Short Term Load Forecasting for Bakhtar Region Electric Co. Using Multi Layer Perceptron and Fuzzy Inference systems

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Abstract

Short Term Load Forecasting (STLF) has received more and more attention during last decade because of economic reasons. In this paper we have designed a Multi Layers Perceptron (MLP) Neural Network (NN). For abrupt weather changes and special holidays, a Fuzzy Inference System (FIS) has been added to modify the forecasted load appropriately. The architecture of the proposed network is a three-layer feedforward neural network whose parameters are tuned by Levenberg-Marquardt Bock Propagation (LMBP) augmented by an Early Stopping (ES) method tried out for increasing the speed of convergence. The FIS modifies the initial forecasted load considering the load variations due to abrupt changes in temperature and the load behavior of special holidays. Simulation examples for Bakhtar Region Electric Co (BREC) demonstrate capabilities of proposed method.

1 Introduction

Quick and accurate load forecasting has a very importance for power system operation. Also 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 results. In literatures, 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.

In recent years, uses of intelligent techniques have increased noticeably for solving engineering problems. Artificial neural network and fuzzy systems are two powerful tools 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) [1], [2], [3], [4], [5], wavelets [6], fuzzy logic [7], [8], [9], expert systems [10], have been developed recently, showing more acceptable results than traditional methods.

Fuzzy logic models have a very excellent transparency, while ANNs use the learning capability. It is very time-consuming to regulate fuzzy model parameters to reach a good result, so it is reasonable to use them only when we need to infer like a human. But ANNs have an excellent automatic learning capability, so we will use them only for modeling an unknown nonlinear function such as short term load forecaster.

In this paper we have designed a short term load forecaster that it benefits advantages of both ANNs and fuzzy systems. At first we create an ANN that accurately predict demand load in next hour in usual days under normal weather condition. Different types of ANNs have been applied to STLF; for example, multilayer feedforward with one hidden layer recurrent and functional links. We have used a multi-layer feed forward ANN for this part. We refine the result of the ANN output using a fuzzy logic system in special days or in occurrence of an abrupt weather change to have a more reliable and more robust load forecaster.

The organization of this paper is as follow. Section 2 outlines the load characteristic. Section 3 derives STLF technique by MLP neural networks. Section 4 and its subsections presents load modification using fuzzy concepts. Section 5 delivers different simulation examples of forecasted loads. Finally, section 6 includes some conclusions and further researches.

2 Load Characteristic

Load forecasting depends on several parameters such as historical load data, weather condition, and day type [11], [12]. Despite using many input parameters gives more acceptable load forecasting results, it leads to a massive computational operations. To establish an appropriate trade off between these objectives, we have divided weekly days into 4 categories that are completely different from view point of load value[12]. So, load forecaster consists four functions as follow

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

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

Among weather information such as cloud coverage, wind speed, temperature, only has the last noticeable effects on load forecasting performance. So for effecting these factor in load forecasting procedure, we have considered temperature inputs of three cities in tropical, moderate, cold and hot areas that are representatives for weather conditions in all cities.

Month input is a vital input that we have interned it here to reduce the number of load forecaster functions. In previous works such as [5], this input is absent, so designers needs to design 16 load forecasters for 4 seasons and 4 weekly days categories. But by considering this input, we can reduce the number of load forecasters to 4 while using it considerably improves the results of load forecasting.

3 STLF Technique by MLP Neural Networks

Neural networks have the capability of modeling any nonlinear unknown function using available input(s)-output(s) data. They do this modeling precisely using learning methods, i. e., it is not to regulate them in a time-consuming manner. Also because of highly non-linear behavior of load, it is reasonable to use them or modeling of load behavior. This section outlines the MLP neural network structure considered for load forecasting and its training algorithms.

We have used MLP fully connected feed-forward neural networks that its capability for modeling has been demonstrated in literature. Transfer function for each neuron is tangent sigmoid that are as follow

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

For avoiding saturation problems that are relates to use of tangent sigmoid neurons, it is vital to scale input and target input to range of $[-1,1]$ as follow

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

where X_{Max} and X_{Min} are maximum and minimum values of previous 21 days. This particular selection for normalization was chosen based on some tries and errors.

For each weakly days group, we considered a neural network that its inputs are the same variables introduced in [12]. Input layer for hourly load forecasting of each weekly group has 13, 19, 16, 19 neurons respectively. In each case three inputs are temperatures of three cities, another input is month number, and the rest o input are 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 to forecast load. Validation subset were trained to networks until overall load forecasting error begin to increase. Learning method in these two stages is chosen Levenberg-Marquart Back Propagation that is noticeably faster than back propagation method [15]. Finally, we verify the performance of trained network using the third subset (test subset). It is shown in load forecasting examples that using this training method considerably increases the accuracy of neural networks for load forecasting.

For forecasting, MLPs are simulated by training results, then simulator can be used. It can be used for one hour up to a week load forecasting. The first hour load is forecasted and then it is used as one of the MLP inputs for the prediction of the next hours' load. Consequently, the error of each hour load's forecast will influence the prediction of next hours' load.

4 Load Modification Using Fuzzy Concepts

MLP neural networks forecast precisely the load values in normal situations. But we need to amend or to modify the forecasted load in occurrence of 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. So, it is necessary for us to design a modifier for these days.

The output of this modifier should be as follow

$$MT = \frac{Load_{Actual} - Load_{Forecasted}}{Load_{Actual}} \quad (4)$$

where MG means modifying term. Because we have a prior knowledge about effects of abrupt weather changes and special holidays on consumed load, it is reasonable to use fuzzy models. Using fuzzy models, we can execute our decision-making procedure for load modification properly. Besides, the transparency of fuzzy models is an impressive factor that it encourages us to use them.

4.1 Fuzzy Modifier for Abrupt Weather Changes

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), Δ T (average temperature changes), LtP (ratio of load to peak load), are defined in the rule base for temperature. Average temperature is used for Hamedan, Khoramabad and Arak cities in the forecasting day (THam, TKho, TArk). 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).

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

Ratio of load to peak load shows the place in load curve. This value is large for loads near the peak load and small for loads near the minimum load.

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

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 appendix 1.

The fuzzy system has 7 inputs which have 6, 8, 8, 7, 7 and 4 membership functions. For covering all possible states, we need 526848 rules in knowledge base, using only one temperature would have resulted in less rules.

We use 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 [8, 11]. Samples of these fuzzy rules are presented as the following:

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)

4.2 Fuzzy Modifier for Special Holidays

Considering load data of BREC, days of a year are categorized into 2 groups: normal and special days. Normal days as discussed in section II, where divided into 4 groups. Special days are religious celebration, national celebration and etc. and are divided into 2 groups: solar and lunar calendar special days. Solar special days occur in specific times of a year, but lunar special days occurrence varies in a year considering difference between the two calendars [8, 10].

Special days' load patterns are dissimilar to those of weekdays, but they are similar to Fridays' load patterns. So for load forecasting of special days, ANN output of the nearest Fridays is used and then, this initial forecasted load is modified by rules of FIS. Two fuzzy variables, time and weekday type are defined in the rule base for special days. According to knowledge base rules, percentage of initial forecasted load is changed in different hours. For example, in Ashoora special day, load of hours 1 to 6 and hours 20 to 24 have little difference with last Friday load, but load of work hours (hours 7 to 19) is lower than last Friday load.

For all special days, membership functions of inputs are as Ashoora day, but membership functions of outputs are different to one another and dependent on the holiday type.

In the special days FIS, we also use the fuzzy centroid defuzzification scheme to translate fuzzy output statements into crisp output values. And so for combining values of different activated rules, AND operator is used. Samples of fuzzy rules of Ashoora day, one of the religious holidays are presented as the following:

1) if (DType = D1) & (1 ≤ Hour ≤ 8) Then (RG = NS2)

if (DType = D1) & (9 ≤ Hour ≤ 15) Then (RG = NM1)

if (DType = D1) & (16 ≤ Hour ≤ 20) Then (RG = NS0)

if (DType = D1) & (21 ≤ Hour ≤ 24) Then (RG = PS)

5 Accessories

NSTLF also contains a data analyzer and a temperature forecaster. The data analyzer can be used for identification and modification of BREC bad data [10]. Temperature forecaster is used for hourly temperature forecast and has ANN architecture based on a three-layered Perceptron building block (like the work presented in [18]). The inputs of the temperature forecaster are the high and low temperatures of the days to be forecasted and also the actual hourly temperatures and the high and low temperatures of the day before the first forecast day.

6 Performance

According to Iran Electricity Market Rules, we categorize the first sex months of each year in hot months group and the rest in cold months group. From view point of consumed load, daily hours in hot months are considered as follow: 5-8 low load hours, 8-20 ordinary load hours and 20-24 peak load hours. These classifications in cold months are as follow: 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 goals.

Designed load forecaster up to a week load forecasting results had MAPE less than in average 2.6% with MLP in most cases and less than in average 2.4% with FIS. Table 1 represents the daily load forecasting errors for each month in year 2002. Fig. 1 and Fig. 2 show examples of up to a week forecasting performance of the designed load forecaster. In these examples, actual load and temperature data of BREC. in the year 2002 have been used.

Fig. 3 is an example of daily load forecasting for Jul. 21, 2002 with MLP that its forecasting error is about 1.5%.

Designed load forecaster results for load variation factors (temperature changes and special holidays) are shown in Fig. 4 and Fig. 5. These figures clearly outline the capabilities of proposed FIS for modification of forecasted load in these cases.

7 Conclusions

In this paper, we have designed an intelligent using MLP and FIS for famous STLF problem. MLP precisely forecasts load values in normal conditions. We have trained MLP using LMBP by using ES method for increasing speed of convergence. In special cases such as abrupt changes in weather conditions or special holidays, a FIS is used to modify initial forecasted load to improve forecasting results. The results of load forecasting should satisfy Iran Electricity Market Rules. Simulations examples for BREC. demonstrate the capabilities of MLP and FIS to satisfy these rules acceptably. Reshaping the load shapes by charging the peak load can address for future work.

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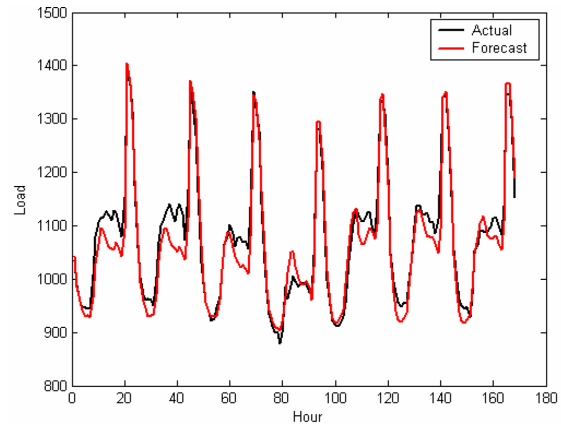

Fig. 1, Actual and forecasted hourly loads from Aug. 12 to Aug. 18, 2002 (MAPE=1.7 %) with MLP.

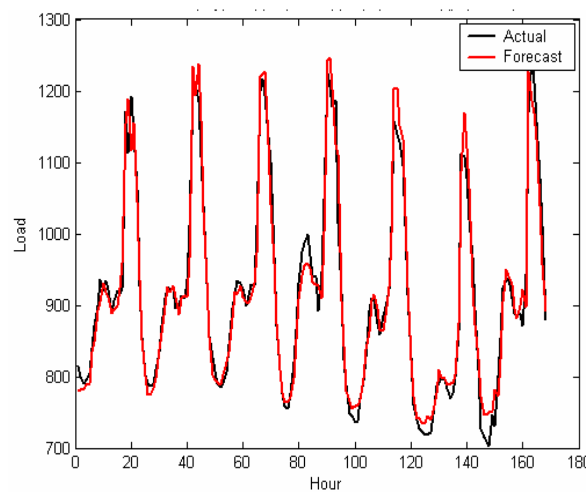

Fig. 2, Actual and forecasted hourly loads from Oct. 27 to Nov. 3, 2002 (MAPE=2.1 %) with MLP.

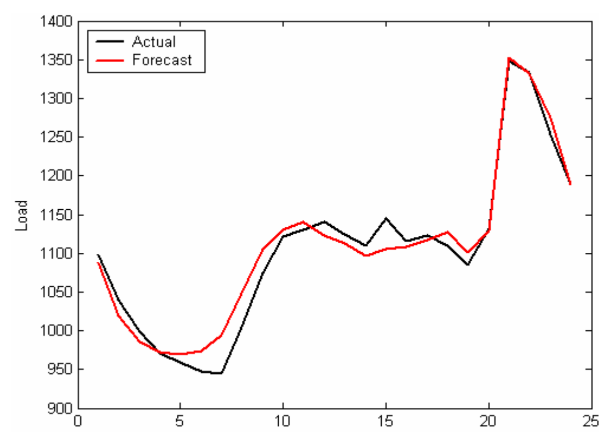

Fig. 3, Actual and forecasted hourly load for Jul. 21, 2002 (MAPE=1.5 %), with MLP.

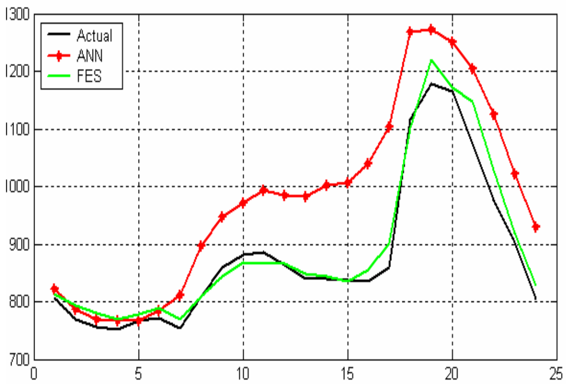

Fig. 4, Actual and forecasted hourly load for Oct. 22, 2002 (MAPE=11.3 %), with MLP and (MAPE=2.1%), with MLP and FIS (changes in temperature)

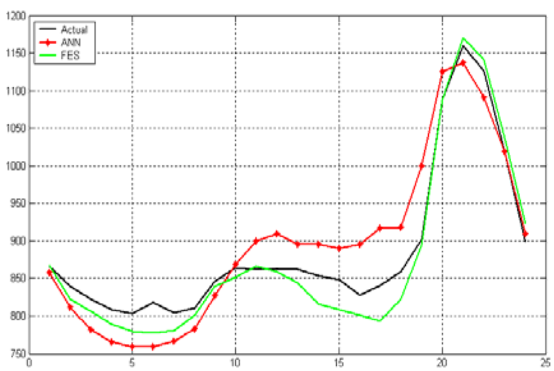

Fig. 5, Actual and forecasted hourly load for Apr, 2, 2002 (MAPE=4.3 %), with MLP and (MAPE=2.3%), with MLP and FIS (holiday)

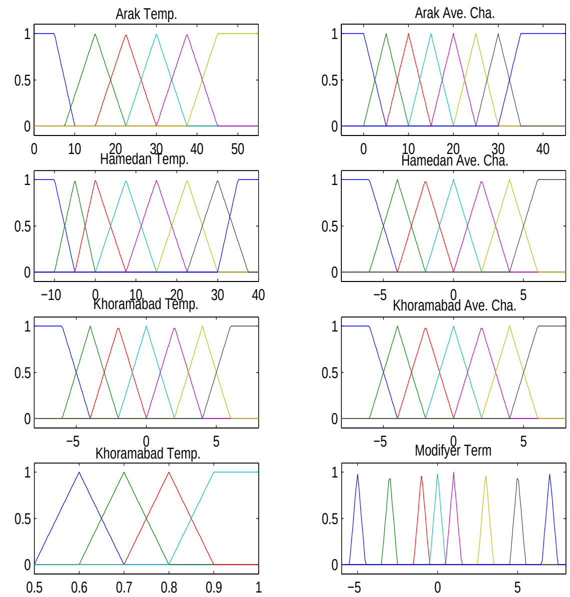

Fig. 6, Membership functions for input-output variables

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

Month Number	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	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***	***2.4***