Research on Grey Neural Network Optimal Combination in Wind Power Generation Forecasting Technique

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Abstract. In this paper, combining BP neural network prediction model with grey prediction model effectively as an optimal combination forecasting technique is proposed. This model not only considers the influence factors such as wind power, wind direction and temperature, but also comprehensively considers the historical wind power generation data, through the effective combination of BP neural network prediction model and grey prediction model, the prediction accuracy is improved. The results show that the error of the new grey neural network optimal combination prediction is lower than that of the single grey prediction and BP neural network prediction, which has a certain research value.

1. Introduction

With the energy and environmental issues becoming increasingly prominent, wind power generation has developed rapidly in the world in recent years. However, due to the particularity that electric energy can not be stored, and the significant intermittence and randomness of wind power generation, there is a certain potential threat to the security of the power grid, so it is very necessary to predict the wind power generation accurately [1-2]. In recent years, many scholars have proposed and studied different forecasting methods of wind power generation, such as support vector machine, expert system, time series, wavelet analysis, grey theory, BP neural network and linear regression. Each forecasting method has its own advantages and disadvantages. Therefore, as a new forecasting method, optimal combination forecasting technology will become the future research trend [2].

Optimal combination forecasting technology is a new forecasting technology in recent years, which combines two or more forecasting technologies to predict different types of influenced factors.[3-4] In this paper, according to the characteristics of the two models, the grey prediction model and BP neural network are selected to construct the optimal combination model to predict the wind power generation. The weights of the two models in the optimal combination are determined according to the size of the two prediction errors, so that the grey prediction model and the BP neural network model are effectively combined, and the prediction error of the final prediction result is reduced. The forecasting data of the example shows that the optimal combination forecasting has a good effect on wind power generation forecasting.
2. Grey Prediction Model

Grey prediction model has been widely used because of its advantages, such as less data, less calculation, easy to test and without considering the distribution law and change trend of sample data. GM (1,1) model is the most commonly used grey model, which is an effective model for power load forecasting.[5-7] GM (1,1) is a first-order differential equation with only one variable, and only one sequence x(0) is needed to establish the model.

Suppose there is an original data sequence with the variable x(0)

\[ x^{(0)} = [x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(n)] \]  

Using 1-AGO to generate the first order accumulation generating sequence

\[ x^{(1)} = [x^{(1)}(1), x^{(1)}(2), \cdots, x^{(1)}(n)] \]  

Where \( x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i) \) (k=1,2,...,n)

Constructing first order linear differential equation

\[ \frac{dx^{(1)}}{dt} + ax^{(1)} = b \]  

The parameters a and b are solved by the least square method to obtain

\[ \begin{bmatrix} a \\ b \end{bmatrix} = (B^T B)^{-1} B^T Y_n \]  

where

\[ Y_n = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix} \]

\[ B = \begin{bmatrix} -\frac{1}{2} [x^{(1)}(1) + x^{(1)}(2)] & 1 \\ -\frac{1}{2} [x^{(1)}(2) + x^{(1)}(3)] & 1 \\ \vdots & \vdots \\ -\frac{1}{2} [x^{(1)}(n-1) + x^{(1)}(n)] & 1 \end{bmatrix} \]

Substituting a and b into the original differential equation, we get

\[ x^{(1)}(k + 1) = \left[ x^{(1)}(1) - \frac{b}{a} \right] e^{-ak} + \frac{b}{a} \quad (k=0,1,2,\ldots) \]  

After accumulation and reduction, we get

\[ \hat{x}^{(0)}(k + 1) = \left( 1 - e^a \right) \left[ x^{(0)}(1) - \frac{b}{a} \right] e^{-ak} + \frac{b}{a} \quad (k=0,1,2,\ldots) \]  

In this paper, the historical power generation is used as the original input data sequence of x(0), and the Python software program can be used to obtain the sequence, that is the predicted wind power generation data.

3. BP Neural Network Prediction Model

Artificial neural network (ANN) is a new information processing system that simulates the structure and function of brain cells, the structure of brain nerves and the processing of thinking problems. BP neural network (Back Propagation Network) is the core part of the feedforward network. BP neural network is the most widely used and successful artificial neural network.[8-10]

BP neural network model is suitable for the prediction of nonlinear data series. In this paper, BP neural network prediction model is used as a part of the optimal combination prediction model to deal with the factors affecting the wind power generation capacity, including: wind speed, wind direction and temperature.
BP neural network model (Figure 1), if the error between the actual output of the output layer and the expected output is not within the allowable range, the output error will be reversely transmitted and distributed to all units of the hidden layer to obtain the error signal of the hidden layer unit, which will be used as the basis for correcting the connection weight of the implicit layer. We will not stop correcting the connection until the difference between the actual output and the desired output within the allowable range.

4. Optimal Combination Forecasting Technique

In view of the respective limitations of grey model and BP neural network, this paper uses grey model and BP neural network through the optimization of combination forecasting technology, so that the two models can be integrated to achieve complementary advantages and disadvantages, and improve the accuracy of prediction.

Firstly, using BP neural network model and grey model to predict a set of wind power generation data $f_1$ and $f_2$ respectively. Then, the predicted values $f_1$ and $f_2$ are subtracted from the detected values to obtain the different values, the errors $e_1$ and $e_2$. The weight coefficients $\omega_1$ and $\omega_2$ of the two models are obtained by formula (13-17). Finally, using the optimal combination forecasting model to forecast the wind power generation. [11-12]

Assuming that $f_1$ and $f_2$ are two sets of unbiased predictors for $f$, $f_c$ is the weighted average of the combined predictors, and the prediction errors are $e_1$, $e_2$, and $e_c$. Assuming $\omega_1$ and $\omega_2$ is the corresponding weight coefficient value, and

$$\omega_1 + \omega_2 = 1$$

(7)

then we get

$$f_c = \omega_1 f_1 + \omega_2 f_2$$

(8)

Let $y^{(0)}(t)$ be the detection sequence, the errors $e_1$, $e_2$, and $e_c$ can be found as:

$$e_1 = y^{(0)}(t) - f_1(t)$$

(9)

$$e_2 = y^{(0)}(t) - f_2(t)$$

(10)

$$e_c = y^{(0)}(t) - f_c(t)$$

(11)

From the formula (8-11) we get
\( \omega_1 e_1 + \omega_2 e_2 = \left[ \omega_1 y^{(0)}(t) - \omega_1 f^c(t) \right] + \left[ \omega_2 y^{(0)}(t) - \omega_2 f^c(t) \right] \)
\[= \left( \omega_1 + \omega_2 \right) y^{(0)}(t) - \left[ \omega_1 f^1(t) + \omega_2 f^2(t) \right] \]
\[= x^{(0)}(t) - f^c(t) \]
\[= e^c \]

The variance of the predict value of the combined wind pow generation \( f^c \) is
\[ Var(e^c) = \omega_1^2 Var(e_1) + \omega_2^2 Var(e_2) + 2 \omega_1 \omega_2 Cov(e_1, e_2) \]
\[= \omega_1^2 \sigma_1^2 + \omega_2^2 \sigma_2^2 + 2 \omega_1 \omega_2 \sigma_{12} \]

\( \omega_1 \) Minimize \( Var(e^c) \), we get
\[ \omega_1 = \frac{Var(e_1) - Cov(e_1, e_2)}{Var(e_1) + Var(e_2) - 2 Cov(e_1, e_2)} \]
\[= \frac{\sigma_2^2 - \sigma_{12}}{\sigma_{11} + \sigma_{22} - 2 \sigma_{12}} \]

And \( \omega_2 = 1 - \omega_1 \). \( Var(e_1) = \sigma_1^2 \), \( Var(e_2) = \sigma_2^2 \), \( Cov(e_1, e_2) = \sigma_{12} \).

The combination forecasting weight coefficients of the two forecasting methods are respectively as the follow:
\[ \omega_1 = \frac{\sigma_{22} - \sigma_{12}}{\sigma_{11} + \sigma_{22} - 2 \sigma_{12}} \]
\[\omega_2 = \frac{\sigma_{11} - \sigma_{12}}{\sigma_{11} + \sigma_{22} - 2 \sigma_{12}} \]

Since the two models are independent of each other and \( e_1 \) and \( e_2 \) are uncorrelated, \( \sigma_{12} = 0 \), so
\[ \omega_1 = \frac{\sigma_{22}}{\sigma_{11} + \sigma_{22}} \]
\[\omega_2 = \frac{\sigma_{11}}{\sigma_{11} + \sigma_{22}} \]

Substituting the calculated \( \omega_1 \) and \( \omega_2 \) into \( f^c = \omega_1 f^1 + \omega_2 f^2 \), the wind power generation forecast quantity of the optimal combination method can be obtained.

It is not difficult to see from the above:
\[ \lim_{\sigma_{11} \to \infty} \omega_1 = 0, \quad \lim_{\sigma_{22} \to \infty} \omega_1 = 1 \]
\[\lim_{\sigma_{11} \to 0} \omega_1 = 1, \quad \lim_{\sigma_{22} \to 0} \omega_1 = 0 \]

The larger the error \( e \) of the wind power generation prediction model is, the larger the variance \( Var(e) \) is, and the smaller the corresponding weight \( \omega \) is. The reverse is the same.

5. Example Verification and Analysis
Assuming the meteorological forecast and wind power generation of province J for 12 consecutive days are as shown in Figure 2:
Figure 2. Province J weather forecast and wind power capacity for 12 days

The grey model, BP neural network and optimal combination model are used to predict the wind power generation respectively, and the prediction results are shown in Figure 3.

Figure 3. Comparison of the predicted values of the three methods and the original wind power generation

Figure 4. The variance of the prediction error of the three prediction methods

According to the comparative broken line chart of the prediction results, the prediction effect of grey model is not as good as that of the BP neural network, and the prediction results of BP neural network model basically track the original data sequence of wind power generation. In this paper, the improved optimal combination forecasting model, through the complementary advantages and disadvantages of the two forecasting models, gets better forecasting results.

By comparing the variance of the prediction errors of the three prediction methods in Figure 4, it can be seen that the prediction error variance of the optimal combination prediction model is less than that of the single BP neural network and grey model, which improves the prediction accuracy.

6. Conclusion
The principle of optimal combination forecasting technology is simple and easy to understand, and it is also convenient to practice. Through the effective weighted combination of the two forecasting methods, the advantages of the two forecasting techniques are combined, and the defects of a single forecasting technique are improved, so that the optimal combination forecasting technique can be used in occasions with a small number of samples.

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