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Short Term Load Forecasting using Multi-layer Perception and Fuzzy Inference Systems for Islamic Countries

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Abstract: Short Term Load Forecasting (STLF) has received more and more attention during the last two decades because of economic reasons. In this study, for initial forecast we have developed a proper Multilayer Feedforward Neural Network (NN). This network has three layers and its parameters are tuned by Levenberg-Marquardt Bock Propagation (LMBP) augmented by an Early Stopping (ES) method to enhance speed of convergence of the learning algorithm. For abrupt weather changes and special holidays, a Fuzzy Inference System (FIS) has been also designed to improve the forecasted load appropriately. To show the effectiveness of the proposed method, some real experimental data taken from some Iranian electrical company have been considered in this study for the purpose of simulation. The results were very promising.

Key words: Fuzzy inference systems, multilayer perception, neural network

INTRODUCTION

Quick and accurate load forecasting is very important for power system operation. Furthermore, it is vital for economic dispatch, hydro-thermal coordination, unit commitment, transaction evaluation and system security analysis among other functions. Market operator, transmission owners and generation plants are the most customers for these predictions that continuously demand for a more reliable and more robust Short Term Load Forecasting (STLF) technique.

STLF has received more and more attention during recent years because of its importance. Many researches have been extensively established diverse techniques to obtain more acceptable load forecasts. In the literature, statistical methods such as auto-regression and time series have been used broadly for STLF. A lot of models using classical techniques were created during last decades, such as Box-Jenkins models, ARIMA models, Kalman filtering models and the spectral expansion techniques-based models. All of these techniques work well on normal conditions but they lead to incorrect results when there are unusual changes in environmental parameters or other effective parameters in STLF. Extreme complicated relationships that lead to immense mathematical operations for load forecasting are one of the most important defects of these techniques. Time-consuming for load forecasting, intrinsic inaccuracy and numerical instability are other their deficiencies (Hagan and Menhaj, 1994).

In recent years, the usage of intelligent techniques has been increased noticeably for solving engineering problems. Artificial neural network and fuzzy systems are the two most powerful tools for solving engineering problems that can be used approximately in every prediction and modeling problem. It has been shown that they are universal approximators with capability of modeling every nonlinear system. Considering this capability, some researchers have designed ANN-based short term load forecaster. Contemporary load forecasting techniques, such as Artificial Neural Networks (ANN) (Dash *et al*., 1997; Vermaak and Botha, 1998; Papalexopoulos *et al*., 1994; Khtanzad *et al*., 1998; Moharari and Debs, 1993), wavelets (Zheng *et al*., 2000), fuzzy logic (Papadakis *et al*., 1998), (Senjyu *et al*., 1998), (Kassaei *et al*., 1999) , expert systems (Daneshdoost *et al*., 1998), have been developed recently, showing more acceptable results than traditional methods.

Although fuzzy logic models have a very excellent transparency, it is very time-consuming to regulate fuzzy model parameters to reach a good result. Therefore, it is reasonable to use them only when we need to infer like a human. In contrast, ANNs have an excellent automatic learning capability to improve their behavior from experimental data. In most practical cases, when you have enough empirical data neuro-based modeling is preferable.

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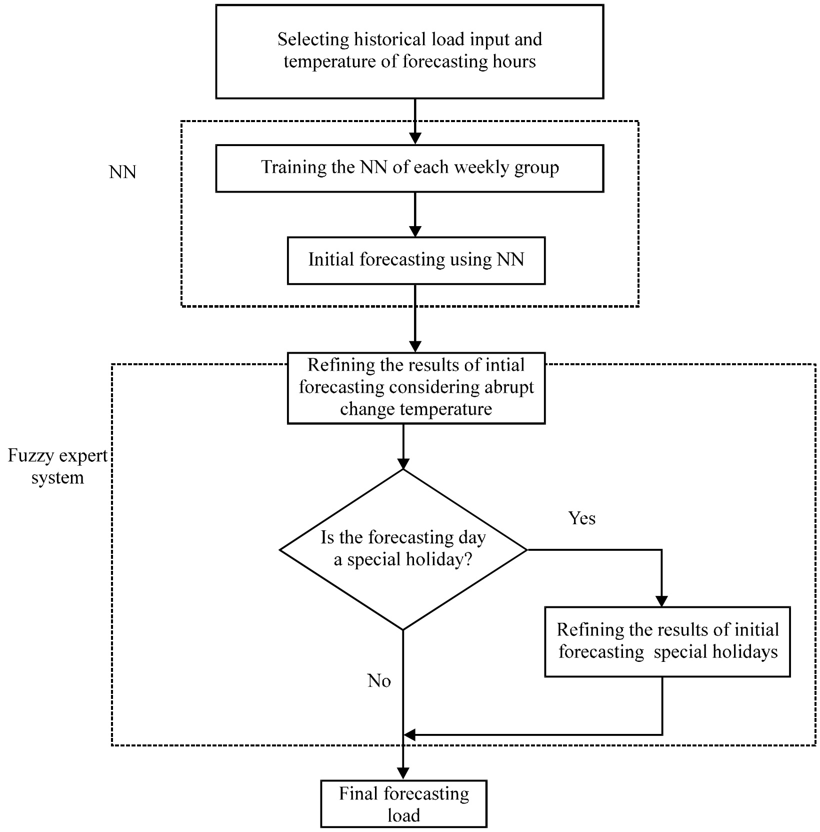

Fig. 1: Overall flowchart of the proposed forecasting method

In this study, we have designed a short term load forecaster that it benefits advantages of both ANNs and fuzzy systems. Flowchart of the proposed method is shown in Fig. 1. At first, we develop a multi-layer feed forward neural network that accurately predicts next hours load demands for usual days under normal weather conditions. We refine the results of the ANN using a fuzzy logic system properly developed for special days or for cases in which an abrupt weather change occurs in order to make the load forecaster more reliable and robust.

MATERIALS AND METHODS

Load characteristic: Load forecasting depends on several parameters such as historical load data, weather condition and day type (Drezga and Rahman, 1998; Barzamini *et al*., 2005). Inclusion of all these parameters in the forecaster yields more acceptable load forecasting results, However, it leads to massive computational operations. To establish an appropriate trade off between these objectives, we have divided weekly days into 4 categories (Barzamini *et al*., 2005). Each category has unique load lags. The load forecaster consists of four functions each described as:

$$L = f_i\,(LL_i, \text{month}, T) \tag{1}$$

where, i = 1,..., 4, LL_i and T denote load lags and temperature, respectively. Load lags inputs for each function are determined through correlation analysis.

Weather information includes cloud coverage, wind speed and temperature. Through some studies we have observed to improve the performance of the load forecaster, temperature information plays a crucial role. Therefore, we have considered temperature inputs of three cities in tropical, moderate, cold and hot areas as weather conditions prototypes in all cities.

The Month input as an extra input plays an important role to reduce the number of load neuro-forecaster. In previous studies such as (Moharari and Debs, 1993), they had to develop 16 load forecasters for 4 seasons and 4 weekly days' categories. But by considering this input, as shown in the next section we could reduce the number of load forecasters to 4 with remarkably better loads forecasting.

STLF technique by MLP neural networks: Neural networks have the capability of modeling any nonlinear unknown function using available input(s)-output(s) data. Also because of highly non-linear behavior of load forecasting systems, it is reasonable to use them to model load behavior. This section outlines the MLP neural network structure considered for load forecasting.

Figure 2 presents the general structure of the MLP used in the study. Each neuron in the hidden layer has a tangent sigmoid transfer function as:

$$f(x) = \frac{1-e^{-x}}{1+e^{-x}} \tag{2}$$

For avoiding saturation problems associated with the nature of tangent sigmoid neurons, it is vital to scale input and target signals to the range of [-1, 1] as follows:

$$X_{Normalization} = 2\frac{X_{Actual} - X_{Min}}{X_{Max} - X_{Min}} - 1 \tag{3}$$

where, X_{Max} and X_{Min} are the maximum and minimum values of the last 21 days which is obtained through a deep sensitivity analysis of the loads.

For each weakly day's group, developed a neuro-load forecaster with the structure given in Fig. 2 with inputs introduced in Barzamini *et al.* (2005). Input layer for hourly load forecasting of each weekly group has 13, 19, 16, 19 entries, respectively. In each case three inputs represent temperatures of three prototype cities (Fig. 2), one input is an integer number from 1-12 to show which month of the year is our concern and the rest of inputs are called load lags. Apparently, each designed network has a single output named forecasted load.

For training these neural networks we divided available inputs into three subsets, namely training subset, validation subset and test subset. At first, we used the training subset to train each network appropriately. Validation subset is applied to networks until the overall load forecasting error begins to increase. Learning method in these two stages is the Levenberg-Marquart Back Propagation that is noticeably faster than the standard back propagation method (Hagan and Menhaj, 1994). Finally, we verify the performance of the trained network through the third subset (test subset). It is shown in load forecasting examples that are using this training method considerably increases the accuracy of neural networks for load forecasting. The designed neuro-load forecaster simulator is then used for one hour up to a week load forecasting as shown in Fig. 3. The first hour load is forecasted and then it is used as one of the MLP load lag inputs for the

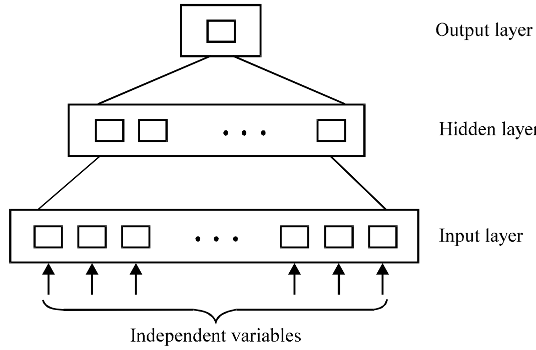

Fig. 2: The MLP architecture for each weekly group

prediction of the next hours' load. Consequently, the error of each hour load's forecast will influence the prediction of next hours' load.

Load forecast modification using fuzzy concepts: However, the designed neuro-simulator forecast precisely the load values in normal situations, it fails to operate successfully for two cases, namely abrupt changes in weather conditions and special holidays. The forecasted load in these days has a noticeable error in comparison with the forecasted values in normal conditions. Some modifications are required.

As shown in Fig. 4, a fuzzy system known as Modifier has been developed for this purpose, because we have a prior knowledge about effects of abrupt weather changes and special holidays on consumed loads and the transparency of fuzzy models is an impressive factor. The output of this modifier is:

$$MT = \frac{Load_{Actual} - Load_{Forecasted}}{Load_{Actual}} \tag{4}$$

The temperature changes in each season of a year influence the daily average temperature and consequently daily minimum and maximum temperatures. Three fuzzy variables T (average temperature), ΔT (average temperature changes), LtP (ratio of load to peak load), are defined in the temperature rule base. The terms of THam, TKho, TArk used in the rule base are the average temperature of Hamedan, Khoramabad and Arak cities, respectively in the forecasting day. Average temperature changes is defined as the difference between the daily average temperature of the forecasting day (T(i)) and the average temperatures of three days ago for those three cities (ΔTHam, ΔTKho, ΔTArk) and obtained as:

$$\Delta T(i) = T(i) - \frac{T(i-1) + T(i-2) + T(i-3)}{3} \tag{5}$$

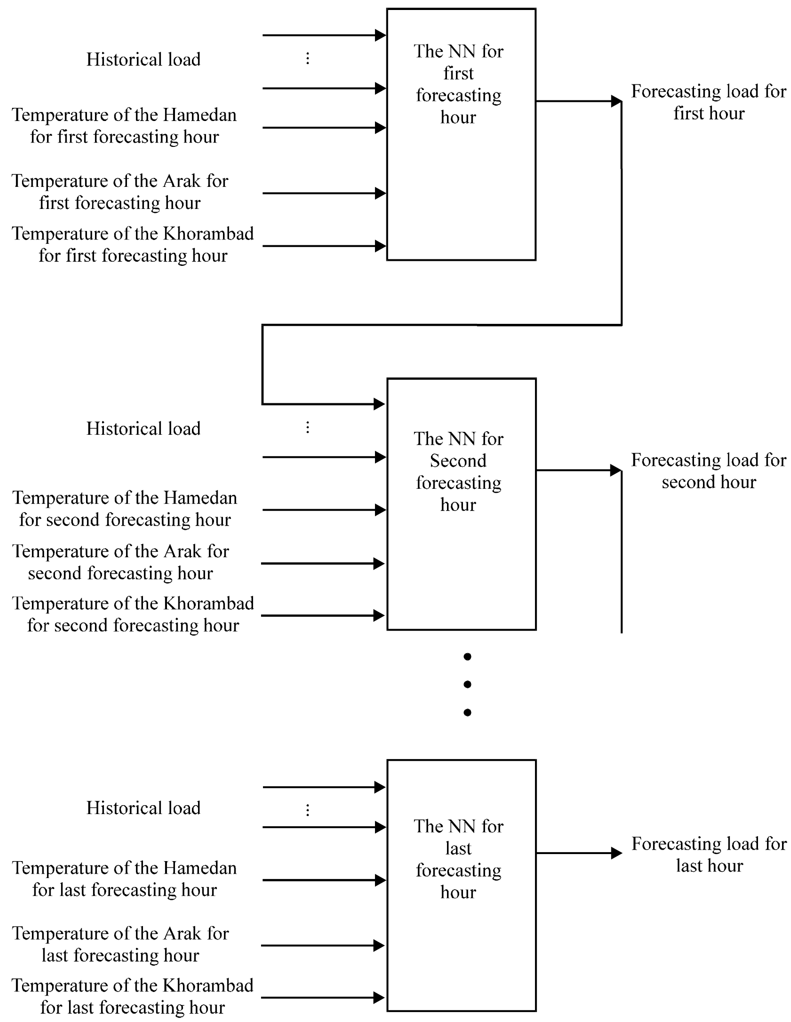

Fig. 3: The NN structure of each weekly group

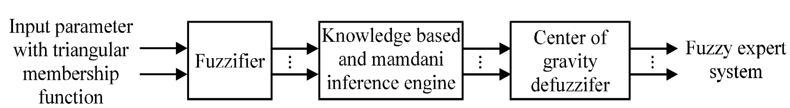

Fig. 4: Schematic of the proposed fuzzy expert system for the STLF

We have also used the term, Ltp in the rule base. This term defined in Eq. 6 is the Ratio of load to peak load that is large for loads near the peak load and it is small for loads near the minimum load:

$$\mathrm{LtP(i)} = \frac{\mathrm{Load(i)}}{\mathrm{Peak}} \tag{6}$$

where, load (i) is the load of hour i and peak is the maximum load of the forecasting day which are gained by initial forecasting. Each of these fuzzy variables, T, ΔT and LtP can take different values. For example, ΔTArk takes seven fuzzy set values: NB (Negative Big), NM (Negative Medium), NS (Negative Small), ZE (Zero), PS (Positive Small), PB (Positive Big). Membership functions of input and output fuzzy sets are shown in Fig. 5.

We used the fuzzy centroid defuzzification scheme to translate fuzzy output statements into crisp output values. Because special inputs have different input-output pairs of fuzzy rules, for combining values of different activated rules and operator is used. Samples of these fuzzy rules are presented as the following:

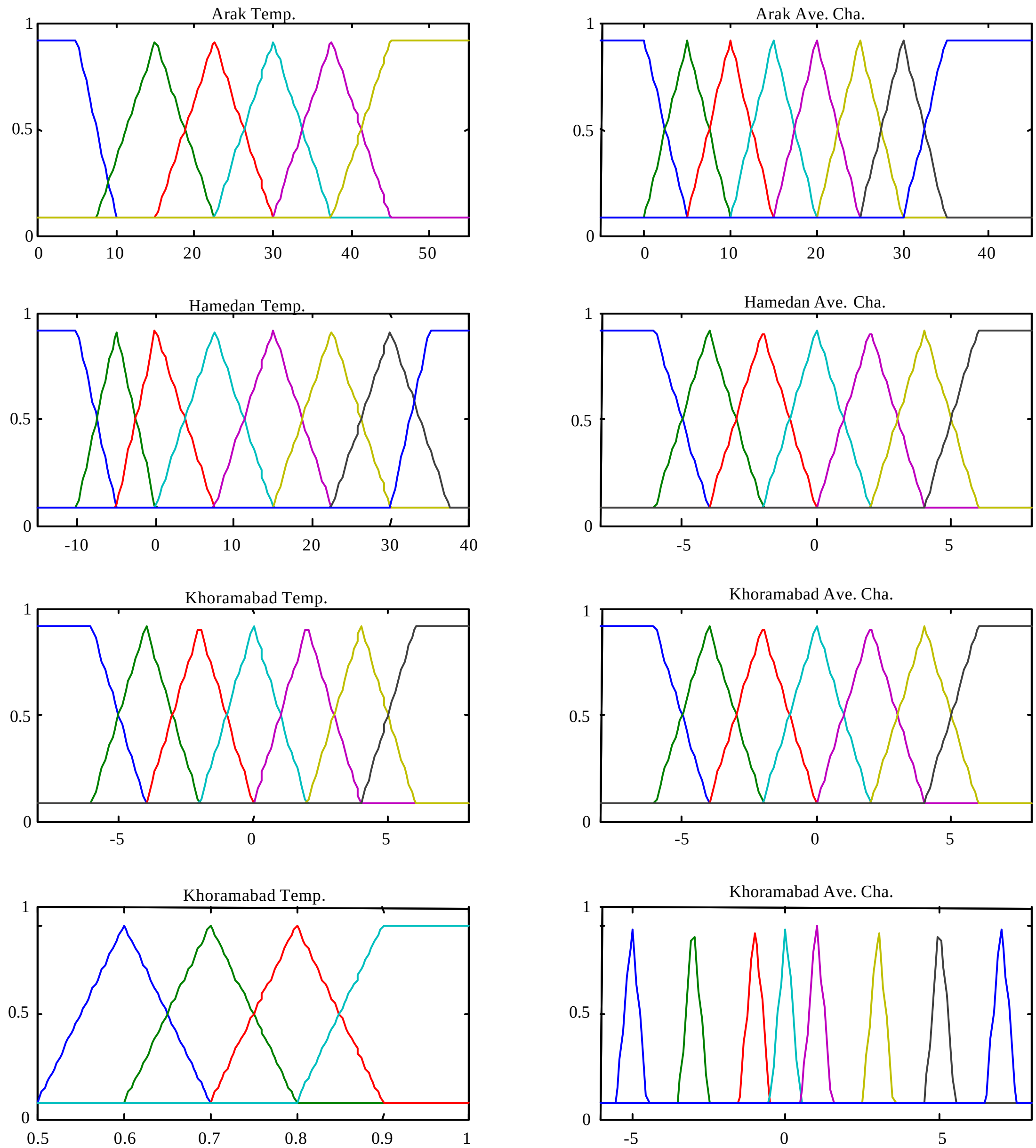

Fig. 5: Membership functions for input-output variables

- if (TArk = PM2) & (THam = PM1) & (Tkho = PS) & (ΔTArk = NS) & (ΔTHam = PS) & (ΔTKho = ZE) & (LtP = S) then (RG = NM)
- if (TArk = PM2) & (THam = PM1) & (TKho =PS) & (ΔTArk = ZE) & (ΔTHam = NS) & (ΔTKho = NM) & (LtP = M1) then (RG = NS)
- if (TArk = PM1) & (THam = PS2) & (TKho =PS) & (ΔTArk = NS) & (ΔTHam = NM) & (ΔTKho = NS) & (LtP = M2) then (RG = ZE)
- if (TArk = PS2) & (Tham = PS2) & (Tkho = PS) & (ΔTArk = PS) & (ΔTHam = NM) & (ΔTKho = ZE) & (LtP = B) then (RG = NS)

Considering load data of BREC, days of a year are categorized into 2 groups: normal and special days. Normal days are divided into 4 groups. Special days are religious celebration, national celebration and etc. are divided into 2 groups: solar and lunar calendar special days. Solar special days occur in specific times of a year but lunar special day's occurrence varies in a year depending on the two calendars.

Special days' load patterns are dissimilar to those of weekdays, however, they are similar to Fridays' load patterns. So, for load forecasting of special days, the outputs of the nearest Fridays' neuro-based forecaster are as inputs of the fuzzy modifier system. The fuzzy rule base employs only two fuzzy variables of time and weekday type to improve the initial load forecasts. For example, in Ashoora special day, loads of hours 1 to 6 and hours 20 to 24 are almost the same as those of the last Friday and loads of work hours (7 to 19) are lower than those of the last Friday.

Inputs membership functions of all special days are the same as those of the Ashoora day while outputs membership functions each is selected based on the holiday type. We also used the fuzzy centroid defuzzification scheme to convert fuzzy outputs into crisp values. Furthermore, to combine different activated rules, AND operator is used. Samples of fuzzy rules of Ashoora day is presented below:

- if (DType = D1) & ($1 \leq$Hour≤ 8) Then, (RG = NS2)
- if (DType = D1) & ($9 \leq$Hour≤ 15) Then, (RG = NM1)
- if (DType = D1) & ($16 \leq$Hour≤ 20) Then, (RG = NS0)
- if (DType = D1) & ($21 \leq$Hour≤ 24) Then, (RG = PS)

Accessories: The NSTLF also contains a data analyzer and a temperature forecaster. The data analyzer is used for identification and filtering of the BREC bad data (Daneshdoost *et al*., 1998). The temperature forecaster is employed for hourly temperature forecast and has an ANN architecture based on a three-layered feedforward neural network. The inputs of the temperature forecaster are the high and low temperatures of the underlying days, the actual hourly temperatures and the high and low temperatures of the day before the first forecast day.

RESULTS AND DISCUSSION

According to Iran Electricity Market Rules, we recognize the first six months of each year as hot months and the rest as cold months. From view point of the consumed load, daily hours in hot months are considered as follows: 5-8 low load hours, 8-20 ordinary load hours and 20-24 peak load hours. The classifications in cold months are: 0-5 and 21-24 low load hours, 5-17 ordinary load hours and 17-21 peak load hours. According to the new Marketing Rules, forecasting errors for peak, ordinary and low hours should be smaller than 2, 5 and 10%, respectively. So, the designed program (load forecaster) for load forecasting should satisfy all of these constraints.

The designed load forecaster without the fuzzy modifier yields up to a week load forecasting results with an MAPE less than in average 1.7% with MLP in most cases and less than in average 1.3% with FIS for INPS and less than in average 2.6% in most cases. This becomes less than 2.4% if the fuzzy modifier is included. Table 1 and 2 represent the daily load forecasting errors for each month in each year. Figure 6, 7 show examples of up to a week forecasting performance of the designed load forecaster. In these examples, actual load and temperature data of the BREC in the year 2002 have been used.

Figure 8 is an example of daily load forecasting for Jul. 21, 2002 without fuzzy modifier. That it's forecasting error is about 1.5%.

Table 1: Average of daily error load forecasting in each month of year 2002

	Month number												
Time periods	1	2	3	4	5	6	7	8	9	10	11	12	AVE
Low load hours	2.4	3.2	2.2	2.9	2.3	1.9	1.9	1.6	2.5	3.4	3.1	3.3	2.6
Ordinary load hours	2.5	2.7	4.2	3.7	2.8	2.6	2.5	1.4	2.7	2.6	2.5	3.4	2.8
Peak load hours	2.3	2.8	2.7	2.9	2.2	2.3	2.4	2.3	2.5	2.4	2.0	2.2	2.4
Total error with MLP	2.4	2.8	3.3	3.3	2.5	2.3	2.3	1.6	2.6	2.8	2.6	3.1	2.6
Total error with MLP and FIS	2.3	2.2	2.7	2.8	2.1	2.3	2.3	1.6	2.4	2.5	2.6	3.0	2.4

Table 2: Average of daily error load forecasting in each month of year 2000 for INPS

	Month number												
Time periods	1	2	3	4	5	6	7	8	9	10	11	12	AVE
Low load hours	2.4	1.9	1.5	2.2	1.7	1.7	1.6	1.1	1.9	2.1	1.6	1.7	1.8
Ordinary load hours	2.4	1.7	1.4	2.8	1.3	1.6	1.3	1.1	1.6	1.9	1.5	1.7	1.7
Peak load hours	1.7	1.5	1.4	3.0	1.6	1.8	1.4	1.3	1.6	1.6	1.4	1.1	1.6
Total error with MLP	2.2	1.7	1.4	2.6	1.4	1.7	1.4	1.1	1.7	1.9	1.5	1.6	1.7
Total error with MLP and FIS	1.3	1.5	1.0	1.5	1.4	0.8	1.4	1.1	1.7	1.7	1.2	1.1	1.3

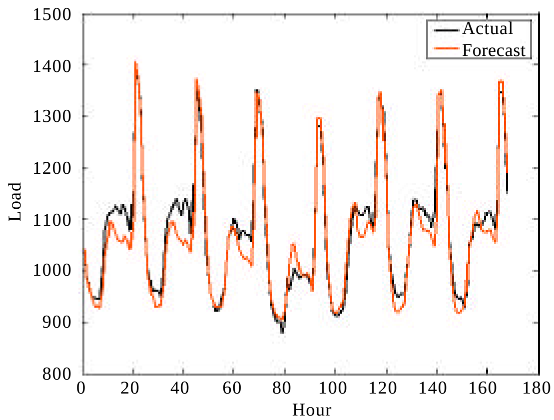

Fig. 6: Actual and forecasted hourly loads from Aug. 12 to Aug. 18, 2002 (MAPE = 1.7%) without fuzzy modifier

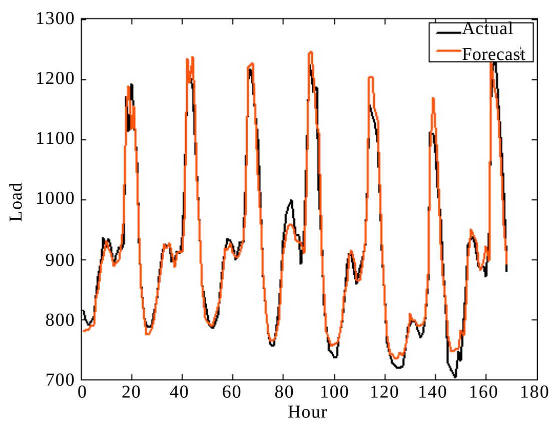

Fig. 7: Actual and forecasted hourly loads from Oct. 27 to Nov. 3, 2002 (MAPE = 2.1%) without fuzzy modifier

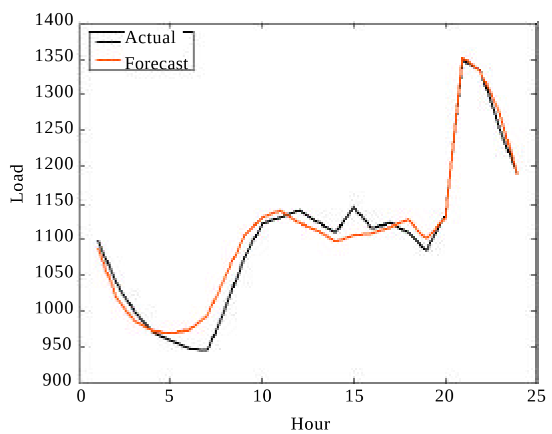

Fig. 8: Actual and forecasted hourly load for Jul. 21, 2002 (MAPE = 1.5%), without fuzzy modifier

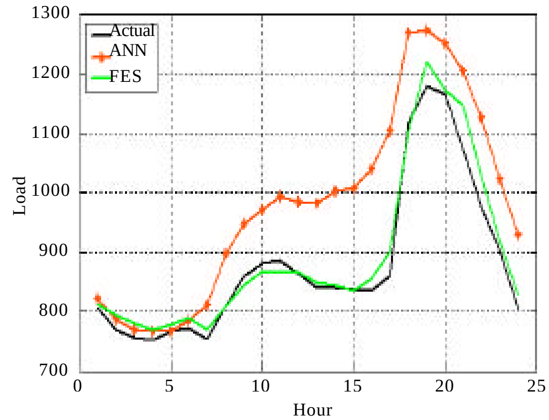

Fig. 9: Actual and forecasted hourly load for Oct. 22, 2002 (MAPE = 11.3%), without fuzzy modifier and (MAPE = 2.1%), with fuzzy modifier (changes in temperature)

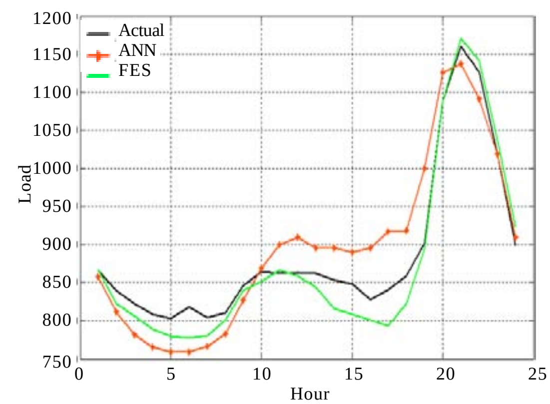

Fig. 10: Actual and forecasted hourly load for Apr, 2, 2002 (MAPE = 4.3%), without fuzzy modifier and (MAPE = 2.3%), with fuzzy modifier (holiday)

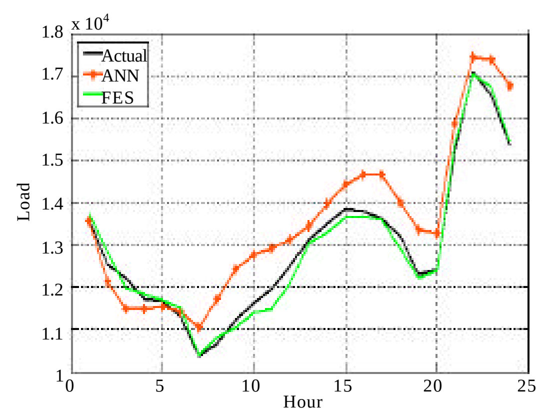

Fig. 11: Actual and forecasted hourly load for June 4, 2000 (MAPE = 5.4%), with MLP and (MAPE = 1.4%), with MLP and FIS for INPS (holiday)

Designed load forecaster results for load variation factors (temperature changes and special holidays) are shown in Fig. 9-11. These figures clearly demonstrate the capabilities of the proposed fuzzy modifier for improvement of the forecasted load for special days.

CONCLUSION

In this study, we have designed an intelligent load forecaster using NN and fuzzy modifier for the famous STLF problem. The MLP precisely forecasts load values in normal conditions. We have trained MLP using the LMBP by using ES method to have a higher convergence rate. In special cases such as abrupt changes in weather conditions or special holidays, a FIS is used to improve initial forecasted loads. The results of load forecasting should satisfy Iran Electricity Market Rules. Simulations results for INPS and BREC easily approve the capabilities the proposed STLF for the Islamic countries. Reshaping the load shapes by charging the peak load will be addressed in near future.

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