Power load forecasting research based on neural network and Holt-winters method

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Abstract. Since the electric load shows a very obvious periodicity in time series, increasing the periodic factor in the power load forecasting is a research direction of power load forecasting. It is by adding trend and seasonality (that is, periodicity) to smoothing values that the Holt-winters algorithm improves the accuracy of predictions. In this paper, Holt-winters algorithm and neural network algorithm are used to build power load prediction models respectively, and data of city A in Shandong province is used for testing. Experimental results show that the prediction results of the two algorithms are similar, but the Holt-winters algorithm is slightly more accurate.

Keywords: electric load forecasting, Holt-winters method, neural network

1. Introduction

The accuracy of short-term load forecasting is very important for power operation management system. Highly accurate power load forecasting can stabilize the operation of the entire power system, coordinate the supply and demand relationship of power, and is conducive to the formulation of the operation plan of the power system [1]. In order to improve the accuracy of power load prediction, it is generally studied from two aspects: the first way is to improve the accuracy of power load by increasing the factors that affect the power load during the prediction process. There are many factors affecting power load prediction, such as weather, temperature, humidity, etc., even including holidays, which have a great impact on power load. Proper consideration of these factors can improve the accuracy of power load. The second way is to construct different prediction models based on the characteristics of power load [2]. The change of power load has a very obvious change rule, the daily and weekly periodic change, the annual periodic change can be easily observed in the data.

The Holt-winters algorithm predicts the time series with trend and seasonality at the same time, and the seasonality here can also index the periodicity of the change in the actual data [3, 4]. Holt-winters algorithm is also called the three-time exponential smoothing method. Holt-winters algorithm is also known as the three-time exponential smoothing method. The exponential smoothing method predicts the changes of recent data by weighting the past time series [5, 6, 7], and the Holt-winters algorithm [8, 9, 10] can be obtained by adding the trend of data changes and the seasonality of data changes to the smoothing value of time series.

The advantage of Holt-winters algorithm is that after observing the period of data change in the time series, the prediction results can be made according to the period of data change. The prediction results
are closely related to the observed period, and the trend of data change can be predicted by controlling the weight of recent data and historical data [11, 12, 13]. Neural networks, on the other hand, study long-term historical data to predict future data. Different neural network models need to be built for data in different situations, and each model can only be formed under a large amount of data training. However, when the model training is completed, different prediction models are available for different data. At the same time, there is no need to add additional calculations when influencing factors on power load are added; it only needs to add influencing factors to the neural network model and retrain the neural network model [14, 15].

In this paper, the Holt-winters algorithm and neural network model are used to study and predict the 32-month power load of City A in Shandong Province respectively. The first section briefly introduces the application of Holt-winters algorithm and neural network model to power load forecasting. The second section introduces the basic theory of the Holt-winters algorithm; In the third section, the Holt-winters algorithm and neural network model are respectively used to build the model. In the fourth section, the data of City A in Shandong Province are substituted into the established model and the experimental results are compared.

2. Holt-Winters algorithm
The Holt-winters algorithm is also called the third exponential smoothing method. As mentioned above, the three-time exponential smoothing method can predict the time series with trend and seasonality at the same time. In fact, the prediction with trend and seasonality is an improvement of the one-time exponential smoothing method. First, the first smoothing method is introduced.

\[ s_t = \alpha x_t + (1 - \alpha)s_{t-1} \]  
\[ x_{t+1} = s_t \]

Equation (1) is the recursive relationship of the first smoothing method. \( s_t \) is the smoothing value of the previous \( t \) data, and \( \alpha \) is the smoothing parameter. It can be seen that when the value of \( \alpha \) is larger, the smoothing value is more affected by the current data. The data tends to be uneven. Conversely, when the value of \( \alpha \) is smaller, the smoothing value is more affected by the previous \( t \) data, and the data is smoother. Equation (2) is the prediction formula of the first smoothing method. Since the first smoothing method only takes the smooth value, the predicted value is the smooth value. It can be seen that the first smoothing method has no trend and seasonal factors, so the predicted time series is one Horizontal straight line.

\[ s_t = \alpha x_t + (1 - \alpha)(s_{t-1} + t_{t-1}) \] 
\[ t_t = \beta(s_t - s_{t-1}) + (1 - \beta)t_{t-1} \] 
\[ x_{t+1} = s_t + t_t \]

Equation (3) is the recursion of the smooth value, and equation (4) is the increasing trend factor, where \( \beta \) is similar to \( \alpha \), and \( t_t \) is the trend parameter, which is the current trend. Equation (5) is the prediction formula of the quadratic exponential smoothing method. Because the quadratic smoothing method retains the trend of the time series, the predicted time series is an oblique straight line.

\[ s_t = \alpha(x_t - p_{l-k}) + (1 - \alpha)(s_{t-1} + t_{t-1}) \] 
\[ t_t = \beta(s_t - s_{t-1}) + (1 - \beta)t_{t-1} \]
On the basis of the two-time exponential smoothing method, the three-time exponential smoothing method adds seasonal factors. According to the different ways of increasing, it can be divided into the cumulative form and the multiplicative form. Equations (6), (7), (8) and (9) are the cumulative form of the three-time exponential smoothing method. Formula (1) and (2) are the recursion of smooth value and trend, respectively. Formula (8) is the seasonal recurrence, k is the seasonal cycle, and $\gamma$ is the current seasonal factor. Different from smooth values and trends, seasonal calculation is the weight of seasonal factors in the same period of the current time series and the previous season, and $\gamma$ is the weight. Equation (9) is the prediction formula of the cubic exponential smoothing method. Different from the first exponential smoothing method and the second exponential smoothing method, the seasonal factors in the prediction formula are not the latest time series, but the seasonal factors at the same stage of the cycle. The formula of the multiplication is as follows:

$$s_i = \alpha \frac{x_i}{p_{i-k}} + (1 - \alpha)(s_i + t_{i-1})$$

$$t_i = \beta(s_i - s_{i-1}) + (1 - \beta)t_{i-1}$$

$$p_i = \gamma \frac{x_i}{s_i} + (1 - \gamma)p_{i-k}$$

$$x_{i+1} = (s_i + t_i)p_{i-k}$$

When the cubic exponential smoothing method is used for calculation, the value of, $\alpha$, $\beta$ and $\gamma$ is $[0,1]$. For the initial value of $s$, $t$ and $p$, $s_0 = x_0$, $t_0 = x_1 - x_0$, $p = 0$ when summing up, and $p = 1$ when multiplying.

3. Algorithm design based on Holt-winters model and neural network

In this section, we respectively built models based on Holt-winters algorithm and neural network algorithm to substitute the data of City A in Shandong Province and compare the predicted results.

3.1. Algorithm design based on Holt-winters model

By observing the power load data of City A in Shandong Province, the cycle of the change of power load can be taken as 24 hours and 7 days. Since the basic data is in hours, the cycle of year is relatively long here, so it is not adopted. We used 24h and 7 days as cycles respectively to carry out the calculation. The algorithm steps of Holt-winters model are as follows:

**Step 1** Calculate $s_0$ and $t_0$. Since the cumulative form is adopted, let $p = 0$.

**Step 2** The initial values of parameters $\alpha$, $\beta$ and $\gamma$ are given;

**Step 3** Calculate according to the initial value, and get the predicted value. Adjust the initial values of parameters $\alpha$, $\beta$ and $\gamma$ according to the error between the predicted value and the actual value;

**Step 4** Forecast the data according to the finally determined values of $\alpha$, $\beta$, $\gamma$.

Since we will use two cycles for prediction, corresponding models need to be established for 24h and 7 days respectively for calculation.

3.2. Algorithm design based on neural network

BP neural network is selected here to build the neural network structure. BP neural network gets the predicted value by learning the historical data, and calculates the loss function. The loss function is used to change the parameters in the network structure to improve the neural network. On the neural network, we use 7 days as a minimum period for learning, and the steps to establish the model are as follows:
Step 1 Build the basic structure of the neural network, determine the number of hidden layers, and initialize the neural network parameters;

Step 2 Import a group of power load data and calculate the predicted value;

Step 3 Calculate the loss function and change the parameters according to the gradient;

Step 4 Enter the next training. When the loss function is less than the threshold value we need, or the learning times reach the maximum value we determine, put in the next set of data and turn Step 2.

Step 5 After all the training data are trained, put the test data into the neural network and calculate the error.

4. Analysis of experimental results

Based on the power load data of City A in Shandong Province for 32 months starting from January 2016, Holt-winters model and neural network model were realized by Matlab.

In the Holt-winters model, 24h and 7 days were used as cycles. When different cycles were used, the results were different, as shown in the figure below.

![Figure 1. Prediction results from the Holt-winters algorithm](image)

In Figure 1, the left side is the Holt-winters model with a cycle of 24h, and the right side is the Holt-winters model with a cycle of 7 days. Due to too much data, we only drew a comparison between the predicted value and the true value for two weeks in order to ensure the clarity of the picture. The blue line is the predicted value and the red line is the true value. It can be observed that the real value and the actual value in the two graphs are very close, so it is difficult to see which period has a better effect, so the two periods are compared by error.

In Figure 2, the red line is the error of 24h and the blue line is the error of 7-day periodic prediction data. It can be seen that the errors of the two have similar fluctuations, but the peak value of the blue line is always above the red line, which indicates that the prediction effect with a cycle of 7 days is less than that with a cycle of 24 hours, but the difference effect is very small. The reason for the poor prediction effect of the 7-day period may be that the 7-day period is too long relative to 24h, leading to a slightly larger difference in the stability trend between the previous period and the predicted period. However, this is only relative to 24h, and actually has no significant impact on the prediction.

When using neural network for prediction, we divided the data of 32 months into training set and test set, 90% of which was training set and 10% of which was test set. To compare the results of the test set with those of the Holt-winters algorithm, we averaged the results over a week.
In Figure 3, the blue line is the predicted value and the red line is the true value. It can be seen that the prediction effect is not the same as the Holt-winters algorithm. Meanwhile, the average relative error of the 24-h cycle Holt-winters algorithm and the 7-day cycle Holt-winters algorithm is 3.08% and 3.65% respectively, while the average relative error of the neural network is 4.82%.

Performance on short-term power forecasting, neural network does not Holt-Winters algorithm performance is good, but you need to take into account the Holt-Winters algorithm prediction is based on time series on a point in time, even taking into account the seasonal factors, but recent data to predict the influence is very big, and the neural network prediction is use historical data to predict the data of one cycle of all data, although the Holt-Winters algorithm algorithm accuracy is very high, but it is much less predictable length of neural network.

5. Conclusion
Accurate power load prediction is of great significance to promote the stable operation of power system. In this paper, the Holt-winters algorithm and neural network algorithm are respectively used to predict power load. Experimental results show that the accuracy of Holt-winters algorithm is higher than that of neural network. However, the advantage of neural network is that the prediction period is new to neural network, and it can predict the power load of a whole cycle. If the Holt-winters algorithm is used to predict the future cycle, a large part of its prediction is based on the data we predicted, which will lead to a large error in the subsequent data. If the two algorithms are combined and the neural network is used to increase the length of the prediction ability of Holt-winters algorithm, the error behind the prediction data of Holt-winters algorithm may be reduced and the practicability of Holt-winters algorithm will be improved. We will try to combine the two algorithms in the later stage, so as to improve the short-term forecasting ability of power load forecasting.

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