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Short-term Power Load Forecasting based on RBF Neural Network

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Abstract

Traditional short-term forecasting of power load is difficult to guarantee a relatively high forecast accuracy when the amount of data is huge and there are many influencing factors. Therefore, a RBF neural network short-term power load forecast is proposed, and fuzzy control algorithm is added on this basis to further improve the forecasting accuracy. In the MATLAB environment, this method is used for short-term power load forecasting simulation and compared with the RBF neural network forecasting alone. The results show that the combination of RBF neural network and fuzzy control algorithm for short-term power load forecasting can speed up the convergence speed, improve the forecasting accuracy, and have a good development and application prospect.

Keywords

Short-term Load Forecasting; RBF Neural Network; Fuzzy Control; Power Systems; MATLAB.

1. Introduction

Load forecasting refers to the use of certain algorithms to analyze the historical load data that has been obtained and preprocessed, analyze and find its characteristics and laws, construct corresponding forecasting models according to the characteristics and laws, and finally estimate the future load data through the built model . With the development of the economy, the construction of infrastructure has become more complete, so the requirements for electricity are getting higher and higher. In order to achieve the dynamic balance of power generation and power consumption, to ensure the safety and stability of the power system, and to avoid unnecessary energy waste, It is necessary to predict the electric load with higher accuracy. Short-term load forecasting is generally to forecast the load from 1 to 7 days in the future. Therefore, short-term load forecasting is of great significance to ensure the grid revenue, the accuracy of electricity trading, and the safety of the power system.

Short-term power load forecasting is mainly divided into traditional forecasting methods and modern forecasting methods [1]. The algorithms of traditional forecasting methods mainly include regression analysis method [2], time series method [3], wavelet analysis method [4], grey forecast method [5], Kalman filter method [6], trend extrapolation method and so on. The basic principles of traditional forecasting methods are relatively simple. Although the application is relatively mature, influencing factors cannot be considered in the forecasting, and when used in nonlinear analysis, the parameters cannot be adjusted in time, which will lead to large errors in the forecasting results. Therefore, modern forecasting methods follow The production. Modern forecasting methods mainly include expert system method, fuzzy control method and artificial neural network method [7]. Artificial neural

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network includes BP neural network [8], RBF neural network [9], Elman neural network [10], support vector machine method [11], etc. When using neural network technology for short-term power load forecasting, some non-linear objects can also be optimized for calculation and self-learning to improve the adaptive ability, so as to achieve higher forecasting accuracy.

Literature [12] uses support vector regression (SVR) algorithm for short-term power load forecasting, and has achieved good results in China; Literature [13] uses BP neural network for short-term power load forecasting, and literature [14] uses Elman neural network performs short-term power load forecasting, and these two algorithms have very good results in forecasting accuracy.

Although the neural network algorithm improves the prediction accuracy to a certain extent, there are still some errors. Therefore, this paper proposes to combine the RBF neural network with the fuzzy algorithm to further improve the prediction accuracy.

2. RBF neural network construction

2.1 Determine model input and output variables

Due to the randomness of power load forecasting, it will be affected by many factors. If the influence of these factors can be predicted, the forecasting accuracy can be improved. After a long period of research, it is found that the factors that have the greatest impact on short-term load forecasting can be divided into economic factors, meteorological factors, time factors and random factors[15]. The influence of economic factors is reflected in the economic growth while the demand for electricity will also increase. However, since economic growth is a long-term slow process, economic factors are not considered for the time being. Meteorological factors mainly include the temperature value, humidity value, weather, wind speed, etc. of the day. Meteorological factors have a great influence on short-term load forecasting, so meteorological factors are the main consideration. The influence of time factors on power load forecasting is mainly reflected in the periodicity of power load. Power load tends to show similar changes according to seasons, weeks, and days. At the same time, the load is also affected by holidays and working days. Random factors generally include special large-scale festivals or events, the start and stop of factory machinery, and the power load impact caused by natural disasters. Such impacts are too uncertain and therefore generally not considered.

In order to obtain a good prediction model, this article considers the meteorological factors and time factors comprehensively. It is proposed to use the simultaneous load value, maximum temperature, minimum temperature, average temperature, rainfall, humidity and date type of the day before the prediction day as well as the meteorological data of the day of the prediction day as the 13 input elements of the RBF neural network to predict the time T of the day. The load is 1 output element.

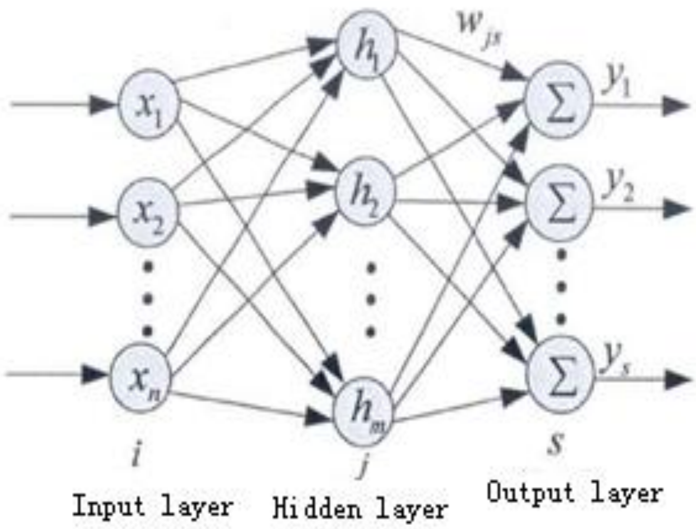

Figure 1. RBF neural network structure

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2.2 RBF neural network prediction model

Radial basis function neural network is a three-layer static forward network composed of input layer, hidden layer and output layer. The input layer is composed of input neurons. The signal node does not do any processing on the data but directly transmits the data to the hidden layer; in the hidden layer, the data is passed to the output layer after being processed by the radial basis function; the output data of the output layer follows The weight of the output layer changes. The RBF neural network can still maintain a good training effect even in the face of objects with sparse samples and non-linear data. The structure of RBF neural network is shown in Figure 1.

The input vector is $X = [x_1, x_2, \cdots x_n]^T$; The radial basis vector of the hidden layer $H = \left[h_1, h_2, \cdots h_j, \cdots h_m\right]^T$, h_j take Gaussian function, The hidden layer weight vector is $W = [w_1, w_2, \cdots w_m]^T$; Output vector $Y = [y_1, y_2, \cdots y_s]^T$.

The RBF neural network consists of two parts:

The first part is to transform the input vector, transform the n-dimensional input to the m-dimensional space, thereby establishing a connection with the hidden layer. The radial basis function in this article is a Gaussian function:

$$h_j(x) = f_j\left(\frac{\|X-C_j\|}{b_j}\right) = exp\left(-\frac{\|X-C_j\|^2}{b_j^2}\right), j = 1,2,\cdots m \tag{1}$$

Where $\|*\|$ is the Euclidean norm; X is the input vector of the neural network; b_j is the width of the jth hidden node of the neural network; C_j is the center vector of the ith hidden node; m is the hidden layer node number.

$\|X - C_j\|$ represents the Euclidean norm of $X - C_j$, which can generally be understood as the distance between the vector X and the center vector C_j; f_j is the radially symmetric activation function, which can be seen from equation (1), when $X = C_j$, the value of f_j is the largest. As $\|X - C_j\|$ increases, f_j quickly decays to zero. The output interval of the Gaussian function is between 0 and 1. The closer the input value is to the central node, the larger the output value. Increasing the value of C can increase the function width of the RBF network, and the smoothness between cutting neuron functions is also better; as the value of C decreases, the shape of the function becomes narrower, so that the input closer to the weight vector can be used. The output is close to 1, and it is not sensitive to the response of other inputs.

The second part is the connection between the hidden layer and the output layer. The specific method is to perform a weighted operation on the output vector of the hidden layer neuron to obtain the output, and realize the linear mapping of $h_j \to y_s$. The expression is:

$$y_s = \sum w_{js} h_j \tag{2}$$

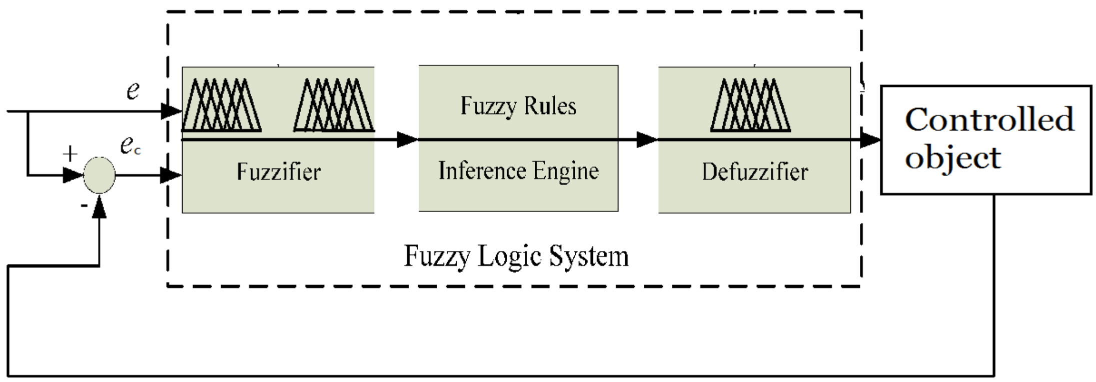

Figure 2. The structure of the dual input single output fuzzy controller

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3. RBF Neural Network Predictive Model Based on Fuzzy Control

When the power load changes, the internal parameters of the neural network will also change. At this time, if you continue to use the original neural network parameter prediction, greater errors will occur. Therefore, this article adds fuzzy control to the RBF neural network algorithm. Reduce the error to a certain extent.

The structure of the fuzzy controller designed in this paper is a two-dimensional fuzzy controller with dual input and single output. The structure is shown in Figure 2:

The absolute error e between the predicted value of the RBF neural network at the current time and the actual load, and the error rate of change of the output error between the current time and the previous time $e_c = e(t) - e(t-1)$ are used as the two parameters of the fuzzy controller. Then, the input variables are fuzzified into E and Ec, fuzzy inference is performed according to the fuzzy rules to obtain U, and finally, the correction factor α (0≦α≦1) for the controlled object, the next load forecast correction amount, is obtained by defuzzification , The calculation method of the correction value is shown in formula (3).

$$U = \alpha e - (1-\alpha)e_c \tag{3}$$

In this paper, E and Ec are used to represent the fuzzy domain of input error e and error rate of change ec=[e(t)-e(t-1)]/e(t), and the variable size is reduced to 9 levels, taking E={-4,-3,-2,-1,0,1,2,3,4}, EC={-4,-3,-2,-1,0, 1, 2, 3, 4 }; Take the five-level membership function: negative large (NB), negative small (NS), zero (ZE), positive large (PB), positive small (PS). The corresponding fuzzy set is expressed as five levels: VS, S, M, B, VB; the corresponding fuzzy single point set is {0, 0.25, 0.5, 0.75, 1}. Establish a dual-input single-output fuzzy controller in the MATLAB fuzzy control toolbox, edit the fuzzy language values of the input and output variables, and select the membership function as triangle.

In this paper, the error and error rate of change of the output result of the RBF neural network are used as the input of the fuzzy controller, and the prediction result is adjusted by the fuzzy controller. The original output result of the RBF neural network is set to X, and the modified value U is obtained through the fuzzy controller. Output prediction result Y=X+U. Judge whether the output result meets the requirements, if it does not meet the requirements, perform sample selection and network training again. Specific steps are as follows:

Step1: Obtain the historical load data of the area to be predicted, analyze the change rule of the daily average load of the area in a year, and summarize the load characteristics of the area according to the data analysis;

Step2: Repair and deal with missing data and abnormal load points in the data;

Step3: Design a fuzzy controller and formulate fuzzy rules;

Step4: Build an RBF neural network, divide the data processed by S2 into a training set and a test set, and train and test the RBF neural network;

Step5: Input the error and error rate of change obtained in S4 into the fuzzy controller designed in S3, and output the correction value;

Step6: Use the RBF neural network constructed in S4 to predict the short-term power load that needs to be predicted, and obtain the prediction result;

Step7: Add the prediction result of S6 and the correction value obtained in S5 to get the final value, and determine whether the accuracy requirements are met, if it is satisfied, the output is the prediction result, if it is not satisfied, return to S4 to reselect samples for training and testing until Until the accuracy meets the requirements.

Based on the combination of RBF neural network and fuzzy control, the overall process of short-term power load forecasting is shown in Figure 3.

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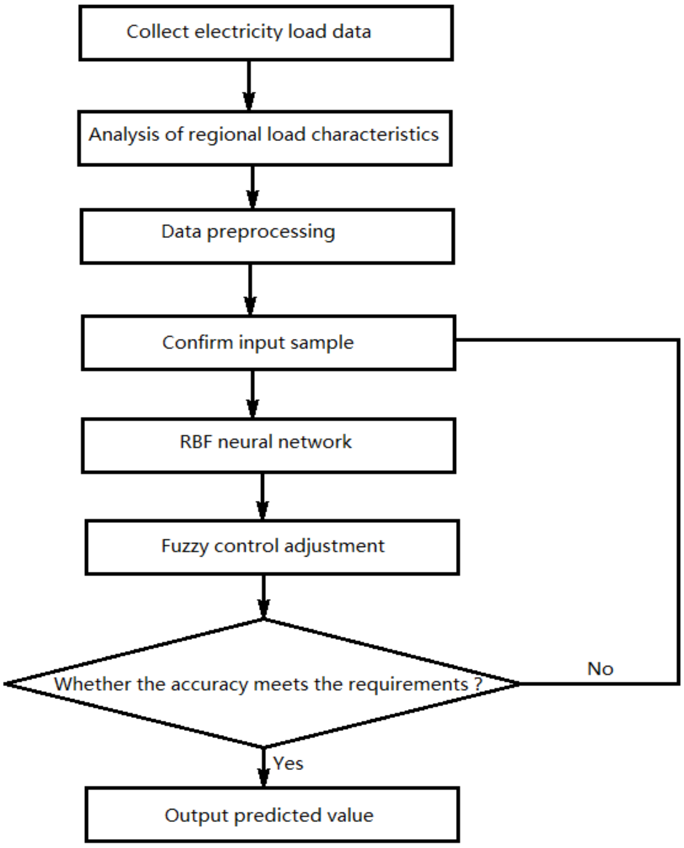

Figure 3. Forecast flow chart

4. Simulation analysis

4.1 Data preprocessing

There will be a lot of "bad data" in historical data. If these data are directly used for predictive calculations, the result will produce large errors. Therefore, the data should be preprocessed before prediction [15].

1) Repair missing data

2) Data normalization processing

When the original data has not been normalized, there are large differences in the order of magnitude and characteristic indicators between the input samples, which are prone to data coverage and neuron saturation, and the normalization of the original data can be speeded up to a certain extent The convergence speed of neural networks [16].

This article uses formula (4) to normalize the data:

$$X_n = (b-a)\frac{X_0 - X_{min}}{X_{max} - X_{min}} + a \tag{4}$$

Let a=-1 and b=1 to normalize the original data to between [-1,1]. In order to facilitate the calculation, the value of the influencing factor also needs to be normalized. The date type is defined by 1 and 0. 1 represents the working day and 0 represents the weekend. All data are converted to the same order of magnitude.

4.2 Verification

In Chapter 3, this paper analyzes the load characteristics of Meizhou area. The weekly and daily cycles in this area are obvious, and the load difference between weekends and workdays is obvious. Therefore, this paper uses the short-term load forecasting model based on RBF neural network proposed above. And the RBF neural network prediction model combined with fuzzy control, predicts

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the 24 hour load values on weekends and working days of the same week in Meizhou area, namely August 3 and August 4, 2014. Calculate the relative error between each predicted value and the actual value, the average relative error of 24 nodes in a day, and the proportion of qualified points, and compare them to analyze the feasibility of combined model prediction.

Table 1. RBF neural network prediction results

		Sunday			Monday	
Time	Actual value	RBF forecast	Relative error	Actual value	RBF forecast	Relative error
0:00	7977.92	7517.55	5.77%	8213.68	8175.96	0.46%
1:00	7696.69	7292.67	5.25%	7985.52	7866.34	1.49%
2:00	7443.39	7083.92	4.83%	7756.03	7511.84	3.15%
3:00	7246.36	6860.65	5.32%	7545.38	7306.49	3.17%
4:00	7065.37	6751.92	4.44%	7357.34	7060.12	4.04%
5:00	6936.31	6592.16	4.96%	7192.77	6918.44	3.81%
6:00	6838.89	6627.11	3.10%	7069.63	6793.10	3.91%
7:00	6977.33	6814.74	2.33%	7163.83	7000.20	2.28%
8:00	8989.26	8901.91	0.97%	9060.71	8834.34	2.50%
9:00	11065.83	11074.29	0.08%	11137.50	10813.87	2.91%
10:00	11488.78	11627.71	1.21%	11608.97	11394.55	1.85%
11:00	11658.63	11690.50	0.27%	11762.45	11641.17	1.03%
12:00	9866.26	9890.47	0.25%	9781.61	10004.76	2.28%
13:00	9482.62	9563.94	0.86%	9141.59	9049.15	1.01%
14:00	11384.60	11482.49	0.86%	10689.50	11074.34	3.60%
15:00	11695.91	11753.51	0.49%	10988.93	11248.63	2.36%
16:00	11808.81	11836.73	0.24%	11036.40	11409.31	3.38%
17:00	11551.29	11519.02	0.28%	10751.41	11378.81	5.84%
18:00	9629.26	9706.08	0.80%	8856.75	8939.13	0.93%
19:00	10541.53	10309.03	2.21%	9778.06	9765.26	0.13%
20:00	10533.65	10463.26	0.67%	9717.45	9764.10	0.48%
21:00	10358.57	10098.39	2.51%	9440.45	9454.30	0.15%
22:00	9787.66	9538.39	2.55%	8774.45	9017.65	2.77%
23:00	9021.12	8801.24	2.44%	8100.46	8142.41	0.52%
		Average relative error	2.19%		Average relative error	2.25%

Table 2. Model prediction results of the combination of fuzzy control and RBF neural network

		Sunday			Monday	
Time	Actual value	RBF forecast	Relative error	Actual value	RBF forecast	Relative error
0:00	7977.92	7517.55	5.77%	8213.68	8175.96	0.46%
1:00	7696.69	7292.67	5.25%	7985.52	7866.34	1.49%
2:00	7443.39	7357.34	1.16%	7756.03	7535.32	2.85%
3:00	7246.36	7099.40	2.03%	7545.38	7391.24	2.04%
4:00	7065.37	6984.66	1.14%	7357.34	7202.41	2.11%
5:00	6936.31	6810.28	1.82%	7192.77	7072.76	1.67%
6:00	6838.89	6829.06	0.14%	7069.63	6966.29	1.46%
7:00	6977.33	6991.84	0.21%	7163.83	7165.99	0.03%
8:00	8989.26	9014.28	0.28%	9060.71	8974.78	0.95%
9:00	11065.83	11155.61	0.81%	11137.50	10913.61	2.01%
10:00	11488.78	11712.62	1.95%	11608.97	11537.34	0.62%
11:00	11658.63	11684.34	0.22%	11762.45	11806.99	0.38%
12:00	9866.26	9814.52	0.52%	9781.61	10112.18	3.38%
13:00	9482.62	9548.06	0.69%	9141.59	9100.02	0.45%
14:00	11384.60	11469.80	0.75%	10689.50	10937.60	2.32%
15:00	11695.91	11710.25	0.12%	10988.93	11248.16	2.36%
16:00	11808.81	11787.91	0.18%	11036.40	11209.94	1.57%
17:00	11551.29	11490.17	0.53%	10751.41	11209.85	4.26%
18:00	9629.26	9687.62	0.61%	8856.75	8642.16	2.42%
19:00	10541.53	10328.73	2.02%	9778.06	9387.36	4.00%
20:00	10533.65	10436.41	0.92%	9717.45	9700.53	0.17%
21:00	10358.57	10218.92	1.35%	9440.45	9463.39	0.24%
22:00	9787.66	9594.62	1.97%	8774.45	8993.06	2.49%
23:00	9021.12	8948.44	0.81%	8100.46	8113.83	0.16%
		Average relative error	1.30%		Average relative error	1.66%

The RBF neural network prediction model in this paper has 13 input layer nodes, the hidden layer node is finally determined to be 20 after training, and the output layer node is 1. This article uses the newrbe function in MATLAB to build and train the RBF neural network. The calling format is:Net=newrbe(P,T,SPREAD)

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The parameter P is an R×Q matrix composed of Q input vectors, and T is an S×Q matrix composed of Q expected output vectors, and the dispersion parameter SPREAD is set to 10.

The specific values of the results predicted by a single RBF neural network model are shown in Table 1.

Continued Table 1.

The fuzzy controller is added to the original RBF neural network prediction model to predict the same two days at the same time. The prediction results are shown in Table 2.

Continued Table 2.

According to the assessment criteria given in the "Electricity Market Formation Plan", the relative error of the single point load forecast is a qualified point when the forecast relative error is less than or equal to 3%.

The prediction results are shown in Table 3.

Table 3. Comparison of prediction results

Sunday	Maximum relative error	Average relative error	Pass point	Accuracy
RBF prediction model	5.77%	2.19%	17	71.3%
Combined forecasting model	5.77%	1.30%	22	91.7%
Monday	Maximum relative error	Average relative error	Pass point	Accuracy
RBF prediction model	5.84%	2.25%	16	66.7%
Combined forecasting model	4.26%	1.66%	21	87.5%

From the comparison of Table 3, it can be seen that compared with the single RBF neural network prediction model, the absolute error of the combined model's prediction results is smaller, and the average relative error of the combined model's forecast results on Sunday has dropped by 0.89%, Forecast accuracy increased by 20.4%; Monday’s average relative error dropped by 0.59%, and forecast accuracy increased by 20.8%.

Figures 4 and 5 show the comparison of the load curves of the two models for the two-day forecast.

From the load curve comparison chart, it is obvious that the model with fuzzy control is closer to the actual load value than the prediction result of the single RBF neural network prediction model, which shows that the short-term load of the power system with fuzzy control based on the RBF neural network The prediction model can effectively improve the prediction accuracy and reduce the prediction error. This combination prediction model based on fuzzy control and RBF neural network is feasible.

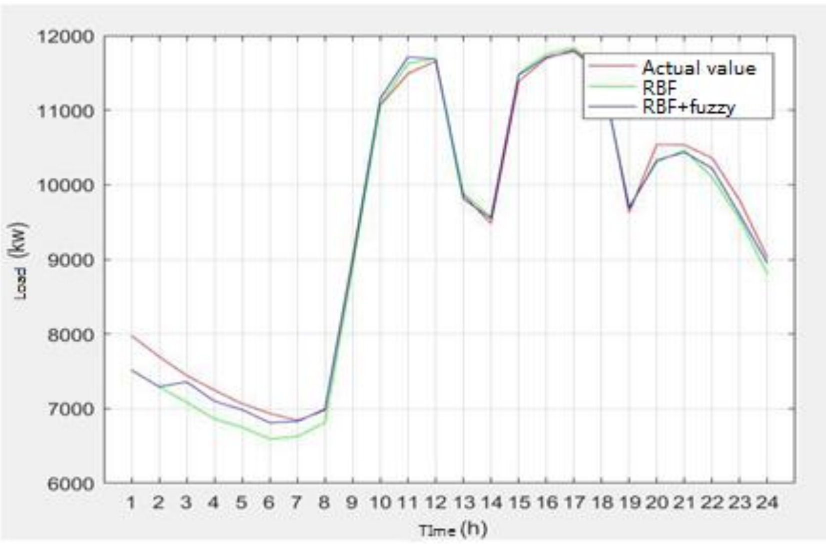

Figure 4. Comparison of forecast results on Sunday

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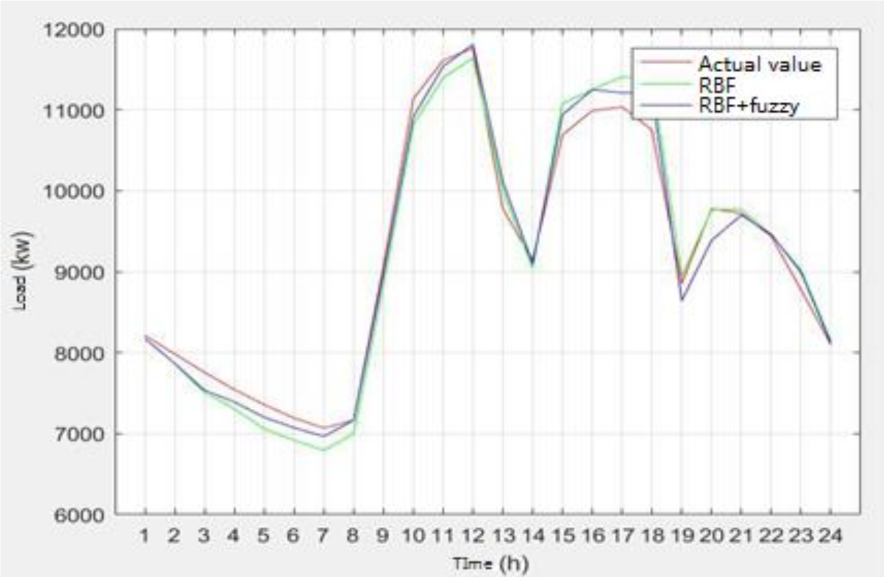

Figure 5. Comparison of forecast results on Monday

5. Conclusion

Aiming at the complex short-term power load forecasting problem, this paper proposes a combined forecasting method based on fuzzy control and RBF neural network. It can be seen from the analysis process and simulation results of the optimization algorithm:

The combined forecasting model of fuzzy control and RBF neural network proposed in this paper has high forecasting accuracy in short-term power load forecasting. It can also be applied to wind speed forecasting, photovoltaic power generation forecasting and forecasting in other fields, and can be further explored and improved.

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