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Short-Term Load Forecasting Based on RBF Neural Network

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Abstract. In order to fully explore and analyze the inherent law of power load data and improve the prediction accuracy of residents' daily electricity consumption, because of analysis and comparison of multiple forecasting methods, the radial basis function (RBF) neural network algorithm with the introduction of clustering idea is used in this paper. The historical load and daily maximum temperature are chosen to cluster by k-means algorithm, according to change rule of the example data and the correlation between load data and other attributes, such as temperature, weather, and holiday. Then, the centres of each cluster in the sample is taken as the centres of the hidden layer of the RBF neural network to realize the training of sample data and forecast short-term power load. The experiment shows this method has higher accuracy in short-term load forecasting compared with time series method and BP neural network.

1. Introduction

In recent years, electricity consumption has greatly increased, and the inability to carry out large-scale storage of electric energy leads to serious waste of power resources. Thus, it is necessary to plan the production of electricity according to the actual usage. Therefore, how to predict the power load accurately and timely has great significance on saving fuel resources, maintaining the economic benefits of power system and improving the utilization rate of electricity resources.

The method of load forecast is divided into two main categories: traditional load forecast technology includes time series, power elasticity coefficient and single consumption [1], which has low accuracy on the prediction. Intelligent load forecasting techniques include artificial neural networks, support vector machines, and combined forecasting methods [2-6]. Artificial neural network is suitable for short-term power load forecasting, it can be divided into forward feedback and backward feedback neural network according to the network topology. The forward feedback neural network such as perceptron, multilayer perceptron (MLP), back propagation (BP) neural network, radial basis function (RBF), is easy to achieve, which use multi-composite of simple nonlinear functions to process information. BP neural network use topology of MLP. Moreover, Sigmoid function is used as transformation function of BP neural network [7], which can achieve arbitrary non-linear mapping from input to output. Li Zuo et al. [8] proposed a method of daily load characteristic curve classifying and short-term load forecasting, which combines fuzzy clustering with BP neural network. However, the Sigmoid function output of the BP neural network may have a local minimum. RBF neural network is proposed to overcome the two defects of the BP neural network [9-10]. RBF neural network select Gaussian function as the hidden layer basis function, using the distance between the input data and the centre of the function to calculate the weight to speed up the convergence rate, and overcome the local minimum problem. When the RBF neural network is used to predict, the most important problem is the selection method of the centres of the hidden layer function.



The time series, BP neural network and RBF neural network improved by k-means clustering algorithm are used to short-term electricity load forecast of residents in this paper. Compared with the time series and the BP neural network, the improved RBF neural network is proved effective in short-term load forecasting. The daily electricity load of a court in eastern China from September 1, 2015 to December 11, 2016 (468 days) is taken as an example in this paper to illustrate the effectiveness of RBF neural network in short-term load forecast.

2. Load Data Analysis and Pre-Treatment

Due to data missing and measurement errors in the raw data, it is necessary for load data to fill the missing value and handle outliers. Using the average load of the last day and the next day to fill the missing value and use 0 to replace the negative value. Thereby, the power consumption in this court can be obtained by summing up the processed data. Because of different magnitude of original data, it has different influence on load forecasting. Thus, the data should be standardized in order to eliminate the influence on prediction result, which is, mapping the value into the interval of [0, 1].

Electricity load will be affected by many factors, including historical data, weather condition, economic factor, forecasting model, etc. The weekly average load is calculated to achieve the load curve, which is shown in Figure 1.

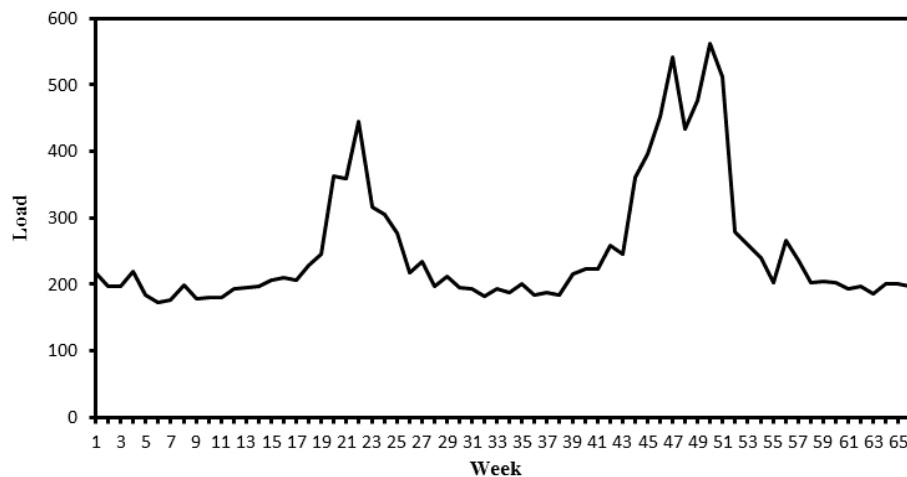


Figure 1. Weekly average load curve.

Figure 1 shows the electricity consumption in summer and winter is obviously higher than that in spring and autumn, especially in February, August and September (the extreme temperature of a year). Thus, temperature attribute is added to the load forecast according to the relevance between the electricity consumption and temperature.

3. Rbf Neural Network Load Forecasting Principle

In order to realize the electricity load forecasting, it is necessary to perform pre-processing on historical load and other attributes, then divide the data into training set and test set. The training set data is input to the RBF network for learning, and the test set is predicted by the RBF network after learning. The flow chart of RBF neural network load forecasting is shown in Figure 2.

RBF neural network is a local approximation network, composed of three layers of neurons. The input layer is responsible for passing the input signal to the hidden layer. The hidden layer uses the basis function to make the input data nonlinearly transformed. The output data of the hidden layer is linearly weighted at the output layer as the output of the network.

This paper selects the historical load of seven days before the forecast day and the maximum temperature of the day as the input data, which is shown as:

$$X=(E_1, E_2, E_3, E_4, E_5, E_6, E_7, T) \quad (1)$$

Gaussian kernel function is used in the hidden layer of RBF neural network in this paper. The weight is calculated by the distance between the input data and the centre of the function. Compared with the Sigmoid function of BP neural network, which is used in the global, the Gaussian function's convergence speed is faster. Which is shown as:

$$R_j = \exp\left(-\frac{\|X - c_j\|^2}{2\sigma_j^2}\right) \quad j=1,2,\dots,m \quad (2)$$

where $X=(E_1, E_2, E_3, E_4, E_5, E_6, E_7, T)$ is an 8-dimensional vector. c_j is the centre of the Gaussian function of the j th node of the hidden layer, and is also an 8-dimensional vector. σ_j is the normalized constant of the j th neuron node in the hidden layer. m is the number of neuron in the hidden layer.

Output layer:

$$y = \sum_{j=1}^m w_{j,1} R_j \quad j=1,2,\dots,m \quad (3)$$

where $w_{j,1}$ is the connection weight between the j th neuron of the hidden layer and the output (Y).

The learning process of RBF neural network is as follows. First, the training set of input data is pre-processed into the form of formula 1. Then the processed data is calculated by the formula 2 to obtain output data of the hidden layer. Then through the formula 3 to get the output layer weight information. Finally, the test set is input to the trained network to get the forecast data.

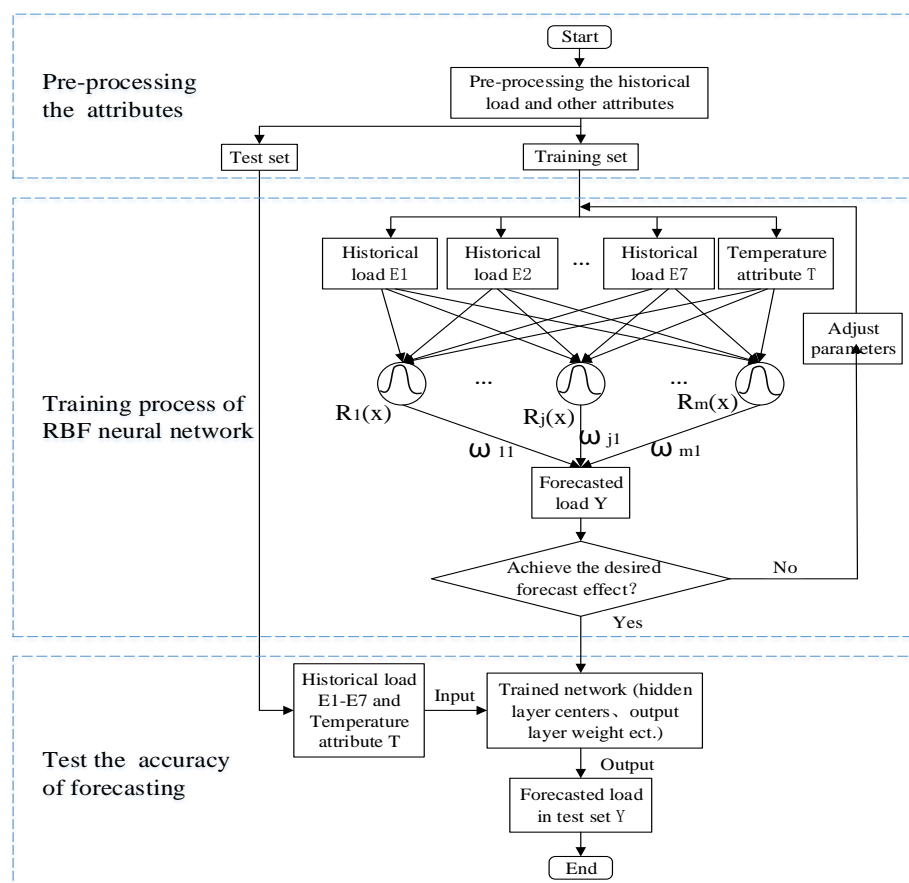


Figure 2. Flow chart of RBF neural network

4. K-Means Clustering Selects the Hidden Layer Centres

There are several kinds of learning method for RBF network hidden layer, such as self-organizing selection algorithm, randomly selected fixed centre algorithm and k-means algorithm. Self-organizing

selection algorithm and randomly selected fixed centre algorithm apply only to static and dynamic teaching methods.

K-means belongs to the partition clustering method. The core idea of this algorithm is to divide n data objects into k clusters according to the distance of Euclidean distance, so that the distance between each data point and its cluster centre is minimized. The clusters themselves are as compact as possible, and the clusters are separated as much as possible with other clusters^[11]. The flow chart of using k-means clustering algorithm to select hidden layer centres of RBF neural network is shown in Figure 3.

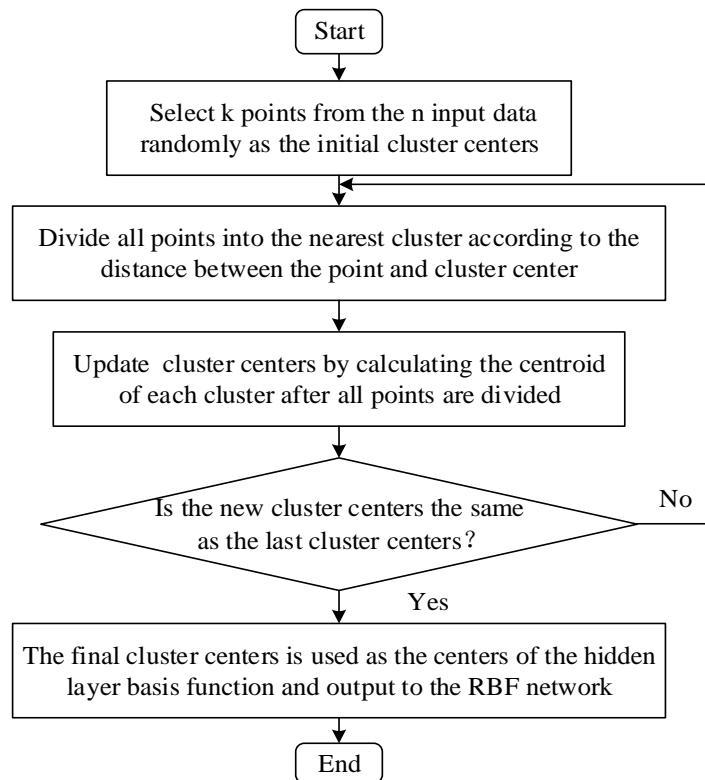


Figure 3. Flow chart of k-means clustering

The hidden layer centres of RBF are calculated by k-means clustering in this paper, which avoids the inaccuracy caused by artificial or random selection. This method can guarantee that the centres of the RBF network hidden layer are relatively dispersed, so that it can cover all the input vectors in the training set, thus improving the prediction accuracy.

5. Experiment

The daily electricity load of a court in eastern China from September 1, 2015 to December 11, 2016 (468 days) is chosen as an object. The performance indicators for comparing predicted results are MAPE (relative error), which is given as below:

$$MAPE = \left(\frac{|Z_i - Y_i|}{Y_i} \right) \times 100\% \quad (4)$$

where Y_i is the actual load for the i th day and Z_i is the predicted value.

According to the two sets of training sets, the load forecasting was carried out in three different ways, the results are as follows:

5.1. Time Series

Table 1. The first group of time series.

Date	Actual(Y)	Predicted(Z)	MAPE
2016/12/5	228.8	234.17	2.35%
2016/12/6	213.6	228.6	7.02%
2016/12/7	214.4	226.62	5.70%
2016/12/8	228.8	231.07	0.99%
2016/12/9	223.2	239.69	7.39%
2016/12/10	234.4	243.01	3.67%
2016/12/11	241.6	245.61	1.66%
Average MAPE			4.11%

Table 2. The second group of time series

Date	Actual(Y)	Predicted(Z)	MAPE
2016/9/26	270.4	225.34	16.66%
2016/9/27	280	219.02	21.78%
2016/9/28	280.8	218.07	22.34%
2016/9/29	276.8	223.79	19.15%
2016/9/30	297.6	234.31	21.27%
2016/10/1	326.4	235.26	27.92%
2016/10/2	352.8	237.6	32.65%
Average MAPE			23.11%

When the load data of 461 days before the forecast is used to predict the load for the next 7 days, the average relative error of the prediction was 4.11%, and the result is given in Table 1. When the load data of 391 days before the forecast is used to predict the load for the next 7 days, the average relative error of the prediction was 23.11%, and the result is given in Table 2.

5.2. BP Neural Network

First, the highest temperature of the day attribute is added. Then the temperature attribute and the historical load of seven days before the forecast are normalize. Finally, the normalized data is input into the network to start training. When the load data of 461 days before the forecast is used to predict the load for the next 7 days, the average relative error of the prediction was 4.03%, and the result is given in Table 3. When the load data of 391 days before the forecast is used to predict the load for the next 7 days, the average relative error of the prediction was 6.05%, and the result is given in Table 4.

Table 3. The first group of BP neural network

Date	Actual(Y)	Predicted (Z)	MAPE
2016/12/5	228.8	217.1	5.11%
2016/12/6	213.6	221.42	3.66%
2016/12/7	214.4	218.88	2.09%
2016/12/8	228.8	202.73	11.39%
2016/12/9	223.2	214.41	3.94%
2016/12/10	234.4	236.74	1.00%
2016/12/11	241.6	239.08	1.04%
Average MAPE			4.03%

Table 4. The second group of BP neural network

Date	Actual(Y)	Predicted (Z)	MAPE
2016/9/26	270.4	234.6	13.24%
2016/9/27	280	273	2.50%
2016/9/28	280.8	268.7	4.31%
2016/9/29	276.8	263.8	4.70%
2016/9/30	297.6	259.7	12.74%
2016/10/1	326.4	322.2	1.29%
2016/10/2	352.8	340.2	3.57%
Average MAPE			6.05%

5.3. Rbf Neural Network Improved by K-Means Clustering

Similar to the BP neural network, the data is pre-processed and then input into the network to start training. When the load data of 461 days before the forecast is used to predict the load for the next 7 days, the average relative error of the prediction was 3.83%, and the result is given in Table 5. When the load data of 391 days before the forecast is used to predict the load for the next 7 days, the average relative error of the prediction was 4.06%, and the result is given in Table 6.

Table 5. The first group of RBF neural network

Date	Actual (Y)	Predicted (Z)	MAPE
2016/12/5	228.8	227.3	0.66%
2016/12/6	213.6	197.7	7.44%
2016/12/7	214.4	210.8	1.68%
2016/12/8	228.8	210.6	7.95%
2016/12/9	223.2	222.3	0.40%
2016/12/10	234.4	221.8	5.38%
2016/12/11	241.6	233.7	3.27%
Average MAPE			3.83%

Table 6. The second group of RBF neural network

Date	Actual (Y)	Predicted (Z)	MAPE
2016/9/26	270.4	248	8.28%
2016/9/27	280	277.2	1.00%
2016/9/28	280.8	277.1	1.32%
2016/9/29	276.8	269.9	2.49%
2016/9/30	297.6	285.7	4.00%
2016/10/1	326.4	307.7	5.73%
2016/10/2	352.8	333.1	5.58%
Average MAPE			4.06%

5.4. Results Analysis

When the load data of 461 days before the forecast is used to predict the load for the next 7 days, the electricity consumption of the forecast day is relatively stable, so the average relative error value of the prediction results using the three methods is not much different. When the load data of 391 days before the forecast is used to predict the load for the next 7 days, the average relative error of the predictions made by the time series method is significantly higher than the other two methods. This is because the electricity consumption from September 26 to October 2, 2015, rises sharply in a short time, and the time series only works better for relatively stable data. When the data change steeply in a short time, time series cannot be accurately predicted.

RBF neural network can be approximated to any nonlinear function, which can make accurate judgment and treatment when the data change steeply. And the temperature attribute is added to the RBF neural network, which can improve the prediction accuracy to a certain extent. Comparing the results of the two predictions, the average relative error of the improved RBF neural network is lower than that of BP neural network, and the prediction accuracy is improved. The results of this paper show that the improved RBF neural network can be effectively applied to Short - term load forecasting.

6. Conclusion

Three different methods are used to predict the electricity load in this paper. Compared with the traditional load forecasting method, the intelligent load forecasting method not only takes the influence of historical load into account, but also adds the temperature attribute. The experiment shows the accuracy of the neural network prediction method is obviously higher than that of the time series method, while the improved RBF neural network with k-means clustering algorithm can further improve the accuracy, which can be effectively applied to short-term load forecasting. As for the steeply change that the time series cannot predict, the neural network can also realize better solution. However, the number of centres of RBF neural networks needs to be manually initialized, the prediction results have some limitations. Therefore, how to optimize the algorithm to select the optimal number of centres and improve the adaptability of neural networks will be one of the future research directions.

7. References

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