Research on short-term electric load forecasting based on extreme learning machine

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Abstract: As an important support for the development of the national economy, the power industry plays a role in ensuring economic operations. Time series prediction can process dynamic data, is widely used in economics and engineering, and especially is of great practical value in using historical data to predict future development. Under the guidance of extreme learning machine and time series theory, this paper applies the extreme learning machine to the study of time series, and builds a model for load forecasting research. Load forecasting plays an important role in power planning, affecting planning operation modes, power exchange schemes, etc., so load forecasting is very necessary in power planning. First, establish an extreme learning machine model; second, the short-term load forecasting is performed by different activation functions to verify the performance of the activation function.[1] After empirical analysis, the activation function with the best predictive ability is obtained.

1 INTRODUCTION

With the marketization of the power industry, economic benefits are gaining more and more attention in the development of the power industry. However, accurate load forecasting can ensure the economics of power system operation, and also contribute to the development of the national economy. As an important part of power planning, power load forecasting affects the planning operation mode and power exchange plan. Therefore, only the high accuracy of power load forecasting can ensure the healthy development of the economic benefits of the power industry. In addition, as a basis for assisting power planning and construction, load forecasting can also play a role in improving energy efficiency and reducing power generation costs. Moreover, it is also possible to implement power system operations in a more economical manner.

In the power sector, load forecasting is performed by predicting trends in power load. In the specific construction of the power grid, load forecasting can help enterprises to make reasonable arrangements for power generation units, thus ensuring the power demand of social production activities. At the same time, the social and economic benefits of the power system are improved by avoiding a large amount of redundant load. In addition, accurate load forecasting can also ensure the rationality of the grid structure, and ensure the balance of power supply and demand between regions with scientific power dispatching. This not only ensures normal production in power-deficient areas, but also solves the problem of oversupply in power production.

A variety of methods[1-3] have emerged in the study of power load forecasting, but mainly include traditional forecasting methods and intelligent forecasting methods. Traditional prediction methods mainly include prediction models such as gray model, trend extrapolation method and elastic coefficient method. These models are fast and simple, but the use of linear models for load prediction is not good, so prediction accuracy is generally not high. The intelligent prediction methods mainly include prediction models such as BP neural network, support vector machine and fuzzy neural network.

2 METHODOLOGY

2.1 Time Series Theory

In many studies, researchers need to process a series of historical observations. As time changes, the data performance of the time series changes constantly, presenting a variation of the time series. Time series, also called dynamic sequences, can not only show the trend of data, but also determine the future direction by predicting future data. In the social and economic development, it is of great practical significance to accurately predict the future development direction on the basis of the analysis of the past development process.

Moreover, since the time series models [4]are linear models, there are great limitations in dealing with complex nonlinear problems, and the function relationships between variables cannot be accurately mapped. Therefore, the prediction accuracy is relatively

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poor.

2.2 Extreme Learning Machine Model

After the continuous updating of the algorithm, due to inherent defects, the traditional intelligent algorithm cannot meet the needs of practical applications. For example, BP neural network not only has a slow training speed, but also easily falls into a local optimal solution. Therefore, the extreme learning machine[5] for the above defects can exhibit higher prediction accuracy in load prediction while only taking less time.

In the extreme learning machine prediction model, in addition to the excellent performance of its own topology, the choice of parameters is the key to determine the prediction accuracy. In BP neural network, load forecasting needs to adjust more parameters, and the choice of learning rate is more sensitive. The excellent topology of the extreme learning machine avoids a large number of parameter selection processes. Only the number of neurons in the hidden layer needs to be determined to obtain the prediction result, which reduces the setting problem of various parameters. In addition, the connection weight between the input layer and the hidden layer randomly generated by the extreme learning machine and the threshold of the hidden layer neurons need not be adjusted during the training process, and the training speed is also accelerated.

In the load forecasting process, time series data is divided into training data and test data. In order to ensure the fitting effect of the prediction results and the test data, more training data is set as much as possible. In this paper, the effect of three different prediction results and test data is studied by changing the activation function, and the influence of the activation function on the prediction performance of the extreme learning machine is analyzed.

2.3 Model Structure

As a feedforward neural network, its network structure is shown in Figure 1. After proposed by Huang Guangbin in 2004, it was widely used in regression, classification and other issues. The extreme learning machine network structure includes input layer, hidden layer, and output layer. The number of neurons in the input layer and the output layer depends on the actual problem, and the number of neurons in the hidden layer can be adjusted according to the empirical formula to obtain the optimal network structure.
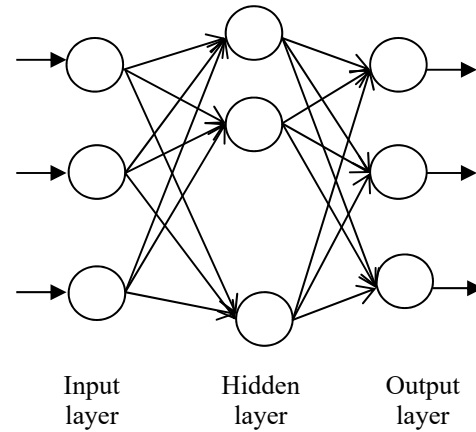

Fig. 1. Network structure of the model

2.4 Model Step

Step 1: Determine the number of network structure layers, and select the number of neurons in the input layer, the hidden layer, the output layer, as well as the activation function.

Step 2: Determine the connection weights randomly generated between the input layer and the hidden layer, and the thresholds of the hidden layer neurons should be determined.

Step 3: Calculate the output. Based on the MATLAB platform, the number of neurons in the hidden layer is continuously adjusted to improve the prediction accuracy.

2.5 Activation Function

In order to compare the performance of the extreme learning machine, the analysis is performed under three different activation functions. The three activation function forms are as follows:

Sinusoidal activation function, simplified as 'sin':

$$f(x) = \sin(ax + b) \qquad (1)$$

S-shaped activation function, simplified as 'sigmoid':

$$f(x) = 1/\left(1 + \exp(ax + b)\right) \qquad (2)$$

Hard limit activation function, simplified as 'hardlim':

$$f(x) = \begin{cases} 1 & ax + b < 0 \\ 0 & ax + b \geq 0 \end{cases} \qquad (3)$$

2.6 Model Test

After the load prediction based on different activation functions, in order to facilitate the comparison between different schemes, the mean absolute percentage error (MAPE) and root mean square error (RMSE) are introduced to test the error between the schemes. The formulas are shown in the following formulas (1) and (2):

$$MAPE = \text{sum}(\text{abs}(y' - y) * \frac{100}{y})/n \qquad (1)$$

$$RMSE = \sqrt{\sum_{i=1}^{n}(y' - y)^2 / n} \qquad (2)$$

In the formulas (1) and (2), n represents the number of samples, y represents the output value of the test data,

and y' represents the predicted value of the test data.

3 RESULTS AND DISCUSSION

This paper chooses to select the half-hour load data from January 1 to January 7, 1998 from the European Intelligent Technology Competition (EUNIT) for simulation. The original data is shown in Figure 2. Forecasting is done in a rolling manner, using the data every three days to predict the fourth day. After normalization, the data range is controlled between 0 and 1. After multiple verifications, the number of neurons in the hidden layer was determined to be 10.
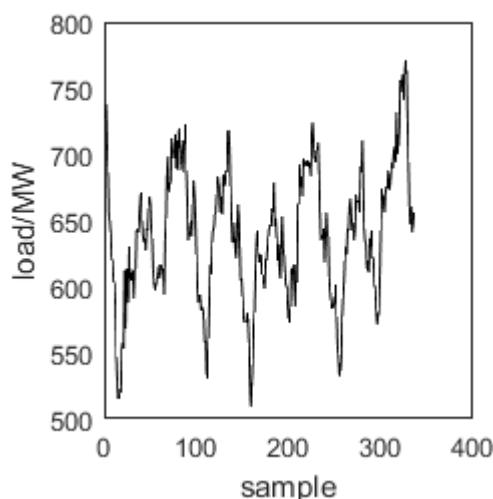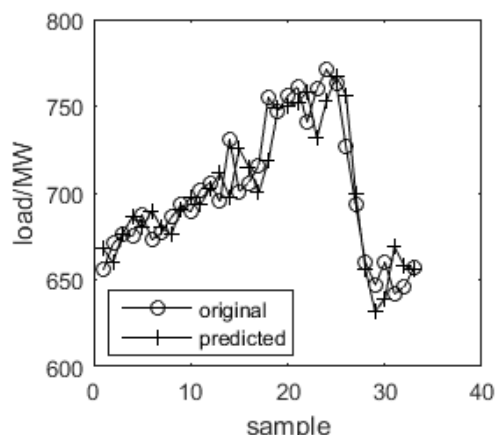

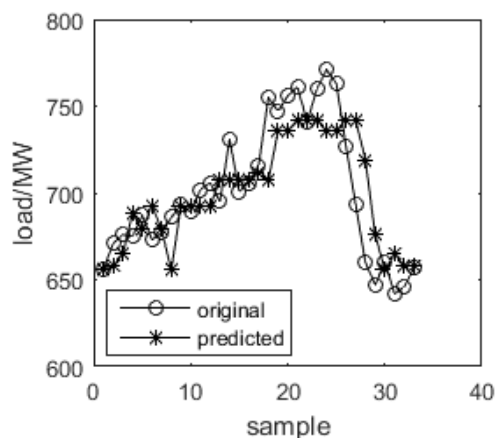**Fig. 2.** Original load data

Analysis was performed using different activation functions, and the effects of the activation function on prediction accuracy were analyzed using the prediction effects shown in Figures 3, 4, and 5，as well as the error indicators in Table 1.
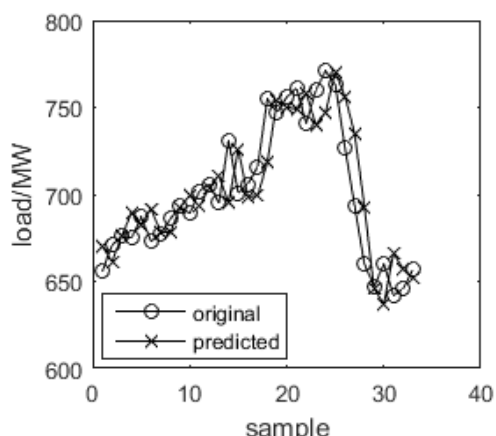
Fig. 3. Predicted effect under the 'sin' function

Fig. 4. Predicted effect under the 'sig' function

Fig. 5. Predicted effect under the 'hardlim' function

It can be seen from Fig. 3 and Fig. 4 that the extreme learning machine model under the 'sin' function and the 'sig' function has a relatively good prediction effect. Moreover, the extreme learning machine model under the 'sig' function is slightly better than the extreme learning machine model under the 'sin' function. As can be seen from Fig. 5, the extreme learning machine model under the 'hardlim' function has poor prediction accuracy.

Table 1. Error indicators under three activation functions

error indictator	'sin'	'sig'	'hardlim'
MAPE （%）	2.12	1.85	2.34
RMSE	18.60	16.18	22.02

As can be seen from Table 1, the MAPE of the prediction result under the "sig" function is 1.85 and the RMSE is 16.18. This is a decrease in the prediction results under the "sin" function and the "hardlim" function. Especially with respect to the prediction results under the "hardlim" function, the MAPE decreases by 20.94%, and the RMSE is reduced by 26.52%.

4 CONCLUSIONS

For the short-term power load forecasting problem, this paper uses the extreme learning machine model to predict. Through the analysis of the results under different

activation functions, the following conclusions can be drawn:（1）In the case of a prediction step size of 3, the extreme learning machine models of different excitation functions have achieved good prediction results;（2）The extreme learning machine model under the "sig" function has better prediction accuracy than other comparison models.

With the advancement of technology, the extreme learning machine model will be better improved. Whether it is the improvement of topology or the improvement of parameter optimization, it will help improve the accuracy of short-term power load forecasting and better control economic benefits.

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