Multiple Criteria Assessment of Methods for Forecasting Building Thermal Energy Demand

A. D'Amico[1]*, G. Ciulla[1], L. Tupenaite[2], A. Kaklauskas[2]

[1]University of Palermo, Italy,
Department of Engineering (DI)

[2]Vilnius Gediminas Technical University
Department of Construction Management and Real Estate

* Corresponding author: antonio.damico@deim.unipa.it.
e-mail: giuseppina.ciulla@unipa.it, laura.tupenaite@vgtu.lt, arturas.kaklauskas@vgtu.lt

ABSTRACT

Nowadays worldwide directives have focused the attention on improving energy efficiency in the building sector. The research of models able to predict the energy consumption from the first design and energy planning phase is conducted to improve building sustainability. Use of traditional forecasting tools for building thermal energy demand tends to encounter difficulties relevant to the amount of data required, implementation of the models, computational costs and inability to generalize the output. Therefore, many studies focused on the research and development of alternative resolution methods, but the choice of the most convenient is not clear and simple. Single comparison of statistical quality indexes does not allow an adequate identification of the most efficient method, as the necessary efforts for implementation of the methods from the initial data collection to the use phase are not considered. In this work, the authors propose to apply, for the first time, the multicriteria assessment to determine the most efficient alternative method, used for forecasting of building thermal energy demand. Three alternative "black-box" methods, previously investigated by the authors, were compared by the multiple criteria Complex Proportional Assessment Method. Such a procedure revealed ranking of the methods in four phases, namely Pre-processing, Implementation, Post-processing and Use, as well as overall assessment and selection of the most efficient method in terms of evaluated criteria. This first application could represent an incentive for future multi-criteria analyses involving a growing number of alternative forecasting methods.

Keywords

Building Thermal Energy Demand; Forecasting Method; Multiple Linear Regression; Dimensionless Analysis; Artificial Neural Network; Multiple Criteria Assessment.

Nomenclature

a_j	j^{th} alternative.
E_j	Overall efficiency index of the j^{th} alternative.
m	Number of attributes.
M	Decision-making matrix.
$\mathcal{M}$	Weighted normalized 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.
$\mathcal{P}$	Weighted normalized 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.
$S_{-\min}$	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 normalized attribute value of the j^{th} alternative.
y_{ij}	Q_j value of the j^{th} alternative.
y_{ij}	Weighted normalized attribute value of the j^{th} alternative, evaluation of phases.
A	Level of significance.
χ^2	Significance of the concordance coefficient.
χ^2_{tbl}	Critical tabular value of χ^2.

1. Introduction

The reduction of energy consumption and CO_2 emissions for heating and cooling needs of a building is an important challenge for the European Union, because the buildings sector contributes up to 36% of the global CO_2 emissions [1] and up to 40% of total primary energy [2–4] Despite the ambitious goals set by the Energy Performance of Buildings Directive (EPBD) [1], which states that, by 2020, all new and existing buildings undergoing major refurbishments will have to be Nearly Zero Energy Buildings (NZEB) [5–9]. 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 energy demand in buildings depends on the combination of several parameters , substantial input data describing structures, environmental conditions [10], envelope thermo-physical properties, geometry, control strategies, and several other parameters [11]. From the first design phases designers and researchers trying to respect the prescriptions of the EPBD directive and to simultaneously ensure the thermal comfort of the occupants, optimizing all possible aspects that represent the key points in a building energy balance.
Literature in the field offers highly numerous complex and simplified approaches under proposal [12]. Some are based on knowledge of the building thermal balance and on the resolution of physical equations (white-box); meanwhile others are on accumulated building data and on implementations of forecast models developed by machine-learning techniques (black-box) [13].
Several numerical approaches are most widespread; these have undergone testing and implementation by employing specialized software tools such as DOE-2 [14], Energy Plus [15], TRNSYS [16] and ESP-r [17]. Such building thermal behaviour modelling can be applied in several ways on different scales; these can be simplified [18,19] or detailed comprehensively by different methods [20]. These evaluate building performance by exploiting different numerical approaches; nevertheless, they are often characterized as lacking 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, there are some practical difficulties involved like collecting detailed building data and/or the evaluation of boundary conditions. Furthermore, their use normally requires an expert user and a careful calibration of the model [21]. These tools do not provide a generalized 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. Based on these considerations, the authors investigated some alternative methods for resolving a traditional building energy balance trying to overcome these limits and to develop a reliable and simpler building evaluation tool. The authors herein investigated several "black-box" approaches to determine the annual thermal energy demand in their previous works. These methods are mainly used to deduce a prediction model from a relevant database, 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.

The reference database was obtained from the parametric analysis of different models, simulated in different climatic zones and cities. For each individual model, the thermal energy requirement of the building necessary to achieve indoor comfort conditions was assessed, not considering primary energy. The validity of the simulation data was guaranteed by the calibration of the base-case model with monitored data; the details of this procedure is indicated in [21–23].

Indeed, the rising trend in building energy demand requires forecasting models for fostering reliable energy consumption [24].

In detail the three different and alternative methods are:

- the Multi Linear Regression (MLR) Method [10,11,21];
- the Buckingham Method (BM) [23];
- the Artificial Neural Network (ANN) Method [22,25,26].

As explained in previous studies, each method can be used to solve building thermal 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, for example, the heating energy demand obtained from each model (H_d) was plotted with respect to the reference thermal energy requirement collected in the database (Target H_d), (Fig. 1) that are the data obtained from the parametric simulation developed in the TRNSYS environment [16].

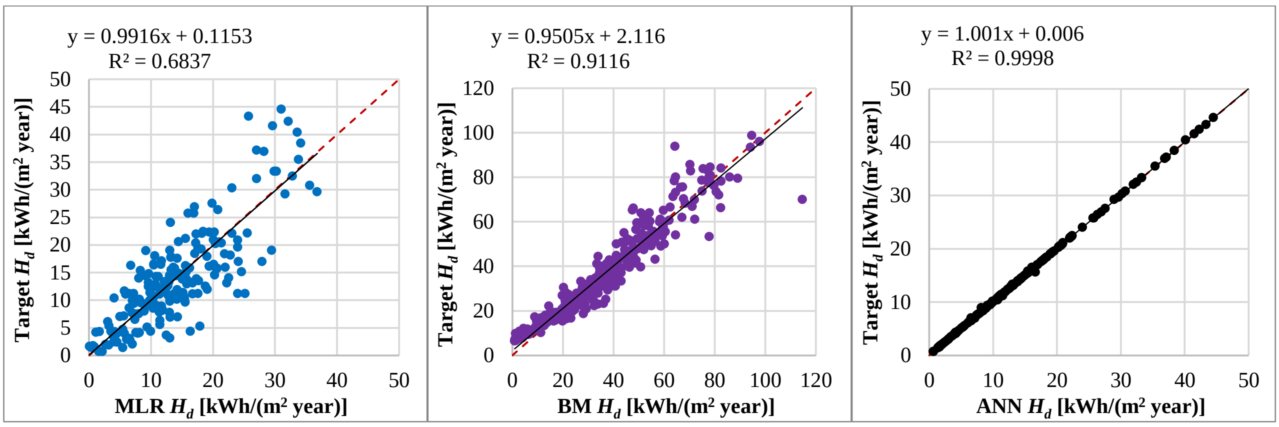

Fig. 1. Trend of predicted H_d by MLR, BM and ANN models versus the target H_d.

As indicated in Fig. 1, each trend is characterized by different R^2 values, revealing that the best solution is represented by the ANN model. This consideration is confirmed also from the calculation of Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) indexes, provided in Table 1.

Table 1
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**

In case of other two models, it is more difficult to identify the more accurate these, because the values of indexes are similar. In terms of R^2, calculated by means of 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 approximates the complex problem of the building thermal balance. In any case, the single comparison of statistical indexes does not allow an adequate identification of the most efficient model, as the necessary efforts for implementation of the methods from the initial data collection to the use phase are not considered.
Nonetheless, the authors asked themselves some questions: Which of these methods can be identified as promising the most efficient solution? Is it possible to compare the performance of these methods? Is it possible to choose the most efficient method based on some specific phase in the evaluation, since several steps and phases require thought, when assessing the thermal needs of a building?
The authors attempted to answer these questions with a comparison of these three alternative forecasting methods 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.
In this work for the first time the authors have applied a multi-criteria procedure to determine the most efficient alternative method between some resolution procedures of a building energy balance. This application has required extra effort in defining the criteria and identifying a team of experts. In this case, it was necessary to identify the salient phases of the procedure for the calculations to explain the most sensitive criteria for acquiring conscious, truthful answers, as only a pool of experts in the field can provide. In detail it was applied the Multiple Criteria Complex Proportional Evaluation (COPRAS) method [27,28] for identifying the most efficient forecasting tool. This is an innovative application of the MCA, because it compares some predictive black box methods for the first time. Moreover, in the illustrated case, an overall assessment of the energy performance forecasting process by each method and an assessment of the individual phases, namely Pre-processing, Implementation, Post-processing and Use, are implemented in terms of selected criteria. Ten experts were involved both for the evaluation of the significance of the criteria, and for the evaluation of each alternative with respect to the single criterion and for the determination of the significance of each evaluation phase.

1.1. Contribution of the work

The expertise needed to analyse the thermal energy demand of any building is often lacking among public administration users; thus, traditional assessment tools are often unusable. The reasons making such tools difficult to use include having knowledge about the physics of a phenomenon, the need for auxiliary knowledge, the complicated data collection phase necessary to implement a large number of parameters to develop a simulation model, the calibration phase and interpretation of the results. All these features involve a great deal of time and cost for the pertinent computations. To overcome these limitations, the authors identified and investigated different methods for resolving the building's energy balance in a non-traditional way, thereby providing a decision support tool that is able to simplify and, at the same time, accelerate the energy planning phase. Therefore, even users who are not highly qualified are able to employ such a tool.

This paper presents the application of an MCA procedure to identify the most efficient of these alternative methods. A detailed application of the COPRAS procedure to evaluate the performance of three methods previously developed by the authors was done. In this way for the first time the MCA is used to determine an accurate choice of the more appropriate forecasting solution of the building thermal energy demand.
Methodology is presented in Section 2; after a brief description of the three alternative forecasting methods (Section 3), the COPRAS method is explained in Section 4.1 and applied in Section 4.2. Discussion of results is available in Section 5; Section 6 concludes the paper. Several criteria were examined and a team of experts evaluated the significance of each criterion in respect to the evaluation of the forecasting method. To assure a high level of reliability, the authors selected a team of 10 highly qualified experts, working 10–15 years in the field of energy balance resolution of buildings and the development of forecasting tools and models.
The active contribution of many researchers and the high interest aroused by the need to improve the energy planning phases and, therefore, in forecasting 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 methods for predicting the building thermal energy demand. Then, following an appropriately calibrated multi-criteria approach, it will be possible to identify which of these is most suitable for the current purpose. Moreover, a new method INVAR (Degree of Project Utility and Investment Value Assessments) [29–31] will be applied for improvement of the alternative methods.

2. Methodology

The authors try to identify, the most efficient forecasting tool for evaluating building thermal demand. Three alternative methods were investigated by the authors in previous works because several strengths and weaknesses characterize each of them could be interest in determining which among these is the most efficient. Furthermore, it may be convenient to use one or another depending on the evaluation phase under consideration. The main steps involved are illustrated in this section; Fig. 2 displays the flow chart of the entire procedure.

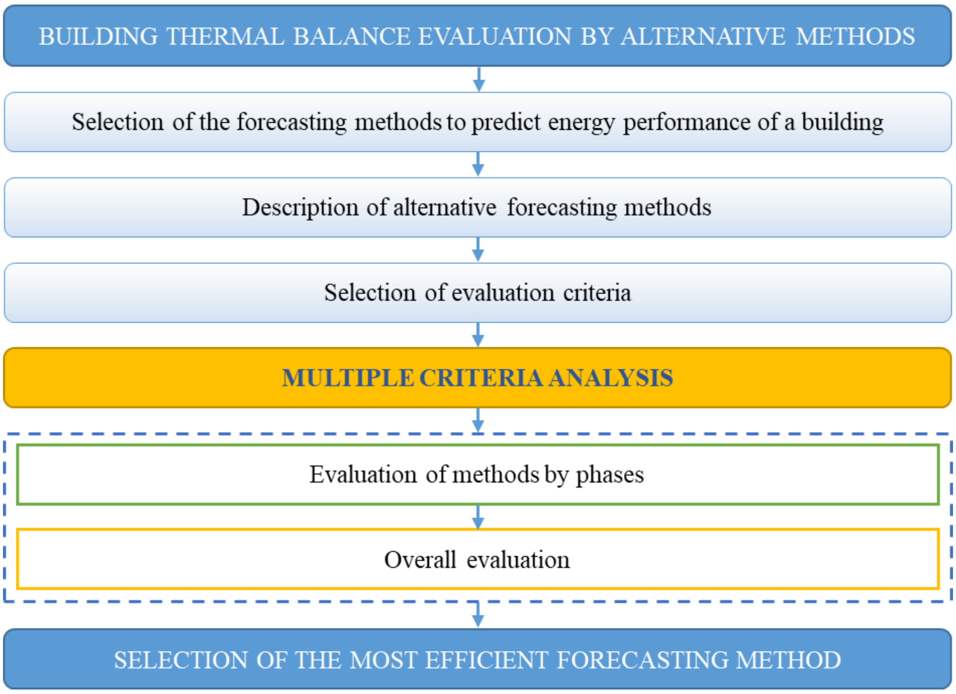

Fig. 2. Main steps procedure.

The selected three alternative methods, belonging in the "black-box" category, were compared; a brief description of MLR, BM and ANN is reported in Section 3.
The procedure to resolve building thermal balance was explored and, after a thorough analysis, four main phases are identified: Pre-processing, Development, Post-processing and Use. As Section 4 indicates, the authors identified several criteria to evaluate each alternative method for each phase based on an analysis of the methods, the pertinent literature and additional consultations with experts. Ten international experts in the field of evaluating building thermal balance and developing forecasting tools conducted a survey to determine the significances and attribute values of the criteria. The COPRAS method was used to determine the priority of the alternative forecasting methods within each phase. The obtained results were used for an overall evaluation of the forecasting methods along with the priority ranking and selection of the most efficient alternative.
The work proposes a methodology for a multi-criteria evaluation of forecasting methods used to estimate the thermal energy demand of a building, analysing alternative forecasting methods within the four phases. Thereby the overall evaluation becomes integrated and it selects the most efficient method in terms of simplicity, user-friendliness and reliability.

3. Alternative methods to resolve the building thermal balance

As it is known, the "black-box" methods permit solving a complex problem easily with respect to the "white-box" methods because they do not require any information about physical phenomena and expert user skills. After the development and validation of the method, all that is required is merely a small amount of data on a few well-known parameters that represent the thermal balance of a building.

3.1. MLR Method

The application of the multiple linear regression allowed the authors to develop a simple model that guarantees a quick evaluation of a building's energy needs [21]. The MLR is the simplest model, which is often used as a forecasting tool, and, at the same time, easy to use even for a non-expert user, and computational costs are low. Moreover the presence of an accurate input analysis guarantees greater speed and simplicity in the data collection phase [32–34].
The basis for this model is the linear regression among the variables under prediction and two or more explanatory variables, as indicated in the following equation (Eq.1) [33,34]:

$$z_i = b_0 + b_1 t_1 + b_2 t_2 + ... + b_p t_p + e, \tag{1}$$

where z_i represents the i^{th} dependent variable; t_i represents the i^{th} explanatory variable; b_0 is the intercept of the relationship; b_i is the i^{th} regression coefficient and e is the error related to the i^{th} observation.
The authors explored the feasibility and reliability of MLR models in several works. In [11], the MLR method was applied on a data set that considered heating energy consumption of non-residential buildings located in seven European countries [16]. All buildings models were developed according to building energy standard requirements of each individual country varying boundary conditions such as different weather conditions. Therefore, the authors determined an equation for each country and thanks a cluster analysis three equations representative three climatic regions were identified.
In a second work [35], the authors applied the same methodology to a set of data referring to buildings located in the Italian peninsula. In this case, the building models are built in accordance to Italian legislative requirements regarding the high energy performance buildings. Also in this case, the authors provided an equation for each climate zone and a unique equation applicable to the entire peninsula, with different degrees of reliability. An extension of this aforementioned work appeared in [10]; here the number of models increased in order to improve the instrument's versatility.

Additionally, the authors highlighted the importance of choosing the climate file relevant to the type of model by means of an MLR analysis.
An improved version of the latest works concerning the Italian case study appeared in a more recent work [21]. The revised model provided an ability to predict the energy needs for both heating and cooling, as well for a complete framework on a building's assessment of sustainability and its energy demands. Furthermore, to streamline the data retrieval phase that is required for the use of the developed MLR tool, an input selection analysis has been performed based on the Pearson coefficient. This way the explanatory variables necessary for an optimal identification of thermal loads were identified.

3.2. BM Method

In [23] the authors employed this model for an innovative approach in developing a flexible and efficient tool, determining some dimensionless parameters through the application of the Buckingham π theorem The Buckingham theorem represents a key theorem of the dimensional analysis since it is able to define the dimensionless parameters representing the phenomenon [36]. These parameters define the relationships between the descriptive variables and the fundamental dimensions. Such a dimensional analysis must guarantee that the relationship between physical quantities remains valid, independent of the magnitudes of the base units of measurement [37].
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. Therefore, this method works well with different applications such as forecasting, planning, control, diagnostics and monitoring in different sectors [36,38,39].
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 (π_0, π_1..., π_{n-1}) obtained by manipulating the original variables. To accomplish that, as explained in [37], first, it is necessary to identify all independent variables (V_1, V_2,…, V_n) that influence the physical quantity of interest V_0, the dependent variable. 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 [36]. The authors applied the BM for predicting the thermal energy demand of buildings by determining nine *ad hoc* dimensionless numbers [23]. The identification of a set of criteria and a critical analysis of the results allowed the authors to determine the dimensionless numbers immediately, without using any software tool, to calculate the heating energy demand with a reliability of over 90%.
Furthermore, the validation of the proposed methodology was done by comparing the heating energy demand calculated by dynamic simulations in TRNSYS [16] and by the dimensionless number.

3.3. ANN Method

The basis for the last examined model is the application of ANNs. They are the most widely used data mining models, guaranteeing one of the highest levels of accuracy with respect to other methods that generally have a low computational cost in the use phase [40]. The characterization 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 [34]. A standard ANN layout involves the many neurons linked together according to a specific network; these neurons could be divided into several layers and different architectures [24]. If a neural network is composed of a single layer of unidirectional connections from the input nodes to output nodes, it is called a perceptron. This configuration is the simplest and it is unable to solve problems inseparable linearly [41].
Generally, the most common ANN divides into three parts: the input layer that collects the inputs, the hidden layer and the output layer and is called multiple layer perceptron (Fig. 3).

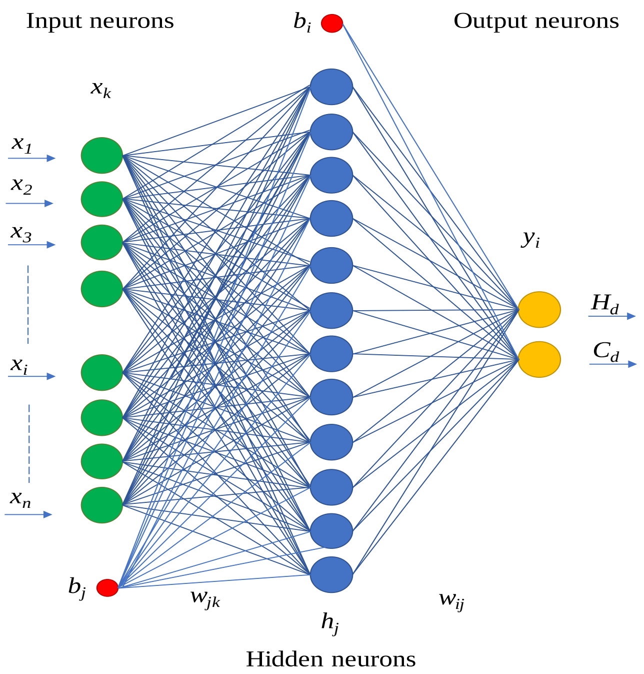

Fig. 3. ANN layout.

The neurons connect to synaptic weights that iteratively update their values in order to modify the signal magnitude that crosses them. Therefore an activation function suitably processes the signal, which has the purpose of scaling, converting and limiting the range of the output signal [22]. The two phases of ANN learning involve training and validation. For the training process, the neural network determines the functions that describe the separation lines between the various categories. The weights are updated directly at each training step according to the characteristics of the data presented to the network, regardless of any hypothesis regarding the statistical distribution of the data or knowledge of the physical laws governing the phenomenon. During the validation phase, the 15% of data extracted from the database before the training phase are used to compare the ANN results with respect to the forecast data [22].

The ANNs, have a high empirical capacity to learn from training patterns, a high elasticity in data interpretation as well as the extrapolation and generalization of the results. Furthermore the presence of distributed memory makes them adaptive as well as able to change independently and gradually in response to the examples received during the learning phase [22].

For these reasons, the ANNs are applied to different sectors for different objectives, from forecasting to control and from classification to decision support. ANNs are the most widely employed algorithms for developing forecasting tools in the building energy prediction sector by virtue of their marked ability to solve complex and non- linear applications [24,42,43]. The authors of the present work investigated the suitability of neural networks to identify a general approach for any context and condition developing a forecasting tool for heating [22] and cooling loads of a building at the European and national levels and then for a comprehensive evaluation of the energy requirements and environmental impacts [26]. The results and the ability to generalize confirm the application of ANNs as an alternative method for resolving the building energy balance and for ensuring the development of reliable decision support tools that can be applied by non-expert users.

4. 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. Its principal objective is to provide a decision maker with tools enabling him to advance the resolution of a decision problem, where several, often conflicting, multiple criteria must be taken into consideration. In the last decades, its role in different application areas has increased significantly as new methods are developed and old are 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 [44]. The MCDM problems can be solved by many available methods; from 2000 have been especially considered, used and compared in literature [45]. Paper [46] presents a panorama of decision making methods and summarizes the most important results. A detailed review of more than 90 papers appears in [47] to analyse the applicability of various methods while, in [48], the authors consider major principles of methods based on quantitative measurements.
The basis for several methods used for energy planning decisions consists of employing weighted averages, priority setting and their combinations. For example, in [49], the authors introduce a comprehensive approach based on data envelopment analysis to provide a ranking of alternatives. Meanwhile, in [50], the MCDM it was used for selecting a renewable energy project according to the Spanish Government's renewable energy plan. The authors of [51] evaluated the multiplicity of energy efficiency and consumption reduction measures with the integration of renewable energy sources for planning and renovation of residential buildings. In the field of building energy performance, it was developed computer-based assessment methodology of integrated buildings based on a multiple-criteria approach in [27].
The selection of an efficient method for forecasting the thermal energy balance of a building is a multidisciplinary problem, which requires a multiple criteria approach. Therefore, the authors of this paper have chosen the COPRAS Method to solve the problem of research.

4.1. COPRAS Method

The COPRAS Method, developed by [45], was used to evaluate three alternative forecasting methods and achieve the aim of the research. Scientific research worldwide has been applying this broadly and comparing it to other methods many times, e.g., in [25,27,28] and many studies affirm that the COPRAS is reliable [52–54]. This method assumes direct and proportional dependence of the efficiency and priority of investigated alternatives on a criteria system. The criteria system is determined *a priori*; 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 consists in 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 (rows) for evaluating the alternatives (columns) to be examined (Eq. 2). 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 of all the scores assigned by the experts for a specific attribute value of an alternative:

$$M=\begin{array}{c} \\ x_1 \\ x_2 \\ \dots \\ x_m \end{array}\begin{array}{c} \begin{array}{cccc} a_1 & a_2 & \dots & a_n \end{array} \\ \left[\begin{pmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \dots & \dots & \dots & \dots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{pmatrix}\right] \end{array}, \; i=\overline{1,m}; \; j=\overline{1,n}, \tag{2}$$

where a_j 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

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. 3. The sum of the significances must equal 1:

$$q_i=\frac{s_i}{\sum_{i=1}^{m} s_i}, \tag{3}$$

where: s_i – sum of estimations (scores) of the i^{th} criterion by the experts.
The concordance coefficient (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, this coefficient is expressed by Eq. 4 [55]:

$$W=\frac{12S}{r^2(m^3-m)-r\sum_{k=1}^{r} T_k}; \; W\in[0,1], \tag{4}$$

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 (Eq. 5) [54]:

$$\chi^2_{\alpha,v}=W\cdot r\cdot(m-1)=\frac{12S}{rm(m+1)-\frac{1}{m-1}\sum_{k=1}^{r} T_k}. \tag{5}$$

If $\chi^2_{\alpha,v}>\chi^2_{tbl}$ then, the concordance coefficient is significant at α level (α = 0.05), where $\upsilon = n - 1$ degree of freedom, and the opinions of the experts are consistent. Otherwise, when $\chi^2_{\alpha,v}<\chi^2_{tbl}$ is obtained, the opinions of experts are not in agreement.

Stage 3. Calculating the weighted, normalized, decision-making matrix M

Now the assessment of each attribute value is in terms of criteria significances and, additionally, dimensionless values obtained (Eq. 6). 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}:

$$x_{ij} = \frac{x_{ij} \cdot q_i}{\sum_{j=1}^{n} x_{ij}}; \quad i = \overline{1,m}; \ j = \overline{1,n}, \tag{6}$$

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 (Eq. 7):

$$q_i = \sum_{j=1}^{n} x_{ij}; \ i = \overline{1,m}; \ j = \overline{1,n}. \tag{7}$$

These dimensionless, weighted, index values x_{ij} represent the components of the matrix M (Eq. 8).

$$M = \begin{array}{c c} & \begin{array}{cccc} a_1 & a_2 & \dots & a_n \end{array} \\ \begin{array}{c} x_1 \\ x_2 \\ \dots \\ x_m \end{array} & \left[\begin{pmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \dots & \dots & \dots & \dots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{pmatrix}\right] \end{array}; \ i = \overline{1,m}; \ j = \overline{1,n}. \tag{8}$$

Stage 4. Calculating the sums of weighted, normalized indexes

For each alternative, the sums that take into account all x_{ij} values for minimizing criteria[1] (S_{-j}) and all x_{ij} values for maximizing criteria[2] (S_{+j}) are calculated. The following equations (Eq. 9) calculate the sums describing the j^{th} alternative:

$$S_{+j} = \sum_{i=1}^{m} x_{+ij}; \qquad S_{-j} = \sum_{i=1}^{m} x_{-ij}; \qquad i = \overline{1,m}; \ j = \overline{1,n}. \tag{9}$$

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.

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 (Eq. 10):

[1] Lower values are preferred.

[2] Higher values are preferred.

$$Q_j = S_{+j} + \frac{S_{-\min} \cdot \sum_{j=1}^{n} S_{-j}}{S_{-j} \cdot \sum_{j=1}^{n} \frac{S_{-\min}}{S_{-j}}}, \; j = \overline{1,n}, \tag{10}$$

where $S_{-\min}$ is the minimum value among the S_{-j} values calculated for each alternative.
Stage 6. Determining the priority order of alternatives
Greater is the Q_j, higher is the efficiency of an alternative.
To visually assess efficiency of the alternative, the utility degree N_j can be calculated [56]. The degree of utility is determined by comparing the assessed alternative with the most efficient one (Eq. 11).

$$N_j = \frac{Q_j}{Q_{\max}} \cdot 100\%, \tag{11}$$

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 forecasting method. The primary results allow evaluating the priority of the alternative forecasting methods within each single phase. To determine the overall priority of the alternatives and to identify the most efficient forecasting method, 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 method

The same as in the case of determining criteria significances, the significance of each phase is calculated as follows (Eq. 12):

$$w_i = \frac{p_i}{\sum_{i=1}^{m} p_i}, \tag{12}$$

where p_i is the sum of the ranks by experts for the i^{th} phase.
The concordance coefficient 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 forecasting methods

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. 13).

$$P=\begin{array}{c} \\ y_1 \\ y_2 \\ \dots \\ y_m \end{array}\begin{array}{c} \begin{array}{cccc} a_1 & a_2 & \dots & a_n \end{array} \\ \left[\begin{pmatrix} y_{11} & y_{12} & \dots & y_{1n} \\ y_{21} & y_{22} & \dots & y_{2n} \\ \dots & \dots & \dots & \dots \\ y_{m1} & y_{m2} & \dots & y_{mn} \end{pmatrix}\right] \end{array}, i=\overline{1,m};\ j=\overline{1,n}, \tag{13}$$

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, normalized, decision-making matrix P

This procedure requires calculating the weighted, normalized, decision-making matrix (Eq. 14):

$$y_{ij}=\frac{y_{ij}\cdot w_i}{\sum_{j=1}^{n} y_{ij}},\ i=\overline{1,m};\ j=\overline{1,n}, \tag{14}$$

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, normalized, indices for the j^{th} alternative from the P matrix (Eq. 15):

$$E_j=\sum_{i=1}^{m} y_{+ij}\ ;\ i=\overline{1,m};\ j=\overline{1,n}. \tag{15}$$

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 resolve any problem characterized by several phases.

4.2. Application of the methodology

As previously explained, the aim of the work is to compare and identify the most efficient alternative method for an evaluation of building thermal energy demand among the three black-box methods previously described. To analyse each method, there is an evaluation of each phase of its application, from data collection for its implementation and to its development, testing and use. Then an MCA was conducted by using the COPRAS Method.
The application of this methodology requires selecting several criteria and assigning significances that explain their importance to evaluate the forecasting methods regarding the building thermal energy demand. As explained in Section 4.1, the basis of the calculation of significances consisted of the careful evaluations by ten international experts in the field of building thermal balance evaluation by means of a questionnaire survey.
The entire evaluation process involved the analysis of four principle phases characterized by different criteria (from Table 2 to Table 5), which are listed as follows:

1. Pre-Processing phase:

    a. Knowledge of the physical phenomenon;
    b. Knowledge of other complementary aspects;
    c. Data collection necessary for the development of the forecasting model;
    d. Data analysis of the collected data to implement a model.
2. Implementation phase:
    e. Model implementation;
    f. Simulation phase to develop the model;
    g. Computational time during the model implementation;
    h. Model calibration.
3. Post-Processing phase:
    i. Data extraction;
    j. Analysis of results;
    k. Accuracy of results.
4. Use phase:
    l. User Skills;
    m. Computational time during the use phase;
    n. Availability of a generalized model;
    o. Sensitivity analysis;
    p. Input data required;
    q. 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 was illustrated in Fig. 4. The authors evaluated the efficiency of three alternative forecasting methods in each phase and selected the most efficient in terms of all assessment criteria.

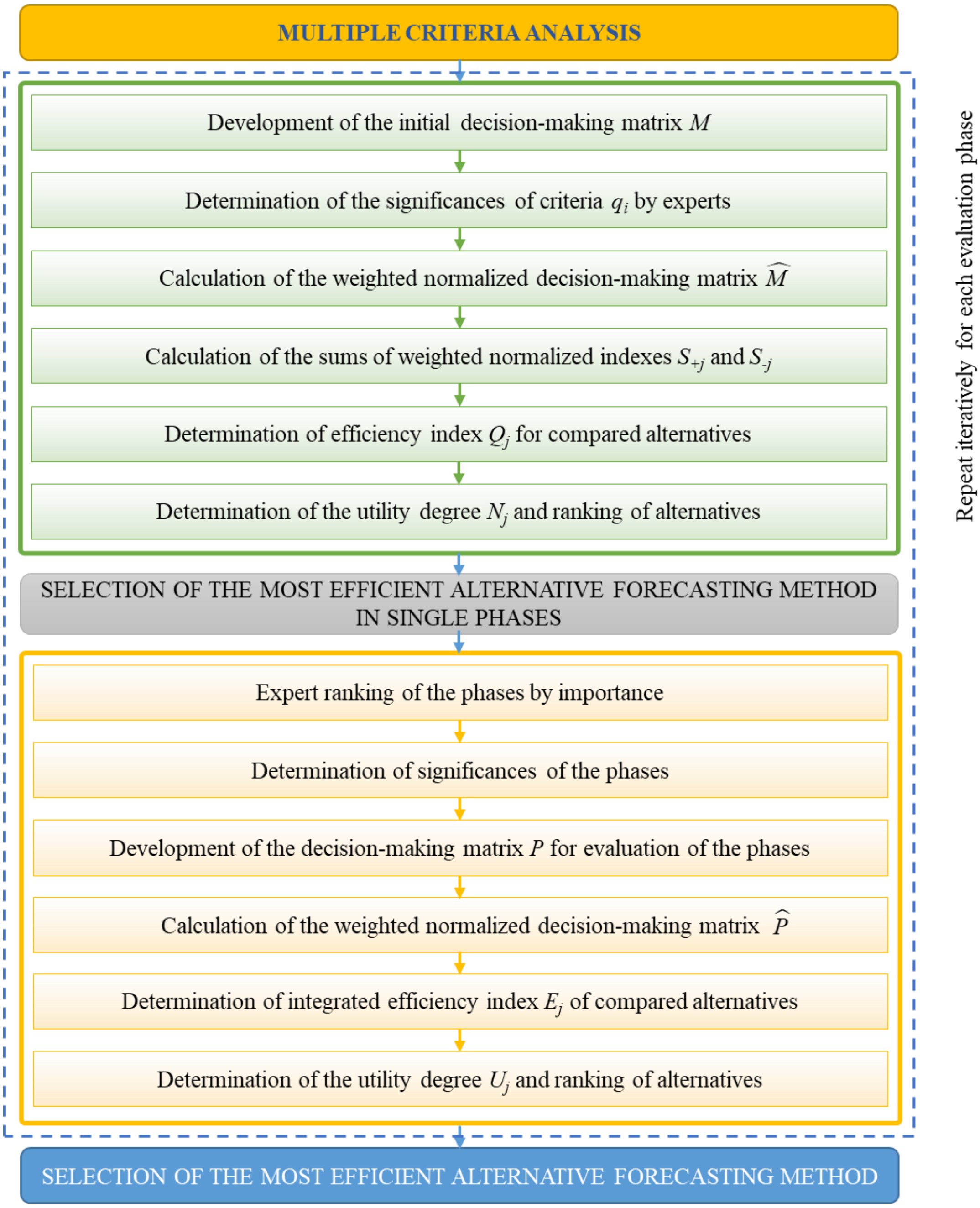

Fig. 4. COPRAS method application

In this case, the generic, decision-making matrix M is composed of 3 columns representing the 3 alternative methods and of several rows representing the evaluation criteria (Stage 1). It was necessary to develop four matrices from M_1 to M_4 , one for each single phase.

$$M_1 = \begin{array}{c} \\ a \\ b \\ c \\ d \end{array} \begin{array}{c} \begin{array}{ccc} MLR & BM & ANN \end{array} \\ \begin{bmatrix} 2.8 & 3.8 & 2.6 \\ 2.8 & 4 & 4.5 \\ 3.2 & 4 & 3.9 \\ 3.7 & 4.1 & 4.5 \end{bmatrix} \end{array}; \quad M_2 = \begin{array}{c} \\ e \\ f \\ g \\ h \end{array} \begin{array}{c} \begin{array}{ccc} MLR & BM & ANN \end{array} \\ \begin{bmatrix} 2.9 & 4 & 4.4 \\ 2.6 & 3.6 & 3.7 \\ 2.8 & 3.9 & 4.2 \\ 3.9 & 4.5 & 4.2 \end{bmatrix} \end{array};$$

$$M_3 = \begin{array}{c} \\ i \\ j \\ k \end{array}\begin{array}{c} \begin{array}{ccc} MLR & BM & ANN \end{array} \\ \begin{bmatrix} 2.5 & 3.7 & 2.7 \\ 2.3 & 3.6 & 3.3 \\ 2.6 & 3.5 & 4.6 \end{bmatrix} \end{array}; M_4 = \begin{array}{c} \\ l \\ m \\ n \\ o \\ p \\ q \end{array}\begin{array}{c} \begin{array}{ccc} MLR & BM & ANN \end{array} \\ \begin{bmatrix} 2.2 & 4.2 & 1.2 \\ 1.9 & 3.8 & 1.1 \\ 3.5 & 3.5 & 4.9 \\ 1 & 1 & 4.3 \\ 1.9 & 3.5 & 3.3 \\ 2.5 & 3 & 4.2 \end{bmatrix} \end{array}.$$

Development of the initial decision-making matrices was based on assessment of the alternative forecasting methods in each energy performance evaluation phase. The team of experts assigned a detailed score based on the indications described in Table 2 to Table 5; each expert assigned a score from 1 to 5. For each matrix, each x_{ij} value was obtained by averaging the scores assigned by all experts.

Table 2
Description of criteria and values for evaluation of methods in Phase 1

Phase	Criterion	Max/Min	Description
1. Pre-Processing	**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 3
Description of criteria and values for evaluation of methods in Phase 2

Phase	Criterion	Max/Min	Description
2. Implementation	**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 4
Description of criteria and values for evaluation of methods in Phase 3

Phase	Criterion	Max/Min	Description

3. Post-processing	**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 5
Description of criteria and values for evaluation of methods in Phase 4

Phase	Criterion	Max/Min	Description
4. Use	**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 generalized 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 4.1), 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 6 with a score from 1 to 5 to each criterion, where 1 is the most insignificant criterion and 5 is the most significant criterion.

Table 6
Scale to evaluate significances of criteria

Score	Importance	Explanation
1	**Very low**	The criterion has a very low significance for evaluating a building thermal energy demand forecasting model.
2	**Low**	The criterion has a low significance for evaluating a building thermal energy demand forecasting model.
3	**Middle**	The criterion has a middle significance for evaluating a building thermal energy demand forecasting model.
4	**High**	The criterion has a high significance for evaluating a building thermal energy demand forecasting model.
5	**Very High**	The criterion has a very high significance for evaluating a building thermal energy demand forecasting model.

The calculated significance q_i of each criterion for each phase appear from Table 7 to Table 10. To clarify the evaluation, each criterion is described; whereas, the last two columns in these tables indicate the calculated sum of all scores assigned by the experts for each criterion and a calculated significance as indicated in Eq. 3, respectively.

Table 7
Criteria Significances in Phase 1

Phase	Criterion	Description	Sum	Significance
1. Pre-Processing	**a.**	Knowledge degree of the building thermal balance from the theoretical and mathematical point of view to apply a method	40	0.27
	b.	Knowledge of software/tool language, standards and laws, mathematical algorithms, design and comfort conditions, etc. to apply a method	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
		Sum	149	1
	$W = 0.29$; $\chi^2 = 8.7$			

Table 8
Criteria Significances in Phase 2

Phase	Criterion	Description	Sum	Significance
2. Implementation	**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
		Sum	157	1
$W = 0.27$; $\chi^2 = 8.1$				

Table 9
Criteria Significances in Phase 3

Phase	Criterion	Description	Sum	Significance
3. Post-processi	**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
		Sum	103	1
$W = 0.48$; $\chi^2 = 9.56$				

Table 10
Criteria Significances in Phase 4

Phase	Criterion	Description	Sum	Significance
4. Use	**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
	Sum	224	1
$W = 0.38$; $\chi^2 = 11.4$			

Calculated concordance coefficients W and their significances χ^2 in each phase revealed 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 4.1), it was possible to develop the weighted, normalized matrices M for each phase. The results are as follows:

$$M_1 = \begin{array}{c} \\ a \\ b \\ c \\ d \end{array} \begin{array}{c} \begin{array}{ccc} MLR & BM & ANN \end{array} \\ \begin{bmatrix} 0.08 & 0.11 & 0.08 \\ 0.05 & 0.08 & 0.09 \\ 0.09 & 0.11 & 0.10 \\ 0.07 & 0.07 & 0.08 \end{bmatrix} \end{array}; \quad M_2 = \begin{array}{c} \\ e \\ f \\ g \\ h \end{array} \begin{array}{c} \begin{array}{ccc} MLR & BM & ANN \end{array} \\ \begin{bmatrix} 0.08 & 0.11 & 0.12 \\ 0.06 & 0.09 & 0.09 \\ 0.06 & 0.08 & 0.09 \\ 0.07 & 0.08 & 0.08 \end{bmatrix} \end{array};$$

$$M_3 = \begin{array}{c} \\ i \\ j \\ k \end{array} \begin{array}{c} \begin{array}{ccc} MLR & BM & ANN \end{array} \\ \begin{bmatrix} 0.09 & 0.13 & 0.10 \\ 0.07 & 0.11 & 0.10 \\ 0.10 & 0.13 & 0.17 \end{bmatrix} \end{array}; \quad M_4 = \begin{array}{c} \\ l \\ m \\ n \\ o \\ p \\ q \end{array} \begin{array}{c} \begin{array}{ccc} MLR & BM & ANN \end{array} \\ \begin{bmatrix} 0.05 & 0.10 & 0.03 \\ 0.05 & 0.09 & 0.03 \\ 0.05 & 0.05 & 0.07 \\ 0.03 & 0.03 & 0.11 \\ 0.03 & 0.06 & 0.06 \\ 0.04 & 0.05 & 0.07 \end{bmatrix} \end{array}.$$

Subsequently the sums of weighted, normalized 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 4.1. The results for each phase appear in Table 11.

Table 11

Sums of weighted normalized indices and 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 methods in each phase was determined (Fig. 5) according to Stage 6 of the COPRAS procedure (Section 4.1). 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 method in terms of the last two phases; instead, the BM is characterized as the intermediate preference.

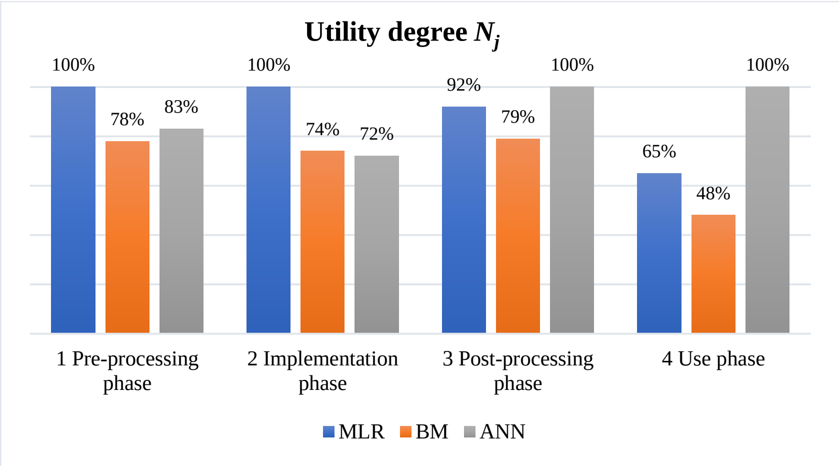

Fig. 5. N_j of the alternative forecasting methods in each phase

To provide a solution that takes into account all the phases included in the evaluation of the thermal energy demand, the authors requested the experts to rank the four phases (Stage 8, Section 4.1) by scoring them from 1 to 4. The assignment is a simple classification (rank) of the phases that the expert determines based on the weight that the single phase has with respect to the entire process and simultaneously taking into account the aim of the tool. The sum of the scores assigned to each phase along with the w_i values calculated according to Eq. 12 (Stage 9) appear in Table 12.

Table 12
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
		1
$W = 0.37$; $\chi^2 = 11.16$		

Matrix P was developed by taking Q_j values of Table 10 for an overall assessment of alternative methods (Stage 10, Section 4.1):

$$P=\begin{array}{c} \\ 1 \\ 2 \\ 3 \\ 4 \end{array}\begin{array}{c} \begin{array}{ccc} MLR & BM & ANN \end{array} \\ \begin{bmatrix} 0.38 & 0.30 & 0.32 \\ 0.41 & 0.30 & 0.29 \\ 0.34 & 0.29 & 0.37 \\ 0.31 & 0.22 & 0.47 \end{bmatrix} \end{array}.$$

Significances of the phases, indicated in Table 12, were used to develop the new, weighted, normalized, decision-making matrix $\hat{P}$ where all components are obtained by applying Eq. 14:

$$\hat{P}=\begin{array}{c} \\ 1 \\ 2 \\ 3 \\ 4 \end{array}\begin{array}{c} \begin{array}{ccc} MLR & BM & ANN \end{array} \\ \begin{bmatrix} 0.06 & 0.04 & 0.05 \\ 0.10 & 0.07 & 0.07 \\ 0.09 & 0.08 & 0.10 \\ 0.10 & 0.08 & 0.16 \end{bmatrix} \end{array}.$$

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 methods considering all phases and distinguishing the most efficient one. The final calculation results appear in Table 13.

Table 13
E_j and U_j degrees of the alternative methods

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 method among the three analysed "black-box" methods used to resolve the thermal balance of a building is the ANN method followed by the MLR and, finally, by the BM.

5. Results and discussion

The MCA applied in this research determined the ranks of the forecasting methods in each energy performance evaluation phase and provided overall ranks. The detailed analysis of the results obtained for each phase (Fig. 2) shows that the MLR method 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 method 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 method follows with a utility degree equal to 92%. At last, there is the BM method 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 characterized 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. 6 displays the utility degree N_j of each model according to each phase.

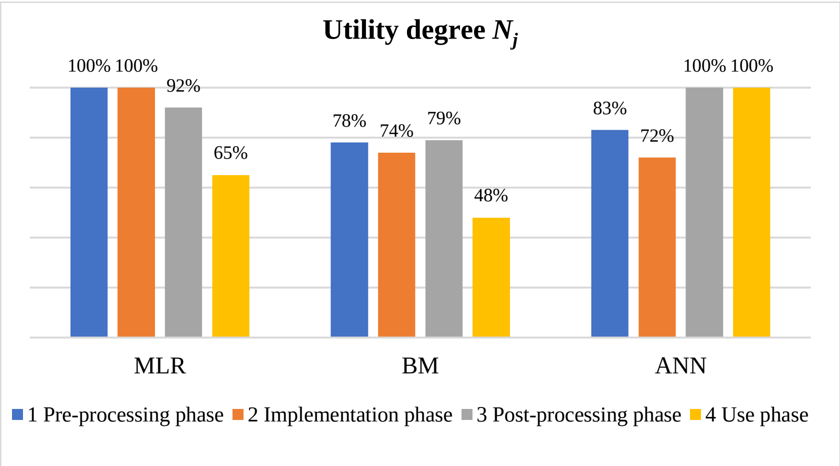

Fig. 6. N_j trends of each phase in each model

Finally, considering the entire energy performance evaluation procedure that takes all four phases, the MCA permitted comparing the performance of the three selected methods and classifying them from the most to the least efficient one. In this case, the utility degree U_3 =100% for the ANN method, U_1 = 93% for the MLR method and U_2= 72% for the BM method (Fig. 7).

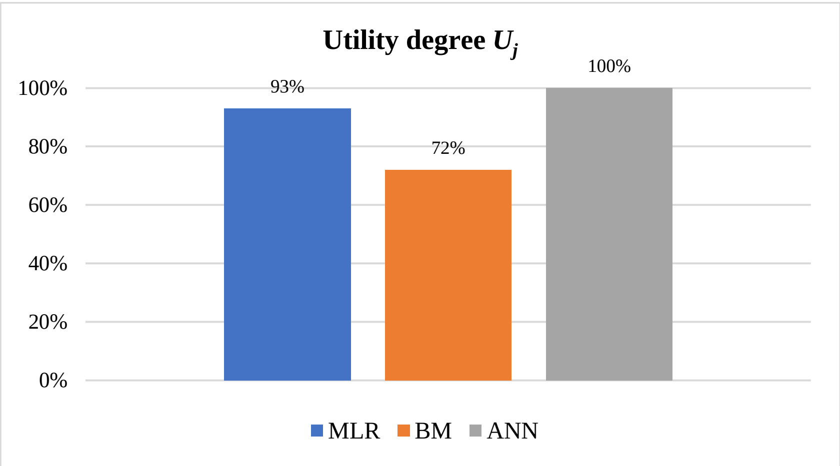

Fig. 7. U_j of each method.

6. Conclusion

The research of alternative and faster solutions to resolve complex problems is one of the major issues addressed by the scientific community. In the field of evaluating the building thermal energy demand, the identification of a simpler, faster and economical method from the computational point of view with highly reliable results and 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. Literature proposes several alternative methods; however, the choice and identification of the most suitable method is still a critical point. Based on these observations, the authors propose a methodology to identify the most efficient alternative method for resolving the energy balance of a building.
The results obtained in previous works provided the basis for the authors to apply for the first time the multi-criteria analysis for comparing three alternative methods belonging to the "black-box" category, the application of this kind of analysis covers many complex decisions.
Direct numerical comparison of the results revealed by each method is not sufficient to identify the most efficient alternative, because the complexity of the model implementation, from the collection of data to the development of the tool, the ease of use and its applicability are not considered. Indeed, each model can be used to solve thermal energy balance of a building, if few parameters, representing the problem, are known. 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. In detail, it was necessary to identify the salient phases of the calculation procedure for the building energy balance and determine the most important criteria. A team of international experts was involved in assessing the significances of criteria and alternative methods. The entire process for the assessment of the building thermal energy demand was divided into the pre-processing, implementation, post-processing and use phases.
The Complex Proportional Evaluation Method by an iterative procedure was applied to determine the priority of the alternative methods in each phase. The use of these results performed an overall multiple criteria assessment of the alternative methods and, finally, identified the most efficient one. The application of this multi-criteria method determined a ranking for the entire development process of the predictive model as well as for each phase separately. Some criteria had 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 multi-criteria analysis of three selected methods revealed as the most efficient the ANN method and the worst performing the Buckingham Method. Although the ANN model is considered as the most efficient one, all three investigated models can be used in the first phase of the energy planning. In other words, the models are three valid tools that can be used by different types of users. The MLR is the simplest model that can be used for the building energy evaluation, when it is necessary to have an overall view with little information, for example, an energy manager can obtain a rough estimate of the energy consumption of a particular building, knowing only two or three fundamental parameters. The dimensionless numbers are suitable for the planning of energy policies at large-scale and for the drafting of guidelines that can help the legislator to identify a reliable and, in any case, simple to use criterion, to propose in laws and standards.
Finally, the ANN model represents the best solution, both in terms of the error indexes and evaluation by MCA. In fact, despite being characterized by a complex implementation phase which involves the presence of an expert user, the development of the model is simple, intuitive, and immediate and has a very high degree of precision in the use phase. This tool allows the evaluation of the thermal energy demand 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 investigating a solution that simultaneously take into account the environmental aspect. All these considerations are derived from the application of MCA approach. For the first time, the procedure compares some predictive models and provides a double evaluation: an overall assessment of the entire process and an assessment of the individual phases. Ten experts were involved for the evaluation of the significance of the criteria, and for the evaluation of each alternative with respect to the single criterion and for the determination of the significance of each evaluation phase.
This methodology is a first application able to represent a replicable procedure for a larger number of alternative methods. It represents a method 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 multi-

criteria analysis, can be used to improve the alternative methods under consideration; these constitute the tasks for future research.

Acknowledgements

This project has received funding from European Regional Development Fund (project No 01.2.2-LMT-K-718-01-0073) under grant agreement with the Research Council of Lithuania (LMTLT).

References

[1] European Parliament and Council, Directive 2010/31/EU on the energy performance of buildings, Off. J. Eur. Union. (2010). https://doi.org/doi:10.3000/17252555.L_2010.153.eng.

[2] Transition to sustainable buildings: Strategies and opportunities to 2050, 2013. https://doi.org/10.1787/9789264202955-en.

[3] N. Aste, F. Leonforte, M. Manfren, M. Mazzon, Thermal inertia and energy efficiency – Parametric simulation assessment on a calibrated case study, Appl. Energy. 145 (2015) 111–123. https://doi.org/10.1016/j.apenergy.2015.01.084.

[4] B.P.I. Europe, Europe's buildings under the microscope, 2011.

[5] I. Sartori, A. Napolitano, K. Voss, Net zero energy buildings: A consistent definition framework, Energy Build. 48 (2012) 220–232.

[6] F. Noris, E. Musall, J. Salom, B. Berggren, S.Ø. Jensen, K. Lindberg, I. Sartori, Implications of weighting factors on technology preference in net zero energy buildings, Energy Build. 82 (2014) 250–262.

[7] A. Straub, Collaboration for Housing Nearly Zero-Energy RENOvation Publishable Report, (2016).

[8] S. Naji, A. Keivani, S. Shamshirband, U.J. Alengaram, M.Z. Jumaat, Z. Mansor, M. Lee, Estimating building energy consumption using extreme learning machine method, Energy. 97 (2016) 506–516. https://doi.org/10.1016/j.energy.2015.11.037.

[9] E.M. Andreas Hermelink, Sven Schimschar, Thomas Boermans, Lorenzo Pagliano, Paolo Zangheri, Roberto Armani, Karsten Voss, Towards nearly zero- energy buildings Definition of common principles under the EPBD, 2013.

[10] A. D'Amico, G. Ciulla, D. Panno, S. Ferrari, Building energy demand assessment through heating degree days: The importance of a climatic dataset, Appl. Energy. 242 (2019) 1285–1306. https://doi.org/10.1016/J.APENERGY.2019.03.167.

[11] G. Ciulla, V. Lo Brano, A. D'Amico, Modelling relationship among energy demand, climate and office building features: A cluster analysis at European level, Appl. Energy. 183 (2016) 1021–1034. https://doi.org/10.1016/j.apenergy.2016.09.046.

[12] S. Ferrari, F. Zagarella, P. Caputo, A. D'Amico, Results of a literature review on methods for estimating buildings energy demand at district level, Energy. 175 (2019) 1130–1137. https://doi.org/10.1016/j.energy.2019.03.172.

[13] A. Foucquier, S. Robert, F. Suard, L. Stéphan, A. Jay, State of the art in building modelling and energy performances prediction: A review, Renew. Sustain. Energy Rev. (2013). https://doi.org/10.1016/j.rser.2013.03.004.

[14] DOE US, M&V guidelines: measurement and verification for performance-based contracts - version 4.0, Fed. Energy Manag. Progr. (2015). https://doi.org/10.1039/c8ew00545a.

[15] EnergyPlus | EnergyPlus, (n.d.). https://energyplus.net/ (accessed March 14, 2019).

[16] S.A. Klein, others, TRNSYS-A Transient System Simulation Tool, Ver 14.2, Sol. Energy Lab. Univ. Wisconsin, MadLson, WI. (1996).

[17] ESP-r, (n.d.). http://www.esru.strath.ac.uk/Programs/ESP-r.htm (accessed March 14, 2019).

[18] T. Atalla, S. Gualdi, A. Lanza, A global degree days database for energy-related applications, Energy. (2018). https://doi.org/10.1016/j.energy.2017.10.134.

[19] K. Gi, F. Sano, A. Hayashi, T. Tomoda, K. Akimoto, A global analysis of residential heating and cooling service demand and cost-effective energy consumption under different climate change scenarios up to 2050, Mitig. Adapt. Strateg. Glob. Chang. (2018). https://doi.org/10.1007/s11027-016-9728-6.

[20] D.B. Crawley, J.W. Hand, M. Kummert, B.T. Griffith, Contrasting the capabilities of building energy performance simulation programs, Build. Environ. 43 (2008) 661–673. https://doi.org/10.1016/J.BUILDENV.2006.10.027.

[21] G. Ciulla, A. D'Amico, Building energy performance forecasting: A multiple linear regression approach, Appl. Energy. 253 (2019) 113500. https://doi.org/10.1016/J.APENERGY.2019.113500.

[22] G. Ciulla, A. D'Amico, V. Lo Brano, M. Traverso, Application of optimized artificial intelligence algorithm to evaluate the heating energy demand of non-residential buildings at European level, Energy. 176 (2019) 380–391. https://doi.org/10.1016/J.ENERGY.2019.03.168.

[23] G. Ciulla, A. D'Amico, V. Lo Brano, Evaluation of building heating loads with dimensional analysis: Application of the Buckingham π theorem, Energy Build. 154 (2017) 479–490. https://doi.org/10.1016/J.ENBUILD.2017.08.043.

[24] K.P. Amber, R. Ahmad, M.W. Aslam, A. Kousar, M. Usman, M.S. Khan, Intelligent techniques for forecasting electricity consumption of buildings, Energy. 157 (2018) 886–893. https://doi.org/10.1016/j.energy.2018.05.155.

[25] A. Kaklauskas, G. Dzemyda, L. Tupenaite, I. Voitau, O. Kurasova, J. Naimaviciene, Y. Rassokha, L. Kanapeckiene, Artificial neural network-based decision support system for development of an energy-efficient built environment, Energies. 11 (2018) 1994.

[26] A. D'Amico, G. Ciulla, M. Traverso, V. Lo Brano, E. Palumbo, Artificial Neural Networks to assess energy and environmental performance of buildings: An Italian case study, J. Clean. Prod. 239 (2019) 117993. https://doi.org/10.1016/J.JCLEPRO.2019.117993.

[27] L. Tupenaite, A. Kaklauskas, I. Voitov, V. Trinkunas, N. Siniak, R. Gudauskas, J. Naimavičiene, L. Kanapeckiene, Multiple criteria assessment of apartment building performance for refurbishment purposes, Int. J. Strateg. Prop. Manag. 22 (2018) 236–251.

[28] T. Nuuter, I. Lill, L. Tupenaite, Comparison of housing market sustainability in European countries based on multiple criteria assessment, Land Use Policy. 42 (2015) 642–651.

[29] A. Kaklauskas, Degree of project utility and investment value assessments, Int. J. Comput. Commun. Control. 11 (2016) 666–683.

[30] A. Kaklauskas, E. Herrera-Viedma, V. Echenique, E.K. Zavadskas, I. Ubarte, A. Mostert, V. Podvezko, A. Binkyte, A. Podviezko, Multiple criteria analysis of environmental sustainability and quality of life in post-Soviet states, Ecol. Indic. 89 (2018) 781–807. https://doi.org/10.1016/j.ecolind.2017.12.070.

[31] A. Kaklauskas, E.K. Zavadskas, A. Radzeviciene, I. Ubarte, A. Podviezko, V. Podvezko, A. Kuzminske, A. Banaitis, A. Binkyte, V. Bucinskas, Quality of city life multiple criteria analysis, Cities. (2018). https://doi.org/10.1016/j.cities.2017.08.002.

[32] Y.T. Chae, R. Horesh, Y. Hwang, Y.M. Lee, Artificial neural network model for forecasting sub-hourly electricity usage in commercial buildings, Energy Build. 111 (2016) 184–194. https://doi.org/10.1016/J.ENBUILD.2015.11.045.

[33] Z. Xuan, Z. Xuehui, L. Liequan, F. Zubing, Y. Junwei, P. Dongmei, Forecasting performance comparison of two hybrid machine learning models for cooling load of a large-scale commercial building, J. Build. Eng. (2019). https://doi.org/10.1016/j.jobe.2018.10.006.

[34] G. Fud, Deep belief network based ensemble approach for cooling load forecasting of air-conditioning system, Energy. (2018). https://doi.org/10.1016/j.energy.2018.01.180.

[35] G. Ciulla, V. Lo Brano, A. D'Amico, Numerical Assessment of Heating Energy Demand for Office Buildings in Italy, in: Energy Procedia, 2016: pp. 224–231. https://doi.org/10.1016/j.egypro.2016.11.029.

[36] L. Russo, M. Sorrentino, P. Polverino, C. Pianese, Application of Buckingham π theorem for scaling-up oriented fast modelling of Proton Exchange Membrane Fuel Cell impedance, J. Power Sources. 353 (2017) 277–286. https://doi.org/10.1016/J.JPOWSOUR.2017.03.116.
[37] A.A. Sonin, The physical basis of dimensional analysis, Dep. Mech. Eng. MIT, Cambridge, MA. (2001) 1–57.
[38] K. Hao Benjamin Toh, E. Wee Chuan Lim, Dimensionless Numbers and Correlations for Characterizing Heat Transfer in a Pulsating Fluidized Bed, Appl. Therm. Eng. (2019) 448–462. https://doi.org/10.1016/J.APPLTHERMALENG.2019.03.039.
[39] F. Salmani, M.R. Mahpeykar, Dimensional analysis for estimating wetness terms of condensing steam using dry flow data, J. Therm. Anal. Calorim. (2019). https://doi.org/10.1007/s10973-019-08108-9.
[40] J. Ma, J.C.P. Cheng, Identifying the influential features on the regional energy use intensity of residential buildings based on Random Forests, Appl. Energy. (2016). https://doi.org/10.1016/j.apenergy.2016.08.096.
[41] M. Beccali, G. Ciulla, V. Lo Brano, A. Galatioto, M. Bonomolo, Artificial neural network decision support tool for assessment of the energy performance and the refurbishment actions for the non-residential building stock in Southern Italy, Energy. (2017). https://doi.org/10.1016/j.energy.2017.05.200.
[42] H.-X. Zhao, F. Magoulès, A review on the prediction of building energy consumption, Renew. Sustain. Energy Rev. 16 (2012) 3586–3592. https://doi.org/10.1016/j.rser.2012.02.049.
[43] C. Fan, F. Xiao, Y. Zhao, A short-term building cooling load prediction method using deep learning algorithms, Appl. Energy. 195 (2017) 222–233. https://doi.org/10.1016/j.apenergy.2017.03.064.
[44] M. Velasquez, P.T. Hester, An analysis of multi-criteria decision making methods, Int. J. Oper. Res. 10 (2013) 56–66.
[45] E.K. Zavadskas, A. Kaklauskas, Multiple criteria evaluation of buildings, Vilnius, Lith. (1996).
[46] E.K. Zavadskas, Z. Turskis, Multiple criteria decision making (MCDM) methods in economics: an overview, Technol. Econ. Dev. Econ. 17 (2011) 397–427.
[47] S.D. Pohekar, M. Ramachandran, Application of multi-criteria decision making to sustainable energy planning-a review, Renew. Sustain. Energy Rev. 8 (2004) 365–381.
[48] L. Ustinovichius, E.K. Zavadkas, V. Podvezko, Application of a quantitative multiple criteria decision making (MCDM-1) approach to the analysis of investments in construction, Control Cybern. 36 (2007) 251.
[49] E. Bernroider, V. Stix, A method using weight restrictions in data envelopment analysis for ranking and validity issues in decision making, Comput. Oper. Res. 34 (2007) 2637–2647. https://doi.org/10.1016/j.cor.2005.10.005.
[50] J.R. San Cristóbal, Multi-criteria decision-making in the selection of a renewable energy project in spain: The Vikor method, Renew. Energy. 36 (2011) 498–502.
[51] D. Campisi, S. Gitto, D. Morea, An evaluation of energy and economic efficiency in residential buildings sector: A multi-criteria analisys on an Italian case study, Int. J. Energy Econ. Policy. 8 (2018) 185–196.
[52] L.E. Wang, H.C. Liu, M.Y. Quan, Evaluating the risk of failure modes with a hybrid MCDM model under interval-valued intuitionistic fuzzy environments, Comput. Ind. Eng. 102 (2016) 175–185. https://doi.org/10.1016/j.cie.2016.11.003.
[53] N. Qiu, Y. Gao, J. Fang, Z. Feng, G. Sun, Q. Li, Crashworthiness analysis and design of multi-cell hexagonal columns under multiple loading cases, Finite Elem. Anal. Des. (2015). https://doi.org/10.1016/j.finel.2015.06.004.
[54] P. Chatterjee, V.M. Athawale, S. Chakraborty, Materials selection using complex proportional assessment and evaluation of mixed data methods, Mater. Des. (2011). https://doi.org/10.1016/j.matdes.2010.07.010.
[55] V. Podvezko, Agreement of expert estimates, Technol. Econ. Dev. Econ. 11 (2005) 101–107.

[56] A. Kaklauskas, Multiple criteria decision support of building life cycle, Vilnius Technika, 1999.