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FORECASTING ENERGY CONSUMPTION IN RESIDENTIAL HOUSE DURING HEATING PERIOD USING FEEDFORWARD NEURAL NETWORKS

Abstract: *The objective of this study is to develop feedforward neural network (FNN) model to predict the energy consumption during heating period in small residential building. The multi layer perceptron neural network (MLP) with Levenberg–Marquardt learning was constructed. A database was generated using simulation in EnergyPlus software. The input variables analyzed in this paper are: temperature of the radiator hot water, thermostat temperature of room, and ventilation air change rate. The house is heated by hot water boiler with natural gas as fuel. The FNN predicted values are in accordance with the values obtained by the simulation of total energy consumption in building.*
Keywords: *Feedforward Neural Network, Energy Consumption, EnergyPlus, Building Heating*

1. INTRODUCTION

Residential energy consumption is an important component of the national energy consumption in most of the developed countries.

Several studies have been conducted on the application of artificial intelligence techniques to forecast short-term consumption such as hourly or daily load and to predict medium and long-term consumption. Many early investigates demonstrated the superior capability of neural networks in forecasting building energy consumption over conventional methods.

The three-layer neural network model was developed in order to estimate hourly heating energy consumption of a model house designed in [1]. The input variables of NN model are month, day of the month, hour of the day, and energy consumption of the previous hour, output value is hourly energy consumption. Artificial neural network (ANN) model is trained and tested with heating energy consumption values which were calculated by degree-hour method utilizing hourly outside temperature values. The respective root mean- squared error, absolute fraction, and mean absolute percentage error values for training are 1.2575, 0.9907, and 0.2091; however for test phase, these values are 1.2125, 0.9880, and 0.2081 respectively.

An artificial neural network model to predict the energy consumption of a passive solar building is proposed in [2]. The recurrent network with dampened feedback with 5 neurons in the input layer, 46 neurons in the hidden layers and 1 output neuron is used. The input parameters are a set of easily measurable values of season, insulation, masonry thickness, function (characterising whether the heat transfer coefficient was constant or variable), and time of day. The output is a single value of the simulated energy consumption of the building. The modelled data was evaluated by using a dynamic thermal building model constructed on the basis of finite volumes and time marching. The coefficient of multiple determination obtained for the validation data set is 0.9991.

In [3] the backpropagation neural network is used for the prediction of the heating energy requirements of different building samples. The inputs of the network are considered as building transparency ratio, orientation and insulation thickness and the output is building heating energy needs. A computer program written in FORTRAN was used for the calculations of energy consumption of buildings by using finite difference approach.

Tso and Yau [4] compared the accuracy in forecasting electricity energy consumption in Hong Kong among three different approaches: the traditional regression analysis, decision trees, and neural networks. The output variable was the total weekly electricity energy consumption.

Sözen [5] employed the different neural network models to estimate the energy dependency based on basic energy indicators and sectoral energy consumption.

Karatasou et al. [6] used the feedforward neural networks for modeling energy consumption in buildings and predicting hourly load profiles. The first model to predict the whole building electric power consumption used only independent variables as inputs (temperature, solar flux, humidity, wind speed, session flag, sine and cosine of the hour of the day, sin and cosine of the day of the week, sin and cosine of the day of the year). In the second model the delays of the signal value have been added.

The multilayer perceptron neural network with two hidden layer has been used for the long-term prediction of Greek energy consumption in [7]. The input variables of the neural network are yearly ambient temperature, installed power capacity, yearly per resident electricity consumption, gross domestic product and output variable is final energy consumption. The neural network model is compared with the linear regression model and support vector machine model.

González and Zamarreño [8] are presented method for short-term electric load forecasting in buildings with high precision, based on a feedback neural network trained by means of a hybrid algorithm. The predictor uses current and forecasted values of temperature, the current load and the hour and the day as inputs

In [9] it is presented the multi-layer perceptron neural network for short-term prediction of total electrical consumption in buildings with several independent processes. Consumption forecasts are obtained from the prediction of each end-use of the total consumption. Temperatures (maximum temperature, minimum temperature, average temperature and the average temperature of the day before) are considered as input variables of the multi-layer perceptron.

Neto and Fiorelli [10] have made a comparison between a simple model based on the neural network and a model that is based on physical principles (EnergyPlus) as forecasting tool for the building energy consumption. Results showed that the ANN model provides a slight better prediction for the energy consumption than the Energy Plus. Created models for energy consumption are based on different input variables. The input variables of the first neural network were daily maximum and minimum external dry-bulb temperatures. The temperature, relative humidity and solar radiation are taken as inputs of the second neural network model. The output was the corresponding daily total consumption.

The objective of this study is to

develop and analyze MLP model to predict the energy consumption during a space heating period in small residential building. The inputs of the network for training and testing are the temperature of the radiator hot water, room temperature and ventilation air change rate and the output is building heating energy consumption.

2. BUILDING SIMULATION

The analyzed building a residential family house. The building is designed for one family and has housing area of 190.08 m^2. The envelope of the building is made by using a porous brick of 190mm, a thermal insulating layer of 50mm and a lime mortar of 20mm. Its U-value is 0,57W/(m2K). The windows are double glazed with U-value at 2.72 W/(m2K). The overall ratio of glass to the exterior walls is 7.32%, where the total area of exterior walls is 264.35m^2 and of windows 19.36m2. Amounts of heat load from electrical appliances, lighting and the presence of people is given in Table 1. The schedules of use of electrical appliances, lighting and the presence of people are taken empirically.

Table 1- Internal loads

IL-R	**LR**	**BR_1**	**BR_2**	**HW**	**T**	**SR**
Max **NP**	4	2	2	2	1	2
L [W]	120	75	75	60	100	120
EE [W]	800	400	400	0	1000	800

IL-R-Internal loads-rooms, **NP**- number of people, **L**-Lights **EE**-Electric equipment **BR**-bedroom, **LR**-living room, **HW**-hallway, **T**-bathroom, **SR**- study room

The analyzed building is located in Kragujevac, Serbia. Elevation of Kragujevac is 209m, latitude is 44^o1N and longitude 20^o55E. The city has a continental climate temperate with different seasons (summer, autumn, winter and spring). The main weather parameters are presented in Table 2.

Table 2- Main weather parameters

Parameters	**Units**	**Values**
Minimum Dry Bulb Temperature	^{0}C	-11.10
Wind Speed	m/s	7.80
Wind Direction	^{o}	270
Average run period temperature	^{0}C	2.71
Solar Heat Gain Coefficient		0.764

In this investigation, the program EnergyPlus 6.0 is used, which allows the simulation of thermal behavior of buildings during the analyzed period. This program is a very useful tool to investigate the behavior of the net-zero energy and green buildings. This software allows using schedule input of the parameters that affect on the thermal behavior of buildings, such as lighting, electrical equipment, the presence of people in the house, etc. This software also takes into account external influences to buildings such as solar radiation, shading, infiltration, wind direction, etc. The mathematical model applied to the heating system used in this study already exists within EnergyPlus [11].

The heating system in the house is radiator heating with central preparation of hot water. To prepare hot water, the boiler of conventional no condensing type uses natural gas as fuel. In each room, a radiator is placed below the window. The radiator releases larger part of heat by convection, while smaller part by radiation. To simplify the simulation in EnergyPlus, the radiators are modeled to release heat only by convection.

3. THE MULTI-LAYER PERCEPTRON NEURAL NETWORK

In this paper two-layer perceptron neural network shown in Fig. 1 with hyperbolic tangent neurons in the hidden layer and linear neuron in the output layer is used to approximate the energy consumption - y. The neural network has three inputs: temperature of the radiator hot water - x_1, room thermostat temperature- x_2 and ventilation air change rate- x_3, and one output: energy consumption- y.

nonlinear function f_1. The output y at a linear output node can be calculated as:

$$y = \sum_{i=1}^{z} \omega_{1,i(2)} \frac{1 - e^{-\left(\sum_{j=1}^{3} x_j \omega_{i,j(1)} + b_{i(1)}\right)}}{1 + e^{-\left(\sum_{j=1}^{3} x_j \omega_{i,j(1)} + b_{i(1)}\right)}} + b_{1(2)} \qquad (1)$$

where z is the number of hidden neurons, $\omega_{i.j(1)}$ is the first layer weight between the input j and the *i*-th hidden neuron, $\omega_{1,i(2)}$ is the second layer weight between the *i*-th hidden neuron and output neuron, $b_{i(1)}$ is a biased weight for the *i*-th hidden neuron and $b_{1(2)}$ is a biased weight for the output neuron.

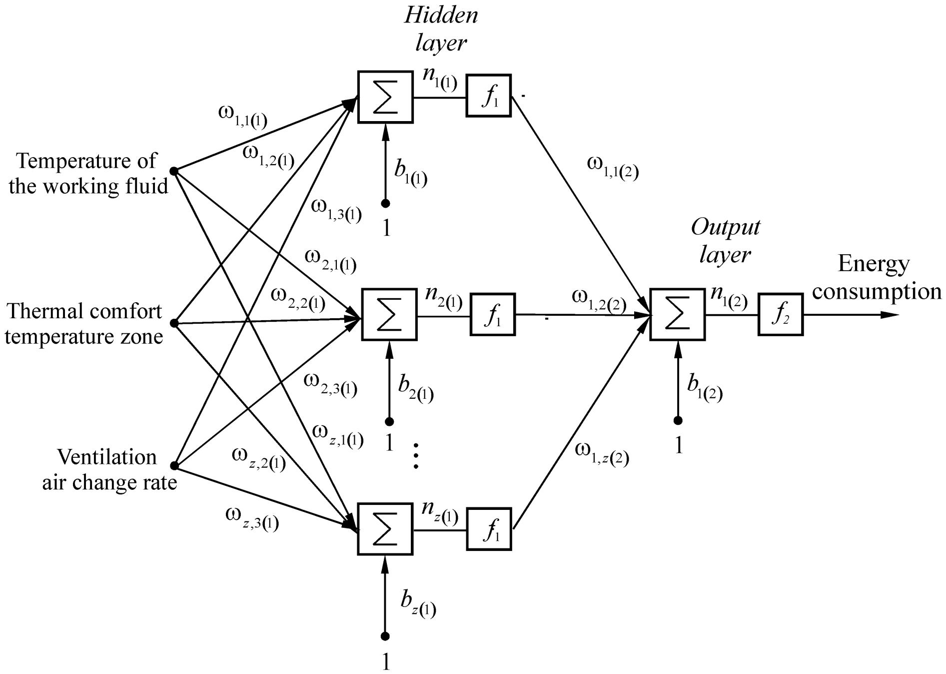

Fig.1. The two-layer perceptron neural network.

The inputs x_1, x_2, x_3 are multiplied by weights $\omega_{i,j(1)}$ and summed at each hidden neuron i. Then the summed signal $n_{i(1)} = \sum_{j=1}^{3} \omega_{i,j(1)} x_j + b_{i(1)}$ at a node activates a

The most popular training algorithm to update the weights and biases of a neural network is the standard backpropagation learning algorithm. The basic algorithm is a gradient descent method in which the network weights and biases are moved along the negative performance function. It has the problems of local minima and slow convergence.

There are many variations of the backpropagation algorithm. In this paper it is used Levenberg–Marquardt backpropagation [12].

4. SIMULATION RESULTS

4.1 EnergyPlus results

To simulate the energy behavior of the object is used EnergyPlus software, which allows the user to apply geometry and materials of building as well as all internal loads and HVAC devices. In the analyzed object is a built-in radiator heating system with non-condensing boiler on natural gas.

For monitoring energy consumption of analyzed building are used the following parameters: inlet water temperature of radiator, air change rate at natural ventilation, mean air temperature of rooms. The input parameters were changed in the following intervals: inlet water temperature of radiator (40 to 80, step interval is 5), mean air temperature of room (11 to 22, step interval is 1) and air change rate at natural ventilation (2 to 5, step interval is 1).

By varying these parameters was obtained database containing 253 results for energy consumption of analyzed building. As a result of simulation of this system is the value of the necessary consumption of gas for heating E_{ng}. ANN uses these results for the prediction energy consumption at different values of input parameters.

4.2 MLP neural network model

In this study, the MLP neural network is used to predict the energy consumption. The MATLAB Neural Network Toolbox is applied for the implementation of the neural network. Data were generated using simulation in EnergyPlus software for the *temperature of the radiator hot water* = $[40\,°C - 80\,°C]$, *room thermostat temperature*= $[18\,°C - 22\,°C]$, *ventilation air change rate*= [2 5].

The data (253) were divided into training and test subsets. In the training process of the MLP, 214 samples were used. The ANN model was tested using 39 selected data. The Pearson correlation coefficient, the mean absolute error and the mean square error are used to evaluate the closeness of fit of network architecture.

Different FNN models were constructed and tested in order to determine the optimum number of neurons in the hidden layer and transfer functions. The two-layer network with a log-sigmoid transfer function at the hidden layer and a linear transfer function at the output layer was used. The optimal network size was the one which resulted in a maximum correlation coefficient for the training and test sets, Table 3. Based on Table 3, it was concluded that the optimal number of hidden neurons is 11. The performance parameters of the artificial neural network models for are given in Table 4.

Table 3 - Correlation coefficient for the training, validation and test sets

ANN-structure	3-8-1	3-11-1	3-14-1
Training	1	1	1
Test	0.9995	0.9999	0.9998

Table 4 - Performance parameters of the artificial neural network models for the energy consumption

	Data set	MAE	MSE
MLP-struc. 3-11-1	Training	$2.9451 \cdot 10^{7}$	$1.4016 \cdot 10^{15}$
	Test	$1.6423 \cdot 10^{8}$	$6.44 \cdot 10^{16}$
	Training + Test	$5.0227 \cdot 10^{7}$	$1.1113 \cdot 10^{16}$

Fig.2 shows the EnergyPlus simulated and MLP model computed values of energy consumption in training and test sets. Levenberg–Marquardt backpropagation.

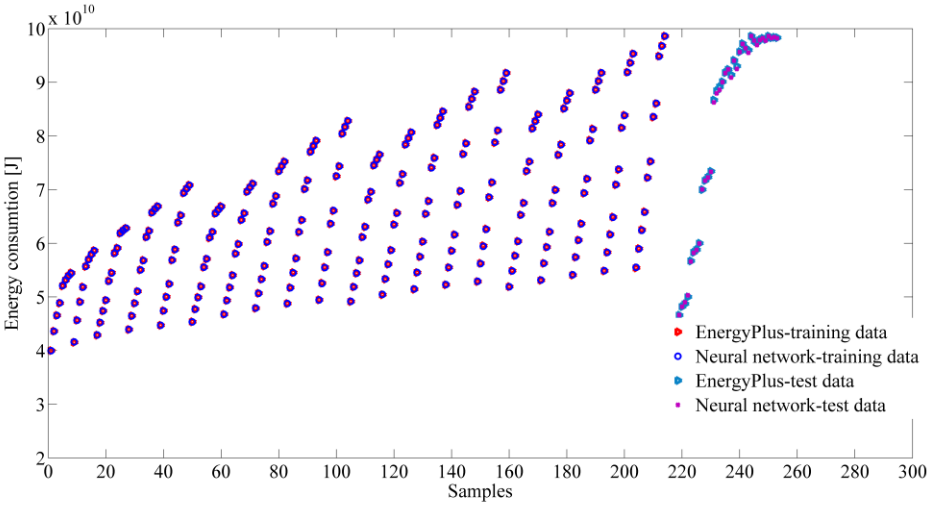

Fig. 2. EnergyPlus simulated and MLP model computed values of energy consumption in trening and test sets.

5. CONCLUSION

The aim of this paper is to develop and analyze neural network method for prediction and estimation energy consumption in residential house during heating period. The results obtained from simulation in EnergyPlus software were used for training and testing the multi-layer perceptron neural network. Training algorithm of the network is chosen as The optimal architecture of the neural network was determined. A two-layer neural network, with a log-sigmoid transfer function at the hidden layer and a linear transfer function at the output layer, was used. The optimal neuron number at the hidden layer was 11 neurons. It is evident that MLP methods can be used to predict new values from the present generated data to reduce the cost of studies and computation time.

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