2.85E+02	8.19E+01	6.21E+06	
		Biogas	7149.8	7149.8	6806.4	104267.8	3376.3	25000.0	460000.0	714000.0	74325.1	42000.0	60000.0	36650.2	4.10E+05	1.77E-02	5.50E+03	2.22E+03	1.07E+02	3.27E+06	
		Electricity	7149.8	7149.8	6806.4	104267.8	3376.3	25000.0	460000.0	714000.0	74325.1	42000.0	60000.0	36650.2	1.72E+06	1.84E-01	8.17E+03	2.29E+03	3.55E+02	1.93E+07	
	Forlì	Natural Gas	7149.8	7149.8	6806.4	104267.8	3376.3	25000.0	460000.0	714000.0	74325.1	42000.0	60000.0	36650.2	4.38E+05	9.59E-02	1.36E+03	2.86E+02	1.44E+02	1.68E+07	
		LPG	7149.8	7149.8	6806.4	104267.8	3376.3	25000.0	460000.0	714000.0	74325.1	42000.0	60000.0	36650.2	3.47E+05	9.18E-02	1.53E+03	3.26E+02	1.04E+02	8.70E+06	
		Biogas	7149.8	7149.8	6806.4	104267.8	3376.3	25000.0	460000.0	714000.0	74325.1	42000.0	60000.0	36650.2	5.16E+05	2.32E-02	8.39E+03	3.42E+03	1.44E+02	4.00E+06	
	E	Trieste	Electricity	7173.2	7173.2	8097.8	104609.0	3387.3	25000.0	360000.0	560000.0	74325.1	42000.0	60000.0	36650.2	1.20E+06	1.25E-01	5.62E+03	1.58E+03	2.50E+02	1.34E+07
			Natural Gas	7173.2	7173.2	8097.8	104609.0	3387.3	25000.0	360000.0	560000.0	74325.1	42000.0	60000.0	36650.2	3.43E+05	6.65E-02	1.07E+03	2.46E+02	1.09E+02	1.18E+07
			LPG	7173.2	7173.2	8097.8	104609.0	3387.3	25000.0	360000.0	560000.0	74325.1	42000.0	60000.0	36650.2	2.82E+05	6.38E-02	1.18E+03	2.73E+02	8.26E+01	6.37E+06
			Biogas	7173.2	7173.2	8097.8	104609.0	3387.3	25000.0	360000.0	560000.0	74325.1	42000.0	60000.0	36650.2	3.95E+05	1.80E-02	5.76E+03	2.34E+03	1.09E+02	3.23E+06
		Torino	Electricity	7173.2	7173.2	8097.8	104609.0	3387.3	25000.0	360000.0	560000.0	74325.1	42000.0	60000.0	36650.2	1.73E+06	1.89E-01	8.33E+03	2.33E+03	3.62E+02	1.97E+07
			Natural Gas	7173.2	7173.2	8097.8	104609.0	3387.3	25000.0	360000.0	560000.0	74325.1	42000.0	60000.0	36650.2	4.18E+05	9.81E-02	1.32E+03	2.72E+02	1.45E+02	1.71E+07
LPG			7173.2	7173.2	8097.8	104609.0	3387.3	25000.0	360000.0	560000.0	74325.1	42000.0	60000.0	36650.2	3.24E+05	9.39E-02	1.49E+03	3.13E+02	1.04E+02	8.77E+06	
Bolzano		Biogas	7173.2	7173.2	8097.8	104609.0	3387.3	25000.0	360000.0	560000.0	74325.1	42000.0	60000.0	36650.2	4.98E+05	2.33E-02	8.55E+03	3.49E+03	1.45E+02	3.94E+06	
		Electricity	7173.2	7173.2	8097.8	104609.0	3387.3	25000.0	360000.0	560000.0	74325.1	42000.0	60000.0	36650.2	1.72E+06	1.86E-01	8.23E+03	2.31E+03	3.57E+02	1.94E+07	
		Natural Gas	7173.2	7173.2	8097.8	104609.0	3387.3	25000.0	360000.0	560000.0	74325.1	42000.0	60000.0	36650.2	4.15E+05	9.69E-02	1.31E+03	2.71E+02	1.43E+02	1.69E+07	
		LPG	7173.2	7173.2	8097.8	104609.0	3387.3	25000.0	360000.0	560000.0	74325.1	42000.0	60000.0	36650.2	3.22E+05	9.28E-02	1.48E+03	3.12E+02	1.03E+02	8.68E+06	
		Biogas	7173.2	7173.2	8097.8	104609.0	3387.3	25000.0	360000.0	560000.0	74325.1	42000.0	60000.0	36650.2	4.94E+05	2.31E-02	8.44E+03	3.45E+03	1.44E+02	3.91E+06	
	Electricity	7126.4	7126.4	8753.3	103926.5	3365.2	25000.0	360000.0	560000.0	74325.1	42000.0	60000.0	36650.2	1.14E+06	1.18E-01	5.30E+03	1.50E+03	2.37E+02	1.27E+07		
F	Cuneo	Natural Gas	7126.4	7126.4	8753.3	103926.5	3365.2	25000.0	360000.0	560000.0	74325.1	42000.0	60000.0	36650.2	3.35E+05	6.29E-02	1.04E+03	2.41E+02	1.05E+02	1.12E+07	
		LPG	7126.4	7126.4	8753.3	103926.5	3365.2	25000.0	360000.0	560000.0	74325.1	42000.0	60000.0	36650.2	2.77E+05	6.03E-02	1.15E+03	2.66E+02	8.00E+01	6.10E+06	
		Biogas	7126.4	7126.4	8753.3	103926.5	3365.2	25000.0	360000.0	560000.0	74325.1	42000.0	60000.0	36650.2	3.83E+05	1.73E-02	5.44E+03	2.20E+03	1.05E+02	3.15E+06	
	Cortina	Electricity	7126.4	7126.4	8753.3	103926.5	3365.2	25000.0	360000.0	560000.0	74325.1	42000.0	60000.0	36650.2	2.63E+06	2.95E-01	1.29E+04	3.59E+03	5.48E+02	3.01E+07	
	Natural Gas	7126.4	7126.4	8753.3	103926.5	3365.2	25000.0	360000.0	560000.0	74325.1	42000.0	60000.0	36650.2	5.43E+05	1.51E-01	1.75E+03	3.12E+02	2.04E+02	2.60E+07		

Model	Climatic Zone	City	Energy Carrier	External plaster	Cement lime plaster	Rock wool	Tuff block	Internal plaster 1	Concrete brick	Concrete screed	Concrete slab	Internal plaster 2	Floor tile	Bitumen	Brick	GWP	ODP	AP	EP	POCP	ADP-fossil
				[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg CO ₂ -eq]	[kg CFC11-eq]	[kg SO ₂ -eq]
7	B	Sestriere	LPG	7126.4	7126.4	8753.3	103926.5	3365.2	25000.0	360000.0	560000.0	74325.1	42000.0	60000.0	36650.2	3.93E+05	1.44E-01	2.02E+03	3.79E+02	1.39E+02	1.28E+07
			Biogas	7126.4	7126.4	8753.3	103926.5	3365.2	25000.0	360000.0	560000.0	74325.1	42000.0	60000.0	36650.2	6.70E+05	3.22E-02	1.32E+04	5.42E+03	2.04E+02	5.12E+06
			Electricity	7126.4	7126.4	8753.3	103926.5	3365.2	25000.0	360000.0	560000.0	74325.1	42000.0	60000.0	36650.2	2.75E+06	3.09E-01	1.35E+04	3.75E+03	5.73E+02	3.15E+07
			Natural Gas	7126.4	7126.4	8753.3	103926.5	3365.2	25000.0	360000.0	560000.0	74325.1	42000.0	60000.0	36650.2	5.59E+05	1.58E-01	1.80E+03	3.18E+02	2.12E+02	2.72E+07
			LPG	7126.4	7126.4	8753.3	103926.5	3365.2	25000.0	360000.0	560000.0	74325.1	42000.0	60000.0	36650.2	4.03E+05	1.51E-01	2.09E+03	3.87E+02	1.44E+02	1.33E+07
			Biogas	7126.4	7126.4	8753.3	103926.5	3365.2	25000.0	360000.0	560000.0	74325.1	42000.0	60000.0	36650.2	6.93E+05	3.34E-02	1.38E+04	5.68E+03	2.12E+02	5.28E+06
		Messina	Electricity	17630.6	13223.0	3904.5	220382.6	8325.6	26880.0	182520.0	428820.0	47075.2	15750.0	45000.0	29744.0	2.82E+05	2.43E-02	1.08E+03	3.11E+02	6.44E+01	2.89E+06
			Natural Gas	17630.6	13223.0	3904.5	220382.6	8325.6	26880.0	182520.0	428820.0	47075.2	15750.0	45000.0	29744.0	1.88E+05	1.79E-02	5.74E+02	1.63E+02	4.89E+01	2.71E+06
			LPG	17630.6	13223.0	3904.5	220382.6	8325.6	26880.0	182520.0	428820.0	47075.2	15750.0	45000.0	29744.0	1.81E+05	1.76E-02	5.86E+02	1.66E+02	4.60E+01	2.11E+06
			Biogas	17630.6	13223.0	3904.5	220382.6	8325.6	26880.0	182520.0	428820.0	47075.2	15750.0	45000.0	29744.0	1.93E+05	1.25E-02	1.09E+03	3.94E+02	4.89E+01	1.76E+06
			Electricity	17630.6	13223.0	3904.5	220382.6	8325.6	26880.0	182520.0	428820.0	47075.2	15750.0	45000.0	29744.0	2.66E+05	2.25E-02	9.97E+02	2.89E+02	6.12E+01	2.71E+06
			Natural Gas	17630.6	13223.0	3904.5	220382.6	8325.6	26880.0	182520.0	428820.0	47075.2	15750.0	45000.0	29744.0	1.86E+05	1.70E-02	5.67E+02	1.62E+02	4.79E+01	2.55E+06
	Palermo	LPG	17630.6	13223.0	3904.5	220382.6	8325.6	26880.0	182520.0	428820.0	47075.2	15750.0	45000.0	29744.0	1.80E+05	1.67E-02	5.77E+02	1.65E+02	4.53E+01	2.04E+06	
		Biogas	17630.6	13223.0	3904.5	220382.6	8325.6	26880.0	182520.0	428820.0	47075.2	15750.0	45000.0	29744.0	1.90E+05	1.24E-02	1.01E+03	3.60E+02	4.79E+01	1.74E+06	
		Electricity	17630.6	13223.0	3904.5	220382.6	8325.6	26880.0	182520.0	428820.0	47075.2	15750.0	45000.0	29744.0	3.73E+05	3.51E-02	1.54E+03	4.38E+02	8.34E+01	3.95E+06	
		Natural Gas	17630.6	13223.0	3904.5	220382.6	8325.6	26880.0	182520.0	428820.0	47075.2	15750.0	45000.0	29744.0	2.00E+05	2.32E-02	6.17E+02	1.68E+02	5.49E+01	3.61E+06	
		LPG	17630.6	13223.0	3904.5	220382.6	8325.6	26880.0	182520.0	428820.0	47075.2	15750.0	45000.0	29744.0	1.88E+05	2.27E-02	6.40E+02	1.73E+02	4.95E+01	2.52E+06	
		Biogas	17630.6	13223.0	3904.5	220382.6	8325.6	26880.0	182520.0	428820.0	47075.2	15750.0	45000.0	29744.0	2.11E+05	1.34E-02	1.56E+03	5.90E+02	5.49E+01	1.88E+06	
	Crotona	Electricity	17630.6	13223.0	3904.5	220382.6	8325.6	26880.0	182520.0	428820.0	47075.2	15750.0	45000.0	29744.0	3.73E+05	3.51E-02	1.54E+03	4.38E+02	8.34E+01	3.95E+06	
		Natural Gas	17630.6	13223.0	3904.5	220382.6	8325.6	26880.0	182520.0	428820.0	47075.2	15750.0	45000.0	29744.0	2.00E+05	2.32E-02	6.17E+02	1.68E+02	5.49E+01	3.61E+06	
		LPG	17630.6	13223.0	3904.5	220382.6	8325.6	26880.0	182520.0	428820.0	47075.2	15750.0	45000.0	29744.0	1.88E+05	2.27E-02	6.40E+02	1.73E+02	4.95E+01	2.52E+06	
		Biogas	17630.6	13223.0	3904.5	220382.6	8325.6	26880.0	182520.0	428820.0	47075.2	15750.0	45000.0	29744.0	2.11E+05	1.34E-02	1.56E+03	5.90E+02	5.49E+01	1.88E+06	
		Electricity	17529.8	13147.4	4676.5	219122.6	8278.0	53670.0	203808.0	428190.0	47046.4	15750.0	45000.0	29744.0	2.23E+05	1.69E-02	7.58E+02	2.16E+02	5.16E+01	2.18E+06	
		Natural Gas	17529.8	13147.4	4676.5	219122.6	8278.0	53670.0	203808.0	428190.0	47046.4	15750.0	45000.0	29744.0	1.82E+05	1.41E-02	5.42E+02	1.53E+02	4.49E+01	2.10E+06	
	C	Cagliari	LPG	17529.8	13147.4	4676.5	219122.6	8278.0	53670.0	203808.0	428190.0	47046.4	15750.0	45000.0	29744.0	1.79E+05	1.40E-02	5.48E+02	1.54E+02	4.37E+01	1.85E+06
			Biogas	17529.8	13147.4	4676.5	219122.6	8278.0	53670.0	203808.0	428190.0	47046.4	15750.0	45000.0	29744.0	1.85E+05	1.18E-02	7.65E+02	2.52E+02	4.49E+01	1.70E+06
			Electricity	17529.8	13147.4	4676.5	219122.6	8278.0	53670.0	203808.0	428190.0	47046.4	15750.0	45000.0	29744.0	2.70E+05	2.24E-02	9.96E+02	2.82E+02	6.14E+01	2.73E+06
			Natural Gas	17529.8	13147.4	4676.5	219122.6	8278.0	53670.0	203808.0	428190.0	47046.4	15750.0	45000.0	29744.0	1.89E+05	1.69E-02	5.65E+02	1.55E+02	4.80E+01	2.57E+06
LPG			17529.8	13147.4	4676.5	219122.6	8278.0	53670.0	203808.0	428190.0	47046.4	15750.0	45000.0	29744.0	1.83E+05	1.66E-02	5.75E+02	1.58E+02	4.55E+01	2.06E+06	
Biogas			17529.8	13147.4	4676.5	219122.6	8278.0	53670.0	203808.0	428190.0	47046.4	15750.0	45000.0	29744.0	1.94E+05	1.23E-02	1.01E+03	3.53E+02	4.81E+01	1.76E+06	
Bari		Electricity	17529.8	13147.4	4676.5	219122.6	8278.0	53670.0	203808.0	428190.0	47046.4	15750.0	45000.0	29744.0	3.63E+05	3.34E-02	1.47E+03	4.12E+02	8.08E+01	3.81E+06	
		Natural Gas	17529.8	13147.4	4676.5	219122.6	8278.0	53670.0	203808.0	428190.0	47046.4	15750.0	45000.0	29744.0	2.02E+05	2.23E-02	6.09E+02	1.60E+02	5.42E+01	3.50E+06	
		LPG	17529.8	13147.4	4676.5	219122.6	8278.0	53670.0	203808.0	428190.0	47046.4	15750.0	45000.0	29744.0	1.90E+05	2.18E-02	6.30E+02	1.65E+02	4.92E+01	2.47E+06	
		Biogas	17529.8	13147.4	4676.5	219122.6	8278.0	53670.0	203808.0	428190.0	47046.4	15750.0	45000.0	29744.0	2.12E+05	1.32E-02	1.49E+03	5.54E+02	5.42E+01	1.88E+06	
		Electricity	17529.8	13147.4	4676.5	219122.6	8278.0	53670.0	203808.0	428190.0	47046.4	15750.0	45000.0	29744.0	3.21E+05	2.59E-02	1.20E+03	3.37E+02	6.93E+01	3.18E+06	
		Natural Gas	17529.8	13147.4	4676.5	219122.6	8278.0	53670.0	203808.0	428190.0	47046.4	15750.0	45000.0	29744.0	2.18E+05	1.88E-02	6.49E+02	1.76E+02	5.23E+01	2.98E+06	
D	Genova	LPG	17529.8	17529.8	5883.2	255643.0	8278.0	26640.0	282996.0	519128.4	46921.6	15750.0	22500.0	29744.0	2.10E+05	1.85E-02	6.62E+02	1.79E+02	4.91E+01	2.33E+06	
		Biogas	17529.8	17529.8	5883.2	255643.0	8278.0	26640.0	282996.0	519128.4	46921.6	15750.0	22500.0	29744.0	2.24E+05	1.30E-02	1.21E+03	4.28E+02	5.23E+01	1.95E+06	
		Electricity	17529.8	17529.8	5883.2	255643.0	8278.0	26640.0	282996.0	519128.4	46921.6	15750.0	22500.0	29744.0	3.31E+05	2.71E-02	1.25E+03	3.52E+02	7.14E+01	3.30E+06	
		Natural Gas	17529.8	17529.8	5883.2	255643.0	8278.0	26640.0	282996.0	519128.4	46921.6	15750.0	22500.0	29744.0	2.19E+05	1.94E-02	6.54E+02	1.77E+02	5.30E+01	3.09E+06	
	Firenze	Electricity	17529.8	17529.8	5883.2	255643.0	8278.0	26640.0	282996.0	519128.4	46921.6	15750.0	22500.0	29744.0	3.31E+05	2.71E-02	1.25E+03	3.52E+02	7.14E+01	3.30E+06	
		Natural Gas	17529.8	17529.8	5883.2	255643.0	8278.0	26640.0	282996.0	519128.4	46921.6	15750.0	22500.0	29744.0	2.19E+05	1.94E-02	6.54E+02	1.77E+02	5.30E+01	3.09E+06	

Model	Climatic Zone	City	Energy Carrier	External plaster	Cement lime plaster	Rock wool	Tuff block	Internal plaster 1	Concrete brick	Concrete screed	Concrete slab	Internal plaster 2	Floor tile	Bitumen	Brick	GWP	ODP	AP	EP	POCP	ADP-fossil	
				[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg CO2 -eq]	[kg CFC11-eq]	[kg SO2 -eq]	[kg PO43--eq]
E	Forlì	LPG	LPG	17529.8	17529.8	5883.2	255643.0	8278.0	26640.0	282996.0	519128.4	46921.6	15750.0	22500.0	29744.0	2.11E+05	1.91E-02	6.68E+02	1.80E+02	4.95E+01	2.38E+06	
			Biogas	17529.8	17529.8	5883.2	255643.0	8278.0	26640.0	282996.0	519128.4	46921.6	15750.0	22500.0	29744.0	2.26E+05	1.31E-02	1.27E+03	4.50E+02	5.30E+01	1.97E+06	
		Electricity	Electricity	17529.8	17529.8	5883.2	255643.0	8278.0	26640.0	282996.0	519128.4	46921.6	15750.0	22500.0	29744.0	5.12E+05	4.85E-02	2.16E+03	6.04E+02	1.09E+02	5.40E+06	
			Natural Gas	17529.8	17529.8	5883.2	255643.0	8278.0	26640.0	282996.0	519128.4	46921.6	15750.0	22500.0	29744.0	2.44E+05	3.01E-02	7.39E+02	1.85E+02	6.50E+01	4.88E+06	
		LPG	LPG	17529.8	17529.8	5883.2	255643.0	8278.0	26640.0	282996.0	519128.4	46921.6	15750.0	22500.0	29744.0	2.25E+05	2.92E-02	7.74E+02	1.94E+02	5.67E+01	3.19E+06	
			Biogas	17529.8	17529.8	5883.2	255643.0	8278.0	26640.0	282996.0	519128.4	46921.6	15750.0	22500.0	29744.0	2.61E+05	1.49E-02	2.21E+03	8.40E+02	6.50E+01	2.21E+06	
		Trieste	Electricity	Electricity	17544.2	17544.2	6754.2	255853.0	8284.8	26595.0	245208.0	402864.0	46892.8	15750.0	22500.0	29744.0	3.66E+05	3.31E-02	1.48E+03	4.15E+02	8.14E+01	3.82E+06
			Natural Gas	Natural Gas	17544.2	17544.2	6754.2	255853.0	8284.8	26595.0	245208.0	402864.0	46892.8	15750.0	22500.0	29744.0	2.10E+05	2.23E-02	6.49E+02	1.71E+02	5.57E+01	3.52E+06
			LPG	LPG	17544.2	17544.2	6754.2	255853.0	8284.8	26595.0	245208.0	402864.0	46892.8	15750.0	22500.0	29744.0	1.99E+05	2.18E-02	6.69E+02	1.76E+02	5.09E+01	2.54E+06
			Biogas	Biogas	17544.2	17544.2	6754.2	255853.0	8284.8	26595.0	245208.0	402864.0	46892.8	15750.0	22500.0	29744.0	2.20E+05	1.35E-02	1.50E+03	5.52E+02	5.58E+01	1.96E+06
		Torino	Electricity	Electricity	17544.2	17544.2	6754.2	255853.0	8284.8	26595.0	245208.0	402864.0	46892.8	15750.0	22500.0	29744.0	5.08E+05	4.98E-02	2.19E+03	6.13E+02	1.11E+02	5.47E+06
			Natural Gas	Natural Gas	17544.2	17544.2	6754.2	255853.0	8284.8	26595.0	245208.0	402864.0	46892.8	15750.0	22500.0	29744.0	2.30E+05	3.07E-02	7.16E+02	1.78E+02	6.51E+01	4.93E+06
	LPG		LPG	17544.2	17544.2	6754.2	255853.0	8284.8	26595.0	245208.0	402864.0	46892.8	15750.0	22500.0	29744.0	2.10E+05	2.98E-02	7.52E+02	1.87E+02	5.65E+01	3.17E+06	
	Biogas		Biogas	17544.2	17544.2	6754.2	255853.0	8284.8	26595.0	245208.0	402864.0	46892.8	15750.0	22500.0	29744.0	2.47E+05	1.49E-02	2.24E+03	8.57E+02	6.52E+01	2.15E+06	
	Bolzano	Electricity	Electricity	17544.2	17544.2	6754.2	255853.0	8284.8	26595.0	245208.0	402864.0	46892.8	15750.0	22500.0	29744.0	4.91E+05	4.78E-02	2.11E+03	5.89E+02	1.07E+02	5.27E+06	
		Natural Gas	Natural Gas	17544.2	17544.2	6754.2	255853.0	8284.8	26595.0	245208.0	402864.0	46892.8	15750.0	22500.0	29744.0	2.27E+05	2.97E-02	7.08E+02	1.77E+02	6.40E+01	4.76E+06	
		LPG	LPG	17544.2	17544.2	6754.2	255853.0	8284.8	26595.0	245208.0	402864.0	46892.8	15750.0	22500.0	29744.0	2.09E+05	2.88E-02	7.42E+02	1.86E+02	5.58E+01	3.09E+06	
		Biogas	Biogas	17544.2	17544.2	6754.2	255853.0	8284.8	26595.0	245208.0	402864.0	46892.8	15750.0	22500.0	29744.0	2.43E+05	1.47E-02	2.15E+03	8.21E+02	6.40E+01	2.13E+06	
	F	Cuneo	Electricity	Electricity	17515.4	17515.4	7324.7	255433.0	8271.2	26565.0	245016.0	402528.0	46873.6	15750.0	22500.0	29744.0	3.07E+05	2.61E-02	1.18E+03	3.30E+02	6.86E+01	3.15E+06
			Natural Gas	Natural Gas	17515.4	17515.4	7324.7	255433.0	8271.2	26565.0	245016.0	402528.0	46873.6	15750.0	22500.0	29744.0	2.01E+05	1.89E-02	6.16E+02	1.64E+02	5.11E+01	2.94E+06
			LPG	LPG	17515.4	17515.4	7324.7	255433.0	8271.2	26565.0	245016.0	402528.0	46873.6	15750.0	22500.0	29744.0	1.94E+05	1.85E-02	6.30E+02	1.67E+02	4.78E+01	2.27E+06
			Biogas	Biogas	17515.4	17515.4	7324.7	255433.0	8271.2	26565.0	245016.0	402528.0	46873.6	15750.0	22500.0	29744.0	2.08E+05	1.28E-02	1.20E+03	4.23E+02	5.11E+01	1.88E+06
		Cortina	Electricity	Electricity	17515.4	17515.4	7324.7	255433.0	8271.2	26565.0	245016.0	402528.0	46873.6	15750.0	22500.0	29744.0	7.01E+05	7.26E-02	3.17E+03	8.80E+02	1.50E+02	7.72E+06
			Natural Gas	Natural Gas	17515.4	17515.4	7324.7	255433.0	8271.2	26565.0	245016.0	402528.0	46873.6	15750.0	22500.0	29744.0	2.56E+05	4.20E-02	8.02E+02	1.83E+02	7.72E+01	6.85E+06
LPG			LPG	17515.4	17515.4	7324.7	255433.0	8271.2	26565.0	245016.0	402528.0	46873.6	15750.0	22500.0	29744.0	2.24E+05	4.06E-02	8.60E+02	1.97E+02	6.33E+01	4.03E+06	
Biogas			Biogas	17515.4	17515.4	7324.7	255433.0	8271.2	26565.0	245016.0	402528.0	46873.6	15750.0	22500.0	29744.0	2.83E+05	1.67E-02	3.24E+03	1.27E+03	7.72E+01	2.40E+06	
Sestriere		Electricity	Electricity	17515.4	17515.4	7324.7	255433.0	8271.2	26565.0	245016.0	402528.0	46873.6	15750.0	22500.0	29744.0	6.29E+05	6.41E-02	2.80E+03	7.79E+02	1.35E+02	6.88E+06	
		Natural Gas	Natural Gas	17515.4	17515.4	7324.7	255433.0	8271.2	26565.0	245016.0	402528.0	46873.6	15750.0	22500.0	29744.0	2.46E+05	3.78E-02	7.68E+02	1.79E+02	7.24E+01	6.13E+06	
		LPG	LPG	17515.4	17515.4	7324.7	255433.0	8271.2	26565.0	245016.0	402528.0	46873.6	15750.0	22500.0	29744.0	2.19E+05	3.65E-02	8.18E+02	1.92E+02	6.05E+01	3.71E+06	
		Biogas	Biogas	17515.4	17515.4	7324.7	255433.0	8271.2	26565.0	245016.0	402528.0	46873.6	15750.0	22500.0	29744.0	2.69E+05	1.60E-02	2.87E+03	1.12E+03	7.25E+01	2.31E+06	
8	B	Messina	Electricity	29894.8	22421.1	11339.3	373684.5	14117.0	78340.0	633360.0	1320760.0	235650.9	67200.0	192000.0	243026.6	8.98E+05	7.78E-02	3.49E+03	1.00E+03	2.15E+02	9.50E+06	
			Natural Gas	29894.8	22421.1	11339.3	373684.5	14117.0	78340.0	633360.0	1320760.0	235650.9	67200.0	192000.0	243026.6	5.51E+05	5.39E-02	1.65E+03	4.56E+02	1.57E+02	8.83E+06	
		LPG	29894.8	22421.1	11339.3	373684.5	14117.0	78340.0	633360.0	1320760.0	235650.9	67200.0	192000.0	243026.6	5.26E+05	5.28E-02	1.69E+03	4.67E+02	1.47E+02	6.63E+06		
		Biogas	29894.8	22421.1	11339.3	373684.5	14117.0	78340.0	633360.0	1320760.0	235650.9	67200.0	192000.0	243026.6	5.72E+05	3.42E-02	3.55E+03	1.30E+03	1.57E+02	5.36E+06		
	Palermo	Electricity	29894.8	22421.1	11339.3	373684.5	14117.0	78340.0	633360.0	1320760.0	235650.9	67200.0	192000.0	243026.6	8.51E+05	7.22E-02	3.25E+03	9.34E+02	2.05E+02	8.96E+06		
		Natural Gas	29894.8	22421.1	11339.3	373684.5	14117.0	78340.0	633360.0	1320760.0	235650.9	67200.0	192000.0	243026.6	5.44E+05	5.11E-02	1.62E+03	4.54E+02	1.54E+02	8.36E+06		

Model	Climatic Zone	City	Energy Carrier	External plaster	Cement lime plaster	Rock wool	Tuff block	Internal plaster 1	Concrete brick	Concrete screed	Concrete slab	Internal plaster 2	Floor tile	Bitumen	Brick	GWP	ODP	AP	EP	POCP	ADP-fossil	
				[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg CO2 -eq]	[kg CFC11 -eq]	[kg SO2 -eq]	[kg PO43--eq]	[kg C2H4 -eq]
C	Crotone	LPG	LPG	29894.8	22421.1	11339.3	373684.5	14117.0	78340.0	633360.0	1320760.0	235650.9	67200.0	192000.0	243026.6	5.22E+05	5.02E-02	1.66E+03	4.64E+02	1.45E+02	6.42E+06	
			Biogas	29894.8	22421.1	11339.3	373684.5	14117.0	78340.0	633360.0	1320760.0	235650.9	67200.0	192000.0	243026.6	5.63E+05	3.37E-02	3.30E+03	1.20E+03	1.54E+02	5.30E+06	
		Electricity	Electricity	29894.8	22421.1	11339.3	373684.5	14117.0	78340.0	633360.0	1320760.0	235650.9	67200.0	192000.0	243026.6	1.18E+06	1.11E-01	4.94E+03	1.40E+03	2.74E+02	1.28E+07	
			Natural Gas	29894.8	22421.1	11339.3	373684.5	14117.0	78340.0	633360.0	1320760.0	235650.9	67200.0	192000.0	243026.6	5.90E+05	7.07E-02	1.78E+03	4.70E+02	1.76E+02	1.17E+07	
		LPG	LPG	29894.8	22421.1	11339.3	373684.5	14117.0	78340.0	633360.0	1320760.0	235650.9	67200.0	192000.0	243026.6	5.48E+05	6.88E-02	1.86E+03	4.89E+02	1.58E+02	7.91E+06	
			Biogas	29894.8	22421.1	11339.3	373684.5	14117.0	78340.0	633360.0	1320760.0	235650.9	67200.0	192000.0	243026.6	6.27E+05	3.70E-02	5.04E+03	1.92E+03	1.76E+02	5.74E+06	
		Cagliari	Electricity	Electricity	29693.2	22269.9	13440.4	371164.5	14021.8	156560.0	695744.0	1319920.0	235612.5	67200.0	192000.0	243026.6	7.74E+05	6.16E-02	2.82E+03	8.00E+02	1.89E+02	7.99E+06
				Natural Gas	29693.2	22269.9	13440.4	371164.5	14021.8	156560.0	695744.0	1319920.0	235612.5	67200.0	192000.0	243026.6	5.45E+05	4.58E-02	1.60E+03	4.41E+02	1.52E+02	7.55E+06
			LPG	LPG	29693.2	22269.9	13440.4	371164.5	14021.8	156560.0	695744.0	1319920.0	235612.5	67200.0	192000.0	243026.6	5.29E+05	4.51E-02	1.63E+03	4.49E+02	1.45E+02	6.10E+06
				Biogas	29693.2	22269.9	13440.4	371164.5	14021.8	156560.0	695744.0	1319920.0	235612.5	67200.0	192000.0	243026.6	5.59E+05	3.28E-02	2.86E+03	1.00E+03	1.52E+02	5.26E+06
			Electricity	Electricity	29693.2	22269.9	13440.4	371164.5	14021.8	156560.0	695744.0	1319920.0	235612.5	67200.0	192000.0	243026.6	9.83E+05	8.62E-02	3.88E+03	1.09E+03	2.33E+02	1.04E+07
				Natural Gas	29693.2	22269.9	13440.4	371164.5	14021.8	156560.0	695744.0	1319920.0	235612.5	67200.0	192000.0	243026.6	5.74E+05	5.81E-02	1.70E+03	4.51E+02	1.66E+02	9.62E+06
	Bari	LPG	LPG	29693.2	22269.9	13440.4	371164.5	14021.8	156560.0	695744.0	1319920.0	235612.5	67200.0	192000.0	243026.6	5.45E+05	5.68E-02	1.75E+03	4.64E+02	1.53E+02	7.03E+06	
			Biogas	29693.2	22269.9	13440.4	371164.5	14021.8	156560.0	695744.0	1319920.0	235612.5	67200.0	192000.0	243026.6	5.99E+05	3.49E-02	3.94E+03	1.45E+03	1.66E+02	5.53E+06	
		Electricity	Electricity	29693.2	22269.9	13440.4	371164.5	14021.8	156560.0	695744.0	1319920.0	235612.5	67200.0	192000.0	243026.6	1.25E+06	1.18E-01	5.23E+03	1.46E+03	2.88E+02	1.35E+07	
			Natural Gas	29693.2	22269.9	13440.4	371164.5	14021.8	156560.0	695744.0	1319920.0	235612.5	67200.0	192000.0	243026.6	6.11E+05	7.38E-02	1.83E+03	4.64E+02	1.83E+02	1.23E+07	
	Termoli	LPG	LPG	29693.2	22269.9	13440.4	371164.5	14021.8	156560.0	695744.0	1319920.0	235612.5	67200.0	192000.0	243026.6	5.66E+05	7.18E-02	1.91E+03	4.84E+02	1.63E+02	8.23E+06	
			Biogas	29693.2	22269.9	13440.4	371164.5	14021.8	156560.0	695744.0	1319920.0	235612.5	67200.0	192000.0	243026.6	6.50E+05	3.75E-02	5.33E+03	2.03E+03	1.83E+02	5.88E+06	
		Electricity	Electricity	29693.2	22269.9	13440.4	371164.5	14021.8	156560.0	695744.0	1319920.0	235612.5	67200.0	192000.0	243026.6	1.10E+06	9.16E-02	4.28E+03	1.20E+03	2.47E+02	1.13E+07	
			Natural Gas	29693.2	22269.9	13440.4	371164.5	14021.8	156560.0	695744.0	1319920.0	235612.5	67200.0	192000.0	243026.6	6.60E+05	6.14E-02	1.94E+03	5.11E+02	1.74E+02	1.04E+07	
	D	Genova	LPG	LPG	29693.2	22269.9	13440.4	371164.5	14021.8	156560.0	695744.0	1319920.0	235612.5	67200.0	192000.0	243026.6	6.28E+05	6.00E-02	2.00E+03	5.25E+02	1.61E+02	7.66E+06
				Biogas	29693.2	22269.9	13440.4	371164.5	14021.8	156560.0	695744.0	1319920.0	235612.5	67200.0	192000.0	243026.6	6.87E+05	3.64E-02	4.36E+03	1.59E+03	1.74E+02	6.04E+06
			Electricity	Electricity	29693.2	22269.9	13440.4	371164.5	14021.8	156560.0	695744.0	1319920.0	235612.5	67200.0	192000.0	243026.6	1.19E+06	1.02E-01	4.74E+03	1.33E+03	2.65E+02	1.23E+07
				Natural Gas	29693.2	22269.9	13440.4	371164.5	14021.8	156560.0	695744.0	1319920.0	235612.5	67200.0	192000.0	243026.6	6.72E+05	6.67E-02	1.99E+03	5.16E+02	1.80E+02	1.13E+07
Firenze		LPG	LPG	29693.2	22269.9	13440.4	371164.5	14021.8	156560.0	695744.0	1319920.0	235612.5	67200.0	192000.0	243026.6	6.35E+05	6.50E-02	2.05E+03	5.32E+02	1.64E+02	8.06E+06	
			Biogas	29693.2	22269.9	13440.4	371164.5	14021.8	156560.0	695744.0	1319920.0	235612.5	67200.0	192000.0	243026.6	7.04E+05	3.73E-02	4.82E+03	1.78E+03	1.80E+02	6.16E+06	
		Electricity	Electricity	29693.2	22269.9	13440.4	371164.5	14021.8	156560.0	695744.0	1319920.0	235612.5	67200.0	192000.0	243026.6	1.69E+06	1.61E-01	7.25E+03	2.02E+03	3.69E+02	1.81E+07	
			Natural Gas	29693.2	22269.9	13440.4	371164.5	14021.8	156560.0	695744.0	1319920.0	235612.5	67200.0	192000.0	243026.6	7.42E+05	9.60E-02	2.22E+03	5.40E+02	2.13E+02	1.63E+07	
Forlì		LPG	LPG	29693.2	22269.9	13440.4	371164.5	14021.8	156560.0	695744.0	1319920.0	235612.5	67200.0	192000.0	243026.6	6.74E+05	9.30E-02	2.35E+03	5.69E+02	1.84E+02	1.03E+07	
			Biogas	29693.2	22269.9	13440.4	371164.5	14021.8	156560.0	695744.0	1319920.0	235612.5	67200.0	192000.0	243026.6	7.99E+05	4.23E-02	7.41E+03	2.85E+03	2.13E+02	6.82E+06	
		Electricity	Electricity	29722.0	22269.9	13440.4	371164.5	14021.8	156560.0	695744.0	1319920.0	235612.5	67200.0	192000.0	243026.6	1.24E+06	1.14E-01	5.17E+03	1.45E+03	2.85E+02	1.33E+07	
			Natural Gas	29722.0	22269.9	13440.4	371164.5	14021.8	156560.0	695744.0	1319920.0	235612.5	67200.0	192000.0	243026.6	6.31E+05	7.26E-02	1.93E+03	4.91E+02	1.84E+02	1.21E+07	
E	Trieste	LPG	LPG	29722.0	22269.9	13440.4	371164.5	14021.8	156560.0	695744.0	1319920.0	235612.5	67200.0	192000.0	243026.6	5.88E+05	7.06E-02	2.01E+03	5.10E+02	1.65E+02	8.29E+06	
			Biogas	29722.0	22269.9	13440.4	371164.5	14021.8	156560.0	695744.0	1319920.0	235612.5	67200.0	192000.0	243026.6	6.68E+05	3.79E-02	5.27E+03	1.98E+03	1.84E+02	6.05E+06	
	Electricity	Electricity	29722.0	22269.9	13440.4	371164.5	14021.8	156560.0	695744.0	1319920.0	235612.5	67200.0	192000.0	243026.6	1.71E+06	1.70E-01	7.54E+03	2.10E+03	3.82E+02	1.88E+07		
		Natural Gas	29722.0	22269.9	13440.4	371164.5	14021.8	156560.0	695744.0	1319920.0	235612.5	67200.0	192000.0	243026.6	6.97E+05	1.00E-01	2.15E+03	5.14E+02	2.15E+02	1.68E+07		
Torino	LPG	LPG	29722.0	22269.9	13440.4	371164.5	14021.8	156560.0	695744.0	1319920.0	235612.5	67200.0	192000.0	243026.6	1.24E+06	1.14E-01	5.17E+03	1.45E+03	2.85E+02	1.33E+07		
		Natural Gas	29722.0	22269.9	13440.4	371164.5	14021.8	156560.0	695744.0	1319920.0	235612.5	67200.0	192000.0	243026.6	6.31E+05	7.26E-02	1.93E+03	4.91E+02	1.84E+02	1.21E+07		

Model	Climatic Zone	City	Energy Carrier	External plaster	Cement lime plaster	Rock wool	Tuff block	Internal plaster 1	Concrete brick	Concrete screed	Concrete slab	Internal plaster 2	Floor tile	Bitumen	Brick	GWP	ODP	AP	EP	POCP	ADP-fossil
				[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg CO ₂ -eq]	[kg CFC11-eq]	[kg SO ₂ -eq]	[kg PO ₄ 3--eq]
9	F	Bolzano	LPG	29722.0	29722.0	19943.1	433445.2	14035.4	77960.0	818944.0	1321152.0	235407.7	67200.0	96000.0	243026.6	6.24E+05	9.69E-02	2.28E+03	5.46E+02	1.84E+02	1.04E+07
			Biogas	29722.0	29722.0	19943.1	433445.2	14035.4	77960.0	818944.0	1321152.0	235407.7	67200.0	96000.0	243026.6	7.58E+05	4.26E-02	7.71E+03	2.99E+03	2.16E+02	6.67E+06
			Electricity	29722.0	29722.0	19943.1	433445.2	14035.4	77960.0	818944.0	1321152.0	235407.7	67200.0	96000.0	243026.6	1.70E+06	1.69E-01	7.49E+03	2.09E+03	3.80E+02	1.87E+07
			Natural Gas	29722.0	29722.0	19943.1	433445.2	14035.4	77960.0	818944.0	1321152.0	235407.7	67200.0	96000.0	243026.6	6.95E+05	9.95E-02	2.14E+03	5.13E+02	2.15E+02	1.67E+07
			LPG	29722.0	29722.0	19943.1	433445.2	14035.4	77960.0	818944.0	1321152.0	235407.7	67200.0	96000.0	243026.6	6.23E+05	9.63E-02	2.28E+03	5.45E+02	1.84E+02	1.03E+07
			Biogas	29722.0	29722.0	19943.1	433445.2	14035.4	77960.0	818944.0	1321152.0	235407.7	67200.0	96000.0	243026.6	7.56E+05	4.25E-02	7.65E+03	2.97E+03	2.15E+02	6.66E+06
		Cuneo	Electricity	29664.4	29664.4	21594.8	432605.2	14008.2	77920.0	818688.0	1320704.0	235382.1	67200.0	96000.0	243026.6	1.21E+06	1.11E-01	5.01E+03	1.40E+03	2.78E+02	1.30E+07
			Natural Gas	29664.4	29664.4	21594.8	432605.2	14008.2	77920.0	818688.0	1320704.0	235382.1	67200.0	96000.0	243026.6	6.26E+05	7.07E-02	1.91E+03	4.82E+02	1.81E+02	1.19E+07
			LPG	29664.4	29664.4	21594.8	432605.2	14008.2	77920.0	818688.0	1320704.0	235382.1	67200.0	96000.0	243026.6	5.85E+05	6.88E-02	1.99E+03	5.01E+02	1.63E+02	8.16E+06
			Biogas	29664.4	29664.4	21594.8	432605.2	14008.2	77920.0	818688.0	1320704.0	235382.1	67200.0	96000.0	243026.6	6.62E+05	3.75E-02	5.11E+03	1.91E+03	1.82E+02	6.02E+06
			Electricity	29664.4	29664.4	21594.8	432605.2	14008.2	77920.0	818688.0	1320704.0	235382.1	67200.0	96000.0	243026.6	2.55E+06	2.69E-01	1.18E+04	3.26E+03	5.56E+02	2.85E+07
			Natural Gas	29664.4	29664.4	21594.8	432605.2	14008.2	77920.0	818688.0	1320704.0	235382.1	67200.0	96000.0	243026.6	8.12E+05	1.49E-01	2.54E+03	5.46E+02	2.70E+02	2.51E+07
	Cortina	LPG	29664.4	29664.4	21594.8	432605.2	14008.2	77920.0	818688.0	1320704.0	235382.1	67200.0	96000.0	243026.6	6.89E+05	1.44E-01	2.77E+03	6.01E+02	2.16E+02	1.41E+07	
		Biogas	29664.4	29664.4	21594.8	432605.2	14008.2	77920.0	818688.0	1320704.0	235382.1	67200.0	96000.0	243026.6	9.18E+05	5.08E-02	1.21E+04	4.79E+03	2.70E+02	7.78E+06	
		Electricity	29664.4	29664.4	21594.8	432605.2	14008.2	77920.0	818688.0	1320704.0	235382.1	67200.0	96000.0	243026.6	2.66E+06	2.81E-01	1.23E+04	3.41E+03	5.78E+02	2.97E+07	
		Natural Gas	29664.4	29664.4	21594.8	432605.2	14008.2	77920.0	818688.0	1320704.0	235382.1	67200.0	96000.0	243026.6	8.27E+05	1.56E-01	2.59E+03	5.51E+02	2.77E+02	2.62E+07	
		LPG	29664.4	29664.4	21594.8	432605.2	14008.2	77920.0	818688.0	1320704.0	235382.1	67200.0	96000.0	243026.6	6.97E+05	1.50E-01	2.83E+03	6.09E+02	2.20E+02	1.46E+07	
		Biogas	29664.4	29664.4	21594.8	432605.2	14008.2	77920.0	818688.0	1320704.0	235382.1	67200.0	96000.0	243026.6	9.39E+05	5.19E-02	1.26E+04	5.02E+03	2.77E+02	7.92E+06	
	B	Messina	Electricity	47144.0	35358.0	13212.6	589299.9	22262.4	97174.0	652696.0	1545236.0	156280.3	55440.0	158400.0	82577.9	7.40E+05	5.47E-02	2.58E+03	7.53E+02	1.64E+02	7.23E+06
			Natural Gas	47144.0	35358.0	13212.6	589299.9	22262.4	97174.0	652696.0	1545236.0	156280.3	55440.0	158400.0	82577.9	5.74E+05	4.33E-02	1.70E+03	4.94E+02	1.36E+02	6.91E+06
			LPG	47144.0	35358.0	13212.6	589299.9	22262.4	97174.0	652696.0	1545236.0	156280.3	55440.0	158400.0	82577.9	5.62E+05	4.28E-02	1.72E+03	4.99E+02	1.31E+02	5.86E+06
			Biogas	47144.0	35358.0	13212.6	589299.9	22262.4	97174.0	652696.0	1545236.0	156280.3	55440.0	158400.0	82577.9	5.84E+05	3.39E-02	2.61E+03	8.99E+02	1.37E+02	5.25E+06
			Electricity	47144.0	35358.0	13212.6	589299.9	22262.4	97174.0	652696.0	1545236.0	156280.3	55440.0	158400.0	82577.9	7.16E+05	5.19E-02	2.46E+03	7.20E+02	1.59E+02	6.95E+06
			Natural Gas	47144.0	35358.0	13212.6	589299.9	22262.4	97174.0	652696.0	1545236.0	156280.3	55440.0	158400.0	82577.9	5.70E+05	4.19E-02	1.69E+03	4.93E+02	1.35E+02	6.67E+06
Palermo		LPG	47144.0	35358.0	13212.6	589299.9	22262.4	97174.0	652696.0	1545236.0	156280.3	55440.0	158400.0	82577.9	5.60E+05	4.15E-02	1.71E+03	4.97E+02	1.30E+02	5.75E+06	
		Biogas	47144.0	35358.0	13212.6	589299.9	22262.4	97174.0	652696.0	1545236.0	156280.3	55440.0	158400.0	82577.9	5.79E+05	3.37E-02	2.48E+03	8.47E+02	1.35E+02	5.22E+06	
		Electricity	47144.0	35358.0	13212.6	589299.9	22262.4	97174.0	652696.0	1545236.0	156280.3	55440.0	158400.0	82577.9	1.02E+06	8.77E-02	3.99E+03	1.14E+03	2.22E+02	1.05E+07	
		Natural Gas	47144.0	35358.0	13212.6	589299.9	22262.4	97174.0	652696.0	1545236.0	156280.3	55440.0	158400.0	82577.9	6.13E+05	5.98E-02	1.83E+03	5.07E+02	1.55E+02	9.68E+06	
		LPG	47144.0	35358.0	13212.6	589299.9	22262.4	97174.0	652696.0	1545236.0	156280.3	55440.0	158400.0	82577.9	5.84E+05	5.85E-02	1.88E+03	5.20E+02	1.42E+02	7.11E+06	
		Biogas	47144.0	35358.0	13212.6	589299.9	22262.4	97174.0	652696.0	1545236.0	156280.3	55440.0	158400.0	82577.9	6.37E+05	3.67E-02	4.06E+03	1.50E+03	1.55E+02	5.62E+06	
C	Crotone	Electricity	46937.4	35203.0	15808.6	586716.9	22164.9	194216.0	730118.4	1544312.0	156238.1	55440.0	158400.0	82577.9	6.38E+05	4.08E-02	2.00E+03	5.74E+02	1.42E+02	5.95E+06	
		Natural Gas	46937.4	35203.0	15808.6	586716.9	22164.9	194216.0	730118.4	1544312.0	156238.1	55440.0	158400.0	82577.9	5.73E+05	3.63E-02	1.66E+03	4.72E+02	1.32E+02	5.83E+06	
		LPG	46937.4	35203.0	15808.6	586716.9	22164.9	194216.0	730118.4	1544312.0	156238.1	55440.0	158400.0	82577.9	5.68E+05	3.61E-02	1.67E+03	4.74E+02	1.30E+02	5.42E+06	
		Biogas	46937.4	35203.0	15808.6	586716.9	22164.9	194216.0	730118.4	1544312.0	156238.1	55440.0	158400.0	82577.9	5.77E+05	3.26E-02	2.01E+03	6.31E+02	1.32E+02	5.18E+06	
	Cagliari	Electricity	46937.4	35203.0	15808.6	586716.9	22164.9	194216.0	730118.4	1544312.0	156238.1	55440.0	158400.0	82577.9	7.65E+05	5.58E-02	2.65E+03	7.52E+02	1.69E+02	7.43E+06	
		Natural Gas	46937.4	35203.0	15808.6	586716.9	22164.9	194216.0	730118.4	1544312.0	156238.1	55440.0	158400.0	82577.9	5.91E+05	4.38E-02	1.72E+03	4.78E+02	1.40E+02	7.09E+06	
		LPG	46937.4	35203.0	15808.6	586716.9	22164.9	194216.0	730118.4	1544312.0	156238.1	55440.0	158400.0	82577.9	5.73E+05	3.63E-02	1.66E+03	4.72E+02	1.32E+02	5.83E+06	
		Biogas	46937.4	35203.0	15808.6	586716.9	22164.9	194216.0	730118.4	1544312.0	156238.1	55440.0	158400.0	82577.9	5.77E+05	3.26E-02	2.01E+03	6.31E+02	1.32E+02	5.18E+06	
Bari	Electricity	46937.4	35203.0	15808.6	586716.9	22164.9	194216.0	730118.4	1544312.0	156238.1	55440.0	158400.0	82577.9	7.65E+05	5.58E-02	2.65E+03	7.52E+02	1.69E+02	7.43E+06		
	Natural Gas	46937.4	35203.0	15808.6	586716.9	22164.9	194216.0	730118.4	1544312.0	156238.1	55440.0	158400.0	82577.9	5.91E+05	4.38E-02	1.72E+03	4.78E+02	1.40E+02	7.09E+06		
	LPG	46937.4	35203.0	15808.6	586716.9	22164.9	194216.0	730118.4	1544312.0	156238.1	55440.0	158400.0	82577.9	5.68E+05	3.61E-02	1.67E+03	4.74E+02	1.30E+02	5.42E+06		
	Biogas	46937.4	35203.0	15808.6	586716.9	22164.9	194216.0	730118.4	1544312.0	156238.1	55440.0	158400.0	82577.9	5.77E+05	3.26E-02	2.01E+03	6.31E+02	1.32E+02	5.18E+06		

Model	Climatic Zone	City	Energy Carrier	External plaster	Cement lime plaster	Rock wool	Tuff block	Internal plaster 1	Concrete brick	Concrete screed	Concrete slab	Internal plaster 2	Floor tile	Bitumen	Brick	GWP	ODP	AP	EP	POCP	ADP-fossil
				[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg CO2 -eq]	[kg CFC11 -eq]	[kg SO2 -eq]
D	Termoli		LPG	46937.4	35203.0	15808.6	586716.9	22164.9	194216.0	730118.4	1544312.0	156238.1	55440.0	158400.0	82577.9	5.78E+05	4.32E-02	1.74E+03	4.84E+02	1.35E+02	5.99E+06
			Biogas	46937.4	35203.0	15808.6	586716.9	22164.9	194216.0	730118.4	1544312.0	156238.1	55440.0	158400.0	82577.9	6.01E+05	3.39E-02	2.68E+03	9.05E+02	1.40E+02	5.35E+06
			Electricity	46937.4	35203.0	15808.6	586716.9	22164.9	194216.0	730118.4	1544312.0	156238.1	55440.0	158400.0	82577.9	1.03E+06	8.73E-02	3.99E+03	1.12E+03	2.24E+02	1.05E+07
			Natural Gas	46937.4	35203.0	15808.6	586716.9	22164.9	194216.0	730118.4	1544312.0	156238.1	55440.0	158400.0	82577.9	6.28E+05	5.95E-02	1.84E+03	4.91E+02	1.58E+02	9.74E+06
			LPG	46937.4	35203.0	15808.6	586716.9	22164.9	194216.0	730118.4	1544312.0	156238.1	55440.0	158400.0	82577.9	5.99E+05	5.82E-02	1.90E+03	5.04E+02	1.45E+02	7.18E+06
			Biogas	46937.4	35203.0	15808.6	586716.9	22164.9	194216.0	730118.4	1544312.0	156238.1	55440.0	158400.0	82577.9	6.52E+05	3.65E-02	4.06E+03	1.48E+03	1.58E+02	5.70E+06
		Genova	Electricity	46937.4	46937.4	20065.2	684503.0	22164.9	96822.0	1015660.8	1871728.3	156055.0	55440.0	79200.0	82577.9	9.03E+05	6.38E-02	3.16E+03	8.93E+02	1.88E+02	8.58E+06
			Natural Gas	46937.4	46937.4	20065.2	684503.0	22164.9	96822.0	1015660.8	1871728.3	156055.0	55440.0	79200.0	82577.9	6.81E+05	4.85E-02	1.98E+03	5.45E+02	1.51E+02	8.15E+06
			LPG	46937.4	46937.4	20065.2	684503.0	22164.9	96822.0	1015660.8	1871728.3	156055.0	55440.0	79200.0	82577.9	6.65E+05	4.78E-02	2.01E+03	5.52E+02	1.44E+02	6.74E+06
			Biogas	46937.4	46937.4	20065.2	684503.0	22164.9	96822.0	1015660.8	1871728.3	156055.0	55440.0	79200.0	82577.9	6.94E+05	3.59E-02	3.20E+03	1.09E+03	1.51E+02	5.93E+06
			Electricity	46937.4	46937.4	20065.2	684503.0	22164.9	96822.0	1015660.8	1871728.3	156055.0	55440.0	79200.0	82577.9	9.42E+05	6.84E-02	3.36E+03	9.47E+02	1.96E+02	9.03E+06
			Natural Gas	46937.4	46937.4	20065.2	684503.0	22164.9	96822.0	1015660.8	1871728.3	156055.0	55440.0	79200.0	82577.9	6.86E+05	5.08E-02	2.00E+03	5.47E+02	1.54E+02	8.54E+06
	Firenze	LPG	46937.4	46937.4	20065.2	684503.0	22164.9	96822.0	1015660.8	1871728.3	156055.0	55440.0	79200.0	82577.9	6.68E+05	5.00E-02	2.03E+03	5.55E+02	1.46E+02	6.92E+06	
		Biogas	46937.4	46937.4	20065.2	684503.0	22164.9	96822.0	1015660.8	1871728.3	156055.0	55440.0	79200.0	82577.9	7.02E+05	3.63E-02	3.40E+03	1.17E+03	1.54E+02	5.98E+06	
		Electricity	46937.4	46937.4	20065.2	684503.0	22164.9	96822.0	1015660.8	1871728.3	156055.0	55440.0	79200.0	82577.9	1.47E+06	1.31E-01	6.04E+03	1.69E+03	3.06E+02	1.52E+07	
	Forlì	Natural Gas	46937.4	46937.4	20065.2	684503.0	22164.9	96822.0	1015660.8	1871728.3	156055.0	55440.0	79200.0	82577.9	7.60E+05	8.20E-02	2.25E+03	5.72E+02	1.89E+02	1.38E+07	
		LPG	46937.4	46937.4	20065.2	684503.0	22164.9	96822.0	1015660.8	1871728.3	156055.0	55440.0	79200.0	82577.9	7.09E+05	7.97E-02	2.35E+03	5.95E+02	1.67E+02	9.29E+06	
		Biogas	46937.4	46937.4	20065.2	684503.0	22164.9	96822.0	1015660.8	1871728.3	156055.0	55440.0	79200.0	82577.9	8.03E+05	4.16E-02	6.16E+03	2.31E+03	1.89E+02	6.68E+06	
	E	Trieste	Electricity	46966.9	46966.9	22994.8	684933.5	22178.8	96756.0	883238.4	1453267.2	156012.8	55440.0	79200.0	82577.9	1.04E+06	8.60E-02	4.03E+03	1.13E+03	2.25E+02	1.05E+07
			Natural Gas	46966.9	46966.9	22994.8	684933.5	22178.8	96756.0	883238.4	1453267.2	156012.8	55440.0	79200.0	82577.9	6.49E+05	5.94E-02	1.97E+03	5.27E+02	1.61E+02	9.79E+06
			LPG	46966.9	46966.9	22994.8	684933.5	22178.8	96756.0	883238.4	1453267.2	156012.8	55440.0	79200.0	82577.9	6.22E+05	5.82E-02	2.02E+03	5.39E+02	1.49E+02	7.34E+06
			Biogas	46966.9	46966.9	22994.8	684933.5	22178.8	96756.0	883238.4	1453267.2	156012.8	55440.0	79200.0	82577.9	6.73E+05	3.75E-02	4.09E+03	1.47E+03	1.61E+02	5.92E+06
		Torino	Electricity	46966.9	46966.9	22994.8	684933.5	22178.8	96756.0	883238.4	1453267.2	156012.8	55440.0	79200.0	82577.9	1.52E+06	1.43E-01	6.46E+03	1.80E+03	3.25E+02	1.61E+07
			Natural Gas	46966.9	46966.9	22994.8	684933.5	22178.8	96756.0	883238.4	1453267.2	156012.8	55440.0	79200.0	82577.9	7.16E+05	8.77E-02	2.20E+03	5.50E+02	1.93E+02	1.46E+07
LPG			46966.9	46966.9	22994.8	684933.5	22178.8	96756.0	883238.4	1453267.2	156012.8	55440.0	79200.0	82577.9	6.59E+05	8.52E-02	2.30E+03	5.75E+02	1.68E+02	9.49E+06	
Bolzano		Biogas	46966.9	46966.9	22994.8	684933.5	22178.8	96756.0	883238.4	1453267.2	156012.8	55440.0	79200.0	82577.9	7.65E+05	4.22E-02	6.59E+03	2.51E+03	1.93E+02	6.55E+06	
		Electricity	46966.9	46966.9	22994.8	684933.5	22178.8	96756.0	883238.4	1453267.2	156012.8	55440.0	79200.0	82577.9	1.50E+06	1.41E-01	6.36E+03	1.78E+03	3.21E+02	1.59E+07	
		Natural Gas	46966.9	46966.9	22994.8	684933.5	22178.8	96756.0	883238.4	1453267.2	156012.8	55440.0	79200.0	82577.9	7.14E+05	8.66E-02	2.19E+03	5.49E+02	1.92E+02	1.44E+07	
LPG		46966.9	46966.9	22994.8	684933.5	22178.8	96756.0	883238.4	1453267.2	156012.8	55440.0	79200.0	82577.9	6.58E+05	8.41E-02	2.29E+03	5.74E+02	1.68E+02	9.41E+06		
		Biogas	46966.9	46966.9	22994.8	684933.5	22178.8	96756.0	883238.4	1453267.2	156012.8	55440.0	79200.0	82577.9	7.62E+05	4.21E-02	6.49E+03	2.47E+03	1.92E+02	6.53E+06	
	Electricity	46907.8	46907.8	24931.0	684072.5	22150.9	96712.0	882956.8	1452774.4	155984.6	55440.0	79200.0	82577.9	9.27E+05	7.31E-02	3.47E+03	9.70E+02	2.01E+02	9.28E+06		
F	Cuneo	Natural Gas	46907.8	46907.8	24931.0	684072.5	22150.9	96712.0	882956.8	1452774.4	155984.6	55440.0	79200.0	82577.9	6.33E+05	5.29E-02	1.91E+03	5.10E+02	1.52E+02	8.71E+06	
		LPG	46907.8	46907.8	24931.0	684072.5	22150.9	96712.0	882956.8	1452774.4	155984.6	55440.0	79200.0	82577.9	6.12E+05	5.20E-02	1.95E+03	5.19E+02	1.43E+02	6.86E+06	
		Biogas	46907.8	46907.8	24931.0	684072.5	22150.9	96712.0	882956.8	1452774.4	155984.6	55440.0	79200.0	82577.9	6.51E+05	3.62E-02	3.52E+03	1.23E+03	1.52E+02	5.78E+06	
	Cortina	Electricity	46907.8	46907.8	24931.0	684072.5	22150.9	96712.0	882956.8	1452774.4	155984.6	55440.0	79200.0	82577.9	2.32E+06	2.37E-01	1.05E+04	2.91E+03	4.90E+02	2.54E+07	
Natural Gas		46907.8	46907.8	24931.0	684072.5	22150.9	96712.0	882956.8	1452774.4	155984.6	55440.0	79200.0	82577.9	8.26E+05	1.35E-01	2.56E+03	5.76E+02	2.44E+02	2.25E+07		

Model	Climatic Zone	City	Energy Carrier	External plaster	Cement lime plaster	Rock wool	Tuff block	Internal plaster 1	Concrete brick	Concrete screed	Concrete slab	Internal plaster 2	Floor tile	Bitumen	Brick	GWP	ODP	AP	EP	POCP	ADP-fossil
				[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg CO ₂ -eq]	[kg CFC11-eq]	[kg SO ₂ -eq]
10	B	Sestriere	LPG	46907.8	46907.8	24931.0	684072.5	22150.9	96712.0	882956.8	1452774.4	155984.6	55440.0	79200.0	82577.9	7.20E+05	1.30E-01	2.76E+03	6.23E+02	1.98E+02	1.31E+07
			Biogas	46907.8	46907.8	24931.0	684072.5	22150.9	96712.0	882956.8	1452774.4	155984.6	55440.0	79200.0	82577.9	9.17E+05	5.00E-02	1.07E+04	4.22E+03	2.45E+02	7.60E+06
			Electricity	46907.8	46907.8	24931.0	684072.5	22150.9	96712.0	882956.8	1452774.4	155984.6	55440.0	79200.0	82577.9	2.25E+06	2.29E-01	1.01E+04	2.81E+03	4.75E+02	2.46E+07
			Natural Gas	46907.8	46907.8	24931.0	684072.5	22150.9	96712.0	882956.8	1452774.4	155984.6	55440.0	79200.0	82577.9	8.17E+05	1.31E-01	2.53E+03	5.73E+02	2.40E+02	2.18E+07
			LPG	46907.8	46907.8	24931.0	684072.5	22150.9	96712.0	882956.8	1452774.4	155984.6	55440.0	79200.0	82577.9	7.14E+05	1.26E-01	2.72E+03	6.18E+02	1.95E+02	1.28E+07
			Biogas	46907.8	46907.8	24931.0	684072.5	22150.9	96712.0	882956.8	1452774.4	155984.6	55440.0	79200.0	82577.9	9.04E+05	4.93E-02	1.04E+04	4.07E+03	2.40E+02	7.51E+06
		Messina	Electricity	14049.4	10537.0	8154.5	175617.4	6634.4	45000.0	540000.0	882000.0	149200.0	75600.0	216000.0	96800.0	1.83E+06	1.91E-01	8.50E+03	2.42E+03	3.89E+02	2.06E+07
			Natural Gas	14049.4	10537.0	8154.5	175617.4	6634.4	45000.0	540000.0	882000.0	149200.0	75600.0	216000.0	96800.0	5.50E+05	1.03E-01	1.70E+03	4.18E+02	1.78E+02	1.81E+07
			LPG	14049.4	10537.0	8154.5	175617.4	6634.4	45000.0	540000.0	882000.0	149200.0	75600.0	216000.0	96800.0	4.59E+05	9.93E-02	1.87E+03	4.59E+02	1.38E+02	1.00E+07
			Biogas	14049.4	10537.0	8154.5	175617.4	6634.4	45000.0	540000.0	882000.0	149200.0	75600.0	216000.0	96800.0	6.28E+05	3.08E-02	8.72E+03	3.54E+03	1.78E+02	5.33E+06
			Electricity	14049.4	10537.0	8154.5	175617.4	6634.4	45000.0	540000.0	882000.0	149200.0	75600.0	216000.0	96800.0	1.72E+06	1.78E-01	7.95E+03	2.27E+03	3.66E+02	1.93E+07
			Natural Gas	14049.4	10537.0	8154.5	175617.4	6634.4	45000.0	540000.0	882000.0	149200.0	75600.0	216000.0	96800.0	5.35E+05	9.69E-02	1.65E+03	4.13E+02	1.71E+02	1.70E+07
	Palermo	LPG	14049.4	10537.0	8154.5	175617.4	6634.4	45000.0	540000.0	882000.0	149200.0	75600.0	216000.0	96800.0	4.50E+05	9.31E-02	1.81E+03	4.50E+02	1.34E+02	9.53E+06	
		Biogas	14049.4	10537.0	8154.5	175617.4	6634.4	45000.0	540000.0	882000.0	149200.0	75600.0	216000.0	96800.0	6.07E+05	2.97E-02	8.15E+03	3.31E+03	1.71E+02	5.18E+06	
		Electricity	14049.4	10537.0	8154.5	175617.4	6634.4	45000.0	540000.0	882000.0	149200.0	75600.0	216000.0	96800.0	2.48E+06	2.68E-01	1.18E+04	3.33E+03	5.24E+02	2.82E+07	
		Natural Gas	14049.4	10537.0	8154.5	175617.4	6634.4	45000.0	540000.0	882000.0	149200.0	75600.0	216000.0	96800.0	6.41E+05	1.42E-01	2.01E+03	4.50E+02	2.21E+02	2.46E+07	
		LPG	14049.4	10537.0	8154.5	175617.4	6634.4	45000.0	540000.0	882000.0	149200.0	75600.0	216000.0	96800.0	5.09E+05	1.36E-01	2.25E+03	5.08E+02	1.64E+02	1.29E+07	
		Biogas	14049.4	10537.0	8154.5	175617.4	6634.4	45000.0	540000.0	882000.0	149200.0	75600.0	216000.0	96800.0	7.53E+05	3.72E-02	1.21E+04	4.95E+03	2.22E+02	6.19E+06	
	C	Cagliari	Electricity	13772.2	10329.1	9500.8	172152.4	6503.5	90000.0	576000.0	882000.0	149200.0	75600.0	216000.0	96800.0	1.52E+06	1.54E-01	6.93E+03	1.98E+03	3.26E+02	1.70E+07
			Natural Gas	13772.2	10329.1	9500.8	172152.4	6503.5	90000.0	576000.0	882000.0	149200.0	75600.0	216000.0	96800.0	5.14E+05	8.48E-02	1.57E+03	3.99E+02	1.60E+02	1.50E+07
			LPG	13772.2	10329.1	9500.8	172152.4	6503.5	90000.0	576000.0	882000.0	149200.0	75600.0	216000.0	96800.0	4.42E+05	8.16E-02	1.70E+03	4.31E+02	1.28E+02	8.66E+06
			Biogas	13772.2	10329.1	9500.8	172152.4	6503.5	90000.0	576000.0	882000.0	149200.0	75600.0	216000.0	96800.0	5.75E+05	2.76E-02	7.10E+03	2.86E+03	1.60E+02	4.96E+06
			Electricity	13772.2	10329.1	9500.8	172152.4	6503.5	90000.0	576000.0	882000.0	149200.0	75600.0	216000.0	96800.0	2.07E+06	2.18E-01	9.67E+03	2.73E+03	4.38E+02	2.33E+07
			Natural Gas	13772.2	10329.1	9500.8	172152.4	6503.5	90000.0	576000.0	882000.0	149200.0	75600.0	216000.0	96800.0	5.89E+05	1.17E-01	1.83E+03	4.25E+02	1.95E+02	2.04E+07
Bari		LPG	13772.2	10329.1	9500.8	172152.4	6503.5	90000.0	576000.0	882000.0	149200.0	75600.0	216000.0	96800.0	4.84E+05	1.12E-01	2.02E+03	4.72E+02	1.50E+02	1.11E+07	
		Biogas	13772.2	10329.1	9500.8	172152.4	6503.5	90000.0	576000.0	882000.0	149200.0	75600.0	216000.0	96800.0	6.79E+05	3.30E-02	9.92E+03	4.03E+03	1.96E+02	5.68E+06	
		Electricity	13772.2	10329.1	9500.8	172152.4	6503.5	90000.0	576000.0	882000.0	149200.0	75600.0	216000.0	96800.0	2.67E+06	2.90E-01	1.27E+04	3.58E+03	5.64E+02	3.03E+07	
		Natural Gas	13772.2	10329.1	9500.8	172152.4	6503.5	90000.0	576000.0	882000.0	149200.0	75600.0	216000.0	96800.0	6.74E+05	1.52E-01	2.11E+03	4.54E+02	2.36E+02	2.64E+07	
		LPG	13772.2	10329.1	9500.8	172152.4	6503.5	90000.0	576000.0	882000.0	149200.0	75600.0	216000.0	96800.0	5.31E+05	1.46E-01	2.37E+03	5.17E+02	1.73E+02	1.38E+07	
		Biogas	13772.2	10329.1	9500.8	172152.4	6503.5	90000.0	576000.0	882000.0	149200.0	75600.0	216000.0	96800.0	7.95E+05	3.90E-02	1.31E+04	5.34E+03	2.36E+02	6.47E+06	
D	Genova	Electricity	13772.2	13772.2	12315.5	200844.5	6503.5	45000.0	828000.0	1285200.0	149200.0	75600.0	108000.0	96800.0	2.09E+06	2.13E-01	9.62E+03	2.71E+03	4.34E+02	2.31E+07	
		Natural Gas	13772.2	13772.2	12315.5	200844.5	6503.5	45000.0	828000.0	1285200.0	149200.0	75600.0	108000.0	96800.0	6.58E+05	1.15E-01	2.00E+03	4.72E+02	1.98E+02	2.03E+07	
		LPG	13772.2	13772.2	12315.5	200844.5	6503.5	45000.0	828000.0	1285200.0	149200.0	75600.0	108000.0	96800.0	5.56E+05	1.10E-01	2.19E+03	5.17E+02	1.53E+02	1.13E+07	
		Biogas	13772.2	13772.2	12315.5	200844.5	6503.5	45000.0	828000.0	1285200.0	149200.0	75600.0	108000.0	96800.0	7.45E+05	3.33E-02	9.86E+03	3.97E+03	1.98E+02	6.01E+06	
	Firenze	Electricity	13772.2	13772.2	12315.5	200844.5	6503.5	45000.0	828000.0	1285200.0	149200.0	75600.0	108000.0	96800.0	2.36E+06	2.44E-01	1.10E+04	3.09E+03	4.89E+02	2.62E+07	
		Natural Gas	13772.2	13772.2	12315.5	200844.5	6503.5	45000.0	828000.0	1285200.0	149200.0	75600.0	108000.0	96800.0	6.95E+05	1.30E-01	2.13E+03	4.85E+02	2.16E+02	2.30E+07	

Model	Climatic Zone	City	Energy Carrier	External plaster	Cement lime plaster	Rock wool	Tuff block	Internal plaster 1	Concrete brick	Concrete screed	Concrete slab	Internal plaster 2	Floor tile	Bitumen	Brick	GWP	ODP	AP	EP	POCP	ADP-fossil	
				[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg CO ₂ -eq]	[kg CFC11-eq]	[kg SO ₂ -eq]	[kg PO ₄ 3--eq]
E	Forlì		LPG	13772.2	13772.2	12315.5	200844.5	6503.5	45000.0	828000.0	1285200.0	149200.0	75600.0	108000.0	96800.0	5.77E+05	1.25E-01	2.35E+03	5.37E+02	1.64E+02	1.25E+07	
			Biogas	13772.2	13772.2	12315.5	200844.5	6503.5	45000.0	828000.0	1285200.0	149200.0	75600.0	108000.0	96800.0	7.96E+05	3.60E-02	1.12E+04	4.55E+03	2.16E+02	6.36E+06	
			Electricity	13772.2	13772.2	12315.5	200844.5	6503.5	45000.0	828000.0	1285200.0	149200.0	75600.0	108000.0	96800.0	3.47E+06	3.76E-01	1.66E+04	4.64E+03	7.20E+02	3.91E+07	
			Natural Gas	13772.2	13772.2	12315.5	200844.5	6503.5	45000.0	828000.0	1285200.0	149200.0	75600.0	108000.0	96800.0	8.50E+05	1.96E-01	2.65E+03	5.38E+02	2.89E+02	3.40E+07	
			LPG	13772.2	13772.2	12315.5	200844.5	6503.5	45000.0	828000.0	1285200.0	149200.0	75600.0	108000.0	96800.0	6.63E+05	1.87E-01	3.00E+03	6.21E+02	2.08E+02	1.74E+07	
			Biogas	13772.2	13772.2	12315.5	200844.5	6503.5	45000.0	828000.0	1285200.0	149200.0	75600.0	108000.0	96800.0	1.01E+06	4.70E-02	1.70E+04	6.94E+03	2.89E+02	7.82E+06	
		Trieste		Electricity	13811.8	13811.8	14651.0	201422.0	6522.2	45000.0	648000.0	1008000.0	149200.0	75600.0	108000.0	96800.0	2.45E+06	2.61E-01	1.16E+04	3.26E+03	5.16E+02	2.77E+07
				Natural Gas	13811.8	13811.8	14651.0	201422.0	6522.2	45000.0	648000.0	1008000.0	149200.0	75600.0	108000.0	96800.0	6.68E+05	1.38E-01	2.09E+03	4.62E+02	2.22E+02	2.42E+07
				LPG	13811.8	13811.8	14651.0	201422.0	6522.2	45000.0	648000.0	1008000.0	149200.0	75600.0	108000.0	96800.0	5.40E+05	1.33E-01	2.33E+03	5.19E+02	1.67E+02	1.29E+07
				Biogas	13811.8	13811.8	14651.0	201422.0	6522.2	45000.0	648000.0	1008000.0	149200.0	75600.0	108000.0	96800.0	7.77E+05	3.69E-02	1.19E+04	4.83E+03	2.22E+02	6.34E+06
				Electricity	13811.8	13811.8	14651.0	201422.0	6522.2	45000.0	648000.0	1008000.0	149200.0	75600.0	108000.0	96800.0	3.51E+06	3.85E-01	1.69E+04	4.73E+03	7.35E+02	3.99E+07
				Natural Gas	13811.8	13811.8	14651.0	201422.0	6522.2	45000.0	648000.0	1008000.0	149200.0	75600.0	108000.0	96800.0	8.15E+05	2.00E-01	2.59E+03	5.13E+02	2.92E+02	3.47E+07
	Torino		LPG	13811.8	13811.8	14651.0	201422.0	6522.2	45000.0	648000.0	1008000.0	149200.0	75600.0	108000.0	96800.0	6.22E+05	1.92E-01	2.94E+03	5.98E+02	2.08E+02	1.76E+07	
			Biogas	13811.8	13811.8	14651.0	201422.0	6522.2	45000.0	648000.0	1008000.0	149200.0	75600.0	108000.0	96800.0	9.79E+05	4.74E-02	1.74E+04	7.10E+03	2.92E+02	7.73E+06	
			Electricity	13811.8	13811.8	14651.0	201422.0	6522.2	45000.0	648000.0	1008000.0	149200.0	75600.0	108000.0	96800.0	3.45E+06	3.78E-01	1.66E+04	4.64E+03	7.23E+02	3.92E+07	
			Natural Gas	13811.8	13811.8	14651.0	201422.0	6522.2	45000.0	648000.0	1008000.0	149200.0	75600.0	108000.0	96800.0	8.06E+05	1.97E-01	2.56E+03	5.10E+02	2.88E+02	3.41E+07	
			LPG	13811.8	13811.8	14651.0	201422.0	6522.2	45000.0	648000.0	1008000.0	149200.0	75600.0	108000.0	96800.0	6.17E+05	1.88E-01	2.91E+03	5.93E+02	2.06E+02	1.73E+07	
			Biogas	13811.8	13811.8	14651.0	201422.0	6522.2	45000.0	648000.0	1008000.0	149200.0	75600.0	108000.0	96800.0	9.67E+05	4.67E-02	1.70E+04	6.97E+03	2.88E+02	7.64E+06	
	Bolzano		Electricity	13732.6	13732.6	15838.8	200267.0	6484.8	45000.0	648000.0	1008000.0	149200.0	75600.0	108000.0	96800.0	2.34E+06	2.48E-01	1.10E+04	3.10E+03	4.92E+02	2.64E+07	
			Natural Gas	13732.6	13732.6	15838.8	200267.0	6484.8	45000.0	648000.0	1008000.0	149200.0	75600.0	108000.0	96800.0	6.52E+05	1.32E-01	2.04E+03	4.53E+02	2.14E+02	2.31E+07	
			LPG	13732.6	13732.6	15838.8	200267.0	6484.8	45000.0	648000.0	1008000.0	149200.0	75600.0	108000.0	96800.0	5.31E+05	1.26E-01	2.26E+03	5.06E+02	1.62E+02	1.24E+07	
			Biogas	13732.6	13732.6	15838.8	200267.0	6484.8	45000.0	648000.0	1008000.0	149200.0	75600.0	108000.0	96800.0	7.55E+05	3.57E-02	1.13E+04	4.58E+03	2.14E+02	6.20E+06	
			Electricity	13732.6	13732.6	15838.8	200267.0	6484.8	45000.0	648000.0	1008000.0	149200.0	75600.0	108000.0	96800.0	5.37E+06	6.05E-01	2.63E+04	7.32E+03	1.12E+03	6.15E+07	
			Natural Gas	13732.6	13732.6	15838.8	200267.0	6484.8	45000.0	648000.0	1008000.0	149200.0	75600.0	108000.0	96800.0	1.07E+06	3.10E-01	3.47E+03	5.98E+02	4.15E+02	5.31E+07	
Cortina			LPG	13732.6	13732.6	15838.8	200267.0	6484.8	45000.0	648000.0	1008000.0	149200.0	75600.0	108000.0	96800.0	7.66E+05	2.96E-01	4.03E+03	7.34E+02	2.81E+02	2.59E+07	
			Biogas	13732.6	13732.6	15838.8	200267.0	6484.8	45000.0	648000.0	1008000.0	149200.0	75600.0	108000.0	96800.0	1.33E+06	6.57E-02	2.70E+04	1.11E+04	4.15E+02	1.02E+07	
			Electricity	13732.6	13732.6	15838.8	200267.0	6484.8	45000.0	648000.0	1008000.0	149200.0	75600.0	108000.0	96800.0	5.63E+06	6.36E-01	2.76E+04	7.69E+03	1.18E+03	6.45E+07	
			Natural Gas	13732.6	13732.6	15838.8	200267.0	6484.8	45000.0	648000.0	1008000.0	149200.0	75600.0	108000.0	96800.0	1.11E+06	3.25E-01	3.59E+03	6.10E+02	4.32E+02	5.57E+07	
			LPG	13732.6	13732.6	15838.8	200267.0	6484.8	45000.0	648000.0	1008000.0	149200.0	75600.0	108000.0	96800.0	7.87E+05	3.11E-01	4.19E+03	7.53E+02	2.91E+02	2.71E+07	
			Biogas	13732.6	13732.6	15838.8	200267.0	6484.8	45000.0	648000.0	1008000.0	149200.0	75600.0	108000.0	96800.0	1.38E+06	6.83E-02	2.84E+04	1.17E+04	4.33E+02	1.05E+07	
Sestriere		Electricity	13732.6	13732.6	15838.8	200267.0	6484.8	45000.0	648000.0	1008000.0	149200.0	75600.0	108000.0	96800.0	5.63E+06	6.36E-01	2.76E+04	7.69E+03	1.18E+03	6.45E+07		
		Natural Gas	13732.6	13732.6	15838.8	200267.0	6484.8	45000.0	648000.0	1008000.0	149200.0	75600.0	108000.0	96800.0	1.11E+06	3.25E-01	3.59E+03	6.10E+02	4.32E+02	5.57E+07		
		LPG	13732.6	13732.6	15838.8	200267.0	6484.8	45000.0	648000.0	1008000.0	149200.0	75600.0	108000.0	96800.0	7.87E+05	3.11E-01	4.19E+03	7.53E+02	2.91E+02	2.71E+07		
		Biogas	13732.6	13732.6	15838.8	200267.0	6484.8	45000.0	648000.0	1008000.0	149200.0	75600.0	108000.0	96800.0	1.38E+06	6.83E-02	2.84E+04	1.17E+04	4.33E+02	1.05E+07		
		Electricity	13732.6	13732.6	15838.8	200267.0	6484.8	45000.0	648000.0	1008000.0	149200.0	75600.0	108000.0	96800.0	2.77E+06	2.92E-01	1.29E+04	3.64E+03	6.04E+02	3.14E+07		
		Natural Gas	13732.6	13732.6	15838.8	200267.0	6484.8	45000.0	648000.0	1008000.0	149200.0	75600.0	108000.0	96800.0	8.23E+05	1.58E-01	2.54E+03	5.96E+02	2.84E+02	2.76E+07		
Messina		LPG	12002.1	9001.6	11778.1	150026.1	5667.7	67500.0	810000.0	1323000.0	299492.8	113400.0	324000.0	296585.6	6.84E+05	1.52E-01	2.79E+03	6.58E+02	2.23E+02	1.53E+07		
		Biogas	12002.1	9001.6	11778.1	150026.1	5667.7	67500.0	810000.0	1323000.0	299492.8	113400.0	324000.0	296585.6	9.42E+05	4.81E-02	1.32E+04	5.35E+03	2.84E+02	8.15E+06		
		Electricity	12002.1	9001.6	11778.1	150026.1	5667.7	67500.0	810000.0	1323000.0	299492.8	113400.0	324000.0	296585.6	2.64E+06	2.77E-01	1.22E+04	3.46E+03	5.77E+02	2.99E+07		
		Natural Gas	12002.1	9001.6	11778.1	150026.1	5667.7	67500.0	810000.0	1323000.0	299492.8	113400.0	324000.0	296585.6	8.05E+05	1.51E-01	2.48E+03	5.90E+02	2.75E+02	2.63E+07		
		Electricity	12002.1	9001.6	11778.1	150026.1	5667.7	67500.0	810000.0	1323000.0	299492.8	113400.0	324000.0	296585.6	2.64E+06	2.77E-01	1.22E+04	3.46E+03	5.77E+02	2.99E+07		
		Natural Gas	12002.1	9001.6	11778.1	150026.1	5667.7	67500.0	810000.0	1323000.0	299492.8	113400.0	324000.0	296585.6	8.05E+05	1.51E-01	2.48E+03	5.90E+02	2.75E+02	2.63E+07		
Palermo		Electricity	12002.1	9001.6	11778.1	150026.1	5667.7	67500.0	810000.0	1323000.0	299492.8	113400.0	324000.0	296585.6	2.64E+06	2.77E-01	1.22E+04	3.46E+03	5.77E+02	2.99E+07		
		Natural Gas	12002.1	9001.6	11778.1	150026.1	5667.7	67500.0	810000.0	1323000.0	299492.8	113400.0	324000.0	296585.6	8.05E+05	1.51E-01	2.48E+03	5.90E+02	2.75E+02	2.63E+07		

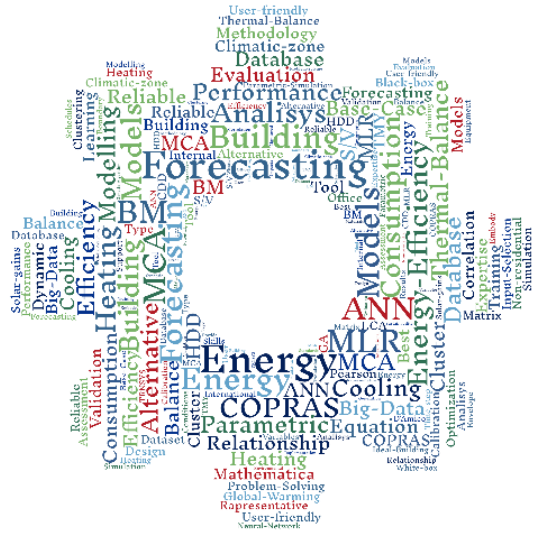
Model	Climatic Zone	City	Energy Carrier	External plaster	Cement lime plaster	Rock wool	Tuff block	Internal plaster 1	Concrete brick	Concrete screed	Concrete slab	Internal plaster 2	Floor tile	Bitumen	Brick	GWP	ODP	AP	EP	POCP	ADP-fossil	
				[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg CO ₂ -eq]	[kg CFC11-eq]	[kg SO ₂ -eq]	[kg PO ₄₃ -eq]	[kg C ₂ H ₄ -eq]
C	Crotone		LPG	12002.1	9001.6	11778.1	150026.1	5667.7	67500.0	810000.0	1323000.0	299492.8	113400.0	324000.0	296585.6	6.74E+05	1.45E-01	2.72E+03	6.48E+02	2.18E+02	1.47E+07	
			Biogas	12002.1	9001.6	11778.1	150026.1	5667.7	67500.0	810000.0	1323000.0	299492.8	113400.0	324000.0	296585.6	9.17E+05	4.68E-02	1.25E+04	5.07E+03	2.76E+02	7.98E+06	
			Electricity	12002.1	9001.6	11778.1	150026.1	5667.7	67500.0	810000.0	1323000.0	299492.8	113400.0	324000.0	296585.6	3.71E+06	4.03E-01	1.76E+04	4.95E+03	8.00E+02	4.23E+07	
			Natural Gas	12002.1	9001.6	11778.1	150026.1	5667.7	67500.0	810000.0	1323000.0	299492.8	113400.0	324000.0	296585.6	9.54E+05	2.14E-01	2.98E+03	6.41E+02	3.46E+02	3.69E+07	
			LPG	12002.1	9001.6	11778.1	150026.1	5667.7	67500.0	810000.0	1323000.0	299492.8	113400.0	324000.0	296585.6	7.57E+05	2.05E-01	3.35E+03	7.28E+02	2.61E+02	1.95E+07	
			Biogas	12002.1	9001.6	11778.1	150026.1	5667.7	67500.0	810000.0	1323000.0	299492.8	113400.0	324000.0	296585.6	1.12E+06	5.74E-02	1.81E+04	7.37E+03	3.47E+02	9.39E+06	
		Cagliari		Electricity	11737.5	8803.1	13693.6	146718.6	5542.7	135000.0	864000.0	1323000.0	299492.8	113400.0	324000.0	296585.6	2.52E+06	2.61E-01	1.16E+04	3.28E+03	5.55E+02	2.84E+07
				Natural Gas	11737.5	8803.1	13693.6	146718.6	5542.7	135000.0	864000.0	1323000.0	299492.8	113400.0	324000.0	296585.6	8.01E+05	1.43E-01	2.45E+03	5.84E+02	2.71E+02	2.51E+07
				LPG	11737.5	8803.1	13693.6	146718.6	5542.7	135000.0	864000.0	1323000.0	299492.8	113400.0	324000.0	296585.6	6.78E+05	1.38E-01	2.68E+03	6.38E+02	2.18E+02	1.42E+07
				Biogas	11737.5	8803.1	13693.6	146718.6	5542.7	135000.0	864000.0	1323000.0	299492.8	113400.0	324000.0	296585.6	9.05E+05	4.56E-02	1.19E+04	4.79E+03	2.72E+02	7.90E+06
				Electricity	11737.5	8803.1	13693.6	146718.6	5542.7	135000.0	864000.0	1323000.0	299492.8	113400.0	324000.0	296585.6	3.35E+06	3.59E-01	1.58E+04	4.43E+03	7.26E+02	3.80E+07
				Natural Gas	11737.5	8803.1	13693.6	146718.6	5542.7	135000.0	864000.0	1323000.0	299492.8	113400.0	324000.0	296585.6	9.15E+05	1.92E-01	2.84E+03	6.23E+02	3.26E+02	3.33E+07
			LPG	11737.5	8803.1	13693.6	146718.6	5542.7	135000.0	864000.0	1323000.0	299492.8	113400.0	324000.0	296585.6	7.42E+05	1.84E-01	3.16E+03	7.00E+02	2.50E+02	1.79E+07	
			Biogas	11737.5	8803.1	13693.6	146718.6	5542.7	135000.0	864000.0	1323000.0	299492.8	113400.0	324000.0	296585.6	1.06E+06	5.37E-02	1.62E+04	6.56E+03	3.26E+02	8.98E+06	
			Electricity	11737.5	8803.1	13693.6	146718.6	5542.7	135000.0	864000.0	1323000.0	299492.8	113400.0	324000.0	296585.6	4.10E+06	4.48E-01	1.96E+04	5.48E+03	8.83E+02	4.67E+07	
			Natural Gas	11737.5	8803.1	13693.6	146718.6	5542.7	135000.0	864000.0	1323000.0	299492.8	113400.0	324000.0	296585.6	1.02E+06	2.36E-01	3.20E+03	6.60E+02	3.76E+02	4.08E+07	
			LPG	11737.5	8803.1	13693.6	146718.6	5542.7	135000.0	864000.0	1323000.0	299492.8	113400.0	324000.0	296585.6	8.00E+05	2.26E-01	3.60E+03	7.57E+02	2.80E+02	2.13E+07	
			Biogas	11737.5	8803.1	13693.6	146718.6	5542.7	135000.0	864000.0	1323000.0	299492.8	113400.0	324000.0	296585.6	1.21E+06	6.12E-02	2.01E+04	8.19E+03	3.76E+02	9.97E+06	
	D	Genova		Electricity	11737.5	11737.5	17841.4	171171.7	5542.7	67500.0	1242000.0	1927800.0	299492.8	113400.0	162000.0	296585.6	3.18E+06	3.27E-01	1.47E+04	4.11E+03	6.76E+02	3.54E+07
				Natural Gas	11737.5	11737.5	17841.4	171171.7	5542.7	67500.0	1242000.0	1927800.0	299492.8	113400.0	162000.0	296585.6	9.86E+05	1.77E-01	3.00E+03	6.80E+02	3.15E+02	3.11E+07
				LPG	11737.5	11737.5	17841.4	171171.7	5542.7	67500.0	1242000.0	1927800.0	299492.8	113400.0	162000.0	296585.6	8.29E+05	1.70E-01	3.28E+03	7.49E+02	2.47E+02	1.72E+07
				Biogas	11737.5	11737.5	17841.4	171171.7	5542.7	67500.0	1242000.0	1927800.0	299492.8	113400.0	162000.0	296585.6	1.12E+06	5.22E-02	1.50E+04	6.04E+03	3.15E+02	9.18E+06
		Firenze		Electricity	11737.5	11737.5	17841.4	171171.7	5542.7	67500.0	1242000.0	1927800.0	299492.8	113400.0	162000.0	296585.6	3.62E+06	3.79E-01	1.69E+04	4.73E+03	7.68E+02	4.05E+07
				Natural Gas	11737.5	11737.5	17841.4	171171.7	5542.7	67500.0	1242000.0	1927800.0	299492.8	113400.0	162000.0	296585.6	1.05E+06	2.03E-01	3.21E+03	7.01E+02	3.44E+02	3.55E+07
			LPG	11737.5	11737.5	17841.4	171171.7	5542.7	67500.0	1242000.0	1927800.0	299492.8	113400.0	162000.0	296585.6	8.63E+05	1.94E-01	3.54E+03	7.82E+02	2.64E+02	1.92E+07	
			Biogas	11737.5	11737.5	17841.4	171171.7	5542.7	67500.0	1242000.0	1927800.0	299492.8	113400.0	162000.0	296585.6	1.20E+06	5.65E-02	1.73E+04	6.99E+03	3.45E+02	9.76E+06	
Forlì			Electricity	11737.5	11737.5	17841.4	171171.7	5542.7	67500.0	1242000.0	1927800.0	299492.8	113400.0	162000.0	296585.6	4.99E+06	5.41E-01	2.38E+04	6.64E+03	1.05E+03	5.63E+07	
			Natural Gas	11737.5	11737.5	17841.4	171171.7	5542.7	67500.0	1242000.0	1927800.0	299492.8	113400.0	162000.0	296585.6	1.24E+06	2.83E-01	3.85E+03	7.67E+02	4.35E+02	4.90E+07	
			LPG	11737.5	11737.5	17841.4	171171.7	5542.7	67500.0	1242000.0	1927800.0	299492.8	113400.0	162000.0	296585.6	9.69E+05	2.71E-01	4.34E+03	8.85E+02	3.18E+02	2.53E+07	
			Biogas	11737.5	11737.5	17841.4	171171.7	5542.7	67500.0	1242000.0	1927800.0	299492.8	113400.0	162000.0	296585.6	1.47E+06	7.01E-02	2.44E+04	9.93E+03	4.35E+02	1.16E+07	
E	Trieste		Electricity	11775.3	11775.3	21231.3	171722.9	5560.6	67500.0	972000.0	1512000.0	299492.8	113400.0	162000.0	296585.6	3.59E+06	3.83E-01	1.69E+04	4.74E+03	7.72E+02	4.06E+07	
			Natural Gas	11775.3	11775.3	21231.3	171722.9	5560.6	67500.0	972000.0	1512000.0	299492.8	113400.0	162000.0	296585.6	9.81E+05	2.04E-01	3.07E+03	6.59E+02	3.42E+02	3.56E+07	
			LPG	11775.3	11775.3	21231.3	171722.9	5560.6	67500.0	972000.0	1512000.0	299492.8	113400.0	162000.0	296585.6	7.95E+05	1.96E-01	3.41E+03	7.41E+02	2.61E+02	1.91E+07	
			Biogas	11775.3	11775.3	21231.3	171722.9	5560.6	67500.0	972000.0	1512000.0	299492.8	113400.0	162000.0	296585.6	1.14E+06	5.61E-02	1.74E+04	7.03E+03	3.43E+02	9.49E+06	
	Torino		Electricity	11775.3	11775.3	21231.3	171722.9	5560.6	67500.0	972000.0	1512000.0	299492.8	113400.0	162000.0	296585.6	5.10E+06	5.61E-01	2.46E+04	6.85E+03	1.09E+03	5.81E+07	
			Natural Gas	11775.3	11775.3	21231.3	171722.9	5560.6	67500.0	972000.0	1512000.0	299492.8	113400.0	162000.0	296585.6	1.19E+06	2.93E-01	3.78E+03	7.31E+02	4.42E+02	5.05E+07	

Model	Climatic Zone	City	Energy Carrier	External plaster	Cement lime plaster	Rock wool	Tuff block	Internal plaster 1	Concrete brick	Concrete screed	Concrete slab	Internal plaster 2	Floor tile	Bitumen	Brick	GWP	ODP	AP	EP	POCP	ADP-fossil
				[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg CO2 -eq]	[kg CFC11-eq]	[kg SO2 -eq]	[kg PO43--eq]
12	F	Bolzano	LPG	11775.3	11775.3	21231.3	171722.9	5560.6	67500.0	972000.0	1512000.0	299492.8	113400.0	162000.0	296585.6	9.12E+05	2.80E-01	4.29E+03	8.54E+02	3.21E+02	2.58E+07
			Biogas	11775.3	11775.3	21231.3	171722.9	5560.6	67500.0	972000.0	1512000.0	299492.8	113400.0	162000.0	296585.6	1.43E+06	7.11E-02	2.52E+04	1.03E+04	4.43E+02	1.15E+07
			Electricity	11775.3	11775.3	21231.3	171722.9	5560.6	67500.0	972000.0	1512000.0	299492.8	113400.0	162000.0	296585.6	5.13E+06	5.65E-01	2.47E+04	6.89E+03	1.09E+03	5.85E+07
			Natural Gas	11775.3	11775.3	21231.3	171722.9	5560.6	67500.0	972000.0	1512000.0	299492.8	113400.0	162000.0	296585.6	1.20E+06	2.95E-01	3.80E+03	7.32E+02	4.44E+02	5.08E+07
			LPG	11775.3	11775.3	21231.3	171722.9	5560.6	67500.0	972000.0	1512000.0	299492.8	113400.0	162000.0	296585.6	9.14E+05	2.82E-01	4.31E+03	8.57E+02	3.22E+02	2.59E+07
			Biogas	11775.3	11775.3	21231.3	171722.9	5560.6	67500.0	972000.0	1512000.0	299492.8	113400.0	162000.0	296585.6	1.43E+06	7.14E-02	2.54E+04	1.03E+04	4.45E+02	1.15E+07
		Cuneo	Electricity	11699.7	11699.7	22942.5	170620.4	5524.9	67500.0	972000.0	1512000.0	299492.8	113400.0	162000.0	296585.6	3.71E+06	3.98E-01	1.76E+04	4.91E+03	7.97E+02	4.20E+07
			Natural Gas	11699.7	11699.7	22942.5	170620.4	5524.9	67500.0	972000.0	1512000.0	299492.8	113400.0	162000.0	296585.6	9.99E+05	2.11E-01	3.13E+03	6.61E+02	3.50E+02	3.68E+07
			LPG	11699.7	11699.7	22942.5	170620.4	5524.9	67500.0	972000.0	1512000.0	299492.8	113400.0	162000.0	296585.6	8.05E+05	2.03E-01	3.49E+03	7.47E+02	2.66E+02	1.96E+07
			Biogas	11699.7	11699.7	22942.5	170620.4	5524.9	67500.0	972000.0	1512000.0	299492.8	113400.0	162000.0	296585.6	1.16E+06	5.73E-02	1.80E+04	7.29E+03	3.51E+02	9.67E+06
			Electricity	11699.7	11699.7	22942.5	170620.4	5524.9	67500.0	972000.0	1512000.0	299492.8	113400.0	162000.0	296585.6	8.04E+06	9.08E-01	3.94E+04	1.09E+04	1.70E+03	9.22E+07
			Natural Gas	11699.7	11699.7	22942.5	170620.4	5524.9	67500.0	972000.0	1512000.0	299492.8	113400.0	162000.0	296585.6	1.60E+06	4.66E-01	5.17E+03	8.69E+02	6.37E+02	7.97E+07
	Cortina	LPG	11699.7	11699.7	22942.5	170620.4	5524.9	67500.0	972000.0	1512000.0	299492.8	113400.0	162000.0	296585.6	1.14E+06	4.45E-01	6.02E+03	1.07E+03	4.37E+02	3.90E+07	
		Biogas	11699.7	11699.7	22942.5	170620.4	5524.9	67500.0	972000.0	1512000.0	299492.8	113400.0	162000.0	296585.6	1.99E+06	1.00E-01	4.05E+04	1.66E+04	6.38E+02	1.54E+07	
		Electricity	11699.7	11699.7	22942.5	170620.4	5524.9	67500.0	972000.0	1512000.0	299492.8	113400.0	162000.0	296585.6	9.08E+06	1.03E+00	4.47E+04	1.24E+04	1.91E+03	1.04E+08	
		Natural Gas	11699.7	11699.7	22942.5	170620.4	5524.9	67500.0	972000.0	1512000.0	299492.8	113400.0	162000.0	296585.6	1.75E+06	5.27E-01	5.67E+03	9.18E+02	7.06E+02	9.00E+07	
		LPG	11699.7	11699.7	22942.5	170620.4	5524.9	67500.0	972000.0	1512000.0	299492.8	113400.0	162000.0	296585.6	1.22E+06	5.03E-01	6.63E+03	1.15E+03	4.78E+02	4.36E+07	
		Biogas	11699.7	11699.7	22942.5	170620.4	5524.9	67500.0	972000.0	1512000.0	299492.8	113400.0	162000.0	296585.6	2.19E+06	1.11E-01	4.59E+04	1.88E+04	7.07E+02	1.67E+07	
	B	Messina	Electricity	15008.2	11256.1	11100.4	187602.5	7087.2	62500.0	750000.0	1225000.0	199616.6	105000.0	300000.0	119233.3	2.56E+06	2.67E-01	1.19E+04	3.39E+03	5.39E+02	2.88E+07
			Natural Gas	15008.2	11256.1	11100.4	187602.5	7087.2	62500.0	750000.0	1225000.0	199616.6	105000.0	300000.0	119233.3	7.46E+05	1.43E-01	2.30E+03	5.57E+02	2.41E+02	2.53E+07
			LPG	15008.2	11256.1	11100.4	187602.5	7087.2	62500.0	750000.0	1225000.0	199616.6	105000.0	300000.0	119233.3	6.17E+05	1.37E-01	2.53E+03	6.14E+02	1.84E+02	1.38E+07
			Biogas	15008.2	11256.1	11100.4	187602.5	7087.2	62500.0	750000.0	1225000.0	199616.6	105000.0	300000.0	119233.3	8.56E+05	4.02E-02	1.22E+04	4.98E+03	2.41E+02	7.18E+06
			Electricity	15008.2	11256.1	11100.4	187602.5	7087.2	62500.0	750000.0	1225000.0	199616.6	105000.0	300000.0	119233.3	2.43E+06	2.53E-01	1.13E+04	3.22E+03	5.13E+02	2.74E+07
			Natural Gas	15008.2	11256.1	11100.4	187602.5	7087.2	62500.0	750000.0	1225000.0	199616.6	105000.0	300000.0	119233.3	7.29E+05	1.36E-01	2.24E+03	5.51E+02	2.33E+02	2.40E+07
Palermo		LPG	15008.2	11256.1	11100.4	187602.5	7087.2	62500.0	750000.0	1225000.0	199616.6	105000.0	300000.0	119233.3	6.07E+05	1.30E-01	2.46E+03	6.04E+02	1.80E+02	1.33E+07	
		Biogas	15008.2	11256.1	11100.4	187602.5	7087.2	62500.0	750000.0	1225000.0	199616.6	105000.0	300000.0	119233.3	8.32E+05	3.89E-02	1.16E+04	4.71E+03	2.33E+02	7.02E+06	
		Electricity	15008.2	11256.1	11100.4	187602.5	7087.2	62500.0	750000.0	1225000.0	199616.6	105000.0	300000.0	119233.3	3.45E+06	3.72E-01	1.64E+04	4.63E+03	7.24E+02	3.91E+07	
		Natural Gas	15008.2	11256.1	11100.4	187602.5	7087.2	62500.0	750000.0	1225000.0	199616.6	105000.0	300000.0	119233.3	8.70E+05	1.95E-01	2.72E+03	5.99E+02	3.00E+02	3.41E+07	
		LPG	15008.2	11256.1	11100.4	187602.5	7087.2	62500.0	750000.0	1225000.0	199616.6	105000.0	300000.0	119233.3	6.86E+05	1.87E-01	3.05E+03	6.81E+02	2.20E+02	1.78E+07	
		Biogas	15008.2	11256.1	11100.4	187602.5	7087.2	62500.0	750000.0	1225000.0	199616.6	105000.0	300000.0	119233.3	1.03E+06	4.90E-02	1.68E+04	6.90E+03	3.00E+02	8.35E+06	
C	Crotone	Electricity	14756.2	11067.1	12922.3	184452.5	6968.2	125000.0	800000.0	1225000.0	199616.6	105000.0	300000.0	119233.3	2.36E+06	2.43E-01	1.09E+04	3.10E+03	4.99E+02	2.64E+07	
		Natural Gas	14756.2	11067.1	12922.3	184452.5	6968.2	125000.0	800000.0	1225000.0	199616.6	105000.0	300000.0	119233.3	7.29E+05	1.31E-01	2.22E+03	5.44E+02	2.31E+02	2.33E+07	
		LPG	14756.2	11067.1	12922.3	184452.5	6968.2	125000.0	800000.0	1225000.0	199616.6	105000.0	300000.0	119233.3	6.13E+05	1.25E-01	2.44E+03	5.96E+02	1.80E+02	1.30E+07	
		Biogas	14756.2	11067.1	12922.3	184452.5	6968.2	125000.0	800000.0	1225000.0	199616.6	105000.0	300000.0	119233.3	8.28E+05	3.81E-02	1.12E+04	4.53E+03	2.31E+02	6.98E+06	
	Bari	Electricity	14756.2	11067.1	12922.3	184452.5	6968.2	125000.0	800000.0	1225000.0	199616.6	105000.0	300000.0	119233.3	3.15E+06	3.35E-01	1.49E+04	4.19E+03	6.63E+02	3.56E+07	
		Natural Gas	14756.2	11067.1	12922.3	184452.5	6968.2	125000.0	800000.0	1225000.0	199616.6	105000.0	300000.0	119233.3	8.38E+05	1.77E-01	2.59E+03	5.82E+02	2.83E+02	3.11E+07	

Model	Climatic Zone	City	Energy Carrier	External plaster	Cement lime plaster	Rock wool	Tuff block	Internal plaster 1	Concrete brick	Concrete screed	Concrete slab	Internal plaster 2	Floor tile	Bitumen	Brick	GWP	ODP	AP	EP	POCP	ADP-fossil	
				[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg CO ₂ -eq]	[kg CFC11-eq]	[kg SO ₂ -eq]	[kg PO ₄ -eq]	[kg C ₂ H ₄ -eq]
D	Termoli	LPG	LPG	14756.2	11067.1	12922.3	184452.5	6968.2	125000.0	800000.0	1225000.0	199616.6	105000.0	300000.0	119233.3	6.74E+05	1.70E-01	2.90E+03	6.55E+02	2.11E+02	1.65E+07	
			Biogas	14756.2	11067.1	12922.3	184452.5	6968.2	125000.0	800000.0	1225000.0	199616.6	105000.0	300000.0	119233.3	9.79E+05	4.59E-02	1.52E+04	6.22E+03	2.83E+02	8.02E+06	
		Electricity	Electricity	14756.2	11067.1	12922.3	184452.5	6968.2	125000.0	800000.0	1225000.0	199616.6	105000.0	300000.0	119233.3	3.89E+06	4.23E-01	1.86E+04	5.23E+03	8.17E+02	4.41E+07	
			Natural Gas	14756.2	11067.1	12922.3	184452.5	6968.2	125000.0	800000.0	1225000.0	199616.6	105000.0	300000.0	119233.3	9.41E+05	2.20E-01	2.94E+03	6.17E+02	3.32E+02	3.84E+07	
		LPG	LPG	14756.2	11067.1	12922.3	184452.5	6968.2	125000.0	800000.0	1225000.0	199616.6	105000.0	300000.0	119233.3	7.31E+05	2.11E-01	3.33E+03	7.10E+02	2.40E+02	1.98E+07	
			Biogas	14756.2	11067.1	12922.3	184452.5	6968.2	125000.0	800000.0	1225000.0	199616.6	105000.0	300000.0	119233.3	1.12E+06	5.32E-02	1.91E+04	7.81E+03	3.32E+02	8.99E+06	
		Genova	Electricity	Electricity	14756.2	14756.2	16795.2	215194.6	6968.2	62500.0	1150000.0	1785000.0	199616.6	105000.0	150000.0	119233.3	3.14E+06	3.23E-01	1.46E+04	4.11E+03	6.47E+02	3.48E+07
				Natural Gas	14756.2	14756.2	16795.2	215194.6	6968.2	62500.0	1150000.0	1785000.0	199616.6	105000.0	150000.0	119233.3	9.26E+05	1.71E-01	2.81E+03	6.43E+02	2.83E+02	3.05E+07
			LPG	LPG	14756.2	14756.2	16795.2	215194.6	6968.2	62500.0	1150000.0	1785000.0	199616.6	105000.0	150000.0	119233.3	7.68E+05	1.64E-01	3.10E+03	7.13E+02	2.14E+02	1.65E+07
				Biogas	14756.2	14756.2	16795.2	215194.6	6968.2	62500.0	1150000.0	1785000.0	199616.6	105000.0	150000.0	119233.3	1.06E+06	4.59E-02	1.49E+04	6.05E+03	2.83E+02	8.41E+06
			Natural Gas	Electricity	14756.2	14756.2	16795.2	215194.6	6968.2	62500.0	1150000.0	1785000.0	199616.6	105000.0	150000.0	119233.3	3.56E+06	3.74E-01	1.67E+04	4.70E+03	7.35E+02	3.97E+07
				Natural Gas	14756.2	14756.2	16795.2	215194.6	6968.2	62500.0	1150000.0	1785000.0	199616.6	105000.0	150000.0	119233.3	9.85E+05	1.96E-01	3.01E+03	6.63E+02	3.11E+02	3.47E+07
	Firenze	LPG	LPG	14756.2	14756.2	16795.2	215194.6	6968.2	62500.0	1150000.0	1785000.0	199616.6	105000.0	150000.0	119233.3	8.01E+05	1.88E-01	3.35E+03	7.45E+02	2.31E+02	1.84E+07	
			Biogas	14756.2	14756.2	16795.2	215194.6	6968.2	62500.0	1150000.0	1785000.0	199616.6	105000.0	150000.0	119233.3	1.14E+06	5.01E-02	1.72E+04	6.96E+03	3.11E+02	8.97E+06	
		Natural Gas	Electricity	14756.2	14756.2	16795.2	215194.6	6968.2	62500.0	1150000.0	1785000.0	199616.6	105000.0	150000.0	119233.3	4.97E+06	5.39E-01	2.38E+04	6.66E+03	1.03E+03	5.60E+07	
			Natural Gas	14756.2	14756.2	16795.2	215194.6	6968.2	62500.0	1150000.0	1785000.0	199616.6	105000.0	150000.0	119233.3	1.18E+06	2.79E-01	3.68E+03	7.30E+02	4.04E+02	4.87E+07	
	Forlì	LPG	LPG	14756.2	14756.2	16795.2	215194.6	6968.2	62500.0	1150000.0	1785000.0	199616.6	105000.0	150000.0	119233.3	9.10E+05	2.67E-01	4.17E+03	8.50E+02	2.86E+02	2.47E+07	
			Biogas	14756.2	14756.2	16795.2	215194.6	6968.2	62500.0	1150000.0	1785000.0	199616.6	105000.0	150000.0	119233.3	1.41E+06	6.41E-02	2.44E+04	9.98E+03	4.04E+02	1.08E+07	
		Natural Gas	Electricity	14792.2	14792.2	19982.7	215719.6	6985.2	62500.0	900000.0	1400000.0	199616.6	105000.0	150000.0	119233.3	3.64E+06	3.90E-01	1.73E+04	4.85E+03	7.60E+02	4.11E+07	
			Natural Gas	14792.2	14792.2	19982.7	215719.6	6985.2	62500.0	900000.0	1400000.0	199616.6	105000.0	150000.0	119233.3	9.38E+05	2.04E-01	2.94E+03	6.29E+02	3.16E+02	3.58E+07	
	E	Trieste	LPG	LPG	14792.2	14792.2	19982.7	215719.6	6985.2	62500.0	900000.0	1400000.0	199616.6	105000.0	150000.0	119233.3	7.46E+05	1.95E-01	3.29E+03	7.14E+02	2.32E+02	1.88E+07
				Biogas	14792.2	14792.2	19982.7	215719.6	6985.2	62500.0	900000.0	1400000.0	199616.6	105000.0	150000.0	119233.3	1.10E+06	5.08E-02	1.77E+04	7.23E+03	3.16E+02	8.86E+06
			Natural Gas	Electricity	14792.2	14792.2	19982.7	215719.6	6985.2	62500.0	900000.0	1400000.0	199616.6	105000.0	150000.0	119233.3	5.16E+06	5.70E-01	2.50E+04	6.98E+03	1.08E+03	5.88E+07
				Natural Gas	14792.2	14792.2	19982.7	215719.6	6985.2	62500.0	900000.0	1400000.0	199616.6	105000.0	150000.0	119233.3	1.15E+06	2.94E-01	3.66E+03	7.02E+02	4.17E+02	5.10E+07
Torino		LPG	LPG	14792.2	14792.2	19982.7	215719.6	6985.2	62500.0	900000.0	1400000.0	199616.6	105000.0	150000.0	119233.3	8.64E+05	2.81E-01	4.18E+03	8.29E+02	2.92E+02	2.56E+07	
			Biogas	14792.2	14792.2	19982.7	215719.6	6985.2	62500.0	900000.0	1400000.0	199616.6	105000.0	150000.0	119233.3	1.39E+06	6.59E-02	2.57E+04	1.05E+04	4.18E+02	1.09E+07	
		Natural Gas	Electricity	14792.2	14792.2	19982.7	215719.6	6985.2	62500.0	900000.0	1400000.0	199616.6	105000.0	150000.0	119233.3	5.15E+06	5.67E-01	2.49E+04	6.96E+03	1.07E+03	5.85E+07	
			Natural Gas	14792.2	14792.2	19982.7	215719.6	6985.2	62500.0	900000.0	1400000.0	199616.6	105000.0	150000.0	119233.3	1.15E+06	2.93E-01	3.65E+03	7.01E+02	4.16E+02	5.08E+07	
Bolzano		LPG	LPG	14792.2	14792.2	19982.7	215719.6	6985.2	62500.0	900000.0	1400000.0	199616.6	105000.0	150000.0	119233.3	8.62E+05	2.80E-01	4.17E+03	8.27E+02	2.91E+02	2.55E+07	
			Biogas	14792.2	14792.2	19982.7	215719.6	6985.2	62500.0	900000.0	1400000.0	199616.6	105000.0	150000.0	119233.3	1.39E+06	6.58E-02	2.56E+04	1.05E+04	4.16E+02	1.08E+07	
		Natural Gas	Electricity	14720.2	14720.2	21599.4	214669.6	6951.2	62500.0	900000.0	1400000.0	199616.6	105000.0	150000.0	119233.3	3.75E+06	4.03E-01	1.79E+04	5.01E+03	7.84E+02	4.24E+07	
			Natural Gas	14720.2	14720.2	21599.4	214669.6	6951.2	62500.0	900000.0	1400000.0	199616.6	105000.0	150000.0	119233.3	9.54E+05	2.11E-01	2.99E+03	6.30E+02	3.23E+02	3.70E+07	
F	Cuneo	LPG	LPG	14720.2	14720.2	21599.4	214669.6	6951.2	62500.0	900000.0	1400000.0	199616.6	105000.0	150000.0	119233.3	7.55E+05	2.02E-01	3.36E+03	7.19E+02	2.36E+02	1.93E+07	
			Biogas	14720.2	14720.2	21599.4	214669.6	6951.2	62500.0	900000.0	1400000.0	199616.6	105000.0	150000.0	119233.3	1.12E+06	5.19E-02	1.83E+04	7.46E+03	3.24E+02	9.02E+06	
		Natural Gas	Electricity	14720.2	14720.2	21599.4	214669.6	6951.2	62500.0	900000.0	1400000.0	199616.6	105000.0	150000.0	119233.3	8.18E+06	9.26E-01	4.02E+04	1.12E+04	1.71E+03	9.38E+07	
			Natural Gas	14720.2	14720.2	21599.4	214669.6	6951.2	62500.0	900000.0	1400000.0	199616.6	105000.0	150000.0	119233.3	1.57E+06	4.71E-01	5.09E+03	8.43E+02	6.17E+02	8.09E+07	
Cortina	Natural Gas	Electricity	14720.2	14720.2	21599.4	214669.6	6951.2	62500.0	900000.0	1400000.0	199616.6	105000.0	150000.0	119233.3	8.18E+06	9.26E-01	4.02E+04	1.12E+04	1.71E+03	9.38E+07		
		Natural Gas	14720.2	14720.2	21599.4	214669.6	6951.2	62500.0	900000.0	1400000.0	199616.6	105000.0	150000.0	119233.3	1.57E+06	4.71E-01	5.09E+03	8.43E+02	6.17E+02	8.09E+07		

Model	Climatic Zone	City	Energy Carrier	External plaster	Cement lime plaster	Rock wool	Tuff block	Internal plaster 1	Concrete brick	Concrete screed	Concrete slab	Internal plaster 2	Floor tile	Bitumen	Brick	GWP	ODP	AP	EP	POCP	ADP-fossil
				[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg CO ₂ -eq]	[kg CFC11-eq]	[kg SO ₂ -eq]	[kg PO ₄ 3--eq]
13	B	Sestriere	LPG	14720.2	14720.2	21599.4	214669.6	6951.2	62500.0	900000.0	1400000.0	199616.6	105000.0	150000.0	119233.3	1.10E+06	4.50E-01	5.95E+03	1.05E+03	4.11E+02	3.91E+07
			Biogas	14720.2	14720.2	21599.4	214669.6	6951.2	62500.0	900000.0	1400000.0	199616.6	105000.0	150000.0	119233.3	1.97E+06	9.58E-02	4.14E+04	1.70E+04	6.18E+02	1.48E+07
			Electricity	14720.2	14720.2	21599.4	214669.6	6951.2	62500.0	900000.0	1400000.0	199616.6	105000.0	150000.0	119233.3	9.15E+06	1.04E+00	4.51E+04	1.25E+04	1.91E+03	1.05E+08
			Natural Gas	14720.2	14720.2	21599.4	214669.6	6951.2	62500.0	900000.0	1400000.0	199616.6	105000.0	150000.0	119233.3	1.71E+06	5.28E-01	5.54E+03	8.89E+02	6.81E+02	9.05E+07
			LPG	14720.2	14720.2	21599.4	214669.6	6951.2	62500.0	900000.0	1400000.0	199616.6	105000.0	150000.0	119233.3	1.17E+06	5.04E-01	6.52E+03	1.12E+03	4.49E+02	4.34E+07
			Biogas	14720.2	14720.2	21599.4	214669.6	6951.2	62500.0	900000.0	1400000.0	199616.6	105000.0	150000.0	119233.3	2.16E+06	1.05E-01	4.64E+04	1.91E+04	6.82E+02	1.61E+07
		Messina	Electricity	22512.3	16884.2	21825.6	281403.7	10630.8	125000.0	1500000.0	2450000.0	404048.6	210000.0	600000.0	248097.3	5.00E+06	5.21E-01	2.33E+04	6.62E+03	1.05E+03	5.63E+07
			Natural Gas	22512.3	16884.2	21825.6	281403.7	10630.8	125000.0	1500000.0	2450000.0	404048.6	210000.0	600000.0	248097.3	1.45E+06	2.77E-01	4.44E+03	1.07E+03	4.67E+02	4.94E+07
			LPG	22512.3	16884.2	21825.6	281403.7	10630.8	125000.0	1500000.0	2450000.0	404048.6	210000.0	600000.0	248097.3	1.20E+06	2.66E-01	4.90E+03	1.18E+03	3.57E+02	2.70E+07
			Biogas	22512.3	16884.2	21825.6	281403.7	10630.8	125000.0	1500000.0	2450000.0	404048.6	210000.0	600000.0	248097.3	1.67E+06	7.60E-02	2.39E+04	9.74E+03	4.68E+02	1.39E+07
			Electricity	22512.3	16884.2	21825.6	281403.7	10630.8	125000.0	1500000.0	2450000.0	404048.6	210000.0	600000.0	248097.3	4.78E+06	4.95E-01	2.22E+04	6.32E+03	1.01E+03	5.37E+07
			Natural Gas	22512.3	16884.2	21825.6	281403.7	10630.8	125000.0	1500000.0	2450000.0	404048.6	210000.0	600000.0	248097.3	1.42E+06	2.64E-01	4.34E+03	1.06E+03	4.53E+02	4.72E+07
	Palermo	LPG	22512.3	16884.2	21825.6	281403.7	10630.8	125000.0	1500000.0	2450000.0	404048.6	210000.0	600000.0	248097.3	1.18E+06	2.54E-01	4.78E+03	1.17E+03	3.48E+02	2.60E+07	
		Biogas	22512.3	16884.2	21825.6	281403.7	10630.8	125000.0	1500000.0	2450000.0	404048.6	210000.0	600000.0	248097.3	1.62E+06	7.39E-02	2.28E+04	9.27E+03	4.53E+02	1.37E+07	
		Electricity	22512.3	16884.2	21825.6	281403.7	10630.8	125000.0	1500000.0	2450000.0	404048.6	210000.0	600000.0	248097.3	6.69E+06	7.21E-01	3.19E+04	8.99E+03	1.40E+03	7.60E+07	
		Natural Gas	22512.3	16884.2	21825.6	281403.7	10630.8	125000.0	1500000.0	2450000.0	404048.6	210000.0	600000.0	248097.3	1.69E+06	3.77E-01	5.24E+03	1.15E+03	5.80E+02	6.62E+07	
		LPG	22512.3	16884.2	21825.6	281403.7	10630.8	125000.0	1500000.0	2450000.0	404048.6	210000.0	600000.0	248097.3	1.33E+06	3.61E-01	5.90E+03	1.31E+03	4.24E+02	3.45E+07	
		Biogas	22512.3	16884.2	21825.6	281403.7	10630.8	125000.0	1500000.0	2450000.0	404048.6	210000.0	600000.0	248097.3	1.99E+06	9.29E-02	3.27E+04	1.34E+04	5.80E+02	1.62E+07	
	Crotona	Electricity	22134.3	16600.7	25383.4	276678.7	10452.3	250000.0	1600000.0	2450000.0	404048.6	210000.0	600000.0	248097.3	4.85E+06	5.00E-01	2.25E+04	6.38E+03	1.02E+03	5.44E+07	
		Natural Gas	22134.3	16600.7	25383.4	276678.7	10452.3	250000.0	1600000.0	2450000.0	404048.6	210000.0	600000.0	248097.3	1.45E+06	2.67E-01	4.42E+03	1.06E+03	4.64E+02	4.78E+07	
		LPG	22134.3	16600.7	25383.4	276678.7	10452.3	250000.0	1600000.0	2450000.0	404048.6	210000.0	600000.0	248097.3	1.21E+06	2.56E-01	4.86E+03	1.17E+03	3.59E+02	2.63E+07	
		Biogas	22134.3	16600.7	25383.4	276678.7	10452.3	250000.0	1600000.0	2450000.0	404048.6	210000.0	600000.0	248097.3	1.66E+06	7.45E-02	2.30E+04	9.36E+03	4.65E+02	1.39E+07	
		Electricity	22134.3	16600.7	25383.4	276678.7	10452.3	250000.0	1600000.0	2450000.0	404048.6	210000.0	600000.0	248097.3	6.38E+06	6.82E-01	3.02E+04	8.52E+03	1.34E+03	7.22E+07	
		Natural Gas	22134.3	16600.7	25383.4	276678.7	10452.3	250000.0	1600000.0	2450000.0	404048.6	210000.0	600000.0	248097.3	1.67E+06	3.57E-01	5.14E+03	1.14E+03	5.66E+02	6.30E+07	
	C	Bari	LPG	22134.3	16600.7	25383.4	276678.7	10452.3	250000.0	1600000.0	2450000.0	404048.6	210000.0	600000.0	248097.3	1.33E+06	3.42E-01	5.76E+03	1.29E+03	4.19E+02	3.32E+07
			Biogas	22134.3	16600.7	25383.4	276678.7	10452.3	250000.0	1600000.0	2450000.0	404048.6	210000.0	600000.0	248097.3	1.95E+06	8.97E-02	3.10E+04	1.27E+04	5.67E+02	1.59E+07
			Electricity	22134.3	16600.7	25383.4	276678.7	10452.3	250000.0	1600000.0	2450000.0	404048.6	210000.0	600000.0	248097.3	7.70E+06	8.37E-01	3.69E+04	1.04E+04	1.62E+03	8.75E+07
		Termoli	Natural Gas	22134.3	16600.7	25383.4	276678.7	10452.3	250000.0	1600000.0	2450000.0	404048.6	210000.0	600000.0	248097.3	1.85E+06	4.35E-01	5.77E+03	1.20E+03	6.53E+02	7.61E+07
			LPG	22134.3	16600.7	25383.4	276678.7	10452.3	250000.0	1600000.0	2450000.0	404048.6	210000.0	600000.0	248097.3	1.43E+06	4.16E-01	6.53E+03	1.39E+03	4.71E+02	3.91E+07
			Biogas	22134.3	16600.7	25383.4	276678.7	10452.3	250000.0	1600000.0	2450000.0	404048.6	210000.0	600000.0	248097.3	2.21E+06	1.03E-01	3.79E+04	1.55E+04	6.54E+02	1.76E+07
	D	Genova	Electricity	22134.3	22134.3	33067.8	322791.8	10452.3	125000.0	2300000.0	3570000.0	404048.6	210000.0	300000.0	248097.3	6.25E+06	6.44E-01	2.91E+04	8.18E+03	1.29E+03	6.94E+07
			Natural Gas	22134.3	22134.3	33067.8	322791.8	10452.3	125000.0	2300000.0	3570000.0	404048.6	210000.0	300000.0	248097.3	1.82E+06	3.40E-01	5.52E+03	1.25E+03	5.58E+02	6.08E+07
			LPG	22134.3	22134.3	33067.8	322791.8	10452.3	125000.0	2300000.0	3570000.0	404048.6	210000.0	300000.0	248097.3	1.50E+06	3.26E-01	6.10E+03	1.39E+03	4.20E+02	3.27E+07
			Biogas	22134.3	22134.3	33067.8	322791.8	10452.3	125000.0	2300000.0	3570000.0	404048.6	210000.0	300000.0	248097.3	2.09E+06	8.86E-02	2.98E+04	1.21E+04	5.58E+02	1.65E+07
		Firenze	Electricity	22134.3	22134.3	33067.8	322791.8	10452.3	125000.0	2300000.0	3570000.0	404048.6	210000.0	300000.0	248097.3	7.11E+06	7.46E-01	3.34E+04	9.39E+03	1.47E+03	7.94E+07
			Natural Gas	22134.3	22134.3	33067.8	322791.8	10452.3	125000.0	2300000.0	3570000.0	404048.6	210000.0	300000.0	248097.3	1.94E+06	3.91E-01	5.93E+03	1.29E+03	6.15E+02	6.93E+07

Model	Climatic Zone	City	Energy Carrier	External plaster	Cement lime plaster	Rock wool	Tuff block	Internal plaster 1	Concrete brick	Concrete screed	Concrete slab	Internal plaster 2	Floor tile	Bitumen	Brick	GWP	ODP	AP	EP	POCP	ADP-fossil
				[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg]	[kg CO ₂ -eq]	[kg CFC11-eq]	[kg SO ₂ -eq]
E	Forlì	LPG	LPG	22134.3	22134.3	33067.8	322791.8	10452.3	125000.0	2300000.0	3570000.0	404048.6	210000.0	300000.0	248097.3	1.57E+06	3.74E-01	6.60E+03	1.46E+03	4.54E+02	3.66E+07
			Biogas	22134.3	22134.3	33067.8	322791.8	10452.3	125000.0	2300000.0	3570000.0	404048.6	210000.0	300000.0	248097.3	2.26E+06	9.71E-02	3.43E+04	1.39E+04	6.15E+02	1.76E+07
			Electricity	22134.3	22134.3	33067.8	322791.8	10452.3	125000.0	2300000.0	3570000.0	404048.6	210000.0	300000.0	248097.3	9.67E+06	1.05E+00	4.64E+04	1.30E+04	2.00E+03	1.09E+08
			Natural Gas	22134.3	22134.3	33067.8	322791.8	10452.3	125000.0	2300000.0	3570000.0	404048.6	210000.0	300000.0	248097.3	2.30E+06	5.41E-01	7.13E+03	1.41E+03	7.84E+02	9.47E+07
			LPG	22134.3	22134.3	33067.8	322791.8	10452.3	125000.0	2300000.0	3570000.0	404048.6	210000.0	300000.0	248097.3	1.77E+06	5.18E-01	8.10E+03	1.65E+03	5.55E+02	4.81E+07
			Biogas	22134.3	22134.3	33067.8	322791.8	10452.3	125000.0	2300000.0	3570000.0	404048.6	210000.0	300000.0	248097.3	2.75E+06	1.23E-01	4.76E+04	1.94E+04	7.85E+02	2.10E+07
		Trieste	Electricity	22188.3	22188.3	39349.0	323579.3	10477.8	125000.0	1800000.0	2800000.0	404048.6	210000.0	300000.0	248097.3	7.15E+06	7.65E-01	3.40E+04	9.54E+03	1.49E+03	8.07E+07
			Natural Gas	22188.3	22188.3	39349.0	323579.3	10477.8	125000.0	1800000.0	2800000.0	404048.6	210000.0	300000.0	248097.3	1.83E+06	3.99E-01	5.72E+03	1.22E+03	6.17E+02	7.04E+07
			LPG	22188.3	22188.3	39349.0	323579.3	10477.8	125000.0	1800000.0	2800000.0	404048.6	210000.0	300000.0	248097.3	1.45E+06	3.82E-01	6.42E+03	1.39E+03	4.52E+02	3.68E+07
			Biogas	22188.3	22188.3	39349.0	323579.3	10477.8	125000.0	1800000.0	2800000.0	404048.6	210000.0	300000.0	248097.3	2.16E+06	9.73E-02	3.49E+04	1.42E+04	6.18E+02	1.73E+07
			Electricity	22188.3	22188.3	39349.0	323579.3	10477.8	125000.0	1800000.0	2800000.0	404048.6	210000.0	300000.0	248097.3	1.01E+07	1.11E+00	4.90E+04	1.37E+04	2.11E+03	1.15E+08
			Natural Gas	22188.3	22188.3	39349.0	323579.3	10477.8	125000.0	1800000.0	2800000.0	404048.6	210000.0	300000.0	248097.3	2.24E+06	5.74E-01	7.12E+03	1.36E+03	8.14E+02	9.99E+07
	Torino	LPG	22188.3	22188.3	39349.0	323579.3	10477.8	125000.0	1800000.0	2800000.0	404048.6	210000.0	300000.0	248097.3	1.68E+06	5.49E-01	8.15E+03	1.61E+03	5.69E+02	5.00E+07	
		Biogas	22188.3	22188.3	39349.0	323579.3	10477.8	125000.0	1800000.0	2800000.0	404048.6	210000.0	300000.0	248097.3	2.72E+06	1.27E-01	5.03E+04	2.06E+04	8.15E+02	2.12E+07	
		Electricity	22188.3	22188.3	39349.0	323579.3	10477.8	125000.0	1800000.0	2800000.0	404048.6	210000.0	300000.0	248097.3	1.02E+07	1.12E+00	4.92E+04	1.37E+04	2.12E+03	1.16E+08	
		Natural Gas	22188.3	22188.3	39349.0	323579.3	10477.8	125000.0	1800000.0	2800000.0	404048.6	210000.0	300000.0	248097.3	2.25E+06	5.76E-01	7.14E+03	1.36E+03	8.17E+02	1.00E+08	
		LPG	22188.3	22188.3	39349.0	323579.3	10477.8	125000.0	1800000.0	2800000.0	404048.6	210000.0	300000.0	248097.3	1.69E+06	5.51E-01	8.18E+03	1.61E+03	5.71E+02	5.02E+07	
		Biogas	22188.3	22188.3	39349.0	323579.3	10477.8	125000.0	1800000.0	2800000.0	404048.6	210000.0	300000.0	248097.3	2.73E+06	1.27E-01	5.05E+04	2.07E+04	8.18E+02	2.12E+07	
	F	Cuneo	Electricity	22080.3	22080.3	42524.0	322004.3	10426.8	125000.0	1800000.0	2800000.0	404048.6	210000.0	300000.0	248097.3	7.67E+06	8.26E-01	3.67E+04	1.03E+04	1.60E+03	8.68E+07
			Natural Gas	22080.3	22080.3	42524.0	322004.3	10426.8	125000.0	1800000.0	2800000.0	404048.6	210000.0	300000.0	248097.3	1.91E+06	4.30E-01	5.98E+03	1.24E+03	6.52E+02	7.56E+07
			LPG	22080.3	22080.3	42524.0	322004.3	10426.8	125000.0	1800000.0	2800000.0	404048.6	210000.0	300000.0	248097.3	1.49E+06	4.12E-01	6.73E+03	1.42E+03	4.73E+02	3.91E+07
			Biogas	22080.3	22080.3	42524.0	322004.3	10426.8	125000.0	1800000.0	2800000.0	404048.6	210000.0	300000.0	248097.3	2.26E+06	1.02E-01	3.76E+04	1.53E+04	6.53E+02	1.80E+07
			Electricity	22080.3	22080.3	42524.0	322004.3	10426.8	125000.0	1800000.0	2800000.0	404048.6	210000.0	300000.0	248097.3	1.64E+07	1.86E+00	8.08E+04	2.25E+04	3.42E+03	1.88E+08
			Natural Gas	22080.3	22080.3	42524.0	322004.3	10426.8	125000.0	1800000.0	2800000.0	404048.6	210000.0	300000.0	248097.3	3.12E+06	9.44E-01	1.01E+04	1.66E+03	1.23E+03	1.62E+08
Cortina		LPG	22080.3	22080.3	42524.0	322004.3	10426.8	125000.0	1800000.0	2800000.0	404048.6	210000.0	300000.0	248097.3	2.17E+06	9.01E-01	1.18E+04	2.08E+03	8.17E+02	7.82E+07	
		Biogas	22080.3	22080.3	42524.0	322004.3	10426.8	125000.0	1800000.0	2800000.0	404048.6	210000.0	300000.0	248097.3	3.93E+06	1.89E-01	8.30E+04	3.41E+04	1.23E+03	2.95E+07	
		Electricity	22080.3	22080.3	42524.0	322004.3	10426.8	125000.0	1800000.0	2800000.0	404048.6	210000.0	300000.0	248097.3	1.90E+07	2.17E+00	9.40E+04	2.61E+04	3.96E+03	2.18E+08	
		Natural Gas	22080.3	22080.3	42524.0	322004.3	10426.8	125000.0	1800000.0	2800000.0	404048.6	210000.0	300000.0	248097.3	3.49E+06	1.10E+00	1.13E+04	1.78E+03	1.40E+03	1.88E+08	
		LPG	22080.3	22080.3	42524.0	322004.3	10426.8	125000.0	1800000.0	2800000.0	404048.6	210000.0	300000.0	248097.3	2.37E+06	1.05E+00	1.34E+04	2.27E+03	9.20E+02	8.99E+07	
		Biogas	22080.3	22080.3	42524.0	322004.3	10426.8	125000.0	1800000.0	2800000.0	404048.6	210000.0	300000.0	248097.3	4.43E+06	2.15E-01	9.66E+04	3.98E+04	1.41E+03	3.29E+07	
Sestriere	Electricity	22080.3	22080.3	42524.0	322004.3	10426.8	125000.0	1800000.0	2800000.0	404048.6	210000.0	300000.0	248097.3	1.90E+07	2.17E+00	9.40E+04	2.61E+04	3.96E+03	2.18E+08		
	Natural Gas	22080.3	22080.3	42524.0	322004.3	10426.8	125000.0	1800000.0	2800000.0	404048.6	210000.0	300000.0	248097.3	3.49E+06	1.10E+00	1.13E+04	1.78E+03	1.40E+03	1.88E+08		
	LPG	22080.3	22080.3	42524.0	322004.3	10426.8	125000.0	1800000.0	2800000.0	404048.6	210000.0	300000.0	248097.3	2.37E+06	1.05E+00	1.34E+04	2.27E+03	9.20E+02	8.99E+07		



ALTERNATIVE MODELS FOR BUILDING ENERGY PERFORMANCE ASSESSMENT

2019/2020

PHD THESIS OF ANTONINO D'AMICO