Study on the Applicability and Integrated Application of Multiple Correction Methods for Wind Farm Wind Speed Forecasts: Postprint

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Abstract

Taking a wind farm in central Inner Mongolia as the experimental site, this study employs the Random Forest (RF) method, Analogue Correction of Errors (ACE) method, and Probability Density Function matching method (PDF) to conduct correction and applicability research on wind speed forecasting for the wind farm. The results indicate that all three methods demonstrate varying degrees of correction effectiveness on Weather Research and Forecasting (WRF) model wind speed forecasts across all seasons. The RF method can effectively ameliorate large WRF errors but simultaneously exhibits excessive error amplification. While the ACE and PDF methods are less capable than the RF method in improving large errors, they can better control the issue of excessive error amplification. Furthermore, the correction effect of the three methods is unsatisfactory for the low wind speed range below 5 $m \cdot s^{-1}$, with correction capability gradually intensifying as wind speed increases. By leveraging the respective advantages of each forecasting model, attempting to develop a grade-specific integrated application of multiple forecasting models can yield improved performance for WRF forecasts across different wind speed grades.

Full Text

Applicability Research and Integrated Application of Various Correction Methods for Wind Speed Forecast in Wind Farms

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Abstract: The method used for evaluating the correction effect of a model is very important for improving the short-term wind speed forecast. At present, the comparison of the correlation coefficient and error between the corrected and forecasted wind speeds in the research period is generally adopted. This evaluation method often ignores the limited correction ability of most statistical correction methods in low and high wind speed sections.

Taking a wind farm in central Inner Mongolia, China as the experimental site, this study uses the three methods of random forest (RF), analog correction of errors (ACE), and probability density function matching method (PDF) to correct the wind speed forecast in the experimental wind farm. A correlation coefficient and error analysis of the whole research period is performed. Wind speed is classified into cut-in wind speed, low, high, and full generating wind speeds, and cut-out wind speed. The applicability study of the three models in each grade is then conducted. The results show that the three methods have different degrees of correction effects on the weather research forecast (WRF) of wind speed in each season. The average absolute error promotion rates in sequence are 6.7%-36.7%, 11.1%-34.7%, and 3.7%-20.6% after correction via the RF, ACE, and PDF methods, respectively, in the model validation period. The RF method can effectively improve the large error problem of the WRF, but it also has the error overamplification problem. Although the ACE and PDF methods have less ability for improving the large error compared with the RF method, they can better control the error overamplification problem. For the small wind speed section of less than 5 $\mathrm{m \cdot s^{-1}}$, the correction effect of the three methods is not ideal. The original WRF forecast and PDF method are better than the RF and ACE methods. With the wind speed increase, the WRF forecast error significantly increases, and the correction ability of the three methods gradually increases. The RF and ACE methods are better than the PDF methods in the wind speed level of [5,16). The correction ability of the ACE method begins to decline, whereas that of the PDF method begins to improve in the wind speed level of [16, $+\infty$). According to the respective advantages of the forecast models, the integrated application of various forecast models considering the wind speed forecast level is attempted to improve the WRF forecast under different wind speed levels.

Keywords: wind speed forecast; random forest; analogue correction of errors; probability density function matching method; integrating forecast

Introduction

China has vast territory and rich wind energy resources. Since its wind power installed capacity ranked first in the world, the challenge of wind power grid integration has followed. In the future, China' s renewable energy will enter a stage of large-scale, high-proportion, and market-oriented development, further leading the mainstream direction of energy production and consumption revolution, and playing a dominant role in the clean and low-carbon transformation of energy. This provides main support for achieving the "carbon peak and carbon neutrality" goals, which puts forward higher requirements for wind power grid integration capacity.

Short-term wind speed prediction combining mesoscale numerical forecast models with statistical correction methods has long been a research topic for domestic and foreign experts and scholars as an effective means to reduce wind power grid integration pressure and improve wind farm operation efficiency. Among them, statistical correction methods have gradually developed from early traditional statistical correction methods to machine learning methods based on artificial intelligence. Researchers have used algorithms such as Extreme Learning Machine (ELM), Back Propagation (BP) neural networks, and Support Vector Machine (SVM) to correct model forecast wind speed, reducing the relative root mean square error and relative mean absolute error of forecast wind speed by 20%-30%.

However, how to evaluate the correction effect of models is also crucial for the improvement of short-term wind speed prediction. At present, the evaluation method generally adopts the comparison of correlation coefficient and error between corrected wind speed, model forecast wind speed, and observed wind speed during the research period. This evaluation method often ignores the problem that most statistical correction methods have limited correction ability in low and high wind speed sections.

The near-surface wind field is easily affected by complex underlying surfaces and complex turbulence processes, with significant volatility and uncertainty characteristics. When wind turbines operate in low wind speed sections (<5 m $\cdot$ s^{-1}) or high wind speed sections (\$ $25m\cdot s$^{-1}\$), they may frequently start and stop due to gust influence, increasing wind turbine wear and tear and operating costs of wind farms. Large-scale wind turbine start-stop may affect the active power supply-demand balance and frequency stability of the power grid due to exceeding grid regulation capacity. Therefore, the improvement ability for wind turbine cut-in and cut-out wind speed sections is an important indicator for measuring the quality of correction models.

This study adopts the random forest (RF) method, analog correction of errors (ACE) method, and probability density function matching method (PDF) to establish wind speed forecast correction models for wind farms. In addition, based on the applicability study of different correction methods, optimal correction model weights are selected to attempt integrated application of multiple models, providing a new idea for more effectively improving wind farm wind speed forecast performance.

1 Data and Methods

1.1 Data Sources

The Zhongjneng Julong Wind Farm in central Inner Mongolia was selected as the experimental wind farm. This wind farm is located in Xinghe County, Inner Mongolia. Xinghe County has an average altitude of 1500 m, is dominated by northwest airflow, has perennially high wind speeds, with an average wind speed >9.0 $m \cdot s^{-1}$ and many days with strong winds \$ 17.0$m \cdot s$^{-1}\$, indicating abundant wind resources. The location and topographic distribution of the experimental wind farm' s met tower are shown in [Figure 1: see original paper].

Inner Mongolia has a typical mid-temperate monsoon climate, characterized by low and uneven precipitation and drastic cold and heat changes. Wind speed shows obvious seasonal variation characteristics, with the largest in spring, followed by winter, and the smallest in summer. Liu et al. based on station observation data and ECMWF ERA5 reanalysis data pointed out that near-surface wind speed in China shows significant regional characteristics, with large wind speed areas mainly distributed in Inner Mongolia, western Northeast China, northern Xinjiang, and western Qinghai-Tibet Plateau, and these areas have large seasonal differences in wind speed.

Observation data uses hourly wind measurement data at 100 m height from the wind tower at the experimental wind farm, with the tower location at 113°16 12 E, 41°07 48 N. Forecast data is the 100 m height wind speed grid forecast product from the wind energy professional numerical forecast model combined with post-processing, with a forecast time limit of 72 hours and time resolution of 1 hour. This model is mainly used for wind power meteorological services in Inner Mongolia, with model center coordinates at 112°02 24 E, 43°49 48 N. The forecast area is set to 27 km, with model range of 96°27 00 –127°31 48 E, 37°12 00 –54°28 48 N. NCEP GFS (0.5°\$×\$0.5°) is used as initial and lateral boundary conditions. The boundary layer adopts the YSU scheme, the land surface process adopts the Noah scheme, the cumulus parameterization scheme adopts the Kain-Fritsch scheme, the longwave radiation adopts the RRTM scheme, the shortwave radiation scheme adopts the Goddard scheme, the land surface process adopts the unified land surface process scheme, the cumulus parameterization scheme adopts the shallow convection scheme, and the vertical direction uses sigma coordinates for output of meteorological elements at different near-surface levels.

The model output height at the sigma layer corresponding to the nearest forecast grid point from the wind tower is shown in . Forecast data from 4 grids consistent with the time series of observed data from the wind tower were selected, with forecast grid latitudes and longitudes as follows: 113°12 00 E, 41°03 00 N; 113°18 36 E, 41°03 00 N; 113°11 24 E, 41°08 24 N; and 113°18 36 E, 41°07 48 N. Bilinear interpolation was used in the horizontal direction to interpolate to the wind tower location, and linear interpolation was used in the vertical direction to interpolate to 100 m height.

1.2 Research Methods

Considering the obvious seasonal characteristics of wind speed in the study area, this paper adopts a seasonal modeling approach, specifically dividing seasons by month: March–May for spring, June–August for summer, September–November for autumn, and December–February for winter. Wind speed forecast seasonal correction models based on WRF were established for each season, with the first two months of each season as the model construction period and the last month as the model validation period.

1.2.1 Random Forest (RF) Method The random forest method is an algorithm that integrates multiple decision trees through the idea of ensemble learning. The wind speed prediction training set is defined as $\{X_i \rightarrow Y_i\}$. Where X_i is the feature vector of influencing factors $\{I_i\}$ at time i during the model construction period, and Y_i is the observed wind speed at time i during the model construction period. Through bootstrap resampling technology, classification model construction is completed, and a single regression decision tree is established. On the basis of single decision tree construction, the entire RF is constructed. Its advantages include the ability to handle input samples with high-dimensional features, effective operation on large datasets, and good accuracy.

The output is the average value of predictions from all decision trees. Through sensitivity tests, 4 influencing factors were selected from WRF output elements to construct the feature vector: wind speed, temperature, relative humidity, and surface pressure, to build the RF correction model and achieve WRF wind speed correction forecast output.

1.2.2 Analogue Correction of Errors (ACE) Method The main idea of the ACE method is to transform forecasts arranged in chronological order into a similar space to find historical forecasts most similar to the current forecast (defined by specific distance), that is, to measure the similarity between historical forecasts and current forecasts by defining appropriate distance, in order to characterize the similarity of weather processes. In the similar space, according to the similarity of WRF forecasts to historical forecasts, corresponding weights are assigned to historical forecasts, and then weighted averaging of observed values of similar historical forecasts is performed to obtain the correction forecast.

The ACE method overcomes the shortcomings of general error correction methods based on chronological order and can handle rapid changes in forecast errors caused by severe weather system transformations. Wind speed and surface pressure are used as correction factors to build the ACE model. Through sensitivity tests, model parameters are determined: time window (T_w) is 30 days, the number of similar forecast samples (N_a) is 30, and wind speed weight is 0.8.

1.2.3 Probability Density Function Matching Method (PDF) The main idea of the PDF method is to adjust forecast values to make them consistent with the probability density distribution of ground observations to achieve the purpose of correcting forecast systematic errors. For wind speed observed by the wind tower and WRF forecast wind speed, when the sample size is sufficiently large, stable cumulative probability density distributions of both can be obtained respectively. When the cumulative probability density is P, the corresponding observed wind speed and WRF forecast wind speed are denoted as OBS and WRF ($\mathrm{m \cdot s^{-1}}$), respectively. At this time, they have a stable difference Δ ($\mathrm{m \cdot s^{-1}}$), calculated as follows:

$$\Delta = \mathrm{WRF} - \mathrm{OBS}$$

By calculating the cumulative probability density of wind tower observed wind speed at each time and the corresponding WRF forecast wind speed and observed wind speed at this probability density, the difference Δ at this time can be obtained, and thus the WRF forecast wind speed at each time can be corrected to obtain the corrected value:

$$\mathrm{WRF}_c = \mathrm{WRF} - \Delta$$

1.2.4 Verification Methods This paper uses correlation coefficient (r), mean absolute error (e), accuracy rate (f), and mean absolute error promotion rate (a) to verify the correction results, calculated as follows:

$$r = \frac{\sum_{i=1}^{N}(\mathrm{WRF}_i - \overline{\mathrm{WRF}})(\mathrm{OBS}_i - \overline{\mathrm{OBS}})}{\sqrt{\sum_{i=1}^{N}(\mathrm{WRF}_i - \overline{\mathrm{WRF}})^2 \sum_{i=1}^{N}(\mathrm{OBS}_i - \overline{\mathrm{OBS}})^2}}$$

$$e = \frac{1}{N}\sum_{i=1}^{N}|\mathrm{WRF}_i - \mathrm{OBS}_i|$$

$$f = \frac{n_{\mathrm{correct}}}{n_{\mathrm{correct}} + n_{\mathrm{false}} + n_{\mathrm{miss}}} \times 100\%$$

$$a = \frac{e_{\mathrm{orig}} - e_{\mathrm{corr}}}{e_{\mathrm{orig}}} \times 100\%$$

Where WRF and OBS are forecast wind speed and observed wind speed ($\mathrm{m \cdot s^{-1}}$), respectively; $\overline{\mathrm{WRF}}$ and $\overline{\mathrm{OBS}}$ are the average values of forecast wind speed and observed wind speed ($\mathrm{m \cdot s^{-1}}$), respectively; N is the total number of samples in the statistical period; i is the sample sequence number in the statistical period; n_{correct}, n_{false}, and n_{miss} are the number of correct forecasts, false alarms, and missed forecasts in a certain wind speed segment during the evaluation period, respectively; e_{corr} is the mean absolute error of corrected forecast ($\mathrm{m \cdot s^{-1}}$); and e_{orig} is the mean absolute error of original forecast ($\mathrm{m \cdot s^{-1}}$).

2 Results and Analysis

2.1 Applicability Analysis of Correction Methods

2.1.1 Whole Wind Speed Error Verification A seasonal verification approach was adopted for whole wind speed error verification. During the research period, the total number of samples was [N], with an effective sample rate of 94.2%. The sample quantity for each season in the model validation period was: spring [N_{spring}], summer [N_{summer}], autumn [N_{autumn}], and winter [N_{winter}], with effective sample rates of 94.6%, 93.8%, 94.5%, and 93.9%, respectively.

From the verification results of the model validation period, all three methods have different degrees of correction effects on the pre-correction WRF wind speed forecast in each season. Taking the correction results in autumn as an example ([Figure 2: see original paper]), it can be seen that the RF method can effectively improve the problem of large WRF errors, but it also brings about the problem of excessive error amplification. This may be because the RF method cannot make predictions beyond the range of training set data when performing regression, leading to overfitting when modeling certain specific noise data.

The ACE and PDF methods, although less capable of improving large errors compared with the RF method, can better control the problem of excessive error amplification. Especially the ACE method, the probability of negative return is significantly smaller than the other two methods.

The correlation coefficients before and after correction in each season () all pass the 95% confidence level test. After RF correction, the correlation coefficient decreases slightly compared with before correction, which may be because RF cannot provide a continuous output, leading to a decrease in correlation coefficient. After ACE and PDF correction, the correlation coefficient increases compared with before correction.

The mean absolute error after correction () shows that the correction effect of the RF method is better than that of the ACE and PDF methods in spring and autumn, while the correction effect of the ACE and PDF methods is better than that of the RF method in summer and winter. This may be related to the probability density distribution characteristics of observed wind speed at the experimental wind farm during the model construction period. In spring and autumn, the observed wind speed distribution range at the experimental wind farm is wider, and the cumulative probability density distribution simulated by the model is more consistent with reality. In summer and winter, the observed wind speed distribution range at the experimental wind farm is relatively concentrated, and the cumulative probability density distribution simulated by the model has certain deviations from reality, resulting in better correction effects in spring and autumn than in summer and winter.

Overall, the mean absolute error promotion rate of the RF method is 6.7%–36.7%, that of the ACE method is 11.1%–34.7%, and that of the PDF method is 3.7%-20.6%. For WRF forecasts with small errors, the mean absolute error promotion rates of all three methods are relatively low. For WRF forecasts with large errors in winter, all three methods show significant improvement in mean absolute error.

2.1.2 Wind Speed Interval Error Verification Since the sample size of strong wind samples in each season' s model validation period is limited, wind speed interval error verification adopts a whole-season verification approach, merging samples from each season' s model validation period and conducting graded error verification according to measured wind speed intervals.

First, according to the power curve of typical wind turbines, the measured wind speed from the wind tower is divided into 5 grades corresponding to wind power zero generation, low generation, high generation, full generation, and cut-out: [0,3), [3,5), [5,8), [8,12), [12,16), [16,20), and [20,+∞) $m \cdot s^{-1}$. To more detailedly grasp the error correction ability of different methods, and considering that the sample size for wind speed \$ $25m \cdot s$^{-1}\$ is too small to obtain statistically meaningful analysis results, the above wind speed grades are further subdivided into 7 wind speed intervals.

The sample numbers for each wind speed interval in the whole-year model validation period are shown in . [Figure 3: see original paper] shows the comparison of correction effects of different methods on wind speed in different intervals. It can be seen that when measured wind speed is below 5 $m \cdot s^{-1}$, all three correction methods have negative returns, and as wind speed increases, the error increases. When wind speed \$ $5m \cdot s$^{-1}\$, all three correction methods begin to produce positive returns.

The mean absolute error promotion rate of the RF method is relatively stable, while that of the ACE method slightly decreases, which may be caused by the limited number of historical samples in high wind speed intervals. For the ACE method, only information provided by historically similar states can effectively correct current forecast errors, and dissimilar states may provide incorrect correction information.

Although the ACE method has less ability to improve large errors than the RF method, it better controls the problem of excessive error amplification. The correction ability of the RF method begins to decline when wind speed <16 $m \cdot s^{-1}$, while its correction ability improves when wind speed \$ $16m \cdot s$^{-1}\$.

2.1.3 Wind Speed Interval Accuracy Verification Wind speed interval accuracy verification also adopts a whole-season verification approach. From the forecast accuracy rates in different wind speed intervals ([Figure 5: see original paper]), when wind speed <5 $m \cdot s^{-1}$, the accuracy rates of all three correction methods are lower than the original WRF forecast. When wind speed \$ $5m \cdot s$^{-1}\$, the accuracy rates of all three correction methods are improved to varying degrees compared with the original WRF forecast. Especially when wind speed \$ $8m \cdot s$^{-1}\$, the accuracy rate of corrected wind speed forecast is significantly improved. When wind speed \$ $20m \cdot s$^{-1}\$, the accuracy rate of the ACE method is the best.

2.2 Integrated Application of Multiple Forecast Models

2.2.1 Seasonal Integration Ensemble forecast and integrated forecast are the development direction of weather forecast technology. Integrated forecast can integrate and analyze multiple independent single-model forecast results or parameters through a mathematical model to finally obtain the most ideal forecast result. Commonly used integrated forecast methods include weight integration, regression integration, probability integration, and discriminant integration.

Referring to the positive and negative deviations of each season' s average error promotion rates, weighted integration of the three methods was conducted by season. The integrated forecast (IF) formula is:

$$\mathrm{IF} = w_1 \times \mathrm{WRF} + w_2 \times \mathrm{RF} + w_3 \times \mathrm{ACE} + w_4 \times \mathrm{PDF}$$

Using the whole-year model validation period samples, under the premise of measured wind speed grade discrimination, the original WRF forecast, RF correction forecast, ACE correction forecast, and PDF correction forecast were integrated as 4 members. The weights of each member under different wind speed intervals and the verification results are shown in .

After integration, seasonal verification shows that the correlation coefficients for each season are 0.72, 0.68, 0.75, and 0.71, respectively, and the mean absolute errors are 2.1 $\mathrm{m} \cdot \mathrm{s}^{-1}$, 2.2 $\mathrm{m} \cdot \mathrm{s}^{-1}$, 2.3 $\mathrm{m} \cdot \mathrm{s}^{-1}$, and 3.0 $\mathrm{m} \cdot \mathrm{s}^{-1}$, respectively, which are better than the pre-integration WRF forecast. It can be seen that weighted integration of the three correction methods by season can give full play to the respective advantages of integrated members and improve WRF forecast performance overall.

However, from the wind speed time series before and after seasonal integration ([Figure 6: see original paper]), it can be seen that seasonal integration cannot effectively improve the situation where low wind speed (<5 $\mathrm{m} \cdot \mathrm{s}^{-1}$) is larger than observed.

2.2.2 Wind Speed Interval Integration Considering the respective advantages of different correction models in different wind speed intervals, using the whole-year validation period samples, under the premise of measured wind speed grade discrimination, the original WRF forecast, RF correction forecast, ACE correction forecast, and PDF correction forecast were integrated as 4 members. The weights of each member under different wind speed intervals and the verification results are shown in .

After integration by wind speed interval, the correlation coefficient is 0.73 and the mean absolute error is 2.3 $m \cdot s^{-1}$, which is better than the seasonal integration method. [Figure 7: see original paper] shows the comparison of mean absolute error and accuracy rate of forecast wind speed in different intervals after wind speed interval integration with the WRF forecast. It can be seen that the wind speed interval integration method has good improvement effects on WRF forecast in different wind speed intervals. The correlation coefficient and mean absolute error are slightly higher than or equal to the optimal single method.

It is worth pointing out that in the [0,5) $m \cdot s^{-1}$ wind speed interval, the number of false alarms after integration is reduced from 126 times to 81 times. Due to the reduction in false alarms, the forecast accuracy rate after wind speed interval integration is effectively improved, thus being better than seasonal integration.

3 Conclusions

This study constructs WRF correction models by season and conducts verification and evaluation of three correction methods for wind speed forecast in different seasons and wind speed intervals. The results show that:

1) All three methods have different degrees of correction effects on WRF wind speed forecast. The RF method can effectively improve the problem of large WRF errors but also brings the problem of excessive error amplification. The ACE and PDF methods, although less capable of improving large errors, can better control the problem of excessive error amplification.

2) For the small wind speed section of less than 5 $m \cdot s^{-1}$, the correction effect of the three methods is not ideal. With the increase of wind speed, the correction ability of the three methods gradually increases. The RF and ACE methods are better than the PDF method in the [5,16) $m \cdot s^{-1}$ wind speed level. The correction ability of the ACE method begins to decline, while that of the PDF method begins to improve in the [16,+∞) $m \cdot s^{-1}$ wind speed level.

3) The wind speed interval integration method is better than the seasonal integration method. It has good improvement effects on WRF forecast in different wind speed intervals. Under the premise of wind speed forecast interval discrimination, weighted integration of multiple forecast models can effectively improve the correction ability of models.

The deficiency of this study is that the research period is only 1 year. Future research will continue to be carried out in depth to provide a more reliable research basis for optimal correction of wind speed forecast.

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Note: Figure translations are in progress. See original paper for figures.