Research on Ultra-Short-Term Wind Power Prediction Considering Source Relevance

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ABSTRACT Wind power forecasting, to a certain extent, will transform the random fluctuation of wind power output into a known situation, which is one of the effective approaches to deal with large-scale wind power integrated into power grid. Due to the use of only historical data and the lack of new information, the accuracy of ultra-short-term wind power prediction (WPP) is still not satisfactory. Therefore, a combined prediction method based on the day-ahead Numerical Weather Prediction (NWP) location technology is proposed. Firstly, the time points with low forecasting accuracy of rolling WPP are approximately located by the NWP information and time windows, and then the hybrid approach combined with neural network and persistence method is presented to predict the future wind power output. The results of the case study show that compared with other classical prediction methods, this method can effectively improve the ultra-short-term prediction accuracy of wind power and verify the effectiveness of the proposed method.

INDEX TERMS Wind power prediction, neural network, persistence forecasting, time window, numerical weather prediction.

I. INTRODUCTION

At present, the energy structure of the world and the problems caused by it force mankind to find new energy solutions, so clean and emission-free new energy is widely developed and utilized. Wind energy is one of the most potential clean energy resources for large-scale development and utilization [1], [2]. Due to the randomness of wind energy and the limitation of forecasting technology, the accuracy of wind power forecasting is unsatisfactory, so improving the accuracy and applicability of wind farm power forecasting methods has become the focus of current research [3]–[6].

Wind power forecasting is divided into long-term forecasting, short-term forecasting and ultra-short-term forecasting. Ultra-short-term forecasting is generally based on historical data of wind farm output and the forecasting method. Among various physical, statistical and artificial intelligent models, the models hybridized with pre-processing or/post-processing methods have seen promising prediction results in wind applications.

Reference [7] proposed a detailed review of the methods of wind power prediction in ultra-short and short term, and interpreted the process of wind power prediction from the perspective of information flow. In Ref. [8], a combined forecasting method for ultra-short-term wind power is presented, where Empirical mode decomposition (EMD) is used to decompose the raw wind power data into sub-sequences, then a extreme learning machine is utilized to model each trace, and the final forecasting value is obtained by reconstruction. To some extent, this method can improve the accuracy of ultra-short-term prediction, but it is too complex.

In Ref. [9], a new ultra-short-term probability prediction method for wind power is proposed, in which the long short-term memory (LSTM) network, wavelet decomposition (WT), and principal component analysis (PCA) are combined together for ultra-short-term probability prediction of wind power. However, this method does not consider the future meteorological information, which leads to the limitation of prediction.
In Ref. [10]–[12], several forecasting models considering high-dimensional historical wind speed information are proposed, which reduce the randomness and uncertainty of wind power output, and improve the efficiency and accuracy of forecasting. In Ref. [13], [14], the chaotic local prediction method is applied to wind power prediction based on the measured power data of a wind farm in China. In Ref. [15], a method to improve the accuracy of wind power prediction is studied in detail, and a combination method based on multi-source data is proposed. In Ref. [16], [17] The historical NWP data of all wind farms are dimensionally reduced by principal component analysis, and a linear regression model is established between the extracted principal components and the measured power in the historical data. When the NWP is updated, the corresponding principal components are calculated and brought into the linear regression model to obtain the wind farms power prediction output. Therefore, NWP is often combined with short-term or long-term prediction of wind power, and the existing ultra-short-term prediction methods are too complex.

In this paper, based on the above discussion, a novel prediction technique combined NWP wind speed with ultra-short-term wind power is proposed, and a combined prediction model based on NWP location is proposed. Firstly, the NWP wind speed before the day is segmented according to the model of ultra-short-term rolling prediction by using time window technology. The similarity of NWP wind speed curves in two adjacent time windows is calculated to obtain the positioning curve. Then, by analyzing the fluctuation of the positioning curve, the time with low accuracy of rolling prediction is approximately located. Finally, a combined prediction model is established based on the rolling prediction of the location time by the neural network and the rolling prediction of the remaining time by the persistence method.

The remainder of this paper is organized as follows: Section 2 presents the proposed NWP wind speed and prediction accuracy. Section 3 introduces Hybrid prediction. Section 4 builds the model of ultra-short-term wind power prediction considering source relevance and stimulation results. Section 5 concludes the paper.

II. NWP WIND SPEED AND PREDICTION ACCURACY

A. ROLLING PREDICTION FRAMEWORK

Wind power ultra-short-term forecasting mainly uses historical data such as wind speed and power recorded by wind farm SCADA system to model and predict wind farm output in the next 4 hours. Numerical weather prediction is a method for predicting atmospheric motion and weather phenomena in a certain period of time in the future, based on the actual conditions of the atmosphere and under certain initial and boundary conditions, a means of making forecasts using current weather conditions as input data. Based on the mapping relationship between the NWP information and the output power of the wind farm, the NWP information is taken as the main input variable to establish the wind farm power prediction model. Wind farm station construction is accompanied by supporting NWP system, data provided by the provincial meteorological bureau. The time resolution of NWP data is usually 15 min and includes wind speed, wind direction, temperature and humidity at different heights in several regions. At the same time, the time window concept is to slide one point at a time, a window is 16 points and roll forward in the ultra short term prediction.

At present, there are several methods to predict wind power, such as persistence method, support vector machine (SVM) method, artificial neural network method and so on. The prediction of persistence method is simple and easy to realize. In this method, the observed wind speed at the nearest point is taken as the predicted wind speed at the next point. The forecasting precision of this method is high, so it is also a benchmark to evaluate other forecasting methods in wind power forecasting.

Due to the use of only historical data and lack of additional information, the effect of ultra-short-term wind power forecasting is worse than that of short-term and long-term forecasting. For this reason, the NWP prediction data and time window technology are used to approximate the rolling prediction time with low accuracy of ultra-short-term rolling prediction. In this paper, the NWP data and the time window technique are used to approximate the time when the accuracy of ultra-short-term rolling prediction is low.

Ultra-short-term wind power prediction refers to the rolling report of wind power values for the next 15 min to 4 hours in a 15-minute cycle. The step size should be 16 steps, which is equivalent to measuring 16 time series. The specific steps are shown in Figure 1.

B. CHEBYSHEV DISTANCE

In classification, it is often necessary to estimate the Similarity Measurement between different samples.

In Euclidean space, point \( x = (x_1, \ldots, x_n) \) and \( y = (y_1, \ldots, y_n) \), the Chebyshev distance \( d(x, y) \) is as follows:

\[
d(x, y) = \lim_{k \to \infty} \left( \sum_{i=1}^{n} |x_i - y_i|^k \right)^{1/k}
\]  

(1)

Firstly, the output of wind farm in the next \( n \) days is predicted by rolling persistence method. At the same time, the NWP wind speed corresponding to each rolling prediction is separated by time window. The positioning curve is obtained by calculating the similarity between the NWP wind speed...
curve corresponding to the (k-1)th rolling prediction and the kth rolling prediction, where \( k = 2, 3, 4, \ldots, 96 \times n \). Through comparison, it is found that there is a certain relationship between the fluctuation of the prediction accuracy curve and the positioning curve.

Firstly, the output of wind farm in the next \( n \) days is predicted by persistence rolling method, and the corresponding NWP wind speed is separated by time window.

Regulations: (1) The upper and lower limits of similarity curve are 50 and 20 respectively, i.e. the value assignment of greater than 50 is 50, and the value assignment of less than 20 is 20. (2) The value assigned in the interval \((i,k] \) is \( k \).

After the above processing, it is very easy to use the code to achieve the low accuracy of location rolling prediction. The approximate positioning method is described as follows:

1) The rolling prediction time \( t_i, i = 1, 2, \ldots, k \) corresponding to all points in the positioning curve equal to 20 is extracted and stored in the set \( T = \{ t_1, t_2, \ldots, t_k \} \).

2) If all the discrete values in the set are removed, then all the values in the set belong to a continuous interval, where \( T = \{ [t_{a_1}, t_{b_1}], [t_{a_2}, t_{b_2}], \ldots, [t_{a_k}, t_{b_k}] \} \).

3) Choose interval \([t_{a_i}, t_{b_i}], i = 1, 2, \ldots, k \) as the approximate time with low accuracy of rolling prediction.

To sum up, we can get a method to locate the time when the accuracy of rolling prediction is low according to the NWP prediction data of the day before. The specific steps are as follows:

Step1: The NWP wind speed corresponding to each rolling prediction is separated by time window.

Step2: The Chebyshev distance between the NWP wind speed curve corresponding to the (k-1)th rolling prediction and the NWP wind speed curve corresponding to the kth rolling prediction is calculated, and the positioning curve with length \( 96 \times (n - 1) \) is obtained, where \( k = 2, 3, 4, \ldots, 96 \times n \).

Step3: Processing the positioning curve technically.

Step4: Through positioning method, we can find the moment when the accuracy of rolling prediction is low.

### III. COMBINED PREDICTION

After a lot of comparison and analysis, due to weather, fan operation and other reasons, the output of wind farm fluctuates greatly when the accuracy of rolling prediction is low. Obviously, it is unreasonable to use persistence method to predict the output of wind farm when the accuracy of rolling prediction is low.

Neural network is a kind of information processing technology similar to human nervous system, which has good non-linear approximation ability, robustness and fault-tolerance, and is widely used in wind power prediction.

The BP neural network is a kind of multi-layer feedforward neural network, which consists of input layer, hidden layer and output layer. The basic structure of BP neural network is shown in Fig. 2.

The strong nonlinear mapping ability of BP neural network can approximate the nonlinear function. Through the forward transmission of the signal and the reverse transmission of the error, the error of the network output can meet certain conditions. The process of network training is to find the right weight and bias to minimize the cost function. In the process of error back propagation, the main work is to obtain the gradient of the parameter based on the cost function which is formed by the difference between the predicted result and the actual result, and to update the weight and offset by the gradient descent, the cost function can be reduced as quickly as possible so that it can complete the training of the network. The better the network training, the higher the prediction accuracy. The characteristics of BP neural network, such as parallel processing, distributed storage, fault-tolerance, self-learning, self-organizing and self-adaptive ability, are very effective in solving complex problems. Therefore, BP neural network is used to forecast the time of positioning and its vicinity, and the persistence method is still used to forecast the other time.

The framework of the proposed wind power prediction model is depicted in Fig. 3.

### IV. CASE STUDY

Taking the measured data of a wind farm in Jilin Province from March 31 to April 16, 2014 and the NWP forecast data from April 1 to 16, 2014 as stimulation, the total installed capacity of the wind farm is 399 MW, and the sampling interval is 15 minutes. The evaluation requirements are the assessment indicators stipulated by the State Energy Administration of China. The accuracy rate of the daily average prediction plan curve and The root mean square error of all-day forecast results.

In the formula, \( r_{1i} \) is the accuracy of i-step real-time prediction, \( P_{Mi}^k \) is the actual wind power output value at k-time in i-step prediction, \( P_{Pi}^k \) is the predicted wind power output value at k-time in i-step prediction, and \( P_{cap} \) is the total installed capacity of the wind farm.

1) The calculation formula of accuracy rate

\[
r_{1i} = \left[ 1 - \frac{1}{16} \sum_{k=1}^{16} \left( \frac{P_{Mi}^k - P_{Pi}^k}{P_{cap}} \right)^2 \right] \times 100\%
\]  

(2)
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FIGURE 3. Algorithm flow chart.

TABLE 1. The specific accuracy rate.

| Location distance type         | Accuracy rate |
|-------------------------------|---------------|
| dynamic time bending distance | 35.34%        |
| Manhattan distance            | 28.66%        |
| Chebyshev distance            | 74.75%        |
| Min distance                  | 34.56%        |
| angle cosine distance         | 56.57%        |
| Mahalanobis distance          | 35.77%        |

\[ r_1 = \frac{1}{96} \sum_{i=1}^{96} r_{1i} \]  

2) The mean absolute error (MAE)

\[ r_2 = \frac{1}{96 \times 16} \sum_{i=1}^{96} \sum_{k=1}^{16} \left| \frac{P_{Mi}^k - P_{Pi}^k}{P_{cap}} \right| \times 100\% \]  

3) The root mean square error of all-day forecast results (RMSE)

\[ r_3 = \sqrt{\frac{1}{96 \times 16} \sum_{i=1}^{96} \sum_{k=1}^{16} \left( \frac{P_{Mi}^k - P_{Pi}^k}{P_{cap}} \right)^2} \times 100\% \]  

Similarity is determined by dynamic time bending distance, Manhattan distance, Chebyshev distance, Min distance, angle cosine distance, Mahalanobis distance and relative distance.

The specific accuracy is shown in Table 1.

It is found that the Chebyshev distance between the NWP wind speed curve corresponding to the (k-1)th rolling prediction and the NWP wind speed curve corresponding to the kth rolling prediction is the best. The positioning effect is shown in Fig. 4.

From Fig. 4, it can be seen intuitively that the positioning curve can approximately find the lowest accuracy point of rolling prediction of persistence method. However, the location curve with more fluctuations is difficult to be applied in practice. Therefore, some technical processing of the location curve is needed to make it easier for the computer to locate the time when the accuracy of rolling prediction is low.

In order to facilitate processing according to section IIB, the positioning curve is still called the positioning curve. The following is a graph of the relationship between the location curve and the prediction accuracy curve of the persistence method when taking different historical values, as shown in Fig. 5. In the appendix, Location curve and accuracy curves are given in tabular form.

The historical values in Fig. 5 are from left to right and from top to bottom are the historical values in Table 2.

In Table 2, the locating time of low accuracy of rolling prediction with persistent method under different historical values is given.

In Fig. 5, it can be found that the rolling prediction accuracy of persistence method is low, and that of adjacent time is relatively low. Therefore, three different BP forecasting methods are proposed in this paper, which are BP single rolling...
BP single rolling prediction refers to the use of BP prediction only at the time of positioning and rolling. For example, in Table 2, the historical value is 1, and the rolling prediction time is the 21st and 86th rolling prediction. Therefore, BP neural network is used for the 21st and 86th rolling prediction, while the persistence method is still used for the rest rolling prediction time.

BP three rolling prediction refers to the use of BP neural network at the time of positioning rolling prediction and the time before and after that time. For example, when the historical value is 1, the BP neural network is used in the 20, 21 and 22 rolling times when the rolling prediction time is 21; when the rolling prediction time is 86, the BP neural network is used in the 85, 86 and 87 rolling prediction times. By analogy, BP five-point prediction can be obtained.

Take the persistence method $+$ BP single rolling prediction as an example. Assuming a historical value, the wind power from 00:00 to 23:45 on April 1 is predicted by rolling method with a prediction step of 16. The prediction accuracy was 77.95% and RMSE was 18.48%. Through the NWP prediction data and positioning technology, we can know that the persistence method is not ideal for the 21st and 86th rolling prediction. So BP neural network is used in the 21st and 86th rolling prediction, and the prediction step is still 16. After 10 tests, the accuracy of persistence method and BP single rolling prediction is 78.22% and the RMSE is 16.77%.

Below is a statistical table of the accuracy and RMSE of the persistence method and BP prediction when taking different historical values, as shown in Table 3.

In Table 3, combination forecasting 1 is persistence method and BP single rolling (PM-BP-1), combination forecasting 2 is persistence method and BP three rolling (PM-BP-3), combination forecasting 3 is persistence method and BP five rolling (PM-BP-5).

Through comparison, it can be concluded that the persistence method and BP three rolling prediction effect is the best. Compared with the persistence method, the accuracy of the hybrid forecasting method can be improved by 7.61% and the RMSE reduced by 8.76%.

Ultra-short-term WPP is made by the results of positioning curve. The concrete results are shown in Figure 6. In the appendix, the prediction maps of rolling location time under different historical values are given in tabular form.

In order to better illustrate the validity of the persistence method $+$ BP three-time rolling prediction, two comparison methods of BP neural network and SVM are used to realize the rolling prediction of wind power under different historical values.

Since BP is a supervised learning method, the historical value begins at 96, i.e., first rolling forecast of wind power from 00:00 to 23:45 on April 2, then forecast wind power from 00:00 to 23:45 on April 3, and so on. In addition, the structure of BP network is the same as that of BP network in persistence $+$ BP prediction.

Table 4 shows the rolling prediction results of BP neural network and SVM after 10 tests.
FIGURE 6. Actual data and the result of PM, PM-BP-1, PM-BP-3 and PM-BP-5.
Table 4 shows that SVM prediction effect is relatively stable, the accuracy rate is in the range of 85%-90%, but the prediction effect is not as good as BP. BP neural network is unstable in ultra-short-term rolling prediction. There are two reasons for this phenomenon: (1) errors are introduced in data acquisition and monitoring of SCADA; (2) errors exist in NWP prediction due to technical constraints.

Compared with Table 3 and Table 4, the accuracy and RMSE of the PM-BP-3 method are improved by 4.73% and reduced by 9.27% respectively, and the method is also superior to the BP neural network with the same network structure.

In order to compare the applicability of the proposed method, the wind farm output data of 31 days in July 2015 of a large wind farm in Jilin Province are taken as the research object. The installed capacity of the wind farm is 249.9 MW, and the wind turbine type is MY1.5 SE-1.5 MW. The data of the first 30 days are used as training, and the wind power of the last day is used as prediction.

It can be seen from Figure 7 that SVM, PM and PM-BP-3 of the method proposed in this paper have better tracking characteristics in prediction, with accuracy of 76.23%, 65.88% and 88.95% respectively. The prediction accuracy of the proposed method is still higher than that of other methods, which shows that PM-BP-3 is also suitable for large-scale wind farms and provides a new prediction method for different scale wind farms.

V. CONCLUSION

In this paper, a combined forecasting method of ultra-short-term wind power is proposed and verified by practical results.

The time window and the NWP prediction data are used to approximate the time when the rolling prediction accuracy is low. The example shows that the positioning technology can accurately locate the time when the accuracy of rolling prediction is low, and provide accurate data for the subsequent combination forecasting model.

Through positioning technology, rolling prediction is divided into positioning rolling time and non-positioning rolling time. Different prediction methods are used at different rolling times. Case study show that the combined forecasting method proposed in this paper improves the accuracy by 5.38% and reduces RMSE by 6.90% compared with the persistence forecasting method. The results show that the proposed method is superior to the traditional persistence method, BP neural network and SVM.
The combination forecasting method proposed in this paper can make full use of NWP information and choose different forecasting methods under different conditions, which has strong practicability. How to improve the prediction accuracy, generalization and robustness of BP neural network model will be the focus of future research.

COMPETING INTERESTS
The authors declare that they have no competing interests.

AUTHORS’ CONTRIBUTIONS
All authors contributed to this research. Xinnan Yu wrote the draft of this paper, conducted the experiments, and performed the experiments. Yong Sun, Zhenyuan Li, Xinnan Yu, Baoju Li and Mao Yang participated in the design of the study, statistical analysis and shared in writing and revising the paper.

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