Short-Term Load Forecasting in Power Systems Using Adaptive Fuzzy Critic Based Neural Network

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Abstract: - Load forecasting constitutes an important tool for efficient planning and operation of power systems and its significance has been intensifying particularly, because of the recent movement towards open energy markets and the need to assure high standards on reliability. Accurate load forecasting is of great importance for power system operation. It is the basis of economic dispatch, hydrothermal coordination, unit commitment, and system security analysis among other functions. Short-term load forecasting (STLF) is for hour to hour forecasting and important to daily maintaining of power plant. Most important factors in load forecasting includes past load history, calendar information (weekday, weekend, holiday, season, etc.) and weather information (instant temperature, average temperature, peak temperature, wind speed, etc.). The forecaster will treat past data as a time series and many kinds of approaches have been applied on this problem. This paper presents a new intelligent approach for short term load forecasting which can model the valuable experiences of the expert operator. This technique is based on emotional critic based fuzzy logic. Emotional learning is a family of intelligent algorithms which can be used for time series prediction, classification, control and identification. This approach is relatively simple and can accurately forecast the hourly loads of weekdays, as well as the weekends and public holidays. It is shown that the proposed method can provide more accurate results than the conventional techniques such as artificial neural networks or ARMA models. Obtained results from extensive testing on power system networks confirm the validity of the developed approach.

Key-Words: - Short-Term load forecasting, Neural network, Fuzzy logic, Power System, Adaptive Critic

1 Introduction

Load forecasting constitutes an important tool for efficient planning and operation of power systems and its significance has been intensifying particularly, because of the recent movement towards open energy markets and the need to assure high standards on reliability. Accurate load forecasting is of great importance for power system operation. It is the basis of economic dispatch, hydrothermal coordination, unit commitment, and system security analysis among other functions. Various load forecasting techniques have been proposed and applied to predict the different classes of power system load requirements. Many statistical methods have been conventionally used for such forecasting [1-6]. Usually, a linear regression model has been practically used in central load dispatching centers. An operator is able to understand the reason and relevance of forecasting results using the linear regression model. However, it is difficult to obtain the accurate forecasting results, because the model is constructed by linear functions. Moreover, it has been difficult to construct a proper nonlinear regression model using nonlinear functions and to investigate complex correlation between electric load and input variables such as weather conditions, seasonal factors, and difference between weekdays and weekends. Recently, a number of artificial neural network (ANN) approaches for electric load forecasting have been proposed [7-11]. Namely, the appropriate load forecasting method with high forecasting accuracy, explainable ability, and handling of continuous values has not been proposed yet. Neural networks which are used in conventional methods use all similar day's data to learn the trend of similarity. However, learning of all similar day's data is a complex task, and it does not suit learning of neural network. Therefore, it is necessary to reduce the neural network structure and learning time. To overcome the problems mentioned above reference [12] has proposed a one-hour-ahead load forecasting method using the correction of similar day data. In that proposed prediction method, the forecasted load power is obtained by adding correction to the selected similar day data.

This paper proposes a new short-term load forecasting method based on emotional learning. This method can forecast accurately with nonlinear forecasting model. Moreover, proposed approach can handle continuous values as input and output variables. This approach is relatively simple and can accurately forecast the hourly loads of weekdays, as well as the weekends and public holidays. Obtained results from extensive testing on power system networks confirm the validity of the proposed method. In the subsequent sections, we discuss the important factors in STLF, our proposed method, and its application in online STLF. Obtained results and some concluding will be represented in this paper.

2 Demand-determining factors in STLF

The power system has a high complexity. Many factors are influential to the electric power generation and consumption. According to [13-16], the factors can be classified into economical, environmental, calendar, weather and random effectors. Weather Conditions include temperature, humidity, thunderstorms, wind speed, rain, fog, snow, cloud cover or, sunshine, and etc. It has been widely observed that, in most cases, there is a strong correlation between weather. Among all those factors, temperature and wind speed are the most important because they have direct influence on many kind of electrical consumption, such as air conditioner, heater and refrigerator. However, the leading weather influential factor for specific consumer may be different. Calendar includes hour-of-day, day-of-week, and month-of-year, weekend and holiday effects. Most load patterns show a very consistent dependence on the calendar. For example, assuming all other factors remaining constant, the demand for energy at 1:00 AM is expected to be different from that at 6:00 PM. similar observations exist for the day-of-week. The month-of-year captures the seasonal effect. Holidays are again special days; they tend to produce behavior that is more like a weekend day. The above effects are those that can be quantified and hence are possible candidates to be used as inputs for emotional learning training and forecasting.

3 Structure of Proposed Adaptive Fuzzy Critic Based Neural Network

Most of new learning algorithms like reinforcement learning, Q-learning and the method of temporal differences are characterized by their fast computation and in some cases lower error in comparison with the classical learning methods. Fast training is a notable consideration in some control applications. However, in prediction applications, two more desired characteristics of a good predictor are accuracy and low computational complexity.

The Emotional learning method is a psychologically motivated algorithm which is developed to reduce the complexity of computations in prediction problems [17]. Using the distinctive properties of this method one can follow multiple goals in prediction. In this method the reinforcement signal is replaced by an emotional cue, which can be interpreted as a cognitive assessment of the present state in light of goals and intentions. The main reason of using emotion in a prediction problem is to lower the prediction error in some regions or according to some features. For example predicting the peak load is important in the power systems. Of course these objectives can be pursued by other methods too, but by emotional learning any complicated multi objective problem can be solved using a fast, efficient computation. This method is based on an emotional signal which shows the emotions of a critic about the overall performance of predictor. The distinctive feature of emotional signal is that it can be produced by any combination of objectives or goals which improve estimation or prediction. The loss function will be defined just as a function of emotional signal and the training algorithm will be simply designed to decrease this loss function. So the predictor will be trained to provide the desired performance in a holistic manner. If the critic emphasizes on some regions or some properties, this can be observed in his emotions and simply affects the characteristics of predictor. Thus the definition of emotional signal is absolutely problem dependent. It can be a function of error, rate of error change and many other features. Then a loss function is defined based on the emotional signal. A simple form can be

$$J = \frac{1}{2}\sum_{i=1}^{N} K_i {es_i}^2 \tag{1}$$

where es_i is the *ith* emotional signal. K_i is the corresponding output weights and N is the total number of outputs. Learning is adjusting the weights of model by means of a nonlinear optimization method, e.g. the steepest descent or conjugate gradient. With steepest descent method the weights will be adjusted by the following variations:

$$\Delta\omega_i = -\eta \frac{\partial J}{\partial \omega_i} \tag{2}$$

where η is the learning rate of the corresponding neurofuzzy model and the right hand side can be calculated by chain rule:

$$\frac{\partial J}{\partial \omega_i} = \frac{\partial J}{\partial es_i} \cdot \frac{\partial es_i}{\partial y_i} \cdot \frac{\partial y_i}{\partial \omega_i} \tag{3}$$

According to (1):

$\frac{\partial J}{\partial es_i} = K_i.es_i$ and calculating the remaining part, $\frac{\partial es_i}{\partial y_i}$, is not straightforward in most cases. This is the price to be paid for the freedom to choose any desired emotional cue as well as not having to impose presuppose any predefined model. However, it can be approximated via simplifying assumptions. If, for example error is defined by

$$e_i = y_{refi} - y_i \tag{4}$$

where y_{refi} is the output to be estimated, then

$$\frac{\partial es_i}{\partial y_i} = -\frac{\partial es_i}{\partial e_i} \tag{5}$$

Since with the incrimination of error, *es* will also be incremented and on the other hand, on-line calculation of $\frac{\partial es_i}{\partial e_i}$ is accompanied with measurement errors, thus producing unreliable results, only the sign of it (+1) is used in our calculations. The algorithm is after all, supposed to be satisfying rather than optimizing. Finally From (1) to (5), the weights, $\Delta\omega_i$, will be updated by the following formula:

$$\Delta\omega_i = -K_i \cdot \eta \cdot es_i \cdot \frac{\partial y_i}{\partial \omega_i} \tag{6}$$

Equation (6) is used for updating the learning parameters. A neurofuzzy model with four layers was chosen as the system's controller. The first task of first layer is the assignment of inputs' scaling factors in order to map them to the range of [-1, +1]. In the Second layer, fuzzification is performed for each input, assigning five labels for each one. For decision-making, max-product law is used in layer 3. Finally, in the last layer, the crisp output is calculated using Takagi- Sugeno formula. The Takagi-Sugeno fuzzy inference system is based on fuzzy rules of the following type:

$$\begin{aligned} &Rule_i: \ If\ u_1 = A_{i1}\ And\ \ldots\ And\ u_p = A_{ip} \\ &then\ \hat{y} = f_i(u_1, u_2, \ldots, u_p) \end{aligned} \tag{7}$$

Where $i = 1 \ldots M$ and M is the number of fuzzy rules. $u_1, \ldots, u_p$ are the inputs of network, each A_{ij} denotes the fuzzy set for input u_j in rule *i* and $f_i(.)$ is a crisp function which is defined as a linear combination of inputs in most applications

$$\hat{y} = \omega_{i0} + \omega_{i1}u_1 + \omega_{i2}u_2 + \ldots + \omega_{ip}u_p \tag{8}$$

Thus the output of this model can be calculated by

$$\hat{y} = \frac{\sum_{i=1}^{M} f_i(\underline{u})\mu_i(\underline{u})}{\sum_{i=1}^{M} \mu_i(\underline{u})}, \quad \mu_i(\underline{u}) = \prod_{j=1}^{p} \mu_{ij}(u_j) \tag{9}$$

From equation (6) and (9) $\Delta\omega_i$ *can be rewritten*

$$\Delta\omega_i = -K_i \cdot \eta \cdot es_i \cdot \frac{\partial y_i}{\partial \omega_i} = -K_i \cdot \eta \cdot es_i \cdot \frac{\sum_{i=1}^{M} u_i \mu_i(\underline{u})}{\sum_{i=1}^{M} \mu_i(\underline{u})}$$

Learning and Forecasting Procedures

Figure 1 shows the proposed load forecasting model. We used learning and forecasting procedures for the proposed emotional learning as follows.

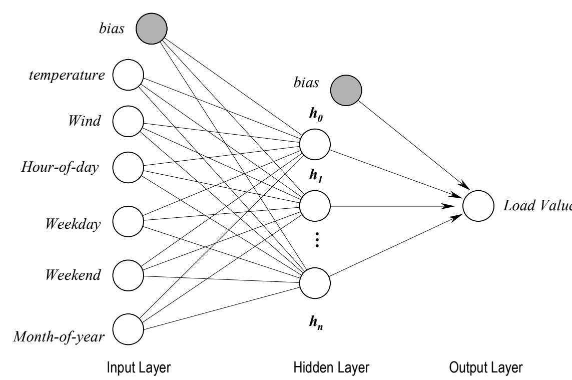

Figure 1- Load forecast model

1- Determine the learning range of the emotional learning.

The emotional learning is trained by using the data of past 60 days from the day before forecast day and past 120 days before and after forecast day in previous year.

2- Determine the limits of selection of similar days for one learning day.

The limits of selection of similar days for one learning day is the past 60 days from the day before a learning day and past 60 days before and after a learning day in previous year.

3- Select similar days for the first learning day.

For the first learning day, N similar days are selected from the limits of selection of similar days.

4- Learning for N similar days.

Emotional learning is trained by using N similar days for the one learning day.

5- Learning for all the days of learning range.

Emotional learning is trained for all the days of learning range in the same method as in Step 3 and 4.

6- Select similar days for forecast day.

Before forecasting load curve, we select M similar days corresponding to the forecast day.

7- Input variables of emotional learning.

Input variables of the emotional learning are as follows. Temperature, wind velocity, hour-of-day, weekday, weekend, and month-of-year.

4 Simulation results

To verify the predictive ability of the proposed method, we perform some simulations. The data used in the simulation are the actual data. We forecast the load power in 2002. The emotional learning is trained by using the data of past 60 days from the day before forecast day, and past 120 days before and after forecast day in previous year. The training performance for emotional learning is shown in figure 2. The fast convergence without oscillation is shown that emotional learning has good performance for prediction and forecasting. The STLF results for May 18, 2002 and May 22, 2002 are depicted in Figs. 3 and 4; observe the satisfactory forecasted results. The adequate performance of the proposed STLF is also illustrated in the absolute percentage error plot for each hour on each day of May 2002 shown in Fig. 5; the Mean Absolute percentage Error(MAPE) is 0.37% and the Peak Absolute percentage Error (PAPE) is 1.73%.

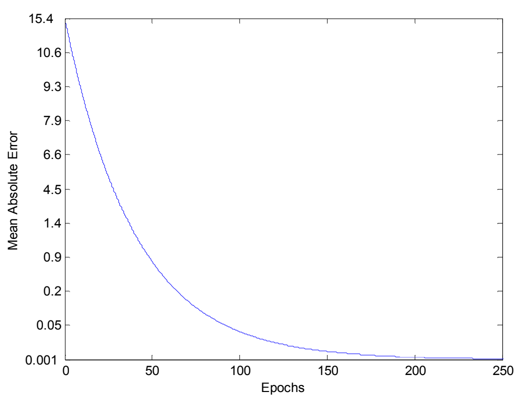

Figure 2. Training Performance of Emotional Learning

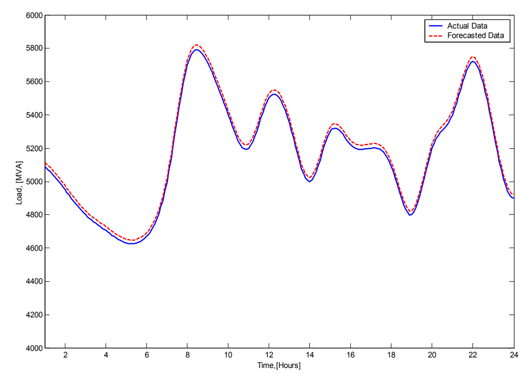

Figure 3. Forecasting result for 18 May 2002

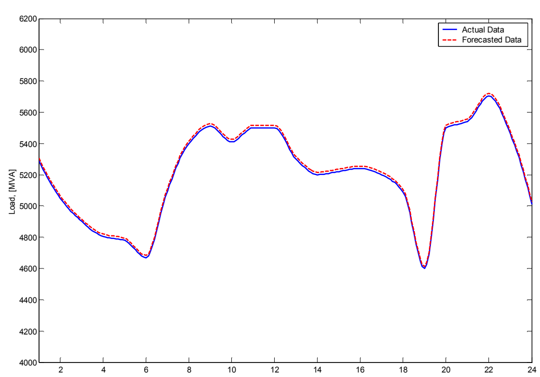

Figure 4. Forecasting result for 22May 2002

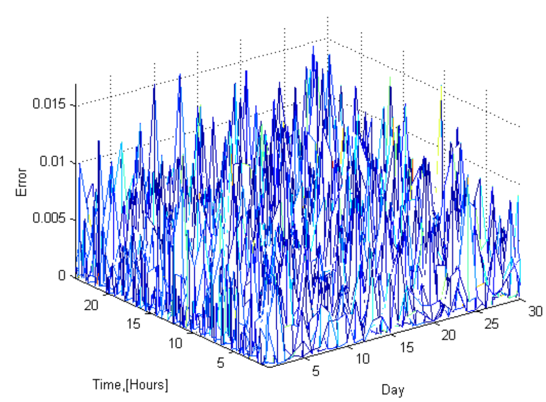

Fig. 5. Absolute percentage error for May 2002 load data set

To evaluate the usefulness of the proposed method some of obtained results from applying the emotional learning method, ANN and ARMA model for hourly loads of 2002 have been represented in table 1. In this Table, MAPE is Mean Absolute percentage Error and PAPE is peak Absolute percentage Error for 24 hours ahead, which have been averaged on 2002. For instance MAPEs and PAPEs in the second row of table 1 are average values for all workingdays of the hot days of 2002. In many of STLF references, only the MAPE values have been presented [6, 7]. For planning purpose this value may suffice but for operational units of a power network, this is insufficient. Dispatching must be able to cope with the worst case. Thus, in addition to MAPE the maximum error of the STLF methods or PAPE has been presented in this paper, which gives a better insight for comparison of the STLF methods. ANN employed in this paper has multi-layer perceptron (MLP) structure with error back-propagation learning (EBPL) algorithm. For parameter tuning of the ARMA and MLP neural network we have used the same historical data. As is seen from Tables 1, accuracy of the emotional learning method is better than the other methods. All programs of the emotional learning method have been written in MATLAB software and JAVA language. These programs have been executed on a Pentium IV personal computer. On this computer, the response time of the proposed method for all testing cases, is less than 0.5 second, which makes feasible the online application of the proposed approach for STLF.

Table 1. Obtained results for hourly loads (2002)

	Proposed Method (MAPE-PAPE)	ANN Method (MAPE-PAPE)	ARMA Method (MAPE-PAPE)
Working days (Hot)	0.43%-1.87%	2.12%-4.37%	4.58%-9.32%
Weekends (Hot)	0.64%-2.27%	2.58%-4.96%	4.89%-11.06%
Working days (Mid)	0.52%-1.76%	1.88%-3.63%	5.07%-11.35%
Weekends (Mid)	0.47%-1.92%	1.49%-3.48%	4.65%-10.17%
Working days (Cold)	0.39%-1.83%	1.40%-3.41%	4.17%-8.83%
Weekends (Cold)	0.45%-1.89%	1.48%-3.38%	4.32%-9.04%

5 Conclusion

The load is a nonstationary process affected by two main factors: time of the day and weather conditions. The time dependence of the load reflects the existence of a daily load pattern which may vary for different week days and seasons. Among the weather factors affecting load, temperature is the primary one. Humidity (summer time) and wind speed (winter time) may also influence power consumption. In this paper a novel approach for STLF has been developed. It has been shown that the proposed method can provide more accurate results than the conventional techniques such that artificial neural networks or ARMA. The historical load data for the HREC were used in this paper for testing the proposed approach. By considering calendar and weather conditions as inputs to emotional learning, obtained results from extensive testing on real power network confirm the validity of the developed approach.

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