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Applying Artificial Neural Networks to Estimate the Energy Performance of Buildings

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Abstract— **The main objective of this study is to present a more accurate method to estimate the energy performance of buildings. This purpose is meant to evaluate the feasibility and relevance of more complex statistical modeling techniques, such as the artificial neural network. The energy performance of buildings may be estimated by their capacity to ensure a healthy and comfortable environment, with low energy consumption during the whole year. The glazed areas have a decisive role in the building energy performance having in view the complex functions that they play in the system. A parametric study, based on another powerful tool - the design of experiment method, which allows us to emphasize the measure in which the geometric and energetic characteristics of glazed areas influence the energy efficiency, estimated by the yearly energy needs, to ensure a comfortable and healthy environment. An artificial neural network - ANN is a computational model inspired by the biological natural neuron. The complexity of real neurons is highly abstracted by mathematical equation when modeling artificial neuron. This transforms the input data in output data depending on the operator's ability of choosing and connecting more neurons or more layers for obtaining the expected performance. The neuron's capacity of learning and adapting to operator demands makes a useful tool in math modeling and optimization of nonlinear processes. ANN presents a high potential of adaption to mathematical modeling of processes or phenomena of the black box type, generally with a pronounced nonlinear character and which are difficult to describe and model with simple mathematical models. ANN has the ability to solve new problems by applying information learned from past experience, as the human brain does.**

Keywords— **buildings energy, artificial neural networks, design of experiment method**

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I. Introduction

The energetic performance of buildings is a problem of present interest in the context of increasingly serious climatic changes and the continuous raise of the energy price. Adapting buildings to climatic conditions has made researchers look for optimum solutions to increase their comfort and consequently lower the energy consumption.

The building answer to the climatic factors reflects the characteristic parameters evolution of the indoor environment, in the absence of some perturbation sources, including the heating/cooling equipments. The answer quality may be estimated from the point of view of adaptability to the climate, meaning that "some buildings are naturally comfortable, while "some others need important technical equipments to ensure acceptable comfort conditions" [1].

The energetic performance of buildings is strongly influenced by various factors among which we can mention the complex designing process that has to provide continuous adjustment of the buildings to the new climatic conditions. We can also include here factors like the location of the building, the constructive elements, volumetry, orientation, the characteristics of materials as well as the ratio between the opaque and glazed surfaces. The energetic performance of buildings [2, 3] is also diminished by the influence of thermal bridges as well as the correcting solutions to their effect.

As a consequence, in an assessment attempt of buildings adaptation to the climate [4], the yearly energy necessary for a comfortable and healthy indoor environment insurance during the whole year may be used as a criterion. This includes two different components, the energy necessary for heating during the cold season and the energy necessary for cooling, in the hot season.

The glazed areas influence in a sufficiently great measure the adaptation potential, estimated by the yearly energy necessary for heating and for cooling, because of the complex and apparently contradictory functions fulfilled in the system frame. Thus, the natural lighting and the solar energy use by means of green house effect require large glazed areas, while for purposes of energy saving and acoustic insulation, a reduction of glazed areas is necessary.

On the other hand, the glazed areas are an important element for the architectural appearance, which justifies the architects' predilection for highly glazed façades. There are some cases, in which the big dimensions of windows related to the opaque ones impede the efficient use of energy, even though there are used materials with high qualities from this point of view. The excessive use of glass is a building problem that dominates the urban landscape after 1950, a problem that will become more important in the climatic changes context.

This paper presents a modern method of assessing the energetic performance of buildings based on the input of artificial neural networks capable of generating spectacular results even outside the initial study field due to their ability to learn and power of adapting.

II. Artificial Neural Networks

Neural networks are a series of simple mathematical models, created on the architecture of human brain which gives a superior capacity of learning based on numerous connections established among neurons. The artificial neurons networks have strong units of processing which are characterized by an extreme simplicity, but because their whole interaction, the results are complex. In the specialty literature [5] the artificial neuronal networks represent groups of elements that make simple processing, are strong interconnected and pursue to interact with the surrounding medium in the same manner with biologic brains, having the capacity to learn from their mistakes and errors [6].

The Multi-layer perceptrons (MLP) have the neurons arranged in layers, with computation nodes called hidden neurons, whose function is to interfere between the external input and the network output. The hidden layers are enabled to extract higher-order statistics. The MLP (Fig. 1) have more than one hidden layer; however, theoretical works have shown that a single hidden layer is sufficient for an ANN to approximate any complex nonlinear function. The most frequent structure for neural networks in investigations specific to engineering is the Multi Layers Perceptron (MLP) type [5].

A back propagation algorithm can be used to train these multilayer feed-forward networks with differentiable transfer functions to perform function approximation, pattern association, and pattern classification. The training of ANNs by back propagation involves three stages: (i) the feed-forward of the input training pattern, (ii) the calculation and back propagation of the associated error and (iii) the adjustment of the weights. This process can be used with a number of different optimization strategies [7, 8].

Once the network is trained, it can be tested on a different set of data than that used for training. It is a good approach to divide the given input/output data into two parts: one part (about 70%) is used for training, whereas the other part, usually smaller, is used for testing the neural network model. The testing data set is reserved to validate the trained network.

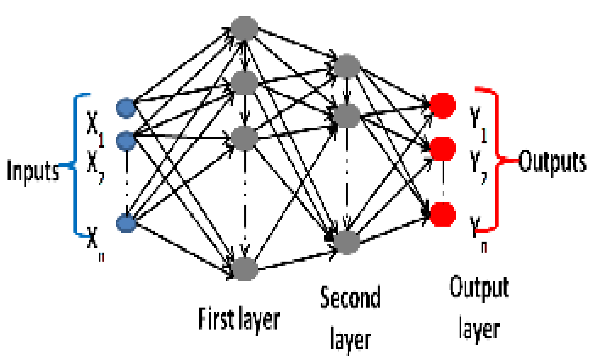

Figure 1. Multi Layers Perceptron modelling

The training and testing of the networks were performed by means of the Matlab software using the Conjugate Gradient or Levenberg Marquardt algorithm. In the same manner as methods quasi-Newton, the algorithm Levenberg-Marquardt was designed for attaining a training speed of second order, without the computation of Hessian matrix being necessary.

In this study, the performances of the ANN were compared with respect to: mean squared error (MSE), mean absolute error (MAE), linear correlation coefficient (r). These performance measures are defined in the following equations (1):

$$MSE = \sum_{i=0}^{N} \frac{(d_i - y_i)^2}{N}$$

$$MAE = \frac{\sum_{i=0}^{N} |d_i - y_i|}{N}$$

$$r = \frac{\dfrac{\sum_i (x_i - \bar{x})(d_i - \bar{d})}{N}}{\sqrt{\dfrac{\sum_i (d_i - \bar{d})^2}{N}}\sqrt{\dfrac{\sum_i (x_i - \bar{x})^2}{N}}} \qquad (1)$$

where: N is the total of training or testing exemplars, yi is network output for exemplar i, di is desired output for exemplar i, xi is network output, is average network output and is average desired output.

III. Case study resultats and discussions

A. *Building characteristics considered in this study*

The case study has been made for a single family dwelling with a spatial configuration and constructive solving according to the saving energy requirements.

Geometrical characteristics of the studied building:

- length of Northern and Southern façade	18,4 m
- height (without roof)	18,6 m
- number of floors:	2
- Ground area	342,2 m^2
- Useful area	547,6 m^2
- Volume total	1574,3m

Windows area

North	14,5 m^2	South	31,7 m^2
East	32,2 m^2	West	40,6 m^2

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The main characteristics that determine the yearly energy consumption for ensuring an indoor environment quality are the following:

- surface - volume ratio 0.7 1/m
- U value of the walls 0,2W/m ^{2}K
- U value of the roof 0.15 W/m ^{2}K
- U value lower floor 0.25 W/m ^{2}K

The microclimate parameters are:

- natural ventilation rate 0.6h^{-1}
- indoor set temperature 20°C
- overheating starts at an indoor temperature higher than 26.9°C.

B. *Parametric studies with design of experiment method*

In temperate climate zones, the yearly necessary energy for ensuring an indoor comfort has two components that result from:

- space heating necessary during the cold period of the year;
- space cooling necessary during the hot period of the year.

It was considered necessary to work with the two components of the required yearly energy, because there are cases in which they do not get the same importance. In general, it is taken into account that during the summer season, the comfort will be naturally ensured, the air conditioning systems being a noise source and, in some cases, a source of lack of comfort.

The parameters through which these components may be expressed are the yearly specific energy necessary for heating, q_h (W/m^2) and the yearly specific energy necessary for cooling the spaces, q_c (W/m^2).

$$q = q_h + q_c \quad (2)$$

The parameters values depend, in different measures, on the following factors:

- glazed areas;
- glazed areas orientation, respectively the solar radiation intensity;
- thermal conductance of the glazed areas, U-value;
- global coefficient of solar energy transmission, or total solar energy transmittance, g- value.

There were not taken into account the factors that may be influenced by the inhabitants' behavior, such as: shadow devices (curtains, window blinds, shutters) and the vegetation around the building.

To make the results of this study easier, smaller and more efficient, a parametric analysis based on design of experiments method [9] by a factorial plan with two levels was made.

Design of experiments (DOE) is a systematic, rigorous approach to engineering problem-solving that applies principles and techniques at the data collection to determine simultaneously the individual and interactive effects of many factors that could affect the output results in any design.

The objective of design of experiment - DOE is the selection of the point where the response should be evaluated. In a traditional DOE, screening experiments are performed in the early stages of the process, when it is likely that many of the design variables initially considered have little or no effect on the response. The purpose is to identify the design variables that have large effect for further investigation. To construct an approximate model that can capture interactions between N design variables, a full factorial approach [9, 10] may be necessary to investigate all possible combinations. A factorial experiment is an experimental strategy in which design variables are varied together, instead one at a time. If the number of design variables becomes large, a fractional of a full factorial design can be used at the cost of estimating only a few combinations between variables. This is called fractional factorial design and is usually used for screening important design variables.

Out of the number of factors identified by their simplified notation (X_1, X_2, X_3, X_4, X_5 and X_6), the following ones were considered to be most important and necessary to control (Table 1).

•Window area (North) - X_1 (% fraction of wall),

•Window area (South) – X_2 (% fraction of wall),

•Window area (East) – X_3 (% fraction of wall),

•Window area (West) – X_4 (% fraction of wall),

• Thermal conductance of window (U-value) – X_5 (W/m^{2}K),

•global coefficient of solar energy transmission (g-value) – X_6 (-).

The responses analyzed in the study can be identified by their coded notation $Y_1 = q_h$ and $Y_2 = q_c$. These values were estimated by means of numerical simulation (Table 2) by the help of CASAnova 3.3 software [11].

The input variables, chosen range for the study and their coded value, are given in Table 1.

TABLE I. RANGE OF VARIABLES AND THEIR CODED FORM

Sample	Variables	Lower limit		Upper limit	
		Coded value	*Real value*	*Coded value*	*Real value*
1	X_1	-1	9	1	18
2	X_2	-1	19	1	38
3	X_3	-1	19	1	38

4	X_4	-1	24	1	48
5	X_5	-1	1	1	6
6	X_6	-1	0.5	1	1

TABLE II. TWO-LEVEL FULL FACTORIAL DESIGN OF EXPERIMENTS

Run	Variables								ANN	ANN	Run	Variables								ANN	ANN
	X_1	X_2	X_3	X_4	X_5	X_6	Y_1	Y_2	Y_1	Y_2		X_1	X_2	X_3	X_4	X_5	X_6	Y_1	Y_2	Y_1	Y_2
1	-1	-1	-1	-1	-1	-1	63.9	2.4	63.5	2.1	33	-1	-1	-1	-1	-1	1	53	10.3	53.0	10.3
2	1	-1	-1	-1	-1	-1	65.5	2.7	65.2	2.5	34	1	-1	-1	-1	-1	1	54	11.5	54.0	11.5
3	-1	1	-1	-1	-1	-1	65	3.4	64.7	3.5	35	-1	1	-1	-1	-1	1	51.2	14.7	51.2	14.8
4	1	1	-1	-1	-1	-1	66.6	3.7	66.5	3.8	36	1	1	-1	-1	-1	1	52.2	16.1	52.3	16.1
5	-1	-1	1	-1	-1	-1	66	4.1	65.9	4.1	37	-1	-1	1	-1	-1	1	53.2	17.2	53.2	17.2
6	1	-1	1	-1	-1	-1	67.7	4.5	67.7	4.5	38	1	-1	1	-1	-1	1	54.2	18.5	54.2	18.5
7	-1	1	1	-1	-1	-1	67.2	5.5	67.3	5.5	39	-1	1	1	-1	-1	1	51.7	22.2	51.7	22.3
8	1	1	1	-1	-1	-1	68.9	5.9	69.1	5.9	40	1	1	1	-1	-1	1	52.8	23.6	52.9	23.6
9	-1	-1	-1	1	-1	-1	67.6	3.8	67.7	3.8	41	-1	-1	-1	1	-1	1	54.8	16.1	54.8	16.1
10	1	-1	-1	1	-1	-1	69.2	4.2	69.3	4.2	42	1	-1	-1	1	-1	1	55.8	17.5	55.8	17.4
11	-1	1	-1	1	-1	-1	68.8	5.2	68.8	5.1	43	-1	1	-1	1	-1	1	53.3	21	53.2	21.1
12	1	1	-1	1	-1	-1	70.5	5.6	70.5	5.4	44	1	1	-1	1	-1	1	54.4	22.4	54.4	22.5
13	-1	-1	1	1	-1	-1	69.9	6.1	70.1	6.1	45	-1	-1	1	1	-1	1	55.2	23.5	55.0	23.7
14	1	-1	1	1	-1	-1	71.5	6.5	71.7	6.6	46	1	-1	1	1	-1	1	56.3	24.9	56.1	25.1
15	-1	1	1	1	-1	-1	71.2	7.6	71.2	7.8	47	-1	1	1	1	-1	1	53.9	29	53.9	28.8
16	1	1	1	1	-1	-1	72.9	8	72.8	8.3	48	1	1	1	1	-1	1	55.1	30.4	55.1	30.0
17	-1	-1	-1	-1	1	-1	72.4	2.2	72.5	2.1	49	-1	-1	-1	-1	1	1	61.2	9.2	61.3	9.3
18	1	-1	-1	-1	1	-1	75.2	2.4	75.2	2.5	50	1	-1	-1	-1	1	1	63.2	10.3	63.2	10.4
19	-1	1	-1	-1	1	-1	75.8	3	75.6	3.1	51	-1	1	-1	-1	1	1	61.3	13.1	61.2	13.1
20	1	1	-1	-1	1	-1	78.5	3.3	78.5	3.3	52	1	1	-1	-1	1	1	63.3	14.2	63.4	14.2
21	-1	-1	1	-1	1	-1	76.8	3.5	76.9	3.5	53	-1	-1	1	-1	1	1	63.2	15.5	63.2	15.2
22	1	-1	1	-1	1	-1	79.5	3.8	79.6	3.8	54	1	-1	1	-1	1	1	65.3	16.6	65.2	16.5
23	-1	1	1	-1	1	-1	80.2	4.6	80.3	4.5	55	-1	1	1	-1	1	1	63.6	19.8	63.6	19.8
24	1	1	1	-1	1	-1	83	4.9	83.1	4.8	56	1	1	1	-1	1	1	65.7	21	65.9	21.0
25	-1	-1	-1	1	1	-1	79	3.3	79.4	3.4	57	-1	-1	-1	1	1	1	65.5	14.5	65.5	14.3
26	1	-1	-1	1	1	-1	81.8	3.6	81.9	3.7	58	1	-1	-1	1	1	1	67.5	15.6	67.5	15.5
27	-1	1	-1	1	1	-1	82.4	4.3	82.5	4.3	59	-1	1	-1	1	1	1	65.9	18.7	65.9	18.8
28	1	1	-1	1	1	-1	85.2	4.6	85.1	4.5	60	1	1	-1	1	1	1	67.9	19.9	68.1	20.0
29	-1	-1	1	1	1	-1	83.5	5.1	83.8	5.0	61	-1	-1	1	1	1	1	67.8	21.1	67.7	21.2
30	1	-1	1	1	1	-1	86.2	5.4	86.2	5.3	62	1	-1	1	1	1	1	69.9	22.3	69.6	22.5
31	-1	1	1	1	1	-1	86.9	6.3	86.9	6.2	63	-1	1	1	1	1	1	68.4	25.7	68.5	25.9
32	1	1	1	1	1	-1	89.7	6.6	89.2	6.5	64	1	1	1	1	1	1	70.5	27	70.6	27.2

In the present study, ANN network was trained using 80% data sets, they were then tested using 20% test data sets for verification of result. For neural modeling the following parameters have been used: the ANN is trained using the back propagation algorithm and the Conjugate Gradient method, maximum epochs of 10,000 and 0.001 learning rate. For the studied functions, the obtained ANN model configuration (Fig. 1) is as follows:

MLP 6:10:2 – 6 neurons in the input layer represent the input variables (such as X_1, X_2, X_3, X_4, X_5, X_6), 2 output layers containing a single neuron for each output (for example, Y_1 and Y_2) and 10 neurons in the hidden layer.

In the training phase, the statistical parameters: linear correlation coefficient (r), mean squared error (MSE) and mean absolute error (MAE - Table 3) indicate that the neural models describe the studied system well. Figure 1 shows the graphical illustration for the ANN architecture.

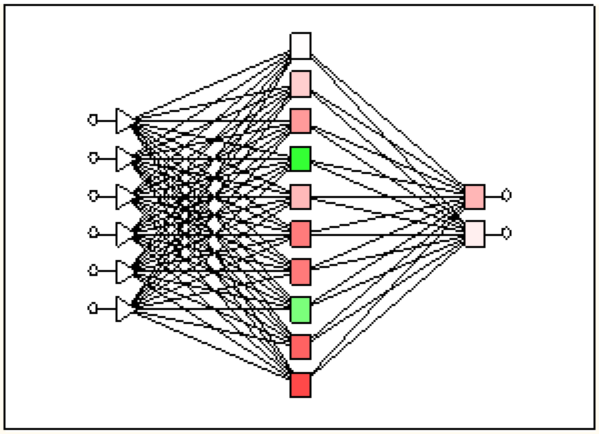

Figure 1. ANN architecture of energy performance of buildings

For the two results which were studied, the neural network allows to predict them with a very high precision - r = 0.99 for Y_1 and r = 0.99 for Y_2 (Table 3) in the stage of training.

TABLE III. TRAINING PERFORMANCES

	Y_1	Y_2
MSE	0.01529	0.02283
MAE	0.09546	0.11156
r	0.99	0.99

The residual errors vary between a minimum of 0.0005 and a maximum of 0.38 for Y_1 and respectively a minimum of 0.006 and a maximum of 0.45 for Y_2, which shows a very accurate assessment done using artificial neural networks. With the help of this network we can also get values of the desired answer outside the study field with multiple configurations of the input variables.

IV. Conclusions

In this paper we presented an up-to-date method of estimating the energy performance of buildings. Thus, artificial neural networks were used, being a powerful tool of data processing based on a process of learning, training and testing, capable of predicting the results of complex systems with increasingly difficult to determine adjustment parameters. It is actually a method that helps us describe the behavior of systems of the black box type in which a process or phenomenon is influenced by a series of variable parameters which are or are not known and can or cannot be controlled.

This study actually aimed at estimating the energy performance of buildings through the two energies analyzed (the yearly specific energy necessary for heating, q_h (W/m^2) and the yearly specific energy necessary for cooling the spaces, q_c (W/m^2).) which were influenced by 6variables parameters among which we can mention:

- glazed surfaces facing the four cardinal directions.,
- thermal conductance of window
- global coefficient of solar energy transmission.

Moreover, the study parametrization was made possible by the use of the experimental planes method that made the study easier for us due to the judicious and efficient way of experimental design and organization.

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