

HEAT LOAD PREDICTION OF SMALL DISTRICT HEATING SYSTEM USING ARTIFICIAL NEURAL NETWORKS

by

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Accurate models for heat load prediction are essential to the operation and planning of a utility company. Load prediction helps a heat utility to make important and advanced decisions in district heating systems. As a popular data driven method, artificial neural networks are often used for prediction. The main 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. To improve the short term prediction accuracy, this paper presents a kind of improved artificial neural network model for 1 to 7 days ahead prediction of heat consumption of energy produced in small district heating system. Historical data set of one small district heating system from city of Nis, Serbia, was used. Particle swarm optimization is applied to adjust artificial neural network weights and threshold values. In this paper, application of feed forward artificial neural network for short-term prediction for period of 1, 3, and 7 days, of small district heating system, is presented. Two test data sets were considered with different interruption non-stationary performances. Comparison of prediction accuracy between regular and improved artificial neural network model was done. The comparison results reveal that improved artificial neural network model have better accuracy than that of artificial neural network ones.

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

Introduction

In urban areas with high density of demand for heat, the most rational and economical means of heat supply for the inhabitants are district heating systems. 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. Sustainable development of heating systems is closely connected with further increases in energy efficiency both on the part of

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consumers and heat producers. The modernization of heat sources, especially in small and medium heating systems, is linked with changes of fuel.

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. As discussed in [2], an important element that will allow heat generation schemes for heating systems to run more efficiently is heat demand forecasting, both at the design and operational stages of the installation. Heat load prediction will inevitably depend heavily in future on short term forecasting, particularly the assessment of chances of extreme weather conditions and their influence on supplying users with sufficient quantities of heat. One way to boost heat production efficiency is to implement appropriate procedures for operating heat sources alongside short-term forecasting of heat demand.

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. Prediction of a short-term horizon make it possible to react promptly, adjusting the source to unforeseen random events.

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.

One condition for achieving optimized regulation of the system is ensuring that the thermal power of the sources is adjusted to the consumers' current demand for heat. This requires accurate near-term prediction of heat demand.

There is various statistical prediction techniques explained in [3] 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 [4] the method of SVR, PLS, and ANN used for short-term prediction of heat consumption of district heating Korean city Suseo. In [5] the 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 ANN application for short-term load prediction is related on short-term prediction of electrical load, as discussed in [6]. On the other hand, compared with previous, 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 [7-10].

In this paper we used a modelling techniques such as *black boxes* based on 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 outside temperature with the aim of prediction for one week in advance.

The ANN 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.

Artificial neural networks

Neural networks, or 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. The ANN 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 inter-connected 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 that is 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 used training algorithm also presented in this paper is back-propagation algorithm. Representation of three layer feed forward network is presented in fig. 1.

Great potential of neural network is ability to do parallel data processing, during the

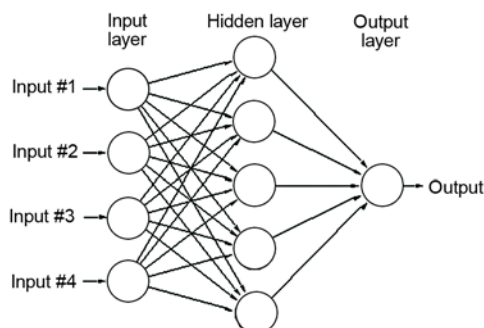


Figure 1. Feedforward neural network architecture with backpropagation learning algorithm

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 ANN 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.

The ANN have some advantages over other prediction models, which make them attractive in prediction tasks. The ANN model delivers good prediction results. The accuracy of the results depends on the kind of network, its architecture, the size and type of input data as well as the forecasting period.

First, ANN have flexible non-linear function mapping capability as mentioned above, that can approximate any continuous measurable function with arbitrarily desired accuracy. Second, being nonparametric and data driven method, ANN impose few prior assumptions on the underlying process from which data are generated. Third, ANN are adaptive in nature. The adaptivity implies that network because of generalization capabilities remain accurate and robust in a non-stationary environment whose characteristics may change over time. In this paper, feed forward artificial neural network with back-propagation algorithm used for heat load short prediction.

Particle swarm optimization

Particle swarm optimization (PSO) is a population based stochastic optimization technique developed by Kennedy and Eberhart in 1995 [11], as a new heuristic method inspired by the social behavior of bird flocking or fish schooling.

The PSO shares many similarities with evolutionary computation technique such as genetic algorithms (GA). The system is initialized with a population of random solutions and searches for optima by updating generations. But, unlike GA, PSO has no evolution operators such as crossover and mutation. In PSO, potential solutions, called particles, fly through the problem space by following the current optimum particles.

Compared to GA, the advantages of PSO are easy implementation and only few parameters to adjust. The PSO has been successfully applied in many areas: function optimization, artificial neural network training, fuzzy system control and other areas where GA can be applied.

In the basic PSO, particle swarm consists of n particles, and the co-ordinates of each particle represent a possible solution called particles associated with position and velocity vector in dimensional space. The PSO algorithm used in this paper is shown in fig. 2.

At each iteration particle move to the optimum solution, through its current velocity, personal best solution obtained by themselves so far and global best solution obtained by all particles.

The position of i^{th} particle of the swarm can be represented by a D-dimensional vector $\vec{x}_i = (x_1, x_2, \dots, x_D)$. The velocity (position change per generation) of the particle x_i can be represented by another D-dimensional vector $\vec{v}_i = (v_1, v_2, \dots, v_D)$. The best position previously visited by the i^{th} particle is denoted as $\vec{p}_i = (p_1, p_2, \dots, p_D)$. If the topology is defined such that all particles are assumed to be neighbors and g as the index of the particle visited the best position in the swarm, then p_g becomes the best solution found so far, and the velocity of the particle and its new position will be determined according to the eqs. (1) and (2):

$$v_i^{k+1} = wv_i^k + c_1r_1(p_i^k - x_i^k) + c_2r_2(p_g^k - x_i^k) \quad (1)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (2)$$

where w is the parameter controlling the dynamics of flying, r_1 and r_2 – the random variables in the range $[0,1]$, and c_1 and c_2 – the acceleration coefficients regulating the relative velocity toward global and local best.

There have been significant research efforts recently to apply evolutionary computation techniques for the purposes of evolving one or more aspects of ANN. Evolutionary computation methodologies have been applied to three main attributes of neural networks: connection weights, network architecture and network learning algorithms. There are several papers reported using PSO to replace the back-propagation algorithm in ANN. It showed PSO is promising method to train ANN. It is faster and gets better results in most cases.

The PSO has several advantages for exploring the hyperspace global optimum, especially the fast convergence. In order to improve its capability of global search and avoid local minima PSO is applied to adjust structures' weights and threshold values. A gradient based training algorithm for neural networks have a strong ability in the aspect of local optima search, but their capability of finding the global optimal solution is quite weak.

A three-layer feed forward neural network with back-propagation training algorithm is constructed for model initialization and for comparison. Then all of the weight and threshold values of the network are regarded as particles' position and PSO algorithm is applied to optimize network parameters. The flow diagram of the PSO ANN model is illustrated in fig. 3.

Mean absolute percentage error (MAPE) is utilized to assess the prediction accuracy and is described in eq. (3):

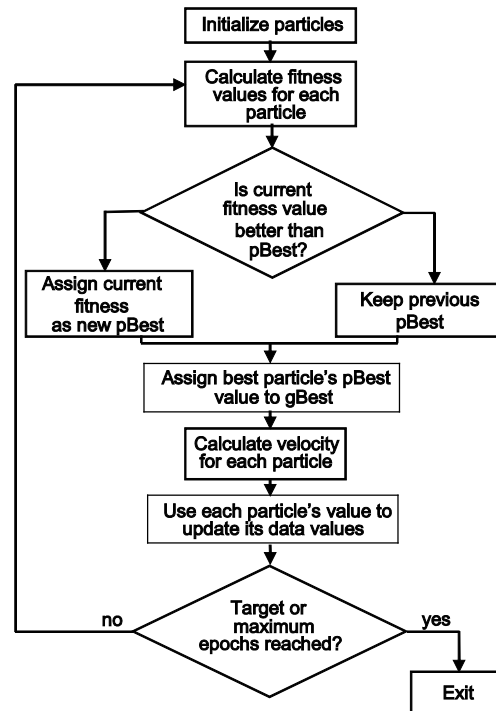


Figure 2. Flow diagram illustrating PSO algorithm

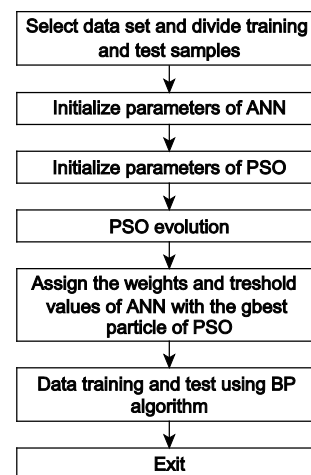


Figure 3. The flow chart of PSO-ANN prediction model

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^n \left(\frac{|y_{\text{pred},i} - y_{\text{data},i}|}{y_{\text{data},i}} \right) \quad (3)$$

where $y_{\text{pred},i}$ is the predicted value of heat load, $y_{\text{data},i}$ – a real heat load value, and n – the number of testing data set. The fitness function is defined:

$$\text{fitness} = \sum_{i=1}^k (|y_{\text{pred},i} - y_{\text{data},i}|) \quad (4)$$

where k is the number of the training data set.

Neural network application

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

The 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 $Q = 8700$ kW, and third one, installed later, UT-H 8200 produced by LOOS with power $Q = 8200$ kW. 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, measurement 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 high schools, 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.

All ten substations are indirect type, designed for temperature regime 130/80 °C on primar side and 90/70 °C on secundar side.

Heat substations in residential campus Nikola Tesla are equipped with heatmeters on primar circulation through secundar circle is provided by work circulation pumps. Beside working pumps on each circulation circle bound reserve pumps are mounted. Regulation is done by combi valves on primar side controlled by control unit based on external temperature sensor information.

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. For the predicted period, two different weeks were used. The first week, period of 7-13 March 2015 was selected and as the second, the last week of March 2015 was chosen, precisely from 23-29 March 2015.

The main difference between two selected weeks for observed period is the fact that in first chosen week there was just one interruption in heat delivery through a day. In the second selected week, there were six of seven days with interruption in heat delivery through a day.

The average ambient temperature for the first selected week was 5 °C and for the second week, 12 °C.

For the observed periods, one of four heat substations from residential campus was considered and data for heat load and consumption was used.

Selected neural network is a feed forward neural network with one hidden layer and backpropagation learning algorithm. The hidden layer has 20 neurons. The input vector has 10 inputs which are respectively given in tab. 1 and the output is power on the heat substation, expressed in MW.

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. Data were arranged to fulfil demands for input vectors but no process of normalization data was done, according to [12].

Since we are talking about interrupt heating regime from 5 a. m. to 9 p. m. 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.

For predicted period March 07-13, 2015, there was no interruption in heat delivery during a heating day period. The maximum ambient temperature was 8 °C and minimum ambient temperature was 1 °C. It means that beside continuation in heat delivery, small difference between maximum and minimum ambient temperature is main characteristic for observed period. That small difference decrease potential oscillation in heat load delivered from heat source and give good preconditions for more accurate prediction. Simulation results for prediction using two ANN are shown in fig. 4. Results of prediction are satisfactory and average prediction errors were from 3.3% and 3.7% for the prediction of one day in advance, 3.4% and 3.65% for prediction of three days in advance and 5.1% and 5.45% for prediction of seven days in advance.

The important fact is that just for predicted March 23-29, 2015, during six 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 predicted period, minimum ambient temperature was 6 °C and maximum temperature was 22 °C. An average temperature for predicted period was 12 °C.

The main parameters used in improved ANN model are also given in tab. 1.

The prediction results illustrate that the optimized ANN model is more effective than traditional ANN model. It is noted that the proposed model needs the knowledge of related weather and historical energy consumption data.

Table 1. Main parameters for ANN and PSO ANN

Main parameters	Values
Input vector heat load for 5 past days ambient temperature for 3 past days ambient temperature for predicted day hours	10
Number of hidden neurons	20
Number of epochs in ANN	200
The initial weight value	0.9
The final weight value	0.4
Acceleration coefficient c_1	2
Acceleration coefficient c_2	1.9

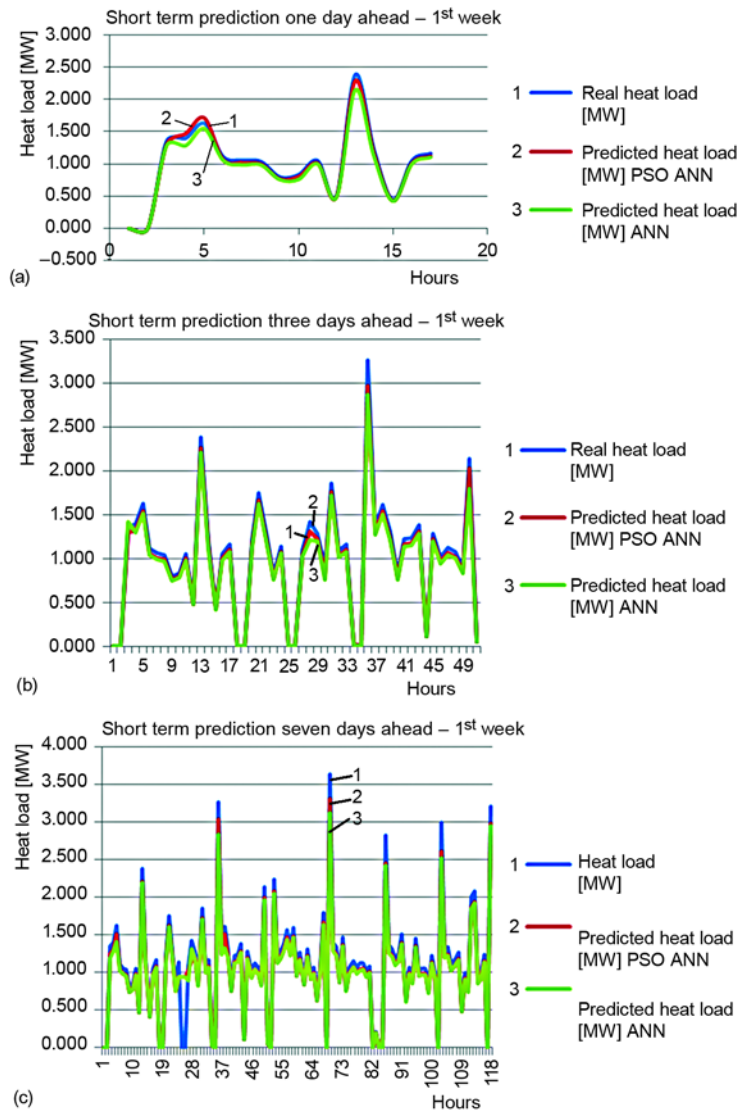


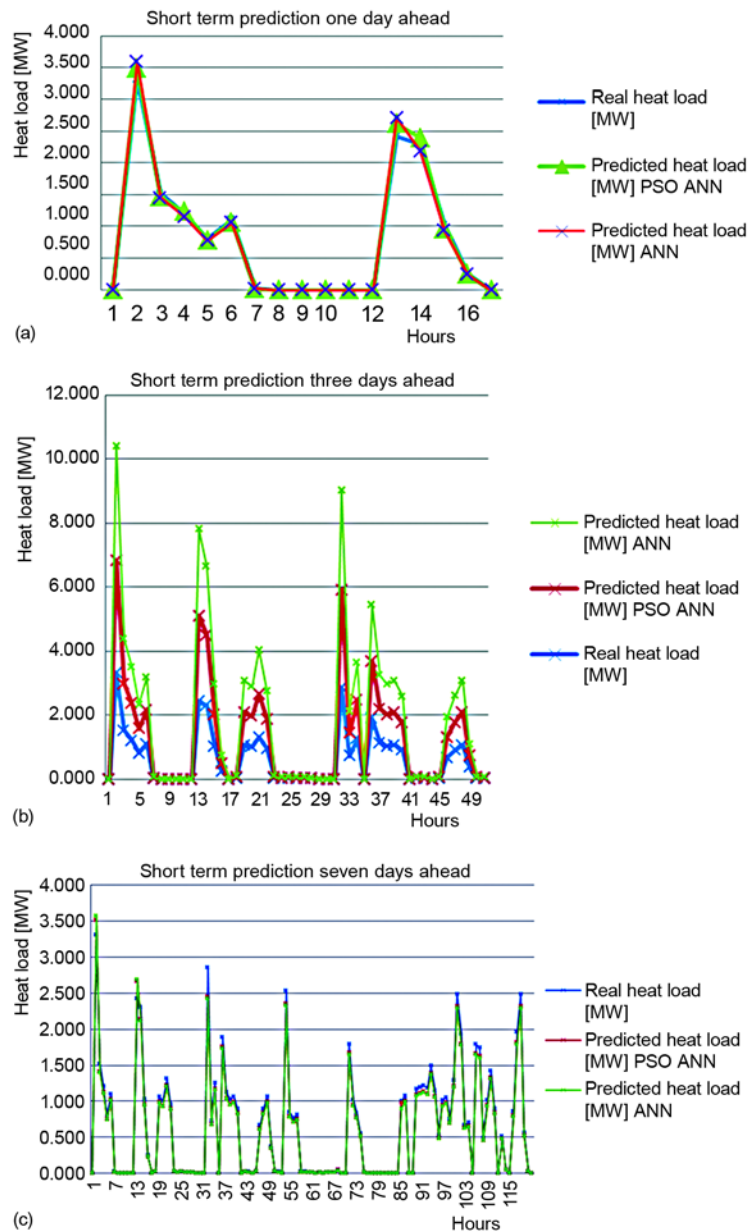
Figure 4. Simulation results and comparison of real load, PSO-ANN and ANN predicted for one, three and seven days (1st week)

Figure 5 shows the simulation results of feed forward neural network and improved PSO neural network, respectively, that realizes the prediction of one, three, and seven days in advance. The obtained results are satisfactory.

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.

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 3.4% and 3.7% for the prediction of one day in advance, 3.5% and 3.77% for prediction of three days in advance and 5.3% and 5.55% for prediction of seven days in advance.

Figure 5. Simulation results and comparison of real load, PSO-ANN and ANN predicted for one, three and seven days



Chosen prediction period is a period where there was stopping of delivery heating energy and good 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 important to point out how large average error is after interruption period where peak is hard for prediction. That is why prediction error is the largest in those situations. In fig. 5, it is shown that error at 5 a. m. is 7% for PSO ANN, and 11.3% for ANN. It

means that peak error is much larger than average error but also that improving ANN structure using PSO gives promising results. But the fact is that further improvements in architecture have to be done for better peak prediction. One of the on-going challenges is to keep peak error lower as possible. In the first selected week analysis, prediction curves give rather uniform average errors which yield to conclusion that non-stationary aspect of heat load prediction is one of crucial issue in research activities.

It should be mentioned that comparative analysis of simulation results for improved ANN model with PSO choice of network parameters and traditional ones show that better prediction results obtained with improved one. On the other hand, differences between average errors are not so big.

Conclusions

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 feed forward neural network with back propagation learning algorithm. Two periods (March 7-13 and March 23-29, 2015) were taken as the periods for prediction. The main difference between selected periods was the fact that in the first period there were no interruptions in heat delivery during a day. On the other hand, in the second selected week period, there were 21 hours interruptions of heat delivery in six days.

The results obtained by simulating neural network prediction are compared with real heat load on the heat source and satisfactory results were obtained with an acceptable average error. The PSO is applied to adjust ANN weights and threshold values. 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 a. m. to 9 p. m. but also high ambient temperatures leads to the turning off heating in certain daily intervals. Improved ANN architecture gives promising results. You must take into account the fact that as an external factor just outside temperature is taken.

Nomenclature

c_1	– acceleration coefficient	$y_{\text{pred},i}$	– predicted value of heat load, [MW]
c_2	– acceleration coefficient	$y_{\text{data},i}$	– real heat load value, [MW]
P	– heat load, [MW]		
\vec{v}	– velocity (position change per generation)		<i>Subscripts</i>
w	– parameter controlling the dynamics of flying	i	– iteration
\vec{x}_i	– position of i^{th} particle		

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