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INPUT VECTOR IMPACT ON SHORT-TERM HEAT LOAD PREDICTION OF SMALL DISTRICT HEATING SYSTEM

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Abstract. *Short-term load prediction is very important for advanced decision making in district heating systems. The idea is to achieve quality prediction for a short period in order to reduce the consumption of heat energy production and increased coefficient of exploitation of equipment. The common thing for each way of prediction is usage of historical data for certain last period which makes possible development of many methodologies for adequate prediction and control. In this paper, application of feedforward artificial neural network for short-term load prediction for period of 1, 3 and 7 days, of one small district heating system, is presented. Three different input vectors are implemented and their impact on quality of prediction discussed. The simulation results are compared and detailed analysis is done where operation in transient regime is of special importance. Satisfied prediction average error is obtained.*

Key words: *short-term load prediction, feedforward artificial neural networks, small district heating system, energy efficiency, heat load, heat demand*

1. INTRODUCTION

District heating companies are responsible for the delivery of heating energy produced in the central plant to the consumer through a hot water system. At the same time, they are expected to keep the cost of produced and delivered heat as low as possible. That is why we have a growing need for optimizing the production of heating energy through better prediction and management needs of consumers. Modern enterprises for the production and distribution of heating energy are faced with new challenges. Many consumers choose to be excluded from the district heating system and change it with decentralized individual heating system.

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It should be noted that the most important part of the price of district heating is price of heat production. By optimizing the production of heating energy price can be reduced. However, this goal cannot be met without a detailed analysis of the profile of user requirements. The goal is to determine a set of typical profiles of heat demands that will suit the typical consumer group. By obtaining such a profile requires annually, long-term optimization of supply heating energy can be achieved. Also a daily requirement profile for short-term optimization is required.

District heating systems can be characterized by a reduction in energy consumption, increasing energy efficiency and reducing the generation of pollution. This means that the optimal operation of the district heating system has significant economic potential, as discussed in [1].

In order to improve economic efficiency in the work of the district heating system, it is first necessary to realize the prediction of heat consumption for the target part. Economic governance consumption of district heating and planning is deeply dependent on accurate prediction.

Prediction of heat consumption can be broadly classified as evaluation and time-dependent prediction. There are long-term, mid-term and short-term predictions. In this paper, we are dealing with short-term prediction.

Short-term prediction shows a period of several days or hours in advance to on a daily basis and manages the planned district heating system.

This prediction is particularly important for transient heating in which unlike the standard heating regime does not take place continuously throughout the time period specified heating. So it is very important to achieve quality prediction for a short period in order to reduce the consumption of thermal energy production and increased coefficient of exploitation of equipment. This gains more importance due to the fact that district heating systems in Serbia, by definition, interrupt. Heating is not being continuously but starts in the morning and turned off in the evening.

There is various statistical prediction techniques explained in [2] that can be applied to short-term prediction. That is why today widely used method with supervisory learning such as support vector machine (SVM), support vector regression (SVR), Artificial neural network (ANN) and partial least squares (PLS). In [3] the method of SVR, PLS and ANN used for short-term predicting of heat consumption of district heating Korean city Suseo. In [4] artificial neural network (ANN) used to predict one hour in advance of the thermal load, including different types of days such as public holidays, Saturdays and Sundays as input variables.

Most of research in area of artificial neural network application for short-term load prediction is related on short-term predicting of electrical load. On the other hand, compared with above, there are not great number of scientific papers and research dealing with short-term heat load prediction for district heating systems. These papers show that ambient temperature together with social component described customer needs and behavior has the greatest influence on heat response from customers and needs for heat energy delivered from heat source. ([5]-[11])

In this paper we used a modelling techniques such as "black boxes" ("black box") based on artificial neural networks (ANN) to predict the thermal energy power on the heating source, in the city of Nis, Serbia Southeast region. As input variables we take time, previous consumption data over power on the heat source and the ambient temperature with the aim of predicting for one week in advance.

Artificial neural networks are capable to learn heat load features which have to be analyzed in detail. Problem appears because of lack of comparable results on different models. That is why it is necessary to provide comparative analysis of features for different models because of application in real time.

2. Artificial Neural Networks

Neural networks, or artificial neural networks (ANN) as they are often called, refer to a class of models inspired by biological nervous systems. The models are composed of many computing elements, usually denoted neurons, working in parallel. The elements are connected by synaptic weights, which are allowed to adapt through a learning process. Neural networks can be interpreted as adaptive machines, which can store knowledge through the learning process. Artificial neural networks are a collection of mathematical models that simulate some of the observed properties of biological nervous system and withdrawing similarities with biological adaptive learning. They made up of a large number of interconnected neurons which, like biological neurons, are associated with their relationships, which include bandwidth (weight) coefficients, which are similar to the role of synapses.

Learning is realizing in biological systems by regulating synaptic connections linking the axons and dendrites of neurons. Learning through examples of typical event is achieved through training or discoveries accurate data sets input-output algorithm that train repetition adjusting bandwidth (weight) ratios of connections (synapses). These links stored knowledge necessary to solve specific problems.

Most neural networks have some kind of rules for "training", which are the coefficients of connections between neurons are adjusted based on the input data. In other words, neural networks "learn" over the case (such as children learn to recognize a specific subject, object, process or development through appropriate examples) and have the ability for generalization after learning data. The most common learning algorithm is backpropagation algorithm shown on Fig. 1.

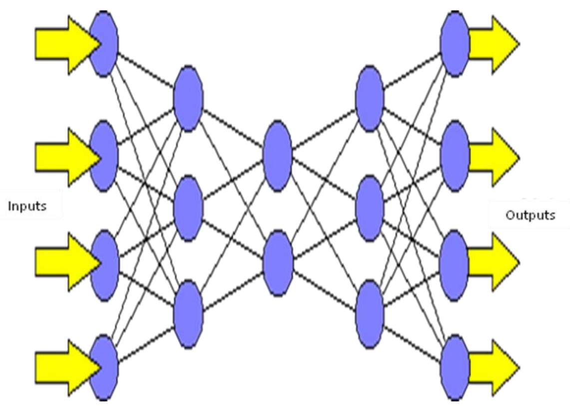

Fig. 1 Backpropagation algorithm

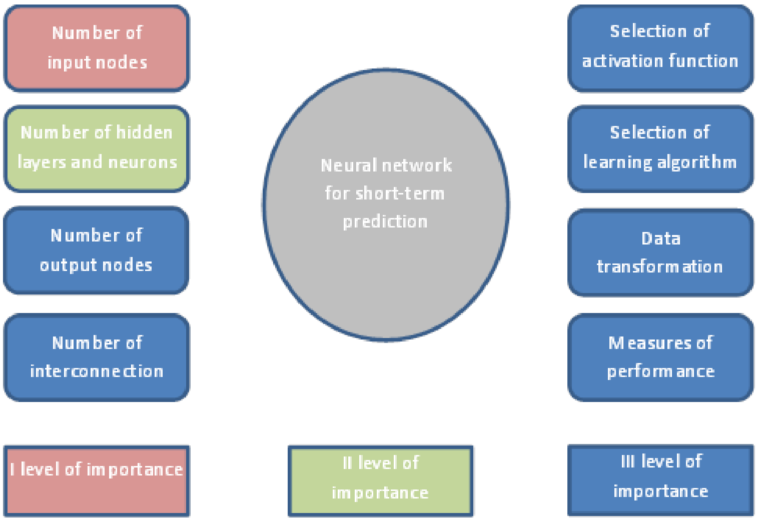

Fig. 2 Impact diagram of selection parameter importance of ANN for short-term prediction

Great potential of neural network is ability to do parallel data processing, during the calculation components that are independent of each other. Neural networks are systems composed of a number of simple elements (neurons) that process information in parallel. Functions that are neural networks able to handle the specific structure of the network, the strength of connection and data processing are performed in neurons.

The application of artificial neural networks to short-term prediction yields encouraging results.

The ANN approach does not require explicit adoption of a functional relationship between past load or weather variables and predicted load. Instead, the functional relationship between system inputs and outputs is learned by the network through a training process. Fig. 2 shows levels of importance for parameter selection of ANN for short-term prediction. Number of input nodes is defined as the most important parameter for design adequate ANN for short-term prediction. The process of selection input variables has to be done carefully considering importance of each variable and number of all chosen variables, in general. The different input vector size gives different ANN performance for prediction.

3. Neural Network Application

For the purpose of research for this paper, Toplification system of Faculty of Mechanical Engineering of University of Niš (TSFME) is considered. This system is owned by Faculty of Mechanical Engineering University of Niš and used on commercial basis for heating educational institutions, student centre and one small residential campus.

TSFME can be categorized as a small district heating system for heating different types of customers with different regime of heating needed.

In the boiler room of TSFME, there are three hot water boilers with temperature regime 130/70°C, where two of them are TE-110 V produced by „MINEL-Kotlogradnja“

with power Q=8700kW, and third one, installed later, UT-H 8200 produced by „LOOS“ with power Q=8200kW. Combined burners for gas and crude oil produced by „SAACKE“ type SKVG-A 102-30, were used for fuel combustion in boilers 2 and 3. They are connected with gas inlet by gas ramps with adequate regulation, mesaurement and safety equipment. Boiler 1 has burner just for crude oil combustion. Primar fuel is natural gas and alternative fuel is crude oil.

Three pumps were used for cold end protection of boilers gathered in one recirculation system. Distribution of heat energy is realized over four branches: for Faculty of Mechanical Engineering, for Faculty of Electronics and Student center, for Technical highschools, and for residential campus "Nikola Tesla". Water circulation to customers are managed by circulation pumps separately for each of four branches. There are totally ten heat substations connected to TSFME.

For the purpose of this paper, the real measured data from winter season 2014-2015 were used, from the heat source TSFME, and one branch for residential campus. In observed period, natural gas was used as a fuel.

The average ambient temperature was 9 °C for a period from 01.10.2014 to 30.04.2015., and minimum temperature was 10°C and maximum 32°C. The average temperature of input water for the same period of time was 73 °C and the average temperature of return water was 46 °C.

For selected heating season, there were 536 hours when heating energy wasn't delivered during operational regime of heating source. As total number of hours in heating season was 2737, it means that for 19.5% potential operational hours there were interruptions in delivery heating energy.

For the prediction period, the last week of March 2015 is chosen, precisely from 23-29. March 2015.

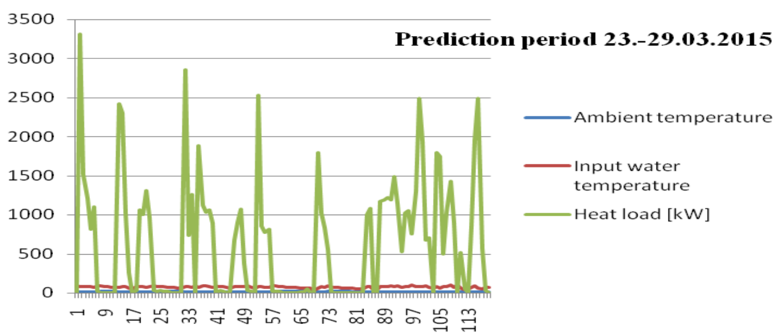

Fig. 3 The main performances of district heating system for selected 7 day prediction period

In order to realize neural network and perform certain conclusions to predict heat load on the heat source in interrupt and transient regimes, it is first necessary to perform rearrangement of inputs or input vectors.

Since we are talking about interrupt heating regime from 5 o'clock in the morning to 21 o'clock in the evening every day, it is important to organize past data on adequate way.

The objective of optimization of heating is to manage to reach lower heat load on the heating source with lower temperature of input water. On that way, fuel consumption would be lower and most important objective would be fulfilled – satisfaction of consumers with appropriate temperature in their premises.

The important fact is that just for predicted 23.-29. March 2015 during 6 days, there were 21 hours without heating energy delivering and where heat load on the heating source was zero, because of high ambient temperature, and just one day heating process without stopping. These facts make worse preconditions for good optimization.

For the prediction period, minimum ambient temperature was 6 degrees and maximum temperature was 22 degrees. An average temperature for predicted period was 12 degrees. The main performances are shown on Fig.3.

Three different input vectors were used.

The first input vector for prediction consists of data for the previous five days for the power generated from the heat source and delivered to heat substations, the ambient temperature for the past three days and the ambient temperature for the day that predicts and the time expressed in hours.

The second input vector for prediction consists of data for the previous three days for the power generated from the heat source and delivered to heat substations, the ambient temperature for the day before and the ambient temperature for the day that predicts and the time expressed in hours.

The third input vector for prediction consists of data for the previous day for the power generated from the heat source and delivered to heat substations, the ambient temperature for the day that predicts and the time expressed in hours. All of three input vectors were implemented on the same neural network.

Selected neural network is a feedforward neural network with one hidden layer and backpropagation learning. The hidden layer has 20 neurons and activation function for hidden layer and output layer is hyperbolic tangent sigmoid function. After process of training network, relatively good measures of performance were obtained. Results are given in Table 1 for all three networks and they show that best results of training were achieved with the largest input vector. However, all of three networks show good learning performances.

Table 1 Results of training network

Feedforward neural network	Measure of performance (MSE)	Regression (R)	Number of Epochs
Input vector 1(10 inputs)	0.185	0.828	200
Input vector 2 (6 inputs)	0.216	0.795	200
Input vector 3 (3 inputs)	0.274	0.732	200

Figures 4, 5 and 6 respectively show the simulation results of feedforward neural network that realizes the prediction of 1, 3 and 7 days in advance, for three input vectors.

Measures of performances show us ability for good prediction of designed neural network. However, we selected non-standard period of heating for prediction as it's already explained. That is why there are larger prediction errors as it shown on above mentioned figures.

By comparing the results obtained with real data show that with great certainty can be used to correctly and accurately predict. Better results were obtained for shorter predicted period, which can be corrected by modifying selected neural network or by selecting another type of neural network that will realize the simulation with a smaller percentage of average error, or a larger set of data.

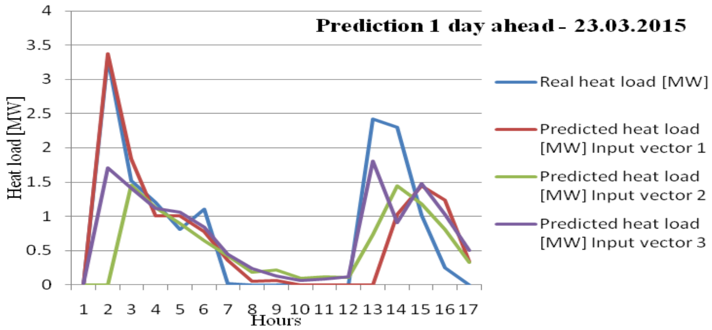

Fig. 4 Predicted heat load 1 day ahead

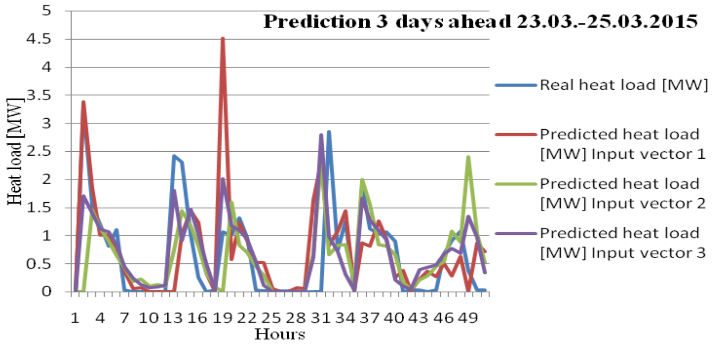

Fig. 5 Predicted heat load 3 days ahead

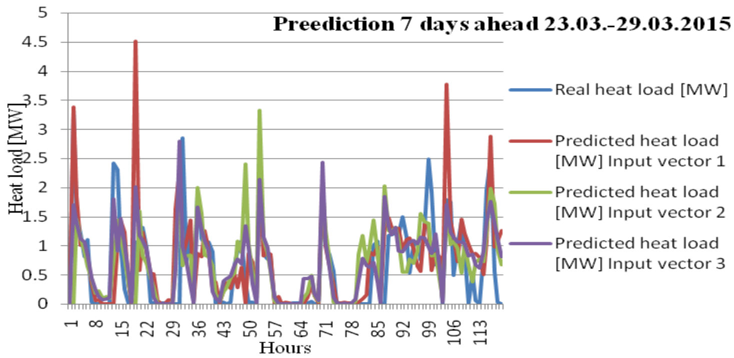

Fig. 6 Predicted heat load 7 days ahead

It is important to point out that despite the fact that the average error is smallest for the shortest prediction, it can be concluded that the error is relatively uniform for all three periods of prediction. It was 3.1% and 3.6% for the predicting of 1 day in advance, 3.2% and 3.62% for predicting of 3 days in advance and 5.2% and 5.4% for predicting of 7 days in advance.

Selected prediction period is a period where there was stopping of delivery heating energy and good but not the best results were obtained. That is of high importance because of the fact that managing and planning heat load and consumption is the most important thing for transient regimes and regimes where big oscillations of ambient temperature are during the day.

It is very interesting to compare how large average error is after interruption period where peak is hard for prediction. That is why prediction error is the largest in that situations. In Figure 4, we can observe two peaks, one at 6 o'clock in the morning and the second one at 5 o'clock on the afternoon. It is obvious for the first one that the best prediction was realized by Input vector 1 and then Input vector 3 and Input vector 2, respectively. However, for the second peak the best prediction was obtained by Input vector 3 and Input vector 2. Input vector 1 network was very far away from good peak prediction. The similar analysis of two other period of prediction, 3 and 7 days ahead yields to conclusion that besides better learning performances Input vector 1 doesn't have advantages for peak prediction compared with other two input vectors. Generally, it means that peak error is much larger than average error and one of the on-going challenges is to keep peak error lower as possible. The common conclusion is that improving prediction for periods where we have interruptions should be done with introducing totally new inputs (with high level of importance) instead of increasing number of instances of same input variables.

It should be mentioned that comparative analysis of simulation results for three different input vectors show that better prediction results obtained with Input vector 1. But, that was expected. On the other hand, differences between average errors are not so big. It means that can be recommended using Input vector 3 or 2 because of simplicity and smaller set of data that implies faster learning process and convergence.

4. CONCLUSION

Short-term heat load prediction on the heat source is realized using real measured data for the winter season, from the heat source TSFME, Serbia South-East region, for the branch distributed heating energy to residential campus. Prediction is performed using feedforward neural network with backpropagation learning algorithm. The period of 23-29. March 2015 was taken as a period for prediction because 6 of 7 days in that period there were interruptions in delivering heating energy. Three different input vectors were used and results obtained by simulating neural network prediction were compared with real heat load on the heat source. Satisfactory results were obtained with an acceptable average error. The obtained satisfactory results are especially important because it is an interrupt regime of operation of district heating system where the heating period is from 5 in the morning to 21 in the evening but also high ambient temperatures leads to the turning off heating in certain daily intervals. Prediction error for peak hours was much bigger and one of challenges should be introducing totally new inputs for decreasing peak prediction error. It must be taken into account the fact that as an external factor just outside temperature introduced, and further research should be taken into account other conditions.

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