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Enhancement the accuracy of daily and hourly Short Time Load Forecasting using Neural Network

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ABSTRACT

In this paper neural network has been attended for short-time load-forecasting, and forecasted results have tried to be more exact by suitable selecting of effectual factors on load forecasting. It also has been tried to increase results accuracy of load forecasting for off-days. The results obtained from load forecasting, here done by both daily and hourly method, are presented and finally these two methods are comprised with each other. Furthermore, a parameter as reliability of load-forecasting is proposed in this paper for these two methods, that forecasting results accuracy level can assessed by using this parameter.
KEY WORDS: Artificial Neural Network (ANN), Back Propagation (BP), daily and hourly model, reliability of load-forecasting, Short-Time Load Forecasting (STLF).

INTRODUCTION

The first and main step in planning and designing power systems, is to have enough information of electrical energy consumption level and increment of this consumption at different times of the year and at different places. Requirement to have such information has led to discussing the load forecasting. According to the aims of load-forecasting, this prediction is done in three forms, short-time, mid-time and long time.

Short-time load-forecasting (STLF) that attended in this study is for short times and usually estimate hourly load. This form of load estimation plays an important role in power systems utilizing, as it is used for planning the Entry and exit of generation units (regarding to these units generating limitations and network limitation), optimum load flow, contingency analysis, short-circuit studies and also analyzing the power system stability. Load forecasting mainly done in two methods:

1) Statistical methods
2) Artificial Intelligence methods.

Mathematical relations is achieved by using the historical data for load-forecasting in statistical methods, but since relationship between electrical energy consumption and its effectual factors is strongly nonlinear and complicated, therefore these mathematical models are very complicated for load-forecasting, and sometimes the results won't be such satisfactory. Human thinking, learning and reasoning method is used for load-forecasting in artificial intelligence methods. Statistical and also artificial intelligence methods each one includes several methods that are introduced briefly in Ref. [2]. In this reference a model of regression tree is used for load-forecasting.

But in recent years, intelligent neural networks have been attended for load-forecasting in different areas. In facts, intelligent neural networks have removed the necessity of mathematical relations for defining load model which is so complicated and nonlinear. In most recent studies it has tried to improve the accuracy of load-forecasting results using neural networks, as much as possible. In order to this, they applied different solutions like determination of effectual parameters on electrical energy consumption for different areas or countries with different cultures, traditions and religions for load-forecasting.

Second solution is to improve the neural network structure, such as changing the number of neurons of hidden layers, and changing its transfer function. The other solution that used more than others, is to divide a year into four season and each season to several groups, a week into several parts (like Ref. [2]), and a day in to same different periods, though the number of neural networks that used for load forecasting increased.

In Ref. [4], the data which are related to weather condition including the temperature and weather moisture levels are also used for load forecasting. In order to this, at first, the weather temperature of specified day predicted by using a separated neural network. Similarly, another neural network, predicts weather moisture level of that day, and finally the results which obtained from these two neural networks will be used as input data for the main neural network, that forecasts the load of specified day. But in this study, the parameters related to temperature have been eliminated for load forecasting, therefore there is no necessity to separated neural network for weather temperature predicting. Therefore, some changes are applied to input parameters of neural networks in the way that results accuracy of load forecasting doesn't reduce.

Ref. [5] has verified one hour-ahead load forecasting. In this reference the forecasted load power is obtained by adding a correction to the selected similar day data.

In the Ref. [6] a hybrid AIS(artificial immune system) is proposed, which is a combination of back-propagation with AIS to get faster convergence, lesser historical data requirement for training with a little compromise in accuracy.

A novel Recurrent Neural Network (RNN) is also proposed in Ref. [8].

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In the Ref. [1] short-time load-forecasting is attended by using both daily and hourly models. In this reference, back-propagation (BP) method has been used for training specified neural network(that is a three-layer network) and for this purpose it has used the load data in Iran(2003-2005) as learning data.

Also, in this reference, in the daily model only one neural network has been used for load forecasting and in the hourly load forecasting model, the daily model is divided into 24 separate neural network. But in this reference, the effect of religious and special off-days has not been regarded. Also for load forecasting, the 24 hour-ago load has been used as an effectual factor on predicting, while for some special days such Friday and Saturday, last day load is different from the other week days(in Iran and some Islamic countries Friday is the weekend). These problems cause to increase the error levels of load forecasting.

In this paper, some changes are applied in comparison with other works in order to improve the results of load forecasting, like considering the effects of religious and special off-days(except Fridays) on load forecasting. Also in this study, two neural networks are used in daily model. Also, for hourly model, against the Ref. [1] where 24 neural networks has been designed, there are 24 neural networks designed for each day of week, and therefore totally 168 neural networks for a week in this paper. Furthermore, here more wide data has been used for network training, this data is Iran consumptive load at 1994-2005. These changes and also other changes which will be explained at the following, cause to reduce error levels of load forecasting. Also, another parameter called as “reliability of short-time load forecasting” has been suggested for more exactly verifying the accuracy levels of results obtained from load forecasting.

USING NEURAL NETWORK FOR SHORT-TIME LOAD-FORECASTING

Neural networks usage for load forecasting has been attended regarding to its convenience. Important problem in using neural network for load forecasting is using proper structure for this network, using proper method for its training, and more exact determination of effectual factors on consumptive load levels. These factors are neural network's input data and if they are not determined correctly, the results obtained from predicting won’t have enough accuracy. In following, the proposed neural network which is used in this study and the method of its training and selecting the effectual factors on prediction is introduced. An introduction of ANNs and STLF has been explained at Ref. [7].

The structure of used neural network

Generally, three layer perception neural networks are used for load forecasting. The structure of this neural network is demonstrated in Fig. 1. The number of input neurons depends on the number of effectual factors. As demonstrated in the Ref. [1], selecting proper number of mediate layer neurons is also very effective on accuracy levels of predicting. Therefore determining the number of neurons of this layer is one of the most important parts of neural network designing. Also the number of output layer neurons depends on the type of forecasting (hourly or daily forecasting).

In this study, linear transfer function for input and output layers, and sigmoid transfer function for mediate layer has been used. As explained in following, 2 neural networks has been designed for short-time load forecasting using daily model with the structure of demonstrated ANN in Fig. 1, and 168 neural networks in the hourly model with the same structure.

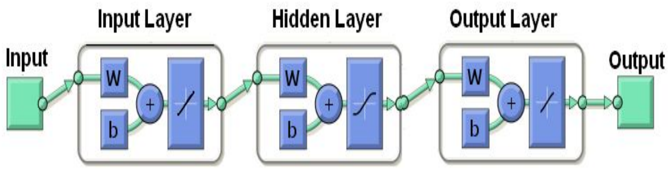

Fig. 1. The structure of three layer neural network used for STLF

Determination of effectual factors on load forecasting

The most sensitive step in designing neural network used in load forecasting, is determining the effectual factors on forecasting. These factors in fact are the inputs of neural network.

In Ref. [3] the following input data attributes has been used:

1) Month of the year
2) Day of the week
3) Holiday
4) Week number

In Ref. [1] effectual factors on load forecasting, have been chosen as follow:

1) Year
2) Week’s day
3) Last-day load
4) Last-day average temperature
5) Last-day maximum temperature
6) Last-day minimum temperature
7) Predicted average temperature for present-day
8) Predicted maximum temperature for present-day
9) Predicted minimum temperature for present-day

Although, temperature parameters of present-day and last-day are some of effectual factors on load forecasting, but having these data related with weather temperature (Specially predicting the temperature of present-day) is a problem of this type of input.

According to these cases, in this study, related parameters to weather temperature have been ignored and instead of that, a simple parameter "summer day" has been used. This parameter with regard to that specified day, which day of summer it is, is a digit between 1- 93 and as it is shown in the next parts, this parameter could be a proper replacement for weather condition parameters.

The other problem in determining these parameters is that last-day load is different for Sundays to Thursdays in comparison with Fridays and Saturdays. Note that Friday is the weekend, in Iran and some other Islamic countries. For Sundays to Thursdays that are usual days, last-day of them also is usual day. But for Friday that is an off-day, the last-day(Thursday) is an usual day, and so on, for Saturday that is an usual day, last-day(Friday) is an off-day. Therefore using last-day load is not a good parameter for load-forecasting in all days of the week. Therefore, if last-day load is used as one of the effectual factors on load-forecasting, designing a single neural network for all days of the week, would reduce the prediction results accuracy. In order to solve this problem in this study, two separate neural network models have been designed for daily model. Model 1, is a neural network that is used for load forecasting of Sunday to Thursday, in which the last-day load is considered as one of the input parameter. But in model 2, that has been designed for load forecasting of Fridays and Saturdays, the load of same day in last week (7 days ago) is considered as one of the input parameters, it means that for Friday, the last-Friday load is and for Saturday, the last-Saturday load is used for load forecasting.

According to the mentioned cases, neural network input for daily model 1 and 120 models of 168 hourly models (that are designed for load forecasting of Sundays to Thursdays) are selected as follow:

1) Year (1994-2006)
2) Day of the Summer(1-93)
3) Day of the week (1-7)
4) Hour of the day (1-24)
5) Last-day load in the same hour

And so on, parameters of inputs for model 2 are selected as follow:

1) Year(1994-2006)
2) Day of the Summer(1-93)
3) Day of the week(1-7)
4) Hour of the day (1-24)
5) Last-week load at the same day and the same hour.

With regard to that designed neural networks for Saturday and Friday load forecasting, are separated from each other, the same input parameter like model 1 can be used for the first 48 models of 168 hourly models. As it is obvious in these two models, the year and hour of day are also considered as other effectual factors on load forecasting in the same hour. 1 to 7 numbers are used for Friday to Thursday respectively.

Normalizing the inputs

With regard to using sigmoid functions in neural network, normalizing the input vectors are done in the way that all of these vector's components put into the range of [0-1]. In this study, we used equation (1) for normalizing data, like Ref. [1]:

$$x(k)_i = \frac{x(k)}{\max(x(k))} \tag{1}$$

Where, x(k) is input vector's component.

Training the neural network

In this paper, back-propagation (BP) method is used for neural network training. In order to control training process and better observation of training stages, BP Algorithm program has been written in MATLAB as m-file, instead of using Neural Network Toolbox of MATLAB.

Power consumption of Iran in 1994-2005 is used as learning data for training neural network and abnormal data is removed. Considerable note in this data, is religious off-days(holidays) and other special off-days that should be assessed, because otherwise neural network training doesn't go well, and results error from load forecasting, will increased. The number of such days in summers of 1994-2005 is 34 days which is about 3% of training data and is very high. Therefore to resolve this problem, in this study, holydays and other special off-days are considered like Friday and the day after these days like Saturday, that finally has led to improved predicted results.

Also, with regard to the different consumption pattern in the Ramezan month, we should consider the effects of this parameter on load forecasting (Ramezan is a special month with different condition for muslim countries), but since during 1994-2005, Ramezan month hasn't interfered with the summer, this parameter is presently ignored.

Accuracy analysis of forecasting using definition of some parameters for determining the error and reliability of forecasting

In order to control training process, Mean Absolute Percentage Error (MAPE) is used as defined in equation (2):

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{|X_t - X_f|}{X_t} * 100$$

(2)

Where, x_t is real load and x_f is forecasted load by neural network.

The parameter MAPE in BP algorithm is used for specifying that when the training process get in steady state. After training neural network also, this parameter is used for verifying the accuracy of results of forecasting.

It is obvious from equation (2) that only having a low MAPE doesn't mean that load forecasting is reliable. Because there is an averaging in equation of MAPE and level of deviation from mean error should be considered.

For example, if calculated MAPE equals to 1% for an period that is a summer season (N=93*24), deviation from MAPE May equal to 3% in some days. In fact, to ensure load forecasting results in used method, we need more reliability. Therefore, in this study, another parameter suggested for verifying forecasting reliability. For this purpose, in a cycle, that MAPE is calculated for(a summer season), the ratio of number of errors that their absolute are less than a special value to total number of hours in a summer, suggested as reliability of forecasting(FR). According to this definition, 4 parameters of reliability are considered as equations (3):

$$\begin{cases} FR\_2000 = \dfrac{\{\ Number\ of\ Errors\ |\ \ |Error| < 2000\ \ MVA\ \}}{93*24} * 100 \\ FR\_1500 = \dfrac{\{\ Number\ of\ Errors\ |\ \ |Error| < 1500\ \ MVA\ \}}{93*24} * 100 \\ FR\_1000 = \dfrac{\{\ Number\ of\ Errors\ |\ \ |Error| < 1000\ \ MVA\ \}}{93*24} * 100 \\ FR\_500 = \dfrac{\{\ Number\ of\ Errors\ |\ \ |Error| < 500\ \ MVA\ \}}{93*24} * 100 \end{cases} \tag{3}$$

Where, FR2000, FR1500, FR1000, FR500 are reliability coefficients of STLF which their related "Error" parameter calculated by using equation (4):

$$Error = real\_load - forecasted\_load \quad (MVA) \tag{4}$$

In above equations, selecting numbers 500, 1000, 1500, 2000 is done with regard to Iran power consumption level. Finally according to this definition, less MAPE and larger FR cause to more proper and more exact load forecasting

SIMULATION RESULTS

As mentioned above, for training the neural network, used in this study, load data of Iran network in 1994-2004 is used.

The learning data after normalizing, is applied to neural network randomly, and after some defined iterations in a period, the training process will stopped, and the 2005-summer data(which is one part of learning data) is applied to neural network for verifying forecasting accuracy level, and MAPE value will be calculated for this season. If MAPE is less than the value user defined, training process will be stopped, and the network will be ready for load-forecasting for summer 2006 and next years. Otherwise, network training will continue, and after the same defined number of training iteration, MAPE will be calculated again, and this training will continue until MAPE value be less than the value defined by user. Of course, maximum number of iterations also defined by user that if MAPE doesn't converge, training process won't continue more than these numbers of iterations.

In training stage, the learning rate equals to 0.018, and the number of hidden layer neurons equals to 20 neurons (this number of neurons are selected after some training stage with different number of neurons). Primary values are selected randomly and small for weigh matrix and bias of specified neural network, equation (5).

$$\begin{cases} |W_i| \le 0.3 \\ |b_i| \le 0.3 \end{cases} \tag{5}$$

After training specified neural networks, summer 2006 data will apply to the trained network for final test of network, MAPE calculating and FR. In following, at first the results of each model of load forecasting (daily and hourly model) and then analyzing and comparing results of these two methods will be presented.

Daily model for STLF

As previously mentioned, two models designed for short-time load forecasting, model 1 and 2, that model 1 estimates Sundays to Thursday load and model 2 estimates Fridays and Saturdays load,

Fig. 2 indicates MAPE changes during training process for that neural network which lonely used for load forecasting of all of the week days. As it is obvious from this figure, MAPE value converged to approximately %3.35 by using this neural network in the training process for summer 2005 and this value is very high. After training stage also applying summer 2006 data causes that MAPE Value reached to 3.45. Error curve for summer 2006 load forecasting has shown in Fig. 3. As it is obvious from this figure, error of load forecasting for Saturday and Friday is much more than the other days. So, using only one neural network for load forecasting of all of the week day is not satisfactory.

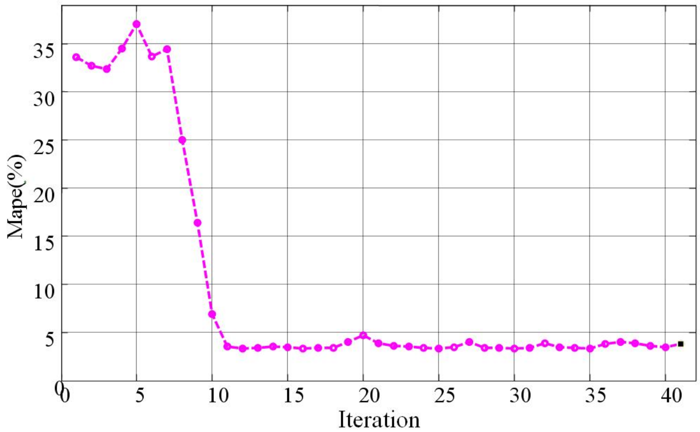

Fig. 2. MAPE changes during neural network training which forecast the load of all of the week days

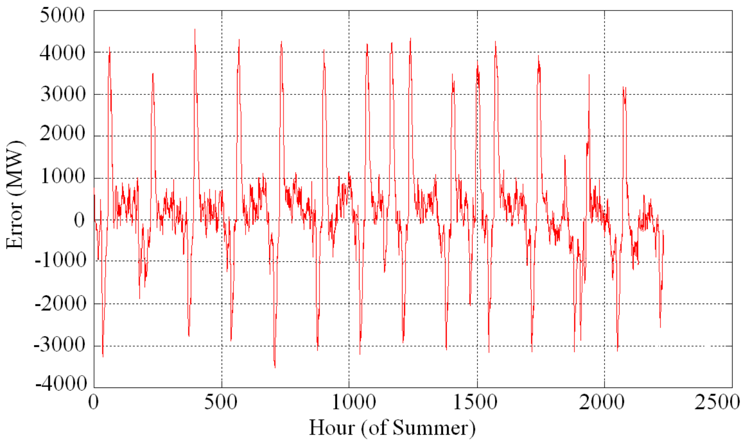

Fig. 3. Error level of load forecasting in summer 2006 by the Neural Network which forecasts all of the week days

Fig. 4 shows MAPE changes, during neural network training of model 1 as previously explained, this neural network, forecast the load of Sunday to Thursday. In this state, MAPE during training is converged to 1.3 % for Sunday to Thursday of summer 2005.

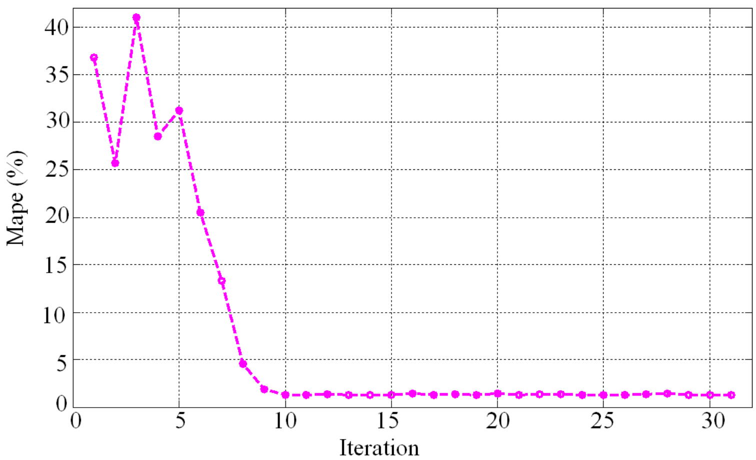

Fig. 4. MAPE changes during neural network training in mode 1

Error level of load forecasting for Sunday to Thursday of summer 2006 by model 1 is shown in Fig. 5. In Fig. 6 also the real and forecasted load are shown in this period.

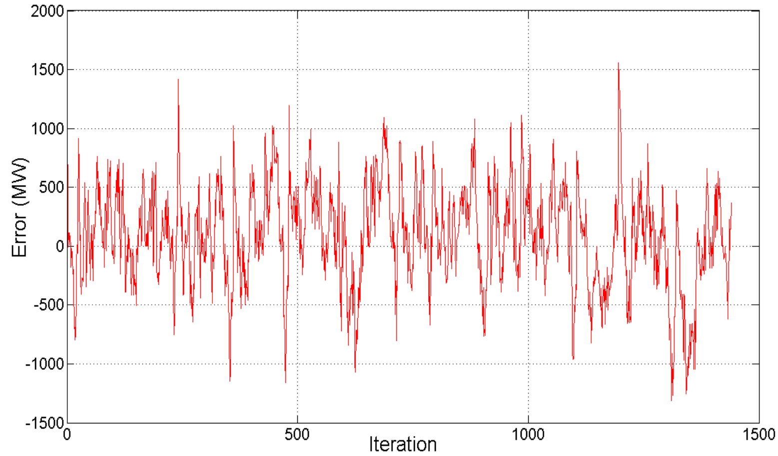

Fig. 5. Error level of load forecasting for Sundays to Thursdays of summer 2006 by model 1

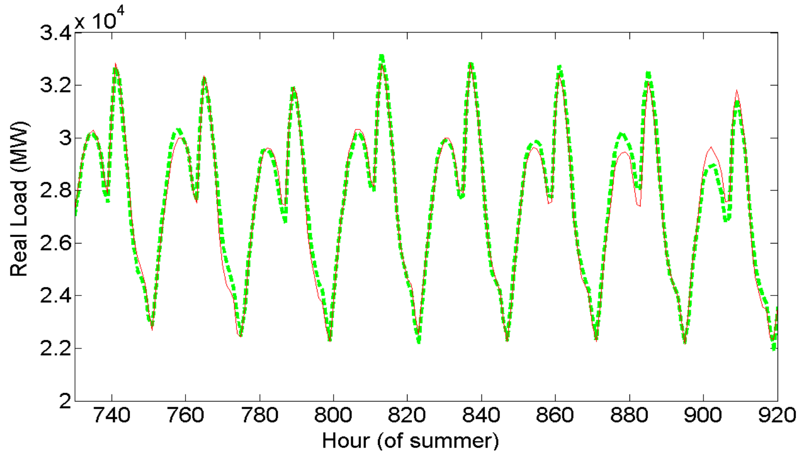

Fig. 6. Forecasted and real load by model 1 for Sundays to Thursdays of summer 2006

Fig. 7 shows MAPE changes during training of model 2. This network forecasts the load on Fridays and Saturdays. In this case, MAPE during training converges to 2% for Fridays and Saturdays of summer 2005.

In figures 8, and 9, error of load forecasting and forecasted and real load of Fridays and Saturdays of this summer are demonstrated.

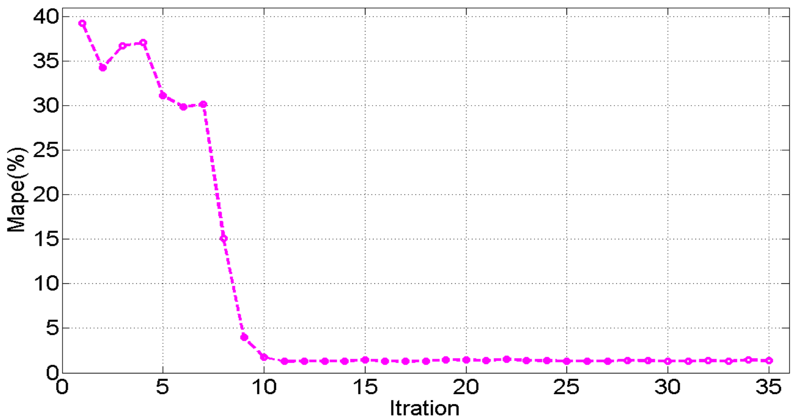

Fig. 7. MAPE changes during neural network training of model 2

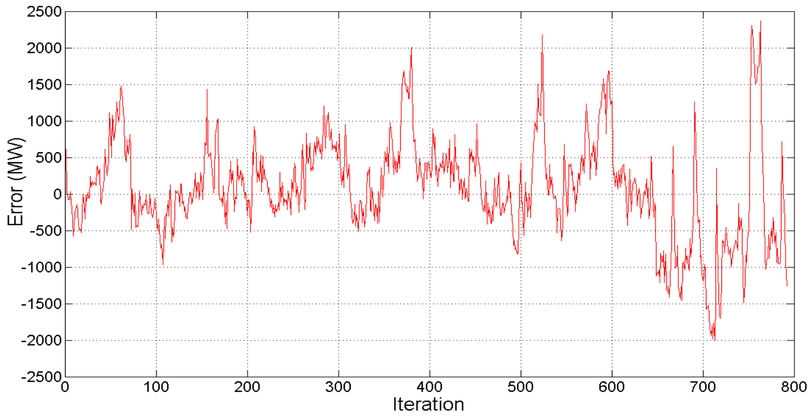

Fig. 8. Error level of load forecasting for Fridays and Saturdays of summer 2006 by model 2

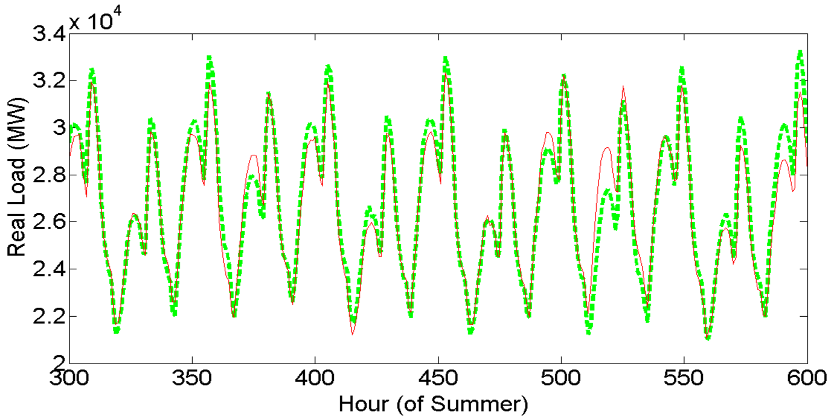

Fig. 9. Real and forecasted load for Fridays and Saturdays of summer 2006 by model 2

Hourly model for STLF

In hourly short-time load forecasting, as mentioned previously, 168 separate neural networks are used for load forecasting of each one of 168 hours of week. Although the training these number of networks is time consuming, but the results obtained by them are more satisfactory. Since, demonstrating MAPE convergence of these 168 neural networks is impossible here, therefore, only final results and total error of these networks for summer 2006 is presented. Fig. 10 shows hourly real and forecasted load of summer 2006 by these 168 neural networks. In fact the results, obtained from these 168 neural networks, put together to achieve total load model as shown in figure10. Similarly, Fig. 11 shows the error of load forecasting of this summer that is produced from 168 networks.

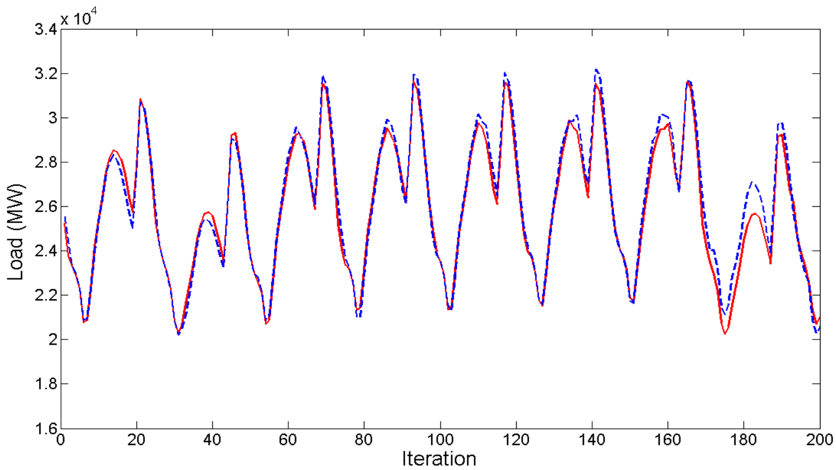

Fig. 10. Real and Forecasted load by 168 hourly models for summer 2006

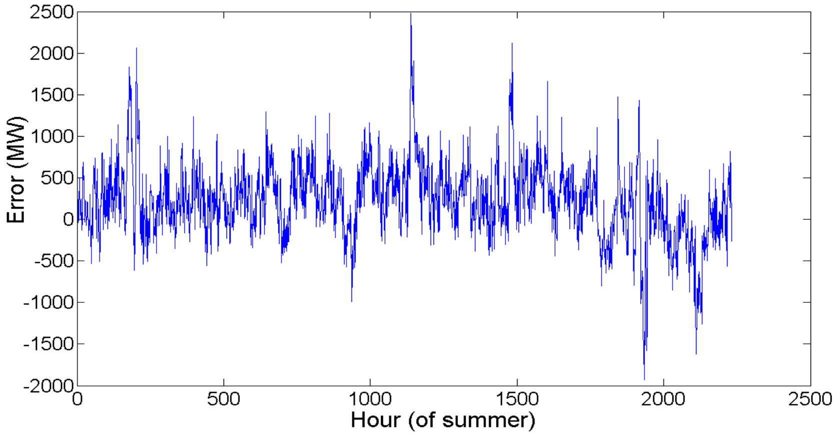

Fig. 11. Error level of load forecasting for summer 2006 by 168 hourly neural network models

Results analysis and comparing both methods of short-time load-forecasting (hourly and daily model)

Considering the difference of Saturday and Friday compared with other week days, designing a separate neural network is necessary for these days in order to reduce forecasting error and increasing FR, and it is considered in both hourly and daily models. Otherwise, as shown in Fig. 2, error level will increase highly.

To compare both STLF methods (hourly and daily), the results of two methods are listed in Table I, and the best results are specified as colored. As it is obvious from this table, if model 1 and 2 are used for load forecasting of all week days at summer, in comparison with the case that 168 models has been used, all parameters of load forecasting accuracy (Overall_MAPE, Overall_FR_2000, Overall_FR_1500, and Overall_FR_1000) are more weak, so if using only one models of hourly and daily load forecasting would be desirable, hourly load forecasting model will have better results (brown color).

But if combination of these two hourly and daily models usage is desirable, for Saturdays and Fridays in summer, load forecasting detected more better results by 48 hourly models (yellow color).

We should think more for other week days, because at many cases, results of two methods are near to each other.

Better results are determined by yellow color in this table. Caring on these results, it can be seen that the difference of MAPE, FR_2000, FR_1500 are negligible for two methods. Therefore, FR_1000 and FR_500 are determinant, and so hourly model seems to be more desirable. Totally, hourly load forecasting is a better method for load forecasting of all of week days.

TABLE I
COMPARING THE MAPE AND FR FOR BOTH MODELS 1 AND 2 AND 168 HOURLY MODELS

Hourly STLF		Daily STLF		
48 models (Saturday and Friday)	120 models (Sunday to Thursday)	Model 2 (Saturday and Friday)	Model 1 (Sunday to Thursday)	
1.73 %	1.31 %	2.00 %	1.24 %	MAPE
99.72 %	99.87 %	99.12 %	100.0 %	FR_2000
99.45 %	99.80 %	95.33 %	99.93 %	FR_1500
95.02 %	98.81 %	86.74 %	97.36 %	FR_1000
73.99 %	80.96 %	61.24%	75.55 %	FR_500
1.45 %		1.52 %		Overall_ MAPE
99.82 %		99.69 %		Overall_FR_2000
99.69 %		98.30 %		Overall_FR_1500
97.58 %		93.59 %		Overall_FR_1000
78.71 %		70.47 %		Overall_FR_500

CONCLUSION

In this study, two models of STLF (hourly and daily model) analyzed, and In order to better forecasting, some changes applied in comparison with other studies, like considering the effect of religious off-days(holidays) and other special off-days(except Fridays) on load forecasting. As discussed, without doing this work, in fact, a percent of incorrect learning data in the training neural networks will be used and final forecasting error will increase. Designing two separate neural network models, one for load forecasting of Fridays and Saturday and another for load forecasting of Sunday to Thursday, are the other applied changes in this study that caused to high improvement in results.

Although last-day weather temperature and temperature forecasting at present day are effectual factors in load forecasting, but in this study it is assumed that information related to weather temperature is not available. In fact, considering the parameters related to weather temperature will reduce error level of load forecasting and FR, achieved in this study.

Finally, to assess load forecasting accuracy level, a parameter as Forecasting Reliability (FR) was defined in addition to MAPE parameter, which make it possible to compare the results of these two hourly and daily models and select more proper option. By using these two parameters of load forecasting, hourly model is detected better results in comparison with daily model and presented as more proper model for STLF.

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