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Short-term Load Forecasting based on ABC and ANN for Smart Grids

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Abstract: Short term load forecasting is a subject about estimating future electricity consumption for a time interval from one hour to one week and it has a vital importance for the operation of a power system and smart grids. This process is mandatory for distribution companies and big electricity consumers, especially in liberalized energy markets. Electricity generation plans are made according to the amount of electricity consumption forecasts. If the forecast is overestimated, it leads to the start-up of too many units supplying an unnecessary level of reserve, therefore the production cost is increased. On the contrary if the forecast is underestimated, it may result in a risky operation and consequently power outages can occur at the power system. In this study, a hybrid method based on the combination of Artificial Bee Colony (ABC) and Artificial Neural Network (ANN) is developed for short term load forecasting. ABC algorithm is used in ANN learning process and it optimizes the neuron connections weights of ANN. Historical load, temperature difference and season are selected as model inputs. While three years hourly data is selected as training data, one year hourly data is selected as testing data. The results show that the application of this hybrid system produce forecast values close to the actual values.

Keywords: *Artificial bee colony, Artificial neural network, Hybrid method, Short term load forecasting, Smart grids*.

1. Introduction

Today existing power system needs to be enlarged so as to meet the future demand for electrical energy. The general purpose of the planning of electric power system is delivering the electric power to end user with some desired features such as continuous, safe, reliable and minimum price. Various plans should be made to achieve these features and load forecasting is one of the most important steps of these plans. In literature, load forecasting is divided into three categories according to the forecasting time horizons. Long term load forecast consists yearly load demand forecasts and it is used for planning future electric generation, transmission and distribution. Generally gross domestic product, population, export, import, etc. are considered as inputs in the long term load forecasting studies. Forecasting which is made in a time period ranging from one week to one year is called midterm load forecasting and it is useful for determining maintenance scheduling, hydrothermal coordination and fuel purchasing strategies [1].

Short-term load forecasting is a subject on which electric utility industry and researchers are studied for several decades and is an important process for the operations of electric power systems and smart grids. It has a critical role on generation scheduling, unit commitment and maintenance plans for generators. Short term load forecast has been made in a time period from one minute to one hour.

The concept of smart grid has become a global trend in the last years and there is not any definition of smart grid acknowledged by all institutions. For example, The Smart Grids European Technology Platform defines smart grid as ‘‘electricity networks that can intelligently integrate the behaviour and actions of all users connected to it – generators, consumers and those that do both – in order to efficiently deliver sustainable, economic and secure electricity supplies’’ [2]. Smart grid is an advanced electrical network that uses control, information and communication technologies to monitoring the power system. In smart grids, energy management is performed with using some forecasts which use real time data. These forecasts are renewable production forecast, load forecast and electric price forecast. The power network can be managed efficiently by making these forecasts. Short term load forecast is also crucially important for smart grids. Recently, the demand side management becomes an emerging emphasis in the electric industry with the development of smart grid technologies. Especially in micro grids, short term load forecast helps to meet the objectives of demand side management issues like determining the electric price, determining the amount of the purchases and sales of energy and reducing the peak load value. It answers the questions of load needs such as when, how much, why and which factor effect [3].

There are many studies under the umbrella of short term load forecasting. Studies can be split into different groups according to the methods, data analysing forms, data sets, the input variable and hourly/half-hour forecast. But, generally in review studies, they are grouped according to the methods. The used methods can be divided into three as statistical methods, artificial intelligence methods and hybrid methods. The most commonly used techniques are based on Regression models [4], Times series models [5], [6], ARIMA models [7], Artificial Neural Network models [8], [9], Fuzzy models [10], [11], Support vector machine models [12], Particle swarm optimization models [13], Genetic algorithm models [14], [15], wavelet transform [16], ANFIS [11].

This paper focuses on a hybrid method based on the combination of artificial bee colony (ABC) and artificial neural network (ANN) for short term load forecasting. Firstly, the data is

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analysed to create an accurate forecasting model and then the system inputs are determined. Historical load, temperature difference and season are selected as model inputs. While three-year hourly data is selected as training data, one year hourly data is selected as testing data.

The rest of the paper is organized as follows. Section 2 presents data analysing. While Section 3 presents a hybrid method based on the combination of ABC and ANN and describes the method in details, the testing results are given in Section 4. Section 5 outlines the conclusion.

2. Data Analysis

In this study, 2009-2012 hourly load consumption of Turkey and daily mean temperature of some cities which have maximum load consumption is considered for forecasting data. While load consumption data are taken from Turkish Electricity Transmission Company (TEIAS), temperature data are taken from Turkish State Meteorological Service. The data of the first three years which can be seen in Fig. 1 are used for creating the forecasting model and the data of 2012 are chosen for testing the forecasting model. There are some factors affecting the amount of electricity consumption and we can group them as time, historical load, weather conditions, major events and random events.

2.1. Time Factor

One of the most important factors which affect the load consumption is time factor, and it can be divided into categories such as hour, day and season. Hourly load forecasting is carried out in this study, hour factor is not considered as a model input. While day factor is discussed by grouping the week days, season factor is considered as an input for forecasting model. The hourly load consumptions of three consecutive weeks are shown in Fig. 2. As can be seen from Fig. 2, load consumption trends of each days are similar with the same day which is in the neighboring weeks. But daily load consumption trends are different from each other. The early hours' consumption of Monday is very low compared to the others, so Monday is selected as the first day

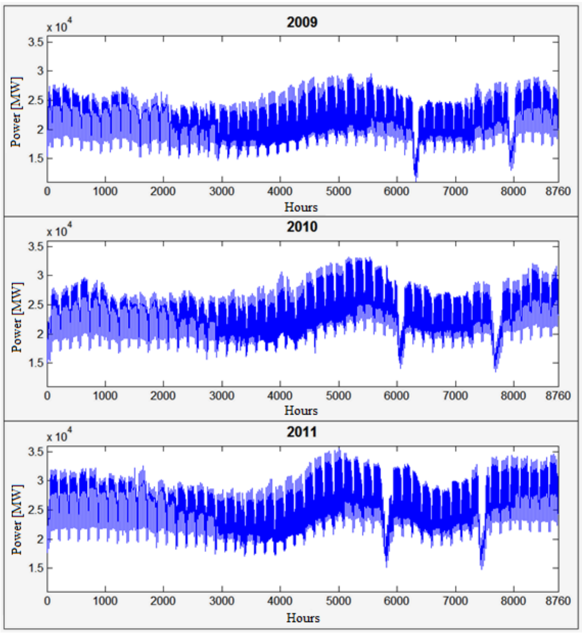


Figure 1. Hourly electrical load data of Turkey

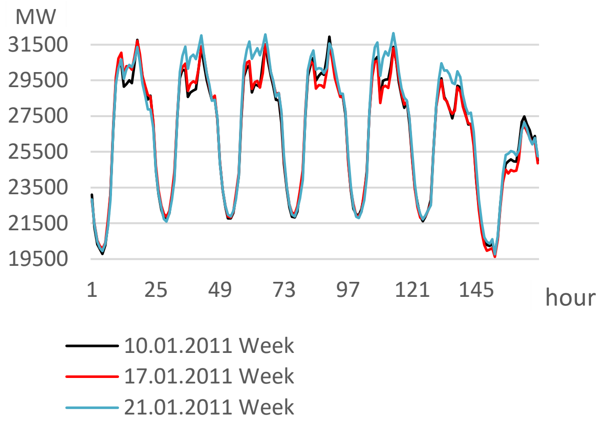


Figure 2. Three consecutive week's hourly electricity consumption

type. Tuesday, Wednesday, Thursday and Friday daily load rhythms are similar with each other, therefore these days are named as Weekday day type. Saturday and Sunday load curves are unlike any other and each other. Thus, more day types named as Saturday day type and Sunday day type are created. So we have grouped the days in 4 day types as Monday type, Weekday type, Saturday type and Sunday type.

Seasons are also acts as time factor for short term load forecasting. Although load consumption changes according to the geography and people's usage habits, the seasons affects meteorological variables and load consumptions. For example Turkey is a country located in the northern hemisphere. The use of electricity increases for heating purposes in winter with decreasing temperature in the air. On the contrary, the use of electricity decreases with increase temperature. In summer, it also has an opposite relationship. When the temperature rises in summer season people need to cool down and run their air conditioners and as a result electric consumption increases. In autumn and spring season, the season effects seem as a transition condition between winter and summer. In summary, season is also a time factor which affect the load consumption and we consider season as an input for short term load forecasting.

2.2. Historical Load Factor

The most important factor is historical load for short term load forecasting and the most of the studies in literature use the historical load as an input. As seen in Fig. 2, load curves are similar to load curves of previous week and next week. Forecasting accuracy increases by taking account previous 1-3 week load values in account, because load consumption trend does not change very much in short time period like 1-3 weeks.

2.3. Weather Factor

Weather factor is also important factor and these are temperature, humidity, wind speed and cloudiness. In literature studies, some various temperature data are used such as daily mean temperature, daily mean temperature difference, hourly temperature and hourly temperature difference. In this study, daily mean temperature difference is chosen as another input.

There are also some random developing major events such as earthquake, disaster and chaos which affect the load consumption, but such conditions are ignored in this study.

3. Forecast Method

3.1. Artificial Neural Networks(ANN)

Artificial Neural Networks (ANN) are the most used method for load forecasting in literature studies. ANN is a very successful method to find the relationship between inputs and outputs. Multilayer Feed Forward Neural Network has one input, one output and usually one or more hidden layers [17]. Each node connects to each other with weights. Each node has a duty to produce result with a transfer or activation function.
Output function calculation:

$$y_i = f_i\left(\sum_{j=1}^{n} w_{ij}x_j + \theta_i\right) \qquad (1)$$

Where f_i is the activation function and d w_{ij} is the weight of between two neuron such as input j to neuron i, x_j is the input neuron number, and θ_i is the bias neuron i.
Graphics of frequently used activation functions are illustrated in Fig. 3 and Fig. 4.
A system that has multiple input and one output is called neuron. Neurons form the network structure by combining. In this study, we used an ANN structure with two layers. The structure has input neurons, hidden layer neurons and an output neuron. Sigmoid function and linear function are used respectively for the hidden layer and the output layer.

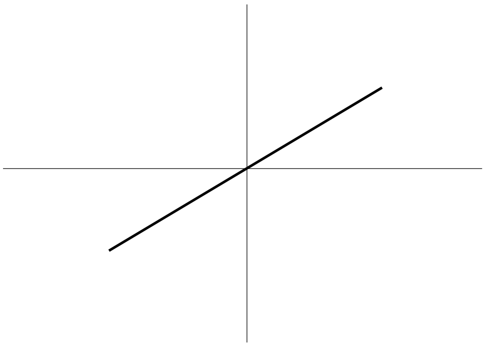


Figure 3. Linear activation function

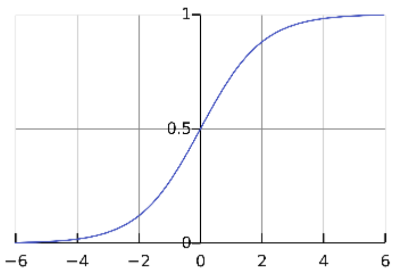


Figure 4. Sigmoid activation function

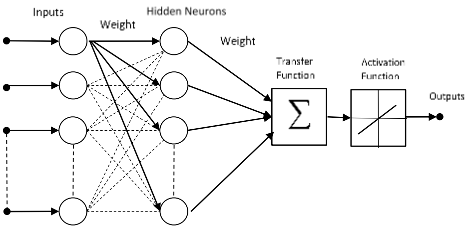


Figure 5. Network structure

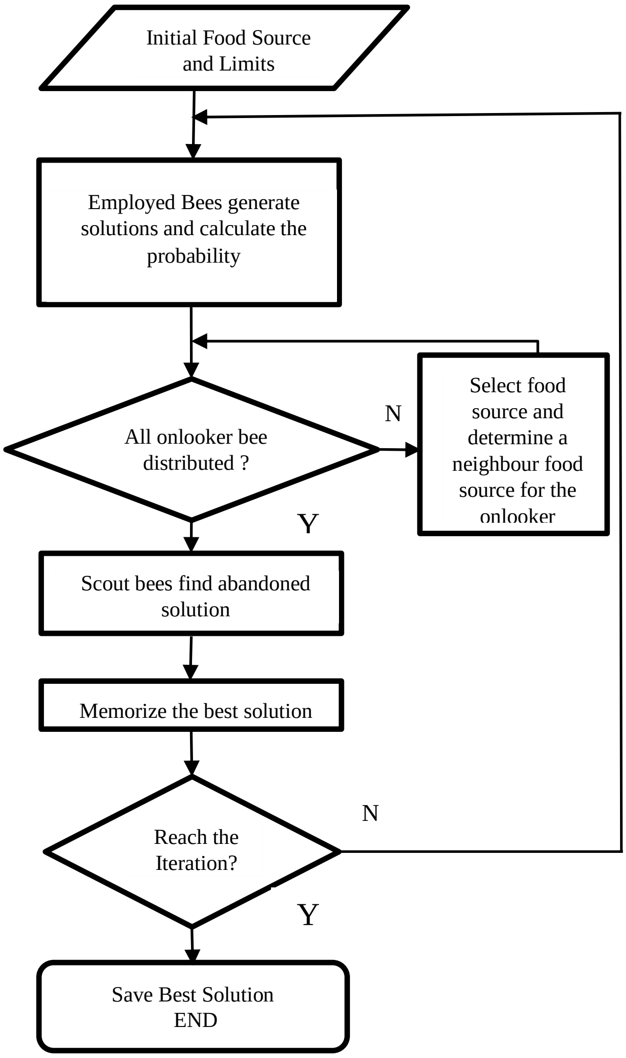


Figure 6. The flowchart of artificial bee colony

The difference between the result which is produced by the network and the target result contains generic information. Learning in back propagation algorithm provides the calculation of weights of network by adding half of the total error. This procedure continues iteratively until it reaches minimum error [18]. General network structure is shown in Fig. 5.
The formula of the total error is half of the total square error:

$$E = \frac{1}{2}\sum_{t=1}^{n}(desired_t - calculated_t)^2 \qquad (2)$$

The data is divided into two as test and learning data for the execution of the algorithm. The weights obtained at the end of the training have to include the entire training data. The training will be completed when the total error reaches its minimum value.

3.2. Artificial Bee Colony(ABC)

Artificial Bee Colony (ABC) algorithm is used as an optimization technique with relation between food and bees. There are three types of artificial bees and these are onlooker (observer) bees, employed bees and scout bees. The onlooker bees give information to the employed bees about food source and distance by dancing on the dance area. The employed bees visit the food source and collect nectar from these sources. The scout bees look for better resources by making a random search [19]. The working principle of the algorithm is shown in Fig. 6.

Artificial observer bees consider the probability value (pi) of the food source (fs) that is shown in Eq. (3), to decide the quality of food source [20]:

$$p_i = \frac{fit_i}{\sum_{n=1}^{fs} fit_n} \qquad (3)$$

fit_i indicates the fitness value of the calculeted solution and it is shown as;

$$\boldsymbol{fit_i} = \begin{cases} \dfrac{\mathbf{1}}{\mathbf{1}+\boldsymbol{x}} & \boldsymbol{if\ x \geq 0,} \\ \mathbf{1}+\boldsymbol{abs}(\boldsymbol{x}) & \boldsymbol{if\ x < 0} \end{cases} \qquad (\mathbf{4})$$

The source of nectar that is abandoned by the observer bee is replaced with new a source that is produced by the scout bee. Formula of the produced new source by scout bee is shown as;

$$x_i^j = x_{min}^j + \boldsymbol{rand}(\mathbf{0},\mathbf{1})(x_{max}^j - x_{min}^j) \qquad (\mathbf{5})$$

The every each food source is processed by employed bee and calculated solution is compared with the previous solutions.
If the new solution is equal or better, the previous solution is replaced by the new solution and saved on memory.

3.3. The Hybrid Model

Employed bees of ABC use the transfer function and the activation function to produce solution with artificial bee colony inputs. ANN total error value is calculated by the solution of ABC produced. Trained ANN by ABC is shown in Fig. 8.
Artificial Bee Colony and artificial neural network methods are utilized intensely on the literature. In this study, we have used a hybrid method that is combination of artificial bee colony and artificial neural network for short term load forecasting. As we mentioned before, the ANN deduces the relationship between inputs and outputs by updating network's weights and uses back propagation algorithm such as Levenberg-Marquardt and quasi-Newton for updating network weights. ABC is a swarm based optimization technique and proves their ability for optimization. The learning speed of ANN is increased by ABC since it reaches better resources.
The interface of the developed software is shown in Fig. 7. The software is developed using Borland Delphi programming language which is one of Pascal programming languages and the data is taken from excel file. The number of input neurons, the number of hidden layer neurons and the number of output layer neurons can be changed by the user. User also can choose the activation functions. Then, the weights of the ANN are calculated by the ABC algorithm while the software is running.
When the program loop reaches the iteration number, the user can test training and test data. Finally, weights can be saved as a text file.

4. Test Results

Generally in literature studies, Mean Absolute Percentage Error (MAPE) is selected to measure the accuracy of short term load forecasting. Because of this, we also use MAPE formula and it is defined as follows:

$$\boldsymbol{MAPE} = \frac{\mathbf{1}}{\boldsymbol{N}} \sum_{\boldsymbol{i}=\mathbf{1}}^{\boldsymbol{N}} \frac{\boldsymbol{P_{ac\,i}} - \boldsymbol{P_{f\,i}}}{\boldsymbol{P_{ac\,i}}} \qquad (\mathbf{6})$$

Where P (ac i) is the actual load, i is the hour, N is the sample number and P (f i) is the forecasted value. The best and the worst forecasted values for each day type are illustrated in Fig. 9.
Because we used artificial bee colony algorithm with artificial neural network, our program doesn't give same results for each run. Thus, we ran our software for ten times and the best, worst and mean MAPE values are shown in Table 1. We can say that weekdays have minimum error rate than the other day types by looking the results. The main reason of this situation that weekdays(Tuesday, Wednesday, Thursday and Friday) are consecutive days and each rhythms are similar each other than the other day types(Monday, Saturday and Sunday).
We can say that our software which is based on ABC and ANN can be used and give good results for hourly short term load forecasting. The learning feature of the ANN and the searching feature of ABC are merged and the mean MAPE results are obtained as 2,87 for Monday, 1,82 for Weekday, 2,35 of Saturday and 2,35 for Sunday for 2012. These results can be seen in Table 1. The number of forecasted hours are 1200, 4848, 1176 and 1200 for Mondays, Weekdays, Saturdays and Sundays, respectively. In this study, any load forecasting for official and religious holidays have been neglected.

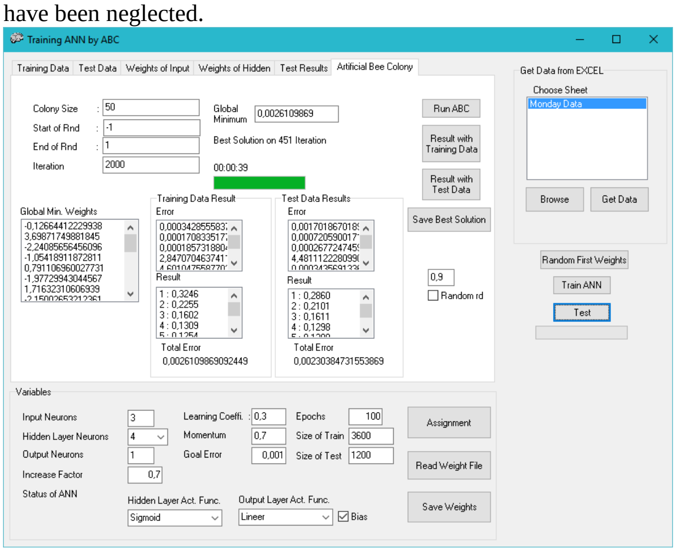


Figure 7. The interface of developed software

Table 1. MAPE errors of hybrid model

Day Type	Best Result	Worst Result	Mean
Monday	2,772661	3,020512	2,878151
Weekdays	1,720396	1,963968	1,824199
Saturday	2,628132	2,774447	2,351175
Sunday	2,652428	2,833766	2,351175
Weighted average			2,125328

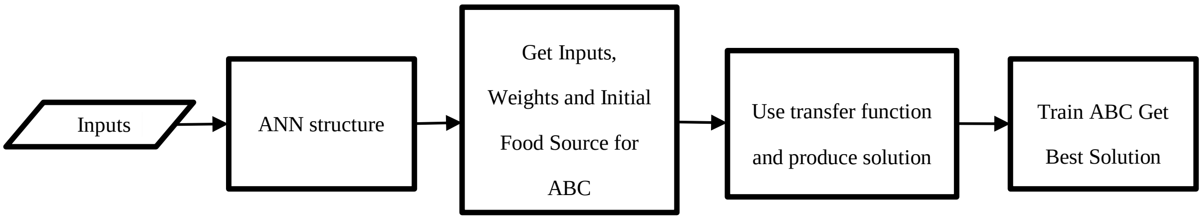
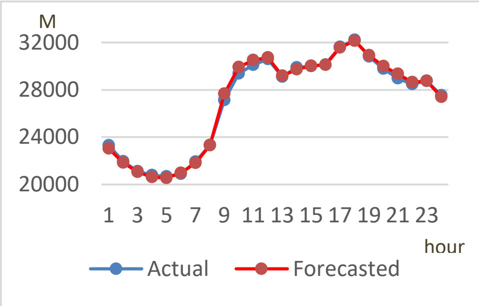
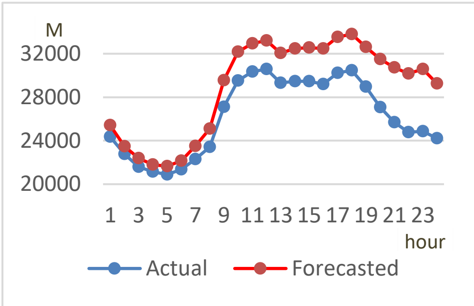


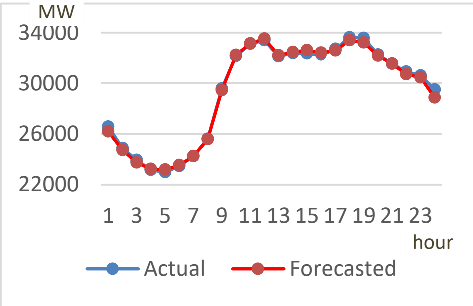
Figure 8. The flowchart of trained ANN by ABC

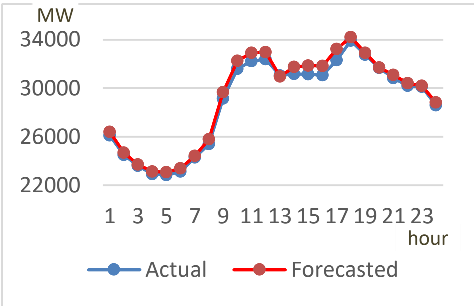




(a) Best Result for Monday Day Type - 03.12.2012

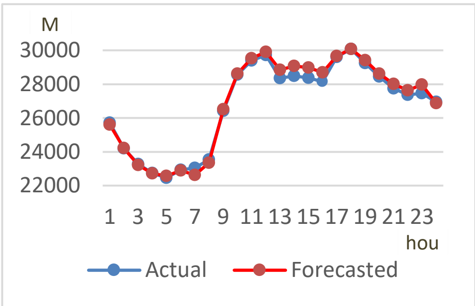
(b) Worst Result for Monday Day Type - 31.12.2012

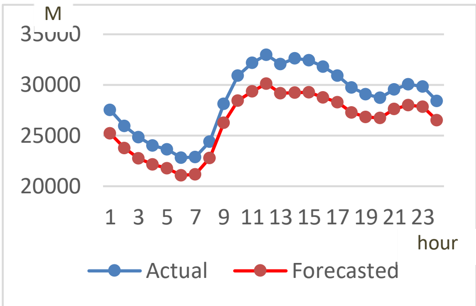




(c) Best Result for Weekday Day Type - 16.02.2012

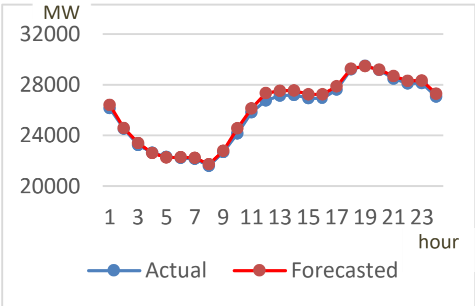
(d) Worst Result for Weekday Day Type -

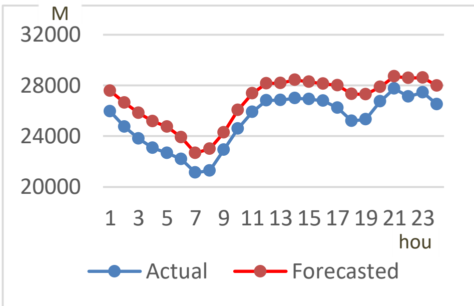




(e) Best Result for Saturday Day Type - 01.12.2012

(f) Worst Result for Saturday Day Type -





(g) Best Result for Sunday Day Type - 29.01.2012

(h) Worst Result for Sunday Day Type -

Figure 9. Actual and Forecasted values

5. Conclusions

This paper presents a hybrid method based on the combination of artificial bee colony (ABC) and artificial neural network (ANN) for hourly load forecasting. ABC algorithm is used in ANN learning process and it optimizes the neuron connection weights of the ANN. Historical load, temperature difference and season, the factors affect the load consumption, are selected as model inputs. While three years hourly data is selected as training data, one year hourly data is selected as testing data. The results show that the hybrid method can perform efficiently.

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