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Short-term wind speed syntheses correcting forecasting model and its application

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ABSTRACT

Wind speed prediction is important to cope with problem that large scale wind power is integrated into grid. A kind of combination forecasting model composed of time series and BP neural network prediction model for short-term wind speed forecasting is proposed. Then, the main causes of speed prediction error is analyzed in this paper. A wind speed forecasting bias correction method on Empirical Orthogonal Function (EOF) is proposed. Wind speed prediction error can be decomposed by EOF, by which the main components of error are got. Then, bias correction mode can be built by regression analysis. Then, syntheses correcting forecasting model is proposed, which consists of combination forecasting model and prediction bias correcting model. The model can be more accurately used in the short-time wind speed forecasting.

1. Introduction

The effectiveness of wind speed forecasting is an important role in the scheduling of wind power. At present, there are many methods for wind speed forecasting, such as the time series method [1,2], Calman filtering method [3], Weibull distribution method [4], neural network method [5] and a variety of combination forecasting methods [6]. And there are many references about application of wind speed forecasting. A stochastic approach was proposed to model wind forecasts in [7]. A strategy including the uncertainty of involved market and wind powers was proposed in [8]. Wang and Yu [9] proposed an optimization model to decide the rated power and capacity of a compressed air energy storage system in a power system with high wind power penetration. Mondal et al. [10] solved economic emission dispatch problem including wind generation. As the random of wind speed distribution, every prediction method has some limitations.

Due to ignore the secondary influence factors and other reasons, any kind of prediction model can generate prediction errors. The prediction error is the difference between the predicted value and real value, the main causes of which are prediction method of mathematical model just considers the major factors, and many of the secondary factors are ignored. While, as effect of the minor factors, the prediction error may form a certain trend. Taking into account these secondary influence factors, error correction is a trend to fit error. The basic idea of prediction error correction is as follows. After forecasting by one predictive method and comparing the actual data, prediction error of the forecasting method is obtained. Using of appropriate prediction method to predict error, error correction can be got, which is used to modify the original prediction results. Using the iterative method to build circular error prediction modification measures, the error is not reduced gradually, until the overall prediction accuracy meet the predetermined requirements. Under the action of error correction model, the prediction model expression is as follows: $Y = Y_0 + \sum Y_{ei}$. Y is final prediction value, Y_0 is original predictive value, $\sum Y_{ei}$ is error correction.

At present, there are some error correction methods commonly used in [11–14], so as, vector error correction model, periodic extrapolation, Bayesian vector error correction model, partial simulation approximate value, and so on, but the relevant literatures about wind speed and wind power error correction methods are very rare. So, this article quotes the error prediction methods used in other fields, so as to expound forecasting methods in wind power generation.

As the random distribution of wind speed, the mentioned forecasting methods have their own limitations. Firstly, this paper proposes a combination model of time series and BP neural network. The inputs of BP neural network are made up of historical data and residual errors calculated by time series model. The model can be more accurately predict the short-time wind speed. The causes of wind speed forecasting error are analyzed, then an error correction prediction model is proposed – EOF model. Making use of this model, main variables can be extracted, and then error correction model is built by EOF regression model. There are some excellences are that the main variables are determined by the features of sequence itself, but not prior artificial regulation, and can

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reflect the actual data base structure, and expansion equation is convergent fast. Finally, syntheses correcting forecasting model is proposed. To verify the correctness of the method, an example is analyzed.

2. Combination forecasting model

2.1. Wind speed time series model

Time series model used to forecast wind speed is relatively simple. Only need a single time series of wind speed. According to Box. Jenkins method, time series can be divided into: AR (auto regression), MA (moving average), and ARMA (auto regression moving average). The main steps of time series model used to forecast wind speed include modeling and smooth processing, model order determination and parameters estimation.

2.1.1. Modeling and smooth processing

ARMA (p,q) is modeled by measured wind speed data. The expression is following:

$$y_t = \sum_{i=1}^{p} \varphi_i x_{t-i} - \sum_{j=1}^{q} \theta_j \alpha_{t-j} + \alpha_t \tag{1}$$

where φ_i is auto-regressive parameter. θ_j is moving average parameter. $\{\alpha_t\}$ is normal white noise, $\alpha_t \in N(0, \sigma_a^2)$.

If the studied time series is non-stationary, smooth processing must be carried out, as follows [15]:

- Ordered differential transformation; there is a differential operator $\nabla = 1 - B$. D-order difference is $\nabla^d y_t = (1 - B)^d y_t$;
- Seasonal differential transformation; there is a differential operator $\nabla_s^D = (1 - B^s)^D$. s is seasonal cycle. Seasonal ARMA model is $\varphi(B^s)\nabla_s^D y_t = \psi(B^s)a_t$.

2.1.2. Model order determination and parameters estimation

Model parameters estimation and order determination of time series model prediction are very critical steps. It is also very complex. The procedure is directly related to prediction.

2.1.2.1. Model order determination. In this paper, the AIC criterion function is used to determine order. The criterion function not only considers the proximity of the historical data when using a model matching, but also takes into account the number of model parameters to be determined. Judge the quality of the models by the value function. The model made criterion function to minimum is the best model.

AIC criterion function is defined as:

$$\mathrm{AIC}(n) = N \ln \sigma_\alpha^2 + 2n \tag{2}$$

where σ_α^2 is variance of residual error. For ARMA (p,q), $n = p + q$. When modeling, increase the order of model gradually, starting from a value. The order made criterion function to minimum is the best model.

2.1.2.2. Parameters estimation. Parameters estimation of AR model is derived as follow:

$$\begin{bmatrix} \hat{\varphi}_1 \\ \hat{\varphi}_2 \\ \cdots \\ \hat{\varphi}_p \end{bmatrix} = \begin{bmatrix} 1 & \hat{\rho}_1 & \hat{\rho}_2 & \cdots & \hat{\rho_{p-1}} \\ \hat{\rho}_1 & 1 & \hat{\rho}_1 & \cdots & \hat{\rho_{p-2}} \\ & & & \cdots & \\ \hat{\rho_{p-1}} & \hat{\rho_{p-2}} & \hat{\rho_{p-3}} & \cdots & 1 \end{bmatrix} \begin{bmatrix} \hat{\rho}_1 \\ \hat{\rho}_2 \\ \cdots \\ \hat{\rho}_p \end{bmatrix} \tag{3}$$

$$\hat{\sigma}_\alpha^2 = \hat{\gamma}_0 \left(1 - \sum_{j=1}^{p} \hat{\varphi}_j \hat{\rho}_j\right) \tag{4}$$

where auto-correlation function is:

$$\hat{\rho}_k = \frac{\hat{\gamma}_k}{\hat{\gamma}_0}, \quad (k = 0 \cdots p) \tag{5}$$

Auto-covariance function is:

$$\hat{\gamma}_k = \frac{1}{N} \sum_{t=1}^{N-k} y_t y_{t+k} \tag{6}$$

Parameters estimation of MA model is derived as follow:

$$\begin{cases} \hat{\gamma}_0 = \hat{\sigma_\alpha}^2 (1 + \hat{\theta}_1{}^2 + \cdots + \hat{\theta}_q{}^2) \\ \hat{\gamma}_1 = \hat{\sigma_\alpha}^2 (-\hat{\theta}_1 + \hat{\theta}_2 \hat{\theta}_1 + \cdots + \hat{\theta}_q \hat{\theta_{q-1}}) \\ \cdots \\ \hat{\gamma}_k = \hat{\sigma_\alpha} 2 (-\hat{\theta}_q) \end{cases} \tag{7}$$

$\hat{\theta}_1, \hat{\theta}_2, \cdots, \hat{\theta}_q, \hat{\sigma_\alpha}^2$ can be calculated from this equation.

Parameters estimation of ARMA model is derived as follow:

$$\begin{bmatrix} \hat{\varphi}_1 \\ \hat{\varphi}_2 \\ \cdots \\ \hat{\varphi}_p \end{bmatrix} = \begin{bmatrix} \hat{\gamma}_q & \hat{\gamma}_{q-1} & \hat{\gamma}_{q-2} & \cdots & \hat{\gamma}_{q-p+1} \\ \hat{\gamma}_{q+1} & \hat{\gamma}_q & \hat{\gamma}_{q-1} & \cdots & \hat{\gamma}_{q-p+2} \\ & & & \cdots & \\ \hat{\gamma}_{q+p-1} & \hat{\gamma}_{q+p-2} & \hat{\gamma}_{q+p-3} & \cdots & \hat{\gamma}_q \end{bmatrix} \begin{bmatrix} \hat{\gamma}_{q+1} \\ \hat{\gamma}_{q+2} \\ \cdots \\ \hat{\gamma}_{q+p} \end{bmatrix} \tag{8}$$

Make $\bar{y}_t = y_t - \sum_{j=1}^{p} \varphi_j y_{t-j}$, then $\bar{y}_t = \alpha_t - \sum_{i=1}^{q} \theta_i \alpha_{t-i}$. Model changes into the MA model. According to the method, $\hat{\theta}_1, \hat{\theta}_2, \cdots, \hat{\theta}_q, \hat{\sigma_\alpha}^2$ can be calculated.

2.2. BP neural network prediction model combined with time series model

Algorithm basic idea is that the learning process is comprised of signal positive propagation and error back propagation. In forward propagation, the input samples from the input layers are processed in hidden layer, and then transmitted to the output level. If the output level does not match the expected output, turn into the error back propagation stage. In error back propagation, through hidden layers to input layers, the output error is propagated by some form. The error is apportioned to all the units on each layer. Gain error signal is used to adjust the weights in each layer. This process continues until the network output error reduced to an acceptable level, or come up to the number of study.

The steps of BP neural network prediction model are following [16]:

(1) Initialize weights and thresholds;
(2) Give input x_k and target output y_k;
(3) Calculate the actual output $\hat{y}_k$ (forward process);
(4) Correct weights (reverse process):

$$\omega_{ij}^{(l)} = \omega_{ij}^{(l)} - \eta \frac{\partial E_k}{\partial \omega_{ij}^{(l)}}, \quad \eta > 0 \tag{9}$$

where $\omega_{ij}^{(l)}$ is the weight coefficient between j neuron in l layer and i neuron in $(l + 1)$ layer; η is gain.

In short-term wind speed forecasting, the sample data are normalized, smoothly processed, firstly. The inputs of BP neural network are made up of historical data and residual errors calculated by time series model. The target output is original value of wind speed next hour.

2.3. Combination forecasting model

BP neural network prediction is y_1; ARMA (p,q) prediction is y_2. Weighted average prediction is y_c.