RBF Neural Network and ANFIS-Based Short-Term Load Forecasting Approach in Real-Time Price Environment

Zhang Yun, Zhou Quan, Sun Caixin, Lei Shaolan, Liu Yuming, and Song Yang

Abstract—**With the appearance of electricity markets, the variation of the price of electricity will influence usage custom of electric energy. This will complicate short-term load forecasting and challenge the existing forecasting methods that are applied to a fixed-price environment. In regard to the influence of real-time electricity prices on short-term load, a model to forecast short-term load is established by combining the radial basis function (RBF) neural network with the adaptive neural fuzzy inference system (ANFIS). The model first makes use of the nonlinear approaching capacity of the RBF network to forecast the load on the prediction day with no account of the factor of electricity price, and then, based on the recent changes of the real-time price, it uses the ANFIS system to adjust the results of load forecasting obtained by RBF network. This system integration will improve forecasting accuracy and overcome the defects of the RBF network. As shown in this paper by the results of an example of factual forecasting, the model presented can work effectively.**

Index Terms—**Adaptive neural fuzzy inference system, power system, radial basis function neural network, real-time price, short-term load forecasting.**

I. Introduction

Electric short-term load forecasting (STLF) is an important guideline for safe scheduling and economic managing of power systems. Under the conditions dictated by electricity markets, electric utilities have to establish reasonable economic models and competitive real-pricing according to accurate and fast forecasting results of a short-term load. And thus, for a long time, STLF has been under great focus and various algorithms have been put forward [1]–[5]. For example conventional techniques include fuzzy logic inference [6]–[8], regression techniques [9], time series approaches [10]–[12], expert system based methods [13] are also commonly used. As for forecasting under real-time price conditions, various types of artificial neural network (ANN) have been proposed for short-term load forecasting [14], [15]. They enhanced the forecasting accuracy compared with the conventional time series and regression methods. The ANN has the ability of self-leaning and nonlinear approximation, but it lacks the inference, common in human beings, and therefore requires massive amounts of training data, which is an intensive time consuming process. The fuzzy logic inference, on the other hand, is a fast approach for fuzzy and uncertain problems. However, the traditional fuzzy system is largely dependent on the knowledge and experiences of experts and operators, and is difficult to obtain a satisfied forecasting result especially when this special information is incomplete or insufficient.

The price of electricity mainly reflects the relationship between demand and supply, guides the decision-making of market supervision and energy transaction, and as a consequence, becomes the most important information of electricity markets. In the case of electricity markets, a change of electricity price will influence the energy-use patterns of customers. In order to reduce the expense of using electric energy, partial customers will shift high energy-use time from periods with high price to periods with low prices. This kind of shift will obviously form a daily load profile different to the one with a fixed price. This explains why forecasting real-time price is very inaccurate if fixed-price based methods are used. Moreover, the reaction of customers to varied price is a gradual process towards a final stabilization, which will result in inadequate historical experience and data, and thus, limit the application of forecasting methods in a fixed price environment.

This paper combines a neural network and a fuzzy system for STLF in the real-time price environment. Section II reveals the relationship between real-time price and short-term load. In Section III, daily loads are firstly forecasted by RBFNN without considering the electric price factors. An adaptive neural fuzzy inference system is introduced to adjust the forecasting results according to the change of the latest electricity price in Section IV. Section V is an example. Finally, a conclusion is reached in Section VI.

II. Technical Analysis of Real-Time Price and STLF

The Power industry is changing from an initial state of monopolization to one of open competition, and as a result, the price of electricity has changed accordingly. Recently, the existing and developing patterns of the electricity market have

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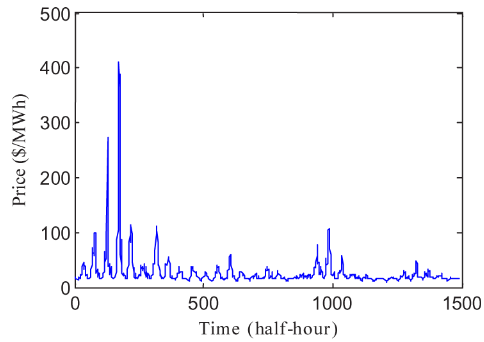

Fig. 1. Price curve of half an hour in January 2004.

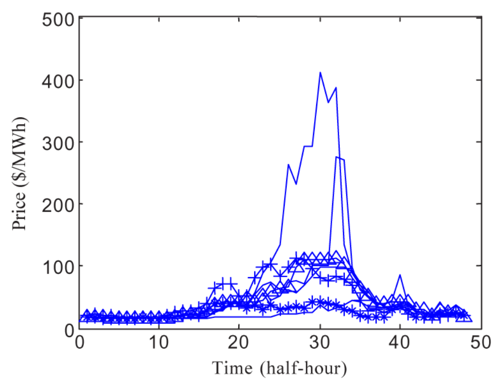

Fig. 2. Price curve of half an hour from 1–7 January 2004.

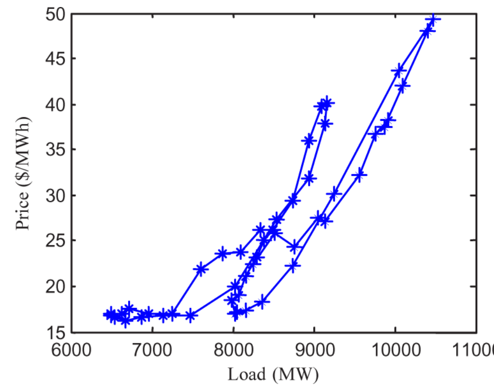

Fig. 3. Curve between load and price for a day.

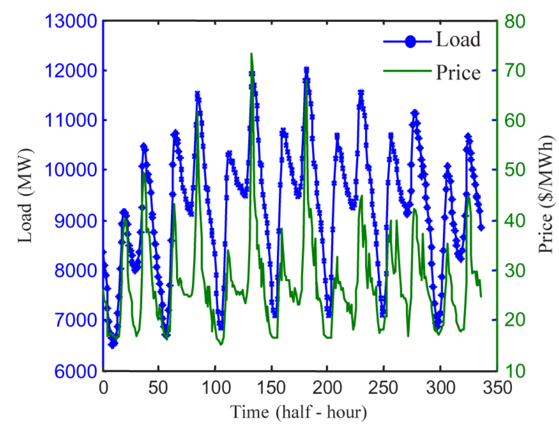

Fig. 4. Curve of load, price, and time for a week.

been different in various countries and regions; the way the price of electricity is established is rarely the same, however a common trend is the fact that the price is strongly time-varying. Figs. 1 and 2 are showing the changes in the price of electricity in January 2004 in an Australian region.

In Figs. 1 and 2 one can infer that the price of electricity behaves differently every day and, the price in different areas varies from each other. That is, the price is real-time and non-linear in some degree. This is a result of various factors: economical conditions, weather, operation of power systems, and customer demands. In Fig. 2, the price during the morning and nighttime is low and fluctuates little. It indicates small energy usage, but on the other hand lower price stimulates electricity consumption.

Under the condition of electricity markets, the price of electricity is connected to the load [6]. Price varies with demand, and consequently, demand influences the fluctuation of the price. Therefore fluctuation in electricity price certainly will lead to a change in load characteristics, and finally the price will also be influenced by the load. Figs. 3 and 4 are, respectively, curves of price and load during August 2004.

In Fig. 3, the horizontal axis is load with a sampling frequency of half an hour, while the vertical axis is for the relevant half an hour price. Under normal conditions, the price rise with increase of load, and price is the approximate linear function of load; there are two peak values of load curve a day, which correspond to two maximum values of price in the same day. Research reveals that real-time price is a function of load demand and redundancy or deficiency of generated energy. Fluctuation in price influences the energy consumption behavior, changes the energy-use pattern, causes new change of short- term load, and furthermore, improves load profile. In the electricity market, accurate load forecasting set the foundation of real-time price prediction. When the forecasted load is greater than real load, exorbitant demand results in higher bid price, and vice versa if the forecasted load is smaller than the actual load the demanded price is lower.

In Fig. 4, the horizontal axis is time with a sampling frequency of half-hour during a week. Vertical coordinates on the left side stand for load, and the on the right side stand for price. The blue line and the green line stand, respectively, for load curve and price curve. It can be inferred from the graph that price fluctuates largely during different hours of a day. The change of load and price are proportional, that is, a large load corresponds to a higher price. So, regulation mechanism of price is exerted adequately, which makes customers choose energy-use time according to real-time price. The shift of time-choice will change the load characteristics to some degree, and play the role of "de-spiking" and "valley filling" of a load graph. Because of these market dynamics, the price of electricity influences the trend of a load to some degree and, will become more influential with the development and generalization of electricity markets.

III. Load Forecasting Using RBFNN

The RBF neural network is a forward network model with good performance, global approximation, and is free from the local minima problems. It is a multi-input, single-output system

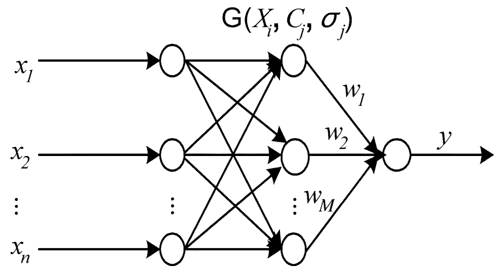

Fig. 5. Structure of RBF neural network.

consisting of an input layer, a hidden layer, and an output layer. During the data processing, the hidden layer performs nonlinear transforms for the feature extraction and the output layer gives a linear combination of output weights. The structure is shown in Fig. 5.

The input is n-dimensions, learning samples are (X, Y), where $X = (X_1, X_2, \cdots, X_N)$ is input variable, $X_i = (x_{i1}, x_{i2}, \cdots, x_{in})^T (1 \leqslant i \leqslant N)$, and the expected output is $Y = (y_1, y_2, \cdots, y_N)$, N is the training number. When the input is X_i, the output of the jth node in the hidden layer can be expressed as

$$G(X_i, C_j, \sigma_j) = \exp\left(-\|X_i - C_j\|/2\sigma^2\right) \tag{1}$$

where $C_j = (c_{j1}, c_{j2}, \cdots, c_{jn})^T$ and σ_j are the center and width of the Gaussian function of the jth node in the hidden layer.

For an input X_i, the expected output of network is

$$y_i = \sum_{j=1}^{M} G(X_i, C_j, \sigma_j) w_j + e_i. \tag{2}$$

In formula (2), w_j is the weight between the jth neuron of the hidden layer and output neuron. M stands for neuron number in the hidden layer, and y_i and e_i are the expected output of X_i and the error of fitting, respectively.

e_i can be obtained by transposition of formula (2), that is

$$e_i = y_i - \sum_{j=1}^{M} G(X_i, C_j, \sigma_j) w_j. \tag{3}$$

As for the selection of the center parameter of the Gaussian function, this paper uses the orthogonal least square algorithm. The least square algorithm is also applied to train the output weight in order to minimize total error, that is

$$\min E = \frac{1}{2} \sum_{i=1}^{N} e_i^2. \tag{4}$$

Formula (2), above, can be written in a matrix form as follows:

$$Y = PW + E \tag{5}$$

where $Y = [y_1, y_2, \cdots, y_N]^T$, $P = [P_1, P_2, \cdots, P_N]$ is output matrix of the hidden layer, and $P_i = [p_{i1}, p_{i2}, \cdots, p_{iN}]$ $(i = 1, 2, \cdots, N)$. W and E are output weights and error vectors.

Carry orthogonal decomposition on P

$$P = HA \tag{6}$$

where A is upper triangular matrix with diagonal value 1, and matrix H contains the orthogonal vectors H_i. Formula (5) can be changed into

$$Y = (PA^{-1})(AW) + E. \tag{7}$$

Suppose

$$S = AW. \tag{8}$$

Then, Y is transformed as

$$Y = (PA^{-1})S + E = HS + E. \tag{9}$$

Therefore, by using the least square algorithm S is obtained from formula (9) as

$$S = (H^T H)^{-1} H^T Y \tag{10}$$
$$e_i = \left(s_i w_i^T w_i\right) / Y^T Y, \quad (1 \leqslant i \leqslant N). \tag{11}$$

Because the number of hidden layers, M, that satisfy the training accuracy and generalization ability are far less than training number, N, the accumulating variance, ρ_i, can be used for sample assessment and center selection. When ρ_i satisfies

$$\rho_i = \sum_{j}^{i} e_j, \quad \rho_i > \rho. \tag{12}$$

The calculation terminates. The ith sample with maximal ρ_i is chosen as network center. $0 < \rho < 1$ is preset tolerant variance limit. Weight can be determined by

$$\hat{W} = A^{-1} S. \tag{13}$$

During the forecasting process, 48 RBFNN are established to predict the half an hour sections of load in one day. Each network has 12 input variables, which includes: load of one interval before forecasted point in the same day, load of two intervals before forecasted point in the same day, load of three intervals before forecasted point in the same day, load of one day before at the same point, load of one interval before forecasted point one day before, load of one interval after forecasted point one day before, load of one week before at the same point, load of one interval before forecasted point one week before, load of one interval after forecasted point one week before, average temperature of forecasted day, average temperature of one day before, the type of forecasted day. Because this model forecasts the short-term load without considering the price of electricity, it influences the accuracy of the prediction and consequently, the results cannot reflect the effect of the electricity price on the load. Therefore ANFIS is applied to adjust the results. This step is described in the next section.

IV. Adaptive Neutral Fuzzy Adjustment

A. Structure of ANFIS

ANFIS is a fuzzy inference system based on the Sugeno model. It incorporates the self-learning ability of ANN with

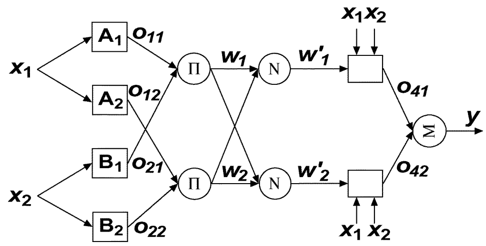

Fig. 6. ANFIS system structure.

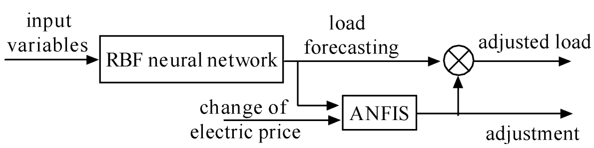

Fig. 7. Load adjustment.

the linguistic expression function of fuzzy inference, whose membership functions and fuzzy rules are acquired from a large lot of existing data instead of experience or intuition. The classical network structure has two inputs, as shown in Fig. 6.

First layer: selection of input parameters and fuzzification

Selection of input variables and fuzzification is the first step to fuzzy rule establishment. In Fig. 6, x_1 and x_2 are input variables. A_i (or B_i) is the fuzzy variables corresponding to the node of interest. o_{1i} and o_{2i} are membership functions of fuzzy set A_i and B_i, $i = 1, 2$. In this paper, the triangular function is chosen as the membership function as follows:

$$o_{1i} = \mu_{Ai}(x_1), \quad o_{2i} = \mu_{Bi}(x_2), \quad i = 1, 2. \tag{14}$$

Second layer: calculation of exciting strength

This step is represented by Π with the output

$$w_i = \mu_{Ai}(x_1)\mu_{Bi}(x_2), \quad i = 1, 2. \tag{15}$$

Third layer: normalization of exciting strength

The output is

$$w'_i = \frac{w_i}{w_1 + w_2}, \quad i = 1, 2. \tag{16}$$

Forth layer:

Each node in this layer is adaptive. After calculating the contribution of each rule, the output is expressed

$$o_{4i} = w'_i f_i = w^i_i (p_i x_1 + q_i x_2 + r_i), \quad i = 1, 2 \tag{17}$$

where p_i, q_i, r_i are parameter sets, which can be identified by the least square algorithm.

The fifth layer: calculation of final output of all rules

$$y = \sum_i w'_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}. \tag{18}$$

B. Adjustment by ANFIS

ANFIS is used to establish a load adjustment system so that it can improve the accuracy of forecasting results of RBFNN effectively under the environment of real-time price. The whole process of load forecasting is illustrated in Fig. 7.

Input variables of ANFIS are forecasted load by BRFNN (x_1) and change of electricity price (x_2), where

$$x_2 = 100 \times (d_1 - d_2)/d_1. \tag{19}$$

where d_1 is the electricity price forecasted in one day (point), and d_2 means the price one point before in the same day (previous point).

Input variables are divided into very low, low, normal, high, very high; and the output of ANFIS is the change of load. The change load is partitioned into very low, low, unchanged, high and very high. The total number of fuzzy rules is 25, each one of which is expressed in the "IF$\cdots$THEN" form like, for example:

IF forecasted load x_1 is normal, AND the change of electric price x_2 is high, THEN the adjustment of load ΔP_i is low;

IF forecasted load x_1 is low, AND the change of electric price x_2 is low, THEN the adjustment of load ΔP_i is high;

IF forecasted load x_1 is very low, AND the change of electric price x_2 is very low, THEN the adjustment of load ΔP_i is very high;

IF forecasted load x_1 is very high, AND the change of electric price x_2 is very high, THEN the adjustment of load ΔP_i is very low;

IF forecasted load x_1 is normal, AND the change of electric price x_2 is low, THEN the adjustment of load ΔP_i is high.

Considering the exciting strength of ANFIS, load adjustment of ANFIS ΔP is calculated as

$$\Delta P = \sum_{i=1}^{n} \Delta P_i w'_i \tag{20}$$

where ΔP_i and w'_i are, respectively, the output and exciting strength of the ith rule. n is the rule number used for fuzzy reasoning.

Finally, the forecasted load of the network is

$$P = x_1 \times (1 + 0.01 \times \Delta P) \tag{21}$$

where P is conclusive forecasted load by adjustment , x1 is forecasted load by BRFNN, ΔP is load adjustment of ANFIS.

In this application of ANFIS, the back propagation algorithm with hybrid least square estimation is adopted as the parameter learning algorithm [16]. In the estimation process, for any given input vector, outputs are acquired by each node function, and the linear least square estimation is used to identify the conclusion parameters of fuzzy rules. Finally, output errors corresponding to each input data are calculated. While in the back-propagation stage, the error is transferred from the output node into the input node by the steepest descent method; and then, the parameters related to the shape of the membership functions are adjusted. When the error standard is satisfied or the established number of iterations is reached, the process is finished.

V. Testing Example

Load data from January to August 2004 of an Australian region are analyzed using the proposed method [17]. and other three methods with the same historical data are used to forecast the load and compare with the proposed method in order to

TABLE I
RESULTS OF DIFFERENT FORECASTED APPROACHES IN AUGUST 1, 2004

Time	Real load (MW)	Method I		Method II		Method III		Proposed method in the paper	
		Forecasted load (MW)	error/%	Forecasted load (MW)	error/%	Forecasted load (MW)	error/%	Forecasted load (MW)	error/%
0:00	8353.2	8243.3	1.316	8384.9	-0.379	8460.9	-1.289	8311.8	0.496
0:30	8094.7	7807.7	3.546	8187.3	-1.144	8215.1	-1.487	7879.6	2.657
1:00	7887.5	7592.2	3.744	7948.2	-0.77	8044.4	-1.991	7696.5	2.422
1:30	7620.9	7161.6	6.027	7341.1	3.671	7639.1	-0.239	7410.9	2.756
2:00	7251.2	6770.3	6.632	6904.3	4.784	7169.2	1.131	7032.7	3.013
2:30	6962.3	6789.5	2.482	7056.9	-1.359	7100.3	-1.982	6810.1	2.186
3:00	6732.8	7145.2	-6.125	6607.8	1.857	6885.3	-2.265	6708.6	0.359
3:30	6628.9	6709.3	-1.213	6638.2	-0.14	6632.4	-0.053	6520.7	1.632
4:00	6506.4	6255.4	3.858	6699	-2.96	6562.5	-0.862	6544	-0.578
4:30	6500.9	6591.4	-1.392	6619.8	-1.829	6650	-2.367	6528.1	-0.418
5:00	6537.8	6625.9	-1.348	6569	-0.477	6531.1	0.102	6639	-1.548
5:30	6683	6825.1	-2.126	6730.5	-0.711	6529.1	2.303	6746.5	-0.95
6:00	6885.7	7142.2	-3.725	6936.7	-0.741	6841.7	0.639	7052.8	-2.427
6:30	7144.6	7104.3	0.564	7227.9	-1.166	7055.1	1.253	7281.9	-1.922
7:00	7483.7	7343.3	1.876	7603.5	-1.601	7405.6	1.044	7605.7	-1.63
7:30	8037.9	8215.9	-2.215	8148.3	-1.373	8026.9	0.137	7970.2	0.842
8:00	8553.7	8504.7	0.573	8681.8	-1.498	8657.3	-1.211	8440.1	1.328
8:30	8936.4	8836	1.123	9096.3	-1.789	9095.3	-1.778	8850.6	0.96
9:00	9146.7	8864.9	3.081	9250.7	-1.137	9394.6	-2.71	8986.3	1.754
9:30	9165.5	8495.4	7.311	9164.3	0.013	9264.9	-1.085	9582.4	-4.549
10:00	9091.7	8972.1	1.315	9213.9	-1.344	9187.7	-1.056	8981.8	1.209
10:30	8936.1	9340.6	-4.527	8916	0.225	8825.7	1.235	8729.2	2.315
11:00	8737.9	8612.8	1.432	8372.3	4.184	8600.8	1.569	8605.4	1.516
11:30	8507.7	8081.4	5.011	8439.6	0.8	8457	0.596	8775.4	-3.147
12:00	8396.5	8051	4.115	7846	6.556	8365.5	0.369	8221.7	2.082
12:30	8300.8	8231.6	0.834	8183.4	1.414	8395.2	-1.137	8265.9	0.42
13:00	8156	7735.3	5.158	8194.1	-0.467	8257.4	-1.243	7843.3	3.834
13:30	8082.2	8281.9	-2.471	8020.6	0.762	8227.9	-1.803	8210.9	-1.592
14:00	7996.2	7866	1.628	7919.4	0.96	8309.2	-3.914	8132.6	-1.706
14:30	8038.5	8369.3	-4.115	7899.5	1.729	8207.8	-2.106	8209.9	-2.132
15:00	8065.2	8022.4	0.531	8059.7	0.068	8433.6	-4.568	7998.5	0.827
15:30	8166.1	8337	-2.093	8046.7	1.462	8584.2	-5.12	8321.7	-1.905
16:00	8361.7	8096.1	3.176	8341.7	0.239	8553.2	-2.29	8518.4	-1.874
16:30	8748.3	8684.1	0.734	8159.2	6.734	8487	2.987	8848.1	-1.141
17:00	9255.1	8993.6	2.825	9018.3	2.559	8727	5.706	9055.1	2.161
17:30	10061.9	9929.6	1.315	9895.3	1.656	9669.2	3.904	9984.9	0.765
18:00	10471.5	10674.2	-1.936	10109	3.462	10023	4.288	10636.2	-1.573
18:30	10419.2	10809.9	-3.75	10431	-0.113	10213	1.977	10637.8	-2.098
19:00	10098.7	9851	2.453	10501	-3.984	10057	0.416	10223.4	-1.235
19:30	9883.2	9624	2.623	10171	-2.912	9774	1.105	9955.3	-0.73
20:00	9912.8	10345.1	-4.361	9965.4	-0.531	9576.9	3.389	9683.2	2.316
20:30	9774.9	9672.1	1.052	9886.6	-1.143	9559.2	2.207	9598.7	1.803
21:00	9555.6	9465.5	0.943	9837.6	-2.951	9538.7	0.177	9605.9	-0.526
21:30	9136.8	9254.7	-1.29	9596.2	-5.028	9392.6	-2.8	9242.7	-1.159
22:00	9061.5	8778.3	3.125	9129.8	-0.754	8954.6	1.18	8885	1.948
22:30	8766.8	8321.4	5.081	8953.9	-2.134	8842.6	-0.865	8549.5	2.479
23:00	8532.2	8476.1	0.658	8301.3	2.706	8606.3	-0.868	8478.5	0.629
23:30	8263.4	8123.7	1.691	8414.9	-1.833	8093	2.062	8311.3	-0.58

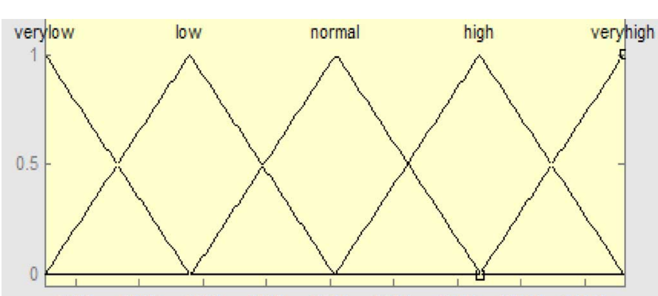

Fig. 8. Membership functions of forecasted load.

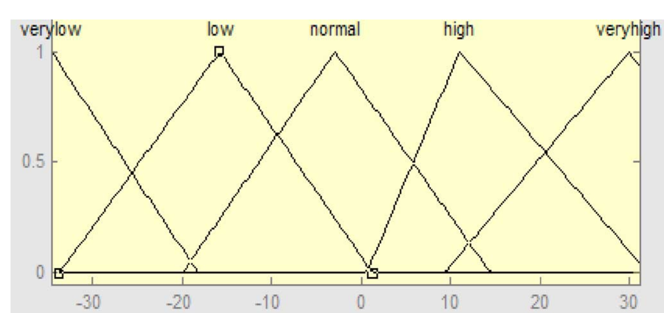

Fig. 9. Membership functions of change of electricity price.

reveal the advantage of proposed method, the three methods include: Method I (RBFNN methodwith historical demand data and without price change), Method II (RBFNN method with historical demand data and price change), Method III (ANFIS method with historical demand data and price change).

In this paper, the triangular function is chosen as the membership function in ANFIS method, the ranges for forecasted load by RBFNN (x_1) and change of electricity price (x_2) are ascertained by ANFIS method with MATLAB software according to large numbers of historical data, and the membership functions are got by training the historical data (Figs. 8 and 9), the parameters of membership functions for the ranges as follows: For x_1: very low [5117 6260 7390], low [6243 7382 8520], normal [7394 8533 9671], high [8532 9671 10810], very high [9671 10810 11950]. For x_2: very low [−51.02 −34.61 −18.19], low [−34.61 −16.69 0.3933], normal [−19.86 −2.762 14.6], high [0.6363 10.97 14.6], very high [9.437 30.13 47.46], the three parameters of each classification express the minimum value, the value whose membership grade is 1 and the maximum value of the range, respectively.

Load data of June and July are used as training data, and the load data of August are tested. The forecasted load for the August 1, 2004 is shown in Table I.

In Table I, the forecasting error is large when real-time price is not considered. The maximum and average errors are, respectively, 7.311% and 2.719%. When real-time price is considered, the maximum and average errors of Method II are 6.734% and 1.836%, the maximum and average errors of method III are 5.706% and 1.810%, with the method proposed in the paper, the forecasting accuracy is improved significantly, and the errors are reduced to 4.549% maximum and 1.669% average. Therefore, in the environment of electricity market, the influence of price on load cannot be neglected. The improved accuracy implies that ANFIS is a necessary supplement for RBFNN. When the two approaches are combined, dealing with the price factor becomes more flexible and practical, and naturally, the accuracy is improved.

VI. Conclusion

This paper uses the RBF network based method for load forecasting. The self-learning and nonlinear mapping ability of the RBF network gives the forecasting results without considering the influence of the electricity price. Aiming at the uncertainty of the real-time price and its effect on load, an ANFIS based adjustment is proposed. This supplement reflects the relationship between price fluctuation and load change and consequently improves the accuracy of predictions. An example demonstrates that the proposed method is flexible and practical for STLF under the condition of real-time prices.

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