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APPLICATION OF ARTIFICIAL NEURAL NETWORKS FOR PREDICTION OF HEATING ENERGY CONSUMPTION IN UNIVERSITY BUILDINGS

Radiša Ž. Jovanović
Aleksandra A. Sretenović
Branislav D. Živković
University of Belgrade, Faculty of Mechanical Engineering
Kraljice Marije 16, 11120 Belgrade, Serbia

ABSTRACT
In this study, the main objective is to predict heating consumption using artificial neural networks with several input parameters. For training and testing, daily meteorological and heating consumption data for Norwegian University of Science and Technology - NTNU University campus Gløshaugen were used. In order to determine the optimal network architecture, various network architectures were designed and different training algorithms were used. Also, the number of neurons and hidden layers and activation functions in the hidden layer/output layer were changed. Training of the network was performed by using Levenberg–Marquardt feedforward backpropagation algorithms. For each network, different indices of the prediction accuracy were calculated and compared.
Keywords: heating energy consumption, prediction, artificial neuron network

1. INTRODUCTION
The study of the building energy demand has become a topic of great importance, because of the significant increase of interest in energy sustainability. In Europe, buildings account for 40% of total energy use and 36% of total CO_2 emission [1]. University campuses represent specific groups of diverse buildings, with significant energy consumption. They consist of many different buildings, representing small-scale town for itself, so they provide an excellent testbed to characterize and understand energy consumption of group of „mixed use“ buildings. The classic approach to evaluate the building`s energy use is based on the application of a model with known system structure and proprieties as well as forcing variables (forward approach). It requires a detailed knowledge of the physical phenomena affecting the system behavior, and the building system operating mode [2]. A different approach for building energy analysis is based on the so called inverse or data-driven models. In recent years, considerable attention has been given to data-driven based methods [1]. Scientists and engineers are moving from calculating energy demand toward analyzing the real energy consumption of buildings. One of the reasons is that non-calibrated models cannot predict well building energy use, so there is a need for real time image of energy use in buildings (using measured and analyzed data). In data-driven approach the input and output variables are known and measured, and the goal is to determine a mathematical description of the relationship between the independent variables and the dependent one. In this paper thermal energy consumption for University campus is predicted. Actual recorded input and output data that influence thermal energy consumption were used for training, validation and testing of artificial neural network.

2. ARTIFICIAL NEURAL NETWORK
Artificial neural network (ANN) has been widely used for a range of applications in different engineering areas, such as industry processes [3], and also in energy modeling [4]. In the building energy modeling the ANNs are used as surrogate of analytic computer codes to evaluate the energy flow and system performance, i.e. they are useful for forecasting and modeling. Instead of complex

rules and mathematical routines, ANNs are able to learn the key information patterns within multidimensional information domain. Several studies have shown that in some cases forecasting models for energy consumption based on neural networks are more accurate. ANN is a computational structure inspired by a biological neural system, which consists of very simple and highly interconnected processors called neurons. They are usually arranged in an input layer, an output layer, and one or more hidden layers. The output of a specific neuron is a function of the weighted input, the bias of the neuron and the activation function. The process of training network is the adjustment of the weights, so that the network can produce the desired response to the given inputs. A schematic diagram of a typical multilayer feedforward neural network architecture is shown in Figure 1. It was used in this paper, along with backpropagation learning method, which uses a gradient descent technique to minimize the cost function which is the mean square difference between the desired and the actual network outputs.

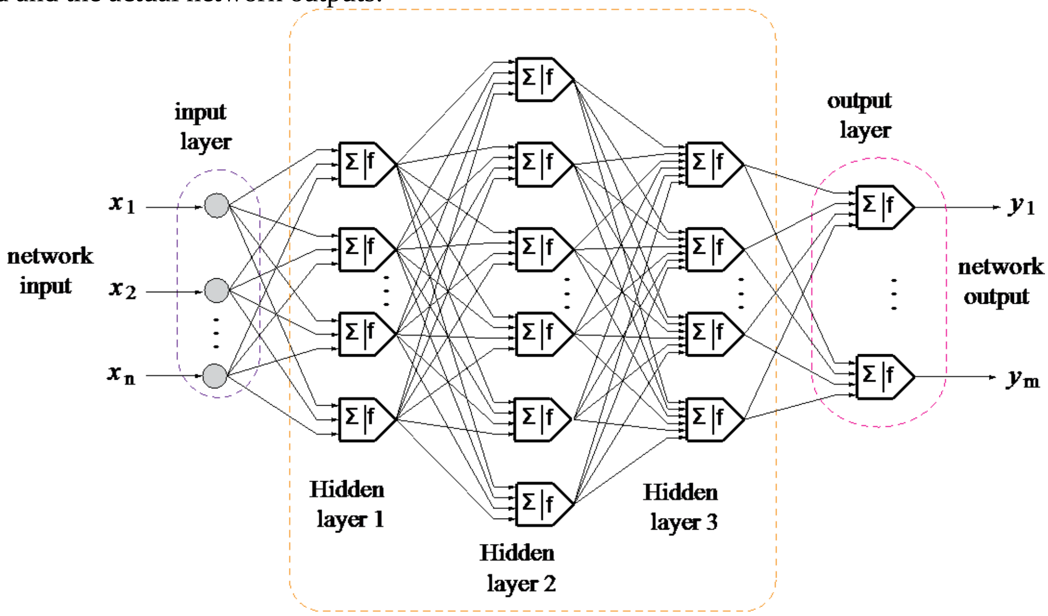

Figure 1. Feedforward neural network

Many studies on ANN theory have been published along with the development of the ANN method and theory of the neural networks can be found in numerous literatures [5].

3. APPLICATION STUDY

In this paper heating energy consumption of one University campus has been analyzed. Norwegian University of Science and Technology (NTNU) campus Gløshaugen consists of 35 buildings, with total area of approximately 300,000 m^2. Depending on their purpose, building types are: office, educational, laboratory workshop and sport facilities. Building and Energy Management System (BEMS) and web-based Energy Monitoring System (Energy Remote Monitoring – ERM) are available at NTNU [6]. Hourly heat and electricity consumption can be collected on ERM. District heating net in university campus is organized in form of a ring, while the Main heater is installed in the Old Electric building. The Main meter is installed by the district heating supplier (Trønderenergi), so it is taken as relevant. In this study, the daily heating energy consumption values for the years 2008–2010, gathered from the Main meter and mean daily outside temperatures, wind speed, solar radiation and relative humidity obtained from the local meteorological station were used to train and test the model. The input parameters of the neural network model were mean daily temperature, day of the week, month of the year, wind speed, solar radiation and outside air relative humidity. Input parameters day of the week and month of the year are coded, using numbers 1 to 7 and 1 to 12 respectively. Because the numerical range of the input and output variables may be quite different for some applications, it is often useful to normalize the input and output variables, so in the following experiments, all input variables are normalized to values between 0 and 1, by a linear scaling function:

$$x_i' = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}}, \quad i = 1, \ldots, N \tag{1}$$

where $x_{\max}$ and $x_{\min}$ are the expected maximum and minimum values of the concerned variable, and N is the number of data points collected for a given input variable. Two data sets were created: daily heating energy consumption for years 2008 and 2009 were used for training the ANN, and for year 2010 for testing the network.

4. RESULTS AND DISCUSSION

The ANN model used in this study is a three-layer feedforward neural network composed of one input layer, one output layer and one hidden layer, because it has been established that such structure can approximate any function of interest [7]. In the model Levenberg–Marquardt (LM) learning algorithm, which is a variant of feedforward backpropagation, was used. In the hidden layer and output layer logistic sigmoid and linear activation functions were used. To evaluate the obtained results the coefficient of determination (R^2), root mean square error (RMSE), as well as the coefficient of variation (CV) and mean absolute percentage error (MAPE), are used. CV and MAPE applied in the ASHRAE context [8] are defined as follows:

$$\mathrm{CV} = \frac{\sqrt{\frac{1}{N}\sum_{k=1}^{N}(y_k - \hat{y}_k)^2}}{\bar{y}}, \qquad \mathrm{MAPE} = \frac{1}{N}\sqrt{\sum_{k=1}^{N}\frac{|y_k - \hat{y}_k|}{y_k}} \cdot 100 \tag{2}$$

where y_k $\hat{y}_k$ are the target and ANN output value for the k-th pattern, respectively, $\bar{y}$ is mean value of y and N is the total number of patterns.

Table 1. Comparison of the prediction error values for training and testing

Neuron number	2008-2009: TRAINING				2010: TEST			
	RMSE [kWh]	CV [-]	MAPE [-]	R^2 [-]	RMSE [kWh]	CV [-]	MAPE [-]	R^2 [-]
6	7754	0.0869	12.01	0.9847	11074	0.1009	10.92	0.9831
7	7702	0.0863	11.79	0.9849	11751	0.1071	11.35	0.9810
8	7162	0.0803	10.34	0.9872	12792	0.1166	10.28	0.9798
9	8046	0.0902	12.30	0.9839	12871	0.1173	11.26	0.9791
10	7405	0.0830	12.28	0.9865	9947	0.0907	10.33	0.9869
11	**7031**	**0.0788**	**10.72**	**0.9876**	**8379**	**0.0764**	**9.57**	**0.9901**
12	7379	0.0827	10.66	0.9862	11048	0.1007	10.48	0.9832
13	7286	0.0816	11.78	0.9867	13998	0.1276	10.67	0.9733
14	7199	0.0807	11.88	0.9876	10165	0.0927	10.44	0.9857
15	7464	0.0837	11.93	0.9858	11432	0.1042	10.31	0.9832
16	7164	0.0803	10.62	0.9870	10374	0.0946	10.18	0.9852
17	7470	0.0837	12.12	0.9866	10981	0.1001	11.65	0.9838
18	6923	0.0876	10.20	0.9877	10498	0.0957	9.66	0.9846
19	7556	0.0847	10.98	0.9858	11234	0.1024	11.27	0.9824
20	7323	0.0821	10.14	0.9862	10316	0.0940	10.37	0.9858
25	7708	0.0864	12.47	0.9850	11440	0.1043	11.00	0.9817
30	7997	0.0896	12.94	0.9840	11540	0.1052	12.86	0.9820

Development process of the ANN started with 6 neurons in the hidden layer and the process was repeated increasing the number of neurons up to 30. As it can be seen from Table 1, the best prediction is obtained by the ANN model with 11 neurons. From obtained results it can be concluded that trends of calculated values and predicted values are very close to each other and future values are predicted with a high degree of accuracy. The comparison of measured and predicted heating energy consumption for the year 2010 (360 samples) is shown in Figure 3.

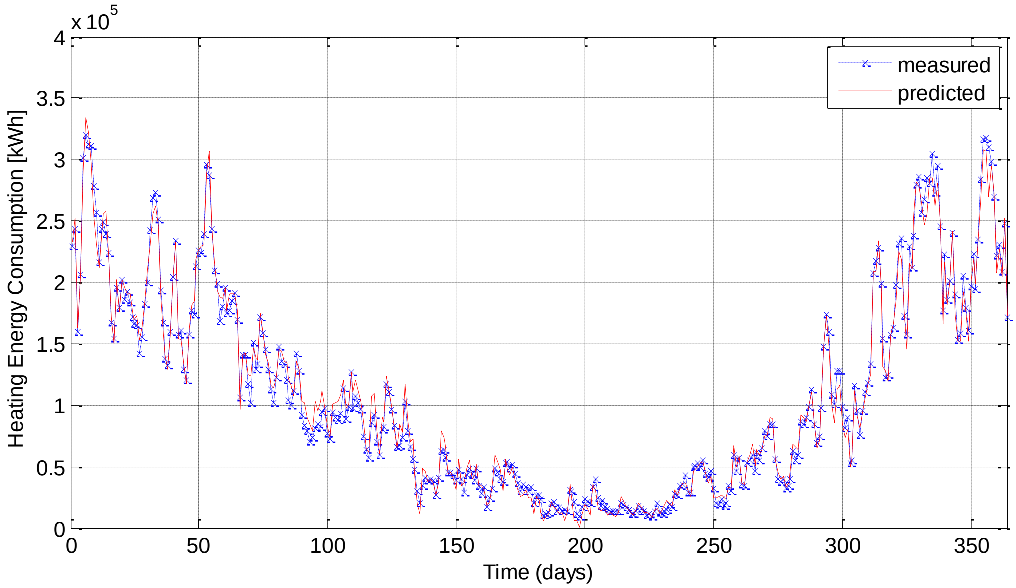

Figure 3. Comparison of the measured and predicted heating energy consumption for the year 2010: test results

5. CONCLUSION

In the present paper, the neural network model for heating energy consumption of the University campus Gløshaugen was trained based on daily data for 2008 and 2009 and tested for the year 2010. Network with different number of neurons was tested, and the best result was obtained using 11 neurons in the hidden layer. Accuracy prediction indices showed that the properly designed and trained multilayer ANN model with backpropagation algorithm can model and predict heating consumption with great accuracy (error is less than 10%). In future work, impact of different meteorological parameters can be analyzed, in order to identify most influencing factors and decrease number of input parameters.

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