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# A Short-term Load Forecasting Method Based on Fuzzy Neural RBF Network Adaptive Control

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**Abstract.** According to historical load data of the power grid in a certain area, by which analyze this area's power load characteristic and consider the load forecasting influence factors such as the date type, temperature, weather conditions in the first. In view of the load has a certain objective laws, but which has a lot of randomness and uncertainty, applying one kind new based on the RBF (Radial Basis Function) Neural Fuzzy Inference to carry on short-term load forecasting. By programming with MATLAB to carry on short-term power system load forecasting, carry on the short-term load forecast experiment to the practical grid and draw the forecasting result curves. The result indicated that the RBF Adaptive Neural Fuzzy Inference of the forecast accuracy is satisfied with the verification of this method is effective and practical.

## 1. Introduction

The load forecasting of power system is the basis of power system security and economic operation. Only by depend on accurate load forecasting, we can improve the security and economy operation of power grid and improve the power quality in the power system. Load forecasting has become an independent content in energy management system (EMS) in the gradual development and improvement of the process for the power system, and load forecasting has become part of power market management system is essential under the inevitable trend of the current power systems market. In practical application, the different components of power system will affect the accuracy and the range of load forecasting to varying degrees. Therefore, the study of the load variation inherent law, load characteristics, the relative factors and the standardized treatment load data had important significance to improve the prediction accuracy and the development of load forecasting.

Rahmat[1] used adaptive neuro-fuzzy inference system (ANFIS) to do rubber milk production forecasting. Ni[2] studied and analyzed the shortcomings of RBF neural network in short-term load forecasting error of power system, and proposed a short-term load forecasting algorithm based on fuzzy control and RBF neural network. The algorithm can improve the prediction accuracy and has good application prospects. Borges[3] presented a combined forecasting method of short-term power load based on offset correction and regression aggregation is proposed, which can be used for global forecasting of classified power load.

Yao[4] presented an interval-based 2-type fuzzy control method for power load forecasting. The gradient optimal descent method is used to train and optimize the parameters of membership function, and obtained the minimum output error. In order to quantify the potential uncertainties associated with prediction, a prediction interval construction method based on neural network is proposed in document [5]. Particle swarm optimization (PSO) algorithm based on mutation operator is used to optimize



multi-objective problems, which improves the accuracy of load forecasting. Chicco[6-7] presented an ant colony clustering based on electrical model for power load planning, and uses centroid model for power customer clustering analysis. Using the concept of entropy introduced by Renyi, a specific clustering process is established, and a method of classifying power users according to their daily load patterns is discussed. The results obtained are helpful for power suppliers to reduce the number of load pattern recognition, and to differentiate load aggregation and load price among related consumers.

In recent years, with the rapid development of our country's economy, the reform of power system is also imminent. The load of power system is becoming larger and larger. It is of great significance to strengthen the power system load forecasting ability. The accurate prediction of the power system load can not only realize the economic operation of the power system, but also guarantee the safety and stability of the power system. Sex. Based on the above analysis, a short-term load forecasting method based on RBF adaptive neural fuzzy control is proposed. This paper selects the historical data of a certain area, and selects the daily maximum quantity of electricity data, then forecasts the load situation in the area in August, and uses MATLAB software for simulation analysis. The rough error in the historical data is processed, the input matrix is set up in MATLAB, and it is normalized, and the model of the neural network is established by using the newrbf function. After the calculation is completed, the actual value of the predicted load is obtained through anti normalization, and good research results are obtained.

## 2. Adaptive Neural Fuzzy Inference System (ANFIS) Method based on RBF

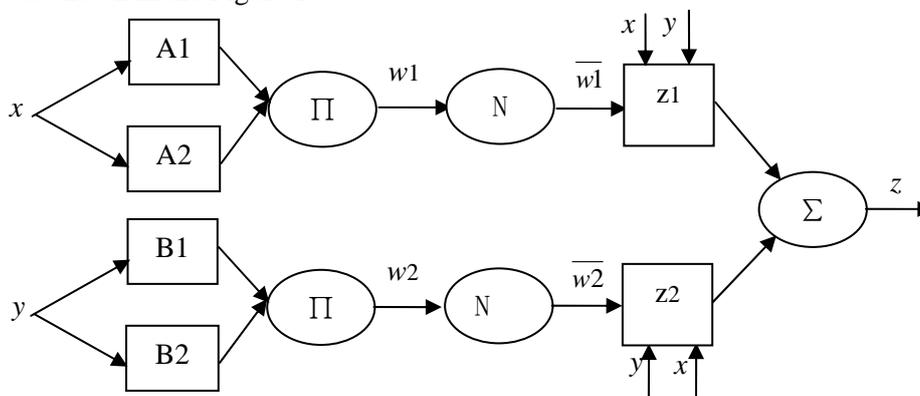
The ANFIS based on radial basis function (RBF) achieves the fuzzy reasoning by using neural network, the three most basic process of fuzzy control is fuzzification, fuzzy inference and the defuzzification that it is realized by neural network. The self-learning mechanism of neural network can extract the input data and fuzzy systems can easily express human knowledge, there is another advantage that we can make up for the deficiency of the traditional fuzzy control, we can establish an input/output mapping the human cognition and the specific input/output data by studying the hybrid algorithm. Therefore, it can overcome the shortcomings that the traditional fuzzy controller must adjust the membership function repeatedly, and then it could reduce the error and improve the efficiency.

### 2.1. The Structure Description and Learning Algorithm of ANFIS based on RBF

Surgeon fuzzy model has a very typical inference rules:

If  $x$  is  $A$  and  $y$  is  $B$  then  $z=f(x, y)$

In the rule:  $A$  and  $B$  can be regarded as the fuzzy premise,  $z=f(x,y)$  is the accurate data of the reasoning results,  $f(x,y)$  is a polynomial of  $X$  and  $y$ . Corresponding, Roger Jang proposed a set of adaptive neural fuzzy inference system, the system could achieve the function of learning Sugeno fuzzy model and its function equivalent to a first order Sugeno fuzzy model, so it can be seen as a reproduction for the fuzzy model of a neural network. The multilayer feed forward network structure of ANFIS was shown in the Figure 1.



**Figure 1.** Structure of ANFIS

The first layer is the fuzzy layer, which is mainly responsible for the fuzzy processing of the input data. The output function of the node  $i$  is:

$$O_i^1 = \mu_{A_i}(x) \quad (1)$$

In the formula  $x$  represents the input of the node  $i$ ,  $A_i$  is the fuzzy set.  $O_i^1$  is the value of membership function  $A_i$  which reflects the genus extent of  $x$ . We choose the bell function, and the span of its maximum value is 1 or 0:

$$\mu_{A_i}(x) = \frac{1}{1 + \left[ \frac{(x - \gamma_i)^2}{\alpha_i} \right]^{\beta_i}} \quad (2)$$

In the above formula,  $\{\alpha_i, \beta_i, \gamma_i\}$  are the premise parameters,  $\alpha_i$  is the width,  $\beta_i$  is the slope,  $\gamma_i$  is the center position. By adjusting these parameters, the membership function shape could change. The membership function in the formula can use arbitrary piecewise continuous functions, such as the trapezoidal function or Gaussian function.

The second layer is the release intensity layer of the rule. the main function of this layer is to multiply the input signal. For example:

$$w_i = \mu_{A_i}(x) \times \mu_{B_i}(y) \quad i = 1, 2 \quad (3)$$

The output of each node shows the credibility of this rule, any AND operator that satisfies the T specification that can be used as " $\times$ ". The calculation results of this formula will define the activation intensity of the different fuzzy rules.

The third layer is the normalization of all the rules intensity. The credibility of the  $i$  rule in the  $i$  nodes, the normalization of the calculation formula is:

$$\bar{w}_i = \frac{w_i}{w_1 + w_2} \quad i = 1, 2 \quad (4)$$

The node in this layer is a circle node (the fixed node) which is to be calculated the weight coefficient of fuzzy rule and carry on the normalized operation of the activation intensity for fuzzy rules.

The fourth layer is the output fuzzy rules. It mainly responsible calculates the output data of different fuzzy rules, each node in the formula corresponds is an adaptive node, and the output data of the  $i$  node is calculated as follows:

$$O_i^4 = \bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + \gamma_i) \quad (5)$$

Where,  $\bar{w}_i$  is the output data of the third layer,  $\{p_i, q_i, \gamma_i\}$  are the different conclusions parameters.

The fifth layer is the defuzzification layer. In this layer there is only one node which represents the sum of all the input signals, namely is the conclusion of the fuzzy reasoning:

$$O_i^5 = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (6)$$

So after giving a specific membership function, the final output data of ANFIS can be described the linear combination of various conclusions parameters:

$$\begin{aligned} f &= \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 = \bar{w}_1 f_1 + \bar{w}_2 f_2 \\ &= (\bar{w}_1 x) p_1 + (\bar{w}_1 y) q_1 + (\bar{w}_1) \gamma_1 + (\bar{w}_2 x) p_2 + (\bar{w}_2 y) q_2 + (\bar{w}_2) \gamma_2 \end{aligned} \quad (7)$$

Combination of the above corollary, the neural network of  $m$  inputs and each input variable with  $k$  Sugeno fuzzy sets, we can get the total control rules  $n = K^m$ .

## 2.2. Learning Algorithm of ANFIS based on RBF

The method can use the neural network to study and can flexibly adjust the parameters and structures of the neural fuzzy control system. There are two types of neural fuzzy controller: structure adjustment and parameters adjustment. The structure adjustment mainly includes the adjustment of the variables number, the universe of the input and output variables and the variable rules. The parameters adjustments are mainly the parameters of the membership function, such as the adjustment of center, width and slope. Since the network structure has been determined, the learning algorithm is actually just to learn the controller parameters, and just adjust the premise parameters and conclusion parameters. At present, there are many methods can update the ANFIS parameters: the ANFIS learning method in this paper adopts the hybrid algorithm based on the gradient descent method and the least square algorithm. The algorithm uses the gradient method and the least square method (LSE) to identify the parameters, and the conclusion parameters are applied by the gradient descent method. The learning process is divided into the forward process and the backward process, the forward process is to the fourth floor of the fuzzy inference system (ANFIS), the conclusion parameters  $\{ p_i,$

$q_i, \gamma_i \}$  can get by the least squares estimation method. By using the study of reverse gradient descent method, the parameters of the output layer are fixed. By adjusting the self-searching optimization of the parameters of the input layer or the mid layers, the system error will reduce. The membership function shape can change by the return error rate of the premise parameters  $\{ \alpha_i, \beta_i, \gamma_i \}$ , until the variances of the entire sample sets are reached the prescribed accuracy requirements.

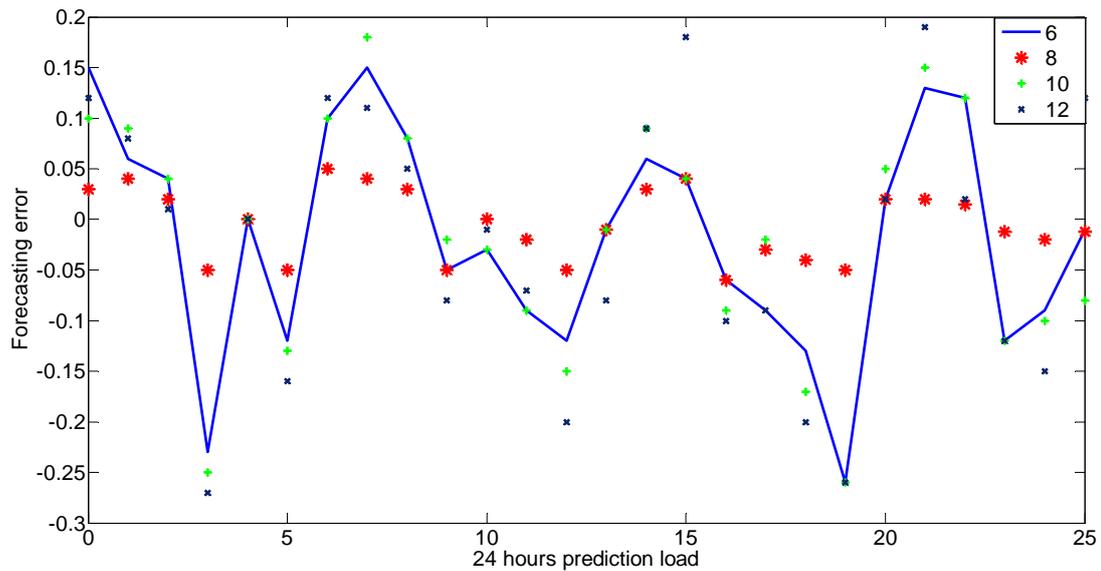
## 3. Results and Analysis of Power Load Forecasting

It is necessary to analyze the load history data which is the important character for the short term load forecasting. Because the power load is inherently uncontrollable, one of the most effective ways to understand the possible change of load in the future short term by observing the historical load. Therefore it is necessary to consider the periodicity affects of daily and weekly load changes, weather factors and human factors when forecasting the grid load. So we can use adaptive neural fuzzy inference method based on RBF to forecast short term load by analyzing the load characteristics and variation regularity, and simulate it by MATLAB.

### 3.1. The Structure Description and Learning Algorithm of ANFIS based on RBF

The prediction model is the adaptive neural fuzzy inference system based on RBF model. According to the characteristics of power load, the date was classified into 4 types to forecast 24 hours' load: Monday load, working days load (from Tuesday to Friday), Saturday load and Sunday load, so in total we established 96 neural network units. The total input node is 96, respectively is yesterday load, the day before yesterday load, the same hour load of last week, the previous moment load of the forecast moment, predicted day, the maximum temperature and minimum temperature of yesterday, the measure values of weather condition and forecast date variables. The output node is 1 which is the predict value of the whole point load. From the above we can see that the number of hidden layer of this paper is to take the testing method by random using a regional power grid for 24 hours to predict the load, the relative error of the results is shown in the figure 2.

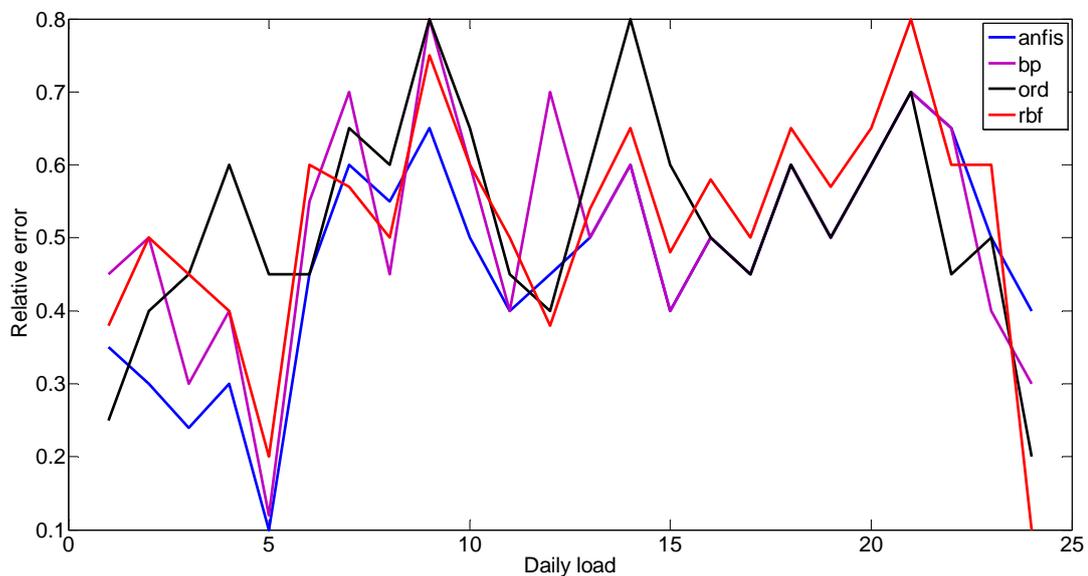
In the Figure 2, the different hidden layers have the different predicted results. when the number of hidden layer neurons is 8, the average error of prediction results is the minimum. There are a lot of results of this experiment, when the hidden layer of neurons for 8, the actual observation results is the most close to the ideal results. So we made sure that the number of hidden layer neurons is the most suitable for 8.



**Figure 2.** Forecasting Error Curves of the Different Hidden Layers

*3.2. Comparison of Load Forecasting Methods*

The article uses the BP neural network algorithm, RBF neural network algorithm and adaptive neural fuzzy inference system based on RBF to forecast the load data of the certain power grid in January 8, 2018. By using the three forecasting methods to compare the daily load and the relative error, the results are shown in the table 1 and the figure 3.



**Figure 3.** The Forecasting Curves of Three Algorithms and the Initial Data

Seen from Figure 3, the ANFIS based on RBF is the best approximation ability. This shows that the ANFIS based on RBF can be very good for the prediction of power load.

**Table 1.** Forecasting Results Comparison based on Different Forecasting Algorithms.

IPV	ID	BPNN		RBFNN		ANFIS	
		PV	ERROR	PV	ERROR	PV	ERROR
1	0.3724	0.2368	0.1356	0.3275	0.0499	0.3754	0.0030
2	0.3143	0.2784	0.0359	0.2752	0.0391	0.3069	0.0074
3	0.2696	0.4939	0.2243	0.2362	0.0334	0.2778	0.0082
4	0.2495	0.2646	0.0151	0.2184	0.0311	0.2503	0.0008
5	0.2399	0.2775	0.0376	0.2201	0.0198	0.2333	0.0066
6	0.2464	0.5193	0.2729	0.2238	0.0226	0.2521	0.0057
7	0.2840	0.3794	0.0954	0.2720	0.0120	0.2826	0.0014
8	0.6894	0.8101	0.1207	0.7054	0.0160	0.6287	0.0067
9	0.7631	0.9626	0.1635	0.8238	0.0607	0.7658	0.0027
10	0.7717	0.9642	0.1925	0.7905	0.0188	0.7811	0.0094
11	0.7915	0.8788	0.0873	0.8202	0.0287	0.7880	0.0035
12	0.3768	0.4389	0.0621	0.4049	0.0281	0.3628	0.0140
13	0.4519	0.6405	0.1866	0.4615	0.0096	0.4811	0.0292
14	0.7519	0.9347	0.1828	0.7935	0.0416	0.7251	0.0268
15	0.7642	0.8307	0.0665	0.8492	0.0850	0.8152	0.0510
16	0.7949	0.9177	0.1228	0.8546	0.0597	0.7611	0.0338
17	0.7860	0.8950	0.1090	0.8520	0.0660	0.7288	0.0572
18	0.6515	0.8610	0.0295	0.6578	0.0063	0.7011	0.0496
19	0.8918	0.9005	0.0087	0.9918	0.1000	0.8934	0.0016
20	0.8597	0.9603	0.0066	0.9550	0.0953	0.8538	0.0059
21	0.8253	0.9329	0.0076	0.8632	0.0379	0.8095	0.0042
22	0.8031	0.5819	0.2212	0.8055	0.0024	0.8016	0.0015
23	0.6430	0.6394	0.0036	0.7097	0.0667	0.6437	0.0007
24	0.4444	0.3096	0.1348	0.3876	0.0568	0.4430	0.0014

Where, IPV is integral point value, ID is the initial data, PV is the prediction value.

In the table 1, the prediction error maximum BP neural network was 0.2729, the prediction error maximum value of RBF neural network was 0.1 and the prediction error maximum of the ANFIS Based on RBF was 0.0572. Obviously, the relative error of the ANFIS Based on RBF is the minimum. The results show that the ANFIS Based on RBF could effectively improve the accuracy of load forecasting and meet the needs of the actual operation.

#### 4. Conclusion

The ANFIS Based on RBF has the advantages of fast convergence speed, strong fitting capability, high prediction precision and the only training results. By using MATLAB programming with the short-term power load of certain area to forecast the future load, the results show that the method could better predict the load, and its forecast error was no difference with the actual situation and achieved satisfactory results. So this method is conducive to the upgrading and transformation of the power system, but also conducive to improve the power quality.

The proposed method in this paper is used to identify the system by RBF neural network, and provide the necessary information for the learning system, modify the experience rule according to the information, and improve the dynamic response of the fuzzy control system. The simulation results show that the controller had good adaptability to the model parameters change and can quickly modify the original control system. The simulation results show that the algorithm has high efficiency, fast convergence speed and high precision of the model. It makes the object output fast tracking the input of the system. It has great superiority in dealing with the problems of nonlinearity and fuzziness, and has great potential in the intelligent information processing.

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