Load forecasting of distribution equipment based on artificial neural network

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Abstract. Distribution network is the key link that affects the level of power supply service. In order to realize first-class modern distribution network and ensure the high quality electric power for residents, it is necessary to change the original working mode of operation and maintenance “passive repair” and the investment mode “treating the symptoms and not the disease” in distribution network. In such a huge distribution network structure, in order to achieve active maintenance and accurate investment construction, load forecasting of distribution network transformers scientifically will play a vital role. This paper proposes a method that realized the reasonable prediction of load in distribution network by using the self-learning and prediction function of artificial neural network and combing with the change characteristics of the load, which has important reference value to guide the construction investment and operation and maintenance of distribution network.

1. Introduction

At present, with the rapid development of society, the distribution network architecture is becoming more complex and larger. People’s demand for power supply quality is getting higher and higher, and this requires more accurate investment in distribution network construction, and the operation and maintenance of power grid should be changed from "passive repair" to " active rush repair and maintenance ". Load forecasting is an important part of distribution network planning and operation, and the accuracy of load forecasting affects the scientific rationality of distribution network planning and operation. In order to meet the growing demand for power quality, forecasting the load of transformer in distribution network accurately plays a vital role.

On the basis of data monitoring and analysis of distribution network, this paper proposes a method to predict the load of distribution transformers effectively by combining with the characteristics of self-learning and generalization ability of artificial neural network, and this method fully considers the load change characteristics of distribution transformers and it can provide a powerful reference for guiding the construction investment and operation and maintenance of distribution network.

2. Basic theory of artificial neural network

In the prediction of artificial neural network, there are many models, such as Elman neural network, BP neural network and wavelet neural network which all have good dynamic model prediction ability. Taking BP neural network as an example, this paper gives a brief introduction about the principle.

BP neural network is divided into three layers: input layer, implicit layer, output layer. The signal is entered from the input layer, processed by the implicit layer and eventually output by the output layer, it's topology is shown in Figure1.
The model of prediction algorithms based on BP neural network includes BP neural network construction, BP neural network training and BP neural network prediction three steps, the algorithm flow is shown in Figure 2:

Figure 1. BP neural network topology diagram

The calculation process of BP neural network consists of forward calculation process and reverse calculation process. In the forward propagation process, the input data are from input layer and processed by implicit layer, and finally turned to output layer. The state of each layer of neurons affects only the state of the next layer of neurons. If the desired output cannot be obtained at the output layer, it is transferred to reverse propagation process, the error signal is returned along the original connection path and minimized by modifying the weights of each neuron.

3. Load forecasting modeling of distribution transformer

Through a large number of data analysis and research, it is found that the main factors affecting the load of distribution transformer are significant electricity retention factors, weather factors, time factors, holidays and so on.

- Significant electricity retention factors. Mainly refers to some important political activities, such as the National People's Congress, APEC meetings, etc;
- Weather factors. The load fluctuation caused by the weather is especially obvious in the distribution transformer, such as the air conditioning load When the temperature is high, the central heating load when the temperature is low, etc.
- Time factor. The load curves showing different characteristics with the seasonal and cyclical changes of time, such as the different change of load at night and daytime, spring and summer, etc.
- Major holidays. The impact of major holidays to the distribution network is self-evident, the most typical example is the load increase sharply during the Spring Festival.

This paper proposes a method that mainly considers the historical law of distribution transformer load, synchronous consideration of weather, major activities and other factors to achieve the purpose...
of prediction. Considering that the main composition of distribution transformer load \( F(t) \) is superimposed by the following parts:

\[
F(t) = N(t) + W(t) + R(t)
\]  

(1)

Among them, \( N(t) \) is the prediction value of distribution transformer load at normal circumstances; \( W(t) \) is the load variation component caused by extreme abrupt weather; \( R(t) \) is the load variation component caused by some special events.

The load variation component caused by extreme abrupt weather mainly considers the abrupt change of temperature in a continuous period of time. A simple linear model is adopted here:

\[
W(T) = \begin{cases} 
  k_1(T-T_y) & \text{if } \Delta T > T_s \\
  k_2(T-T_y) & \text{if } T_s < \Delta T < T_x \\
  0 & \text{if } T_x < \Delta T
\end{cases}
\]  

(2)

\( T \) represents the temperature value corresponding to the forecast moment \( t \); \( T_y \) is the temperature value corresponding to the previous reference time, and \( \Delta T \) is the difference of \( (T-T_y) \); \( T_s \) is the critical value of temperature sudden rise, and \( K_1 \) is the influencing factor of temperature sudden rise. \( T_x \) is the critical value of sudden temperature drop, and \( K_2 \) is the influencing factor of sudden temperature drop. If \( T \) is between \( T_s \) and \( T_x \), the influence factors of temperature are not considered. However, the load change \( R(t) \) of distribution transformer caused by some special events (such as major holidays, major political meetings, etc.) should be revised manually for the time being.

The following part is a brief introduction to the predicted value \( N(t) \) of distribution transformer load under normal conditions. The prediction of \( N(t) \) mainly adopts BP neural network algorithm in artificial neural network, and we can use hour, day or week as unit to forecast the load of distribution transformer through its historical load data. Before training samples, data should be preprocessed:

- Correction of abnormal data. Load information may be affected by unexpected factors which may lead to data effectiveness when the signal is being collected, and some uncontrollable factors such as blackouts may also lead to abnormal load information data. If we don't correct the data, it will affect the learning of load change law. Therefore, this part of the data will be smoothed before training.

- Data normalization. Since the activation function of BP Neural network is a continuous micro function and the S-type logarithmic function is used, it requires that the input and output value intervals must be in \([-1,1]\). Therefore, it is necessary to preprocess the original number of short-term power load, the pretreatment formula is as follows:

\[
P_n = \frac{P - P_{\text{min}}}{P_{\text{max}} - P_{\text{min}}}
\]  

(3)

\( P_n \) - the input sample matrix after preprocessed;

\( P \) - the data matrix after normalized;

\( P_{\text{Max}} \) - the maximum value in the historical input data;

\( P_{\text{min}} \) - the minimum value of the historical input data.

4. Data Training and forecasting

In this paper, we use the day as the unit, the daily maximum load of a distribution transformer in Hunan Province from 1 January to 31 December 2018 is selected as the training sample of the network, and the daily maximum load of this distribution transformer from 1 January to 31 January 2019 was taken as the test sample. Using the neural network toolbox of MATLAB to train and predict the data and setting an expected target error of 5%. As shown in Table 1, after the sample training, prediction results show that the maximum error between the actual value and the predicted value is only 4.9%. Thus, it can be seen that, without considering the special weather changes and major power conservation activities, the load forecasting through BP neural network is very effective and can fully meet the actual needs.
Table 1. Statistical analysis table of test samples

| Date      | Actual value (KW) | Predicted value (KW) | Error | Date      | Actual value (KW) | Predicted value (KW) | Error |
|-----------|-------------------|----------------------|-------|-----------|-------------------|----------------------|-------|
| January 1 | 66.51             | 67.24                | -0.011| January 16| 63.29             | 63.99                | -0.011|
| January 2 | 80.77             | 81.50                | -0.009| January 17| 63.57             | 64.52                | -0.015|
| January 3 | 66.1              | 68.68                | -0.039| January 18| 58.87             | 56.40                | 0.042 |
| January 4 | 72.05             | 75.29                | -0.045| January 19| 60.04             | 61.30                | -0.021|
| January 5 | 65.35             | 65.35                | 0.000 | January 20| 70.53             | 73.77                | -0.046|
| January 6 | 66.97             | 67.44                | -0.007| January 21| 58.55             | 59.78                | -0.021|
| January 7 | 64.23             | 63.40                | 0.013 | January 22| 54.78             | 54.51                | 0.005 |
| January 8 | 67.82             | 66.94                | 0.013 | January 23| 48.43             | 49.64                | -0.025|
| January 9 | 66.05             | 66.45                | -0.006| January 24| 52.1              | 54.60                | -0.048|
| January 10| 68.21             | 65.21                | 0.044 | January 25| 53.42             | 52.46                | 0.018 |
| January 11| 64.57             | 64.25                | 0.005 | January 26| 54.54             | 54.05                | 0.009 |
| January 12| 74.53             | 77.59                | -0.041| January 27| 53.42             | 50.80                | 0.049 |
| January 13| 65.35             | 64.37                | 0.015 | January 28| 57.09             | 59.60                | -0.044|
| January 14| 62.51             | 62.38                | 0.002 | January 29| 58.46             | 60.04                | -0.027|
| January 15| 62.56             | 61.75                | 0.013 | January 30| 48.07             | 46.15                | 0.040 |

Figure 3. Contrastive analysis of actual value and predicted value

5. Conclusion
This paper presents a load forecasting method for distribution transformer based on artificial neural network. After full demonstration, the prediction results have achieved high prediction accuracy, which proves the effectiveness of this method. Accurate load forecasting of distribution transformer is of great significance to guide the design and maintenance of distribution network. In the next step, we will try to account all factors for improving the analysis of load variation characteristics of distribution transformers in different regions, and do our best to meet the actual needs of production.

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