Application of optimized artificial intelligence algorithm to evaluate the heating energy demand of non-residential buildings at European level

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ABSTRACT

A reliable preliminary forecast of heating energy demand of a building by using a detailed dynamic simulation software typically requires an in-depth knowledge of the thermal balance, several input data and a very skilled user. The authors will describe how to use Artificial Neural Networks to predict the demand for thermal energy linked to the winter climatization of non-residential buildings. To train the neural network it was necessary to develop an accurate energy database that represents the basis of the training of a specific Artificial Neural Networks. Data came from detailed dynamic simulations performed in the TRNSYS environment. The models were built according to the standards and laws of building energy requirements in seven different European countries, for 3 cities in each country and with 13 different shape factors, obtaining 2184 detailed dynamic simulations of non-residential buildings designed with high energy performances. The authors identified the best ANN topology developing a tool for determining, both quickly and simply, the heating energy demand of a non-residential building, knowing only 12 well-known thermo-physical parameters and without any computational cost or knowledge of the thermal balance. The reliability of this approach is demonstrated by the low standard deviation less than 5 kWh/(m²·year).

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1. Introduction

Improvements in energy saving and energy efficiency are needed for the reduction of atmospheric emissions which contribute to the greenhouse effect. One of the main areas, where a considerable energy saving can be achieved, is the building sector, by attaining acceptable conditions of indoor thermal comfort [1]. The issue of limiting energy consumption pertaining to the building stock within the European Union has become the main objective of various legislative measures at international, national and local levels [2–4]. Indeed, about 40% of the European energy consumption is related to the building sector and most is linked to satisfying the heating energy demand. In order to achieve significant primary energy savings, many steps can be implemented by acting on the

thermo-physical characteristics of the building envelope, on the geometry, and on the operational strategy of plants management as written in Ref. [5].

In order to mitigate this significant commitment to energy resources, the European Union has promulgated the “Energy Performance of Buildings Directive” (EPBD) [6]; it aims to impose the achievement of certain energy performances in the building heritage of new and old constructions. In order to maximize the energy performance of buildings, architects, designers and engineers have to optimize all those thermo-physical and plant parameters (thermal transmittance, shadowing, thermal plant components, plant regulation, etc.), while at the same time making indoor spaces comfortable [7–9]. The energy efficiency in buildings is related to the concept of a reduction in the energy demand needed to achieve desirable environmental conditions [10], and careful heating and cooling design is one of the best methods for reducing such energy costs [11]. To achieve this goal, all parameters that influence the thermal balance of the building must be carefully evaluated [12]. A building is a thermodynamic system that continuously carries out energy exchanges with the surrounding environment through the

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Nomenclature		V	heated volume [m ³]
<i>Model Parameters</i>		<i>ANN parameters</i>	
C_d	cooling energy demand [kWh/(m ² ·year)]	A_i	activation potential
C_T	total thermal capacity [kWh/(m ³ ·K)]	E_w	error function
CDD	cooling Degree Days [K day]	h	hidden layers
H_d	heating energy demand [kWh/(m ² ·year)]	k	scale parameter
HDD	heating Degree Days [K day]	K	tanh-sigmoid function shape
Q_G	internal gains [kWh/year]	T	number of iteration
Q_S	solar gains [kWh/year]	t_i	output pattern
Q_T	heat transmission losses [kWh/year]	v_{jk}	interconnection synaptic weights between j -th and k -th layers
Q_V	ventilation losses [kWh/year]	w_{ij}	interconnection synaptic weights between i -th and j -th layers
S	losses surface [m ²]	Δw_{ij}	variation of the interconnection synaptic weights
S_{op}	opaque losses surface [m ²]	x_i	input data
S_w	window losses surface [m ²]	y_i	output data
S/V	shape factor [m ⁻¹]	α	momentum
U	thermal transmittance [W/(m ² ·K)]	η	learning rate
U_0	overall U-value [W/(m ² ·K)]	μ	specific input pattern
U_w	window thermal transmittance [W/(m ² ·K)]	θ_i	neuron activation threshold
U_{op}	overall opaque thermal transmittance [W/(m ² ·K)]		

envelope [13]. Thus, the thermal-physical properties of the building envelope, the climate of the considered location, and the heating system have a direct impact on the building energy balance and, therefore, determine the intensity of energy demand. For this reason, changing and increasing the energy performance of a building requires the accurate knowledge of a great deal of data relating to the aforementioned quantities.

Many other authors have focused their studies on the evaluation of energy consumption of buildings, developing alternative models, as described and compared in Ref. [14]. For example, a numerical method to evaluate the non-linearity of the systems and its temporal response has been proposed [15] while in Ref. [16] the authors have described a new hybrid dynamic approach that links genetic programming with a grey model to forecast energy consumption.

In Ref. [17] the authors have proposed the adoption of a data-driven, feedforward decision framework for building cluster operation, employing noise-tolerant data fusion techniques, while in Ref. [18] a method for deploying models is described for the energy assessment of a building, this is useful for the control of the building at runtime using a system identification approach.

Recently, some works have appeared which modularly build a model of a building, which can be eventually used for predicting heating demand. Such methods use first-principle models or grey-box model which can be eventually identified via neural networks or parameters estimation technique [19,20].

A careful analysis of heating energy demand in the preliminary design stage and/or renovation stage allows the technician to identify the criticalities of the building-plant system and to select the most appropriate design choices; it strongly affects the consumption of energy and can improve the energy performance of the building. To simplify the calculation procedures, several simulation tools [21] have been developed and tested [22]. All these methods and tools, briefly summarized above, allow a very precise evaluation of the energy performance but need a huge amount of technical information and many parameters, which are not always easy to find. Furthermore, a detailed and in-depth knowledge of relevant software and great skill in understanding the underlying physical phenomena are required. To accelerate the phase of preliminary assessment, it might be easier to use a simplified model which allows the evaluation of the energy demand with a good level of

accuracy and without excessive computational cost or user experience.

An alternative approach to the traditional methods for the definition of the building energy balance (e.g. those characterized by a steady state approach [23,24] or those characterized by a dynamic approach of the problem [21]) is presented through the use of evolutionary algorithms that are based on the operating logic of AI [25]. 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 characterized 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 and their reliability is not very high.

In this contribution, the authors will show how it is possible to use Artificial Neural Networks (ANNs) to predict the demand for thermal energy connected to the winter climatization of non-residential buildings [26].

2. Materials and method

In order to determine the heating energy demand, it was necessary to study the influence of various parameters that come into play in the overall energy balance of the building.

The database used by the ANNs was built using results that emerged from over 2184 detailed dynamic simulations performed in the TRNSYS environment [27]. After the implementation of an “ideal building” model built according to the highest standards and laws of energy requirements in different European countries, these models were calibrated with empirical data reported in the scientific literature. Taking into consideration the differences that exist in the regulations and technical standards about the building

energy performance of various European countries, the authors developed several detailed dynamic simulation models that refer to seven countries: Germany, Spain, the United Kingdom, Belgium, Italy, France, and Sweden. Moreover, to take into account the different climatic characteristics of each nation, three locations were evaluated for each country which represent the hottest, the coolest and the mildest climate. The shape factors of buildings, which represent the ratio between the total of the loss surfaces to the gross heated volume of a building, were varied from 0.24 to 0.90 obtaining 273 models. Each model is characterized by 13 main parameters which directly influence the energy performance of the building system. Finally, to take into account the effects of solar radiation, each building model was considered in eight different positions with respect to cardinal south, with a step of 45° [28].

These data represent the database used to train different ANN architectures. In this paper, only the best-obtained results from optimal ANN are reported; 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 (R^2) higher than 0.95 and Mean Absolute Percentage Error (MAPE) lower than 9%) show the suitability of the calculation method based on the use of adaptive systems for the evaluation of energy performance of buildings. The developed tool provides a practical, efficient and fast methodology for forecasting energy consumption for winter air-conditioning of non-residential buildings in the European Union, taking into account different requirements in different locations. This tool could help in energy planning, in accelerating the design process and in supporting public administration in the evaluation of the energy demand of a large set of building clusters.

2.1. Artificial neural network

AI techniques are implemented in several applications due to their strong reasoning, fault tolerance, flexibility and generalization capabilities. As one of the most popular AIs, the ANN, which is a mathematical paradigm imitating the behaviour of biological neural networks, has been implemented to solve many practical problems in different fields. The attempt to simulate the behaviour of the biological neural system conduct to the implementation of the ANNs. ANN is a collection of individually interconnected processing units acting as parallel-distributed computing networks. Unlike conventional computers which 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 [29]. 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 [30]. 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 [31]. 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 [32]. 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 (cell body) 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. 1).

ANNs have surprisingly similar characteristics to those of the human brain; an empirical ability to learn, limited precision associated with high elasticity of input interpretation, and extrapolation and generalization capabilities. 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.

Artificial neurons are arranged in layers; each neuron is connected and exchanges information with other neurons and/or with itself, and the interconnectivity defines the topology of the ANN. Neurons sum up the weighted contributions that reach them through synaptic connections, filter them through a function, and produce an output. In general, the effect of an input signal x_j on the i -th postsynaptic neuron is simply equal to the product $w_{ij} \times x_j$ 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:

$$A_i = \sum_j w_{ij} x_j - \vartheta_i \quad (1)$$

where ϑ_i is the threshold activation value of the neuron. An output is obtained only if the signal is propagated through a particular activation function:

$$y_i = \Phi(A_i) = \Phi\left(\sum_j w_{ij} x_j - \vartheta_i\right) \quad (2)$$

The activation function can also limit the range of values that the signal can take. In fact, the values of input and output variables are often normalized 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 [34]. 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 [35–38]. 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.

Fig. 1. [33] Artificial neuron schema.

Schematically, three different blocks of neurons can be recognized in a simple feed forward neural network: input, hidden, and output neurons (Fig. 2); the first collects the inputs x_i ; the last issues the outputs y_i and the hidden layer h_i connects inputs to outputs.

The architecture of a simple neural network of this type provides the flow of information in a single direction, from the input layer to the output layer, without forming any type of cycle or loop. Except for the input nodes, each node is a neuron or processing element (PE) with an activation function [39]. As you can see, this structure is aimed at constructing an approximate function describing the behaviour of very complicated systems by ensembles of simpler functions [40].

2.2. Building energy balance

In the field of building energy planning, often a first summary evaluation of the indoor heating/cooling load is necessary. Nevertheless, this evaluation is often very complex: the thermal balance of the buildings depends on several mutually linked factors. Generally, the standard conditions to be maintained in indoor environments are represented by two ranges of temperature: 18–20 °C in winter and 24–26 °C in summer [41]. As depicted in Fig. 3, the energy balance of a building is characterized by energy losses and gains; furthermore, the climate context, as well as the building construction type and its use are key parameters.

By solving the system of equations describing the building thermal balance, it is possible to assess the Heating (H_d) and Cooling (C_d) demands that represent the necessary amount of energy to maintain the desired ambient temperature in winter or summer [42].

For example, according to the approach described in Ref. [43], the heating energy demand in kilowatt-hours can be estimated by:

$$E_d = \frac{86400}{3.6 \times 10^6} \cdot DD \cdot (Q_v + \sum A \cdot U) = 0.024 \cdot DD \cdot U' \quad [kWh] \quad (3)$$

where.

- Q_v is the ventilation loss term [W/K];
- A is the surface area [m²];
- U is the thermal transmittance [W/m²K];

Fig. 2. An ANN schema.

Fig. 3. Building energy balance.

- DD are the Degree Days [K day].

Generally, it is possible to state that H_d or C_d are functions of:

$$H_d = f(HDD, Q_T, Q_v, Q_s, Q_G) \quad \text{and} \quad C_d = f'(CDD, Q_T, Q_v, Q_s, Q_G) \quad (4)$$

where.

- HDD is the Heating Degree Days [K day];
- CDD is the Cooling Degree Days [K day];
- Q_T is the transmittance losses and are dependent on the construction type of the building and also on the thermal transmittance of all the enclosure surfaces [kWh/year];
- Q_v is the ventilation loss term reported in the actual standards and laws [23] [kWh/year];
- Q_G are the internal gains reported in the actual standards and laws [23] and are dependent on the intended use [kWh/year];
- Q_s are the solar gains that depend on the relationship between the glass surface and the opaque surface and on the exposure [kWh/year].

Eqs. (3) and (4) show that the energy demand is strongly correlated to the climate context (DD and Q_s), the intended use (Q_v) and the thermo-physical parameter (U'). This last parameter represents the mean quality of the building envelope, but does not take into account the geometry or orientation of the building, thus neglecting important parameters which could influence the energy balance (e.g. it does not evaluate the area of loss surface to heated/cooled volume, S/V) [28].

This simplified and steady state method was indicated to identify, in a fast way, those variables that describe the physical phenomenon and are fundamental in the building thermal balance. The identification of the main parameters was necessary to select the essential input data that constitutes the base to create and store numerical data used to train an ANN.

2.2.1. 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 in the world, 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. The western part of the European continent is characterized 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 characterized by a drier, continental climate and Southern Europe enjoys a Mediterranean climate (with distinct wet and dry seasons) [44].

Our study attempts to collect at least one example of all possible climatic situations that can be observed in the European Union and for this reason three different locations for each of the aforementioned countries were chosen. As shown in Table 1, for each city the HDD values representing the maximum, minimum, and mean national values were evaluated.

2.2.2. 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 heating energy demand, while the input data are all the data that describe the building balance, such as: the constructive typology, the intended use and the climate context.

To create a reliable database the authors have used the results obtained by dynamic models of an ideal office building, built in the TRNSYS environment [27], and designed with high energy performance (ideal building) according to the minimum standard requirements of each European country.

As indicated in Ref. [28] an “ideal building” model having high energy performance according to the minimum standard requirements was designed. In detail, the “ideal building” was created with thirteen different shape factors (from 0.24 to 0.9) and each model was simulated in seven European countries with different climates.

For each country, three cities were chosen by identifying three different HDDs. The geometric characteristics of the thirteen “ideal building” models are summarized in Ref. [28].

Each model was built with respect to the European standard on energy consumption of office buildings, EN ISO 13,790: 2008 [23], and by implementing detailed information, such as thermo-physical characteristics of the building envelope, glazed-opaque

surface ratio, employment rate, internal gains, heating period, and switching on/off of the heating system. For each model, the authors defined the stratigraphy of the walls, roofs, and floors by ensuring that U-values respect the standard national limits [13]. To evaluate the average energy performance of a building as a function of incident solar radiation, each model for each city was simulated eight times, varying the orientation of the building by 45° and averaging the obtained results. By integrating and averaging the simulation results, annual heating energy demands were calculated.

In total 13 models, with different shape factors ranging from 0.24 to 0.9, were simulated eight times in 7 different countries for 3 different cities obtaining 2184 different simulations connoted by hourly time-step that were stored in a MySQL database [28,47,48]. The collected data are related to the following parameters:

1. Heating Degree Days HDD [K];
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 [$W/(m^2 \cdot K)$];
6. Overall opaque thermal transmittance U_{op} [$W/(m^2 \cdot K)$];
7. Overall thermal transmittance U_o [$W/(m^2 \cdot K)$];
8. Solar gains Q_s [kWh/year];
9. Heating operating hours h [h];
10. Total thermal capacity C_T [kWh/($m^3 \cdot K$)];
11. Internal gains Q_G [kWh/year];
12. Wind speed v [m/s];
13. Heating energy demand H_d [kWh/($m^2 \cdot year$)].

Table 2 shows the results obtained for Italy:

3. 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

Table 1
Climate parameters and heating period of examined European cities.

European Country	City	HDD [K/day]	Wind speed [m/s]	Heating period	Operating hours [h]
Belgium	Hubert	3190.72	3.86	1 st September–15th May	1512
	Bruxelles	2239.30	3.51	15 th October–30 th April	1152
	Liège	1975.16	3.88	1 st November–15th March	824
France	Bordeaux	1602.05	3.42	1 st November–15th March	888
	Bourge	2226.74	3.73	1 st November–31st March	1064
	Nice	1123.38	3.94	1 st November–31st March	800
Germany	Fichtelberg	4982.19	6.63	1 st September–15th June	1696
	Frankfurt	2829.51	2.34	15 th October–30 th May	1240
	Hof	3425.53	2.65	15 th October–30 th May	1328
Italy	Palermo	662.65	3.73	1 st December–31st March	712
	Venice	2077.81	2.50	15 th October–30 th April	808
	Sestriere	5265.20	5.83	15 th September–15th June	1608
Spain	Seville	702.80	4.05	15 th November–15th March	488
	Madrid	1615.32	4.10	1 st November–31st March	888
	Salamanca	2379.29	3.29	15 th October–15th May	1240
Sweden	Lund	3202.40	6.39	1 st September–30 th June	1240
	Umea	5299.05	3.32	1 st September–30 th June	1696
	Kiruna	6986.21	2.68	15 th October–15th May	1784
UK	Camborne	2026.30	5.38	1 st November–15th May	1088
	Birmingham	2773.73	4.32	1 st October–15th May	1336
	Aviemore	3483.33	3.55	1 st September–15th May	1512

Data provided by the Meteonorm software [45] have been used to characterize the climate of each location. The software allows the use of real data monitored by a network of weather stations in the period 2000–2009. Taking into account the activity periods of HVAC systems defined by the various national regulations, it was therefore possible to calculate the HDD indexes [28,46].

Table 2
Characteristics and features of the Italian models.

Model	City	HDD	S/V	S_w	S_{op}	U_w	U_{op}	U_0	Q_5	h	v	C_T	Q_G	H_d
A	IT-Palermo	662.65	0.24	860.68	4935.85	2.76	0.42	0.76	46,838.08	712	3.73	0.0690	647,566.44	1.33
	IT-Venezia	2077.81	0.24	860.68	4935.85	2.76	0.42	0.76	50,605.89	808	2.50	0.0690	647,566.44	20.70
	IT-Sestriere	5265.20	0.24	860.68	4935.85	2.76	0.42	0.76	173,001.52	1608	5.83	0.0690	647,566.44	49.34
B	IT-Palermo	662.65	0.27	838.80	4015.15	2.76	0.42	0.82	45,567.40	712	3.73	0.0656	483,948.36	1.46
	IT-Venezia	2077.81	0.27	838.80	4015.15	2.76	0.42	0.82	49,223.84	808	2.50	0.0656	483,948.36	21.91
	IT-Sestriere	5265.20	0.27	838.80	4015.15	2.76	0.42	0.82	166,952.85	1608	5.83	0.0656	483,948.36	50.33
C	IT-Palermo	662.65	0.32	545.60	4094.41	2.76	0.41	0.69	29,550.93	712	3.73	0.0226	293,940.19	5.23
	IT-Venezia	2077.81	0.32	545.60	4094.41	2.76	0.41	0.69	31,929.21	808	2.50	0.0226	293,940.19	35.86
	IT-Sestriere	5265.20	0.32	545.60	4094.41	2.76	0.41	0.69	109,292.63	1608	5.83	0.0226	293,940.19	78.19
D	IT-Palermo	662.65	0.35	460.34	1654.66	2.76	0.43	0.93	24,271.69	712	3.73	0.1841	483,948.36	2.89
	IT-Venezia	2077.81	0.35	460.34	1654.66	2.76	0.43	0.93	26,225.68	808	2.50	0.1841	483,948.36	31.02
	IT-Sestriere	5265.20	0.35	460.34	1654.66	2.76	0.43	0.93	90,371.86	1608	5.83	0.1841	483,948.36	64.60
E	IT-Palermo	662.65	0.40	318.26	1271.74	2.76	0.42	0.89	16,979.68	712	3.73	0.0585	459,580.17	3.91
	IT-Venezia	2077.81	0.40	318.26	1271.74	2.76	0.42	0.89	18,342.81	808	2.50	0.0585	459,580.17	35.31
	IT-Sestriere	5265.20	0.40	318.26	1271.74	2.76	0.42	0.89	62,475.56	1608	5.83	0.0585	459,580.17	72.16
F	IT-Palermo	662.65	0.50	530.91	11,455.80	2.76	0.41	0.51	29,213.65	712	3.73	0.0824	293,940.19	10.94
	IT-Venezia	2077.81	0.50	530.91	11,455.80	2.76	0.41	0.51	31,562.32	808	2.50	0.0824	293,940.19	42.65
	IT-Sestriere	5265.20	0.50	530.91	11,455.80	2.76	0.41	0.51	107,276.82	1608	5.83	0.0824	293,940.19	89.16
G	IT-Palermo	662.65	0.56	454.66	10,745.34	2.76	0.41	0.50	24,969.20	712	3.73	0.1056	459,580.17	9.28
	IT-Venezia	2077.81	0.56	454.66	10,745.34	2.76	0.41	0.50	26,976.68	808	2.50	0.1056	459,580.17	37.41
	IT-Sestriere	5265.20	0.56	454.66	10,745.34	2.76	0.41	0.50	91,735.03	1608	5.83	0.1056	459,580.17	78.31
H	IT-Palermo	662.65	0.58	303.10	5496.89	2.76	0.41	0.53	16,450.43	712	3.73	0.0902	836,139.47	9.42
	IT-Venezia	2077.81	0.58	303.10	5496.89	2.76	0.41	0.53	17,774.76	808	2.50	0.0902	836,139.47	39.63
	IT-Sestriere	5265.20	0.58	303.10	5496.89	2.76	0.41	0.53	60,842.73	1608	5.83	0.0902	836,139.47	81.62
I	IT-Palermo	662.65	0.62	153.29	1251.30	2.76	0.41	0.67	8210.59	712	3.73	0.0874	165,341.36	11.30
	IT-Venezia	2077.81	0.62	153.29	1251.30	2.76	0.41	0.67	8870.57	808	2.50	0.0874	165,341.36	54.94
	IT-Sestriere	5265.20	0.62	153.29	1251.30	2.76	0.41	0.67	30,297.10	1608	5.83	0.0874	165,341.36	107.36
L	IT-Palermo	662.65	0.69	291.74	4078.26	2.76	0.41	0.56	16,037.81	712	3.73	0.1052	165,468.547	9.07
	IT-Venezia	2077.81	0.69	291.74	4078.26	2.76	0.41	0.56	17,324.91	808	2.50	0.1052	165,468.547	41.13
	IT-Sestriere	5265.20	0.69	291.74	4078.26	2.76	0.41	0.56	58,565.63	1608	5.83	0.1052	165,468.547	82.51
M	IT-Palermo	662.65	0.70	254.60	5817.39	2.76	0.41	0.50	13,867.16	712	3.73	0.1181	247,754.888	9.29
	IT-Venezia	2077.81	0.70	254.60	5817.39	2.76	0.41	0.50	14,984.87	808	2.50	0.1181	247,754.888	37.99
	IT-Sestriere	5265.20	0.70	254.60	5817.39	2.76	0.41	0.50	51,438.65	1608	5.83	0.1181	247,754.888	77.61
N	IT-Palermo	662.65	0.76	155.62	2255.12	2.76	0.41	0.56	8443.36	712	3.73	0.0400	103,338.35	8.00
	IT-Venezia	2077.81	0.76	155.62	2255.12	2.76	0.41	0.56	9122.14	808	2.50	0.0400	103,338.35	37.38
	IT-Sestriere	5265.20	0.76	155.62	2255.12	2.76	0.41	0.56	31,082.33	1608	5.83	0.0400	103,338.35	74.91
O	IT-Palermo	662.65	0.90	300.45	2372.40	2.76	0.41	0.68	16,412.41	712	3.73	0.1215	486,170.64	9.66
	IT-Venezia	2077.81	0.90	300.45	2372.40	2.76	0.41	0.68	17,726.97	808	2.50	0.1215	486,170.64	49.75
	IT-Sestriere	5265.20	0.90	300.45	2372.40	2.76	0.41	0.68	59,652.30	1608	5.83	0.1215	486,170.64	94.63

In Appendix A, all data for each model in each city are collected; this matrix represents the dataset used to train the ANN to determine the heating energy demand as a unique output.

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, the authors explored different topologies of ANN and four ANNs were developed in this study for the evaluation of heating energy demand. The basic configuration of ANN was the Multi-Layer Perceptron (MLP) investigating two different topologies and for each of them two different configurations, varying the number of hidden layers and the number of neurons. For the modelling of physical systems and the resolution of regression problems, a feed-forward Back-Propagation MLP structure is commonly used. 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. 4):

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

B topology: MLP with two hidden layers (Fig. 5):

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

Figs. 4 and 5 represent the schemas of A1 and B1 topologies respectively, and in these configurations, it is possible to identify different activation functions. An activation function determines the response that a neuron is capable of delivering. In this paper, the authors used two continuous activation functions: linear and hyperbolic tangent functions (tanh-sigmoid) [49].

In a linear function, a number of such linear neurons perform a linear transformation of the input vector:

$$y_i = \Phi(A_i) = kA_i \quad (5)$$

in which k is a scale parameter.

A tanh-sigmoid function instead produces an output value between -1 and 1 ; furthermore, the tanh-sigmoid function is continuous and differentiable. Generally, the tanh-sigmoid function

Fig. 4. "A1-ANN" topology.

Fig. 5. "B1-ANN" topology.

is defined by the following formula:

$$\Phi(A_i) = \frac{1 - e^{-KA}}{1 + e^{-KA}} \quad (6)$$

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

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. 4); 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. 5). All topologies are characterized by a Back-propagation learning algorithm (Appendix B.1).

To better analyse the reliability of the selected ANNs, different

Table 3
ANN Design and characteristics.

ANN Design						
Models	Topology	Hidden layers	Input layer	1° hidden layer	2° hidden layer	Learning
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

simulations were carried out changing the time of the training phase and/or the epochs; in all cases, the training phase has been suspended in order to avoid over-fitting. 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 3:

Given the complexity of the building system that the authors intend 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 optimized result.

A hybrid system capable of matching the characteristics of intelligent algorithms can be constituted by ANN and a Genetic Algorithm (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 optimization 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 (Appendix B.2). 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 [49].

The authors, in the initial optimization phase based on the use of the evolutionary process of the GA, identified a population of 20 networks, each of which has random weight values. 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 1000 epochs: a total of 10,000,000 epochs for the entire process. The simulations were carried out with Peltarion synapse software [50] 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 min for the simplest network configuration (A1-ANN).

4. Results and discussions

In the following tables the features of the two best ANN architectures after the optimization phase are shown. In Table 4 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 5 the values of η , α and noise level are collected for each weight and activation layers for B-ANN topologies.

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 6; the A1 topology is the fastest (1 min and 7 s), and the B2 topology the slowest (about 8 h).

The post processing phase allows the statistical evaluation of the accuracy of the tested ANNs and the error results are summarized in Table 7 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;

Table 4
Features of the best A-ANN configurations.

Model A	1° weight layers			2° weight layers			1° activation functions		2° activation functions	
	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 5
Features of the best B-ANN configurations.

Model B	1° weight layers			2° weight layers			3° weight layers			1° activation functions		2° activation functions		3° activation functions	
	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

Table 6
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

- 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.

The 95% confidence range values are summed in the last column of Table 7; the bold values indicate the lower absolute values, and generally, the B-ANN architecture has the best results, despite being characterized 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 characterized 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. 6) and validation phases (Fig. 7) of A1 topology are shown.

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 Mean Absolute Error (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. 8.

In Fig. 8, 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. Furthermore, in Fig. 9, the authors display 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.

To better understand the validity of these results, in the following graphs (Figs. 10 and 11) the Absolute Percentage Error (APE), and the Mean Absolute Percentage Error (MAPE), between the simulated data with respect to the ANN data are plotted. Regarding the A1 ANN results Fig. 10 illustrates a MAPE of about 9% instead the B1 ANN presents a MAPE of about 8.5% (Fig. 11).

Fig. 6. Error frequency in the training phase of A1 topology.

Fig. 7. Error frequency in the validation phase of A1 topology.

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. 12; the desired H_d versus B1-ANN is shown in Fig. 13. In both cases, the data are well distributed on the diagonal of the first quadrant with determination coefficient values (R^2) higher than 95%

5. Conclusions

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

Table 7
Post processing error data of ANNs.

Post processing error							
Models	Training			Validation			Confidence range [kWh/(m ² ·year)]
	Mean	Median	StD	Mean	Median	StD	
A1	−0.869,289	−0.960,003	2.292,850	0.767,037	0.812,436	5.082,879	±9.947,962
A2	0.048,863	0.230,784	3.641,756	0.839,429	0.951,314	6.318,410	±12.33,428
B1	0.000326	0.039,369	1.979,777	1.028,433	0.531,214	4.837,094	±9.572,819
B2	0.000239	0.000914	2.628,834	0.270,659	1.056,509	4.866,031	± 9.429,152

Fig. 8. Confidence plot of MLP A1 topology.

Fig. 9. Learning curves of MLP A1 topology at 100, 1,000, 10,000 and 100,000 epochs.

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.

In this paper, the authors 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. With this aim, it was necessary to create a reliable database of training and validation data. The authors have developed a set of models of non-residential buildings with different shapes and characteristics, but all complying with the strictest technical legislation in use in seven countries of the European Union. Furthermore, three different locations have been chosen

Fig. 10. APE and MAPE of MLP A1 validation samples.

Fig. 11. APE and MAPE of MLP B1 validation samples.

Fig. 12. The distribution of the desired H_d versus the provided A1-ANN.

Fig. 13. The distribution of the desired H_d versus the provided B1-ANN.

problems in buildings is a valid and attractive alternative solution for thermal balance resolution. Once trained and validated, the ANNs can be easily used, even by users with no specific knowledge in the field of thermo-physical simulation of buildings, to estimate the thermal load necessary for winter air conditioning. Indeed, this method allows the implementation of this algorithm in a software program to act as a suitable decision support tool, which is simple, reliable and handy for immediate use. These first results encourage the authors to explore in the future new and more complex ANN topologies such as the dynamic neural networks.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.energy.2019.03.168>.

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representing different climatic situations in the European territory. As it is well known, the accuracy of the building energy database is essential to obtain a truthful response by an ANN. Indeed, if the data are affected by errors, the ANN learns a wrong relationship. An accurate energy database is guarantee if, as in this case, the simulation data obtained from the dynamic software were correctly calibrated.

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 7, it is possible to observe that the B architecture, in general, is characterized 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

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