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Wind power forecasting error evaluation and decoupling methods

Jie Yan[a], Yuhao Li[a]

[a] School of New Energy, North China Electric Power University, 102206, Beijing, PR China
E-mail: yanjie@ncepu.edu.cn (Jie Yan)

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Wind power forecasting is a key technology to support power system operation and power market trading decision-making. In recent years, with the joint efforts of academia and industry, the forecasting accuracy has been significantly improved, but the forecasting error has always existed and cannot be eliminated. Therefore, understanding the sources of uncertainty and quantitatively decoupling them is of great significance for implementing reasonable and targeted model improvement strategies. In response, IEA TASK 51 established a working group to create a standardized platform for quantifying uncertainty in wind power forecasting, and we have done a bit of work guided by that task: 1) A systematic error analysis system is established, including overall error statistics and refined error assessment; 2) In according with the modeling process, the source of uncertainty is divided into four parts: the uncertainty of weather, the uncertainty of input data, the uncertainty of wind to power conversion, and the uncertainty of the forecasting model, and uncertainty quantification indexes are proposed for each part; 3) On the basis of the above, we achieved the full-process decoupling of the day-ahead wind power forecasting error, which provides a reliable basis for the improvement of forecasting models. Integrating these work, we preliminarily established a standardized platform for wind power forecasting error evaluation and decoupling, which has been publicly tested (http://59.110.123.174:8066/).

1. Error analysis

1.1 Overall error statistics

This section calculates the forecasting error and gives an overview of the forecasting error in terms of multiple statistical indicators, multiple statistical periods, and multiple visualizations. Metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Coefficient of Determination (R^2) are integrated into the platform, and the statistical periods include daily, monthly, quarterly, and yearly, and the visualization formats include histograms, scatter plots, and line charts.

1.2 Detailed error analysis

The magnitude of forecasting error is affected by a variety of factors, and the forecasting error under different scenarios shows different regular characteristics. In order to get a better grasp of which samples affect the overall performance of the forecasting model, a detailed error analysis system is proposed, including the distribution of power forecasting error under different Numerical Weather Prediction (NWP) wind speed error intervals, the distribution of power forecasting error under different fluctuation scenarios and the trend of ultra-short-term forecasting error with respect to the step.

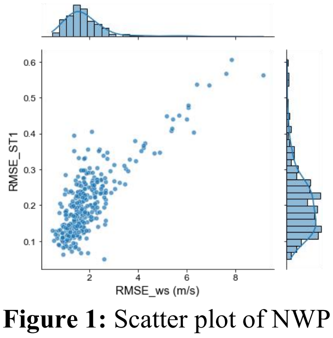

Figure 1: Scatter plot of NWP wind speed error and power forecasting error

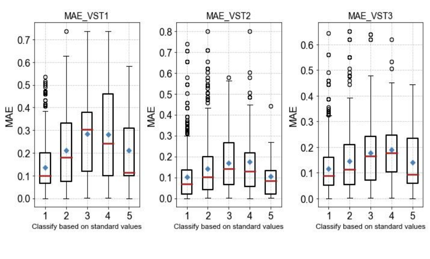

Figure 2: Error distribution under different fluctuation scenarios

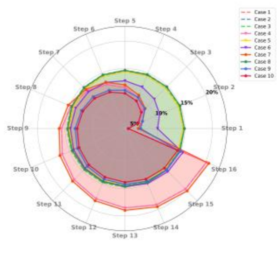

Figure 3: Forecasting error at each step

2. Analysis and quantification of sources of uncertainty

Following the modeling process of wind power forecasting, the sources of forecasting uncertainty are categorized into four main segments, which are weather uncertainty, input data uncertainty, wind to power conversion uncertainty, and forecasting model uncertainty[1].

2.1 Weather uncertainty

Weather uncertainty leads to errors in weather prediction, which in turn introduces errors into power forecasting. In order to quantify weather uncertainty, the temporal correlation of the wind speed series is first computed to quantify the local wind resource predictability, and then the distribution of NWP wind speed prediction errors is counted for different wind speed intervals to measure the NWP performance.

Figure 4 shows the autocorrelation and partial autocorrelation analysis of the observed wind speed series. As the lag order increases, the autocorrelation gradually weakens, indicating that the uncertainty in wind speed evolution increases over time, making the prediction more difficult. Figure 5 summarizes the distribution of forecasting wind speed errors under different wind speed intervals. It can be observed that as the wind speed increases, the sample size gradually decreases, while the proportion of large errors gradually increases.

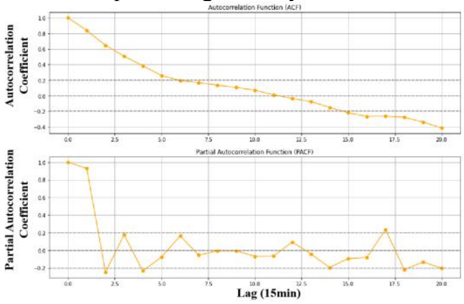

Figure 4: Autocorrelation and partial correlation coefficients of the wind speed

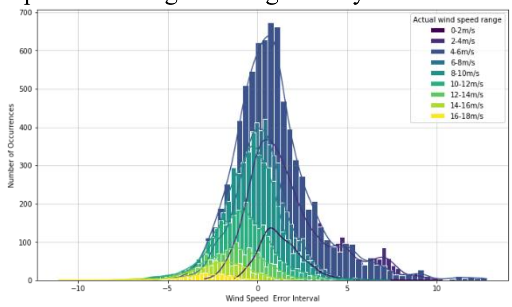

Figure 5: Distribution of NWP wind speed errors

2.2 Input data uncertainty

Uncertainty in the input data refers to the poor representation of the training set, which further introduces errors into the power forecasting, and mainly includes two aspects: 1) the introduction of disturbing "knowledge" by anomalous data; 2) the large difference in the distribution between the training set and the test set. To address 1), we first identify the anomalous data based on the bidirectional quartile method and calculate the proportion of anomalous data; to address 2), we propose the scenario balance degree and the uncertainty degree of power sequence evolution metrics, which are applicable to the point-to-point forecasting model and sequence-to-sequence forecasting model, respectively, and quantify the difference in the distributions of the training set and the test set.

As shown in Figure 6, the scenario balance degree indicator is positively correlated with forecasting accuracy, and it can accurately measure the representativeness of point-to-point model training samples. As shown in Figure 7, Scene 1 represents a stable wind process with the lowest evolution uncertainty. The other scenes are transitional wind scenarios, with the highest evolution uncertainty observed in Scenes 5, 6, 8, and 9, which represent continuous upward ramping, upward ramp transitioning to downward ramp, downward ramp transitioning to upward ramp, and continuous downward ramp scenarios, respectively.

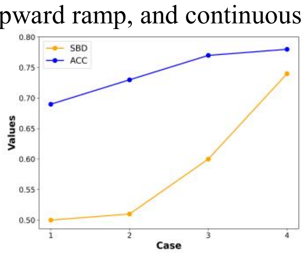

Figure 6: The relationship between SBD and forecasting accuracy

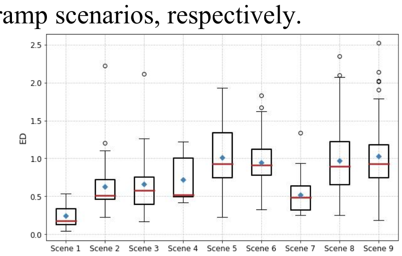

Figure 7: The degree of sequence evolution uncertainty under different scenarios

2.3 Uncertainty in wind to power conversion process

Due to the mechanical inertia of wind turbines, the wind speed-power scatter plot forms a "band," meaning that the same wind speed corresponds to a range of power values rather than a fixed value. This represents the uncertainty in wind to power conversion process. In order to quantify this uncertainty, the power confidence intervals under fixed confidence level are counted in each wind speed interval, and the uncertainty of wind to power conversion is quantitatively characterized by the length of the confidence intervals. As shown in Figure 8 and Figure 9, the 95% confidence interval width for the 4-5 m/s and 6-7 m/s wind speed intervals are 48.93 MW and 87.05 MW, respectively, indicating higher uncertainty in the 6-7 m/s wind speed interval.

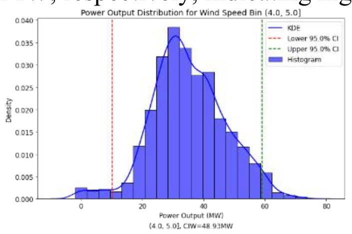

Figure 8: Power distribution under the 4-5 m/s wind speed interval

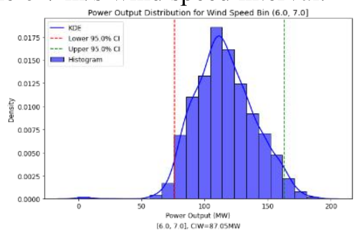

Figure 9: Power distribution under the 6-7 m/s wind speed interval

2.4 Uncertainty in forecasting models

The uncertainty of the forecasting model is caused by the lack of model fitting ability, which is quantitatively characterized by calculating the fitting error of the forecasting model on the training set.

3. Error decoupling case of day-ahead wind power forecasting

According to section 2, we take the day-ahead wind power forecasting as an example for error decoupling. The calculation method and steps are as follows:

First, model the forecasting and calculate the errors according to the following instructions: e_t：Forecasting error of the test set when the training set contains anomalous power data and the input feature is NWP wind speed; e_1：Forecasting error of the test set when the training set does not contain anomalous power data and the input feature is NWP wind speed; e_2：Forecasting errors for the test set when reanalyzed data is used in place of NWP; e_3：Forecasting errors for the test set when using measured wind speed data in place of NWP; e_4：Forecasting errors for the test set after artificially restricting the power range for each wind speed interval for both the training and test sets.

Then, the forecasting errors for each stage are obtained according to the following formulas, where, e_d is the error caused by the uncertainty of the input data, e_p_i is the error caused by the initial conditions of the NWP model, e_p_m is the error caused by the inference process of the NWP model, e_c is the error caused by the uncertainty in wind to power conversion process, and e_f_m is the error caused by the power forecasting model. The proportion of errors at each stage is shown in Figure 10.

$$e\_d = e\_t - e\_1 \tag{1}$$

$$e\_p\_i = e\_1 - e\_2 \tag{2}$$

$$e\_p\_m = e\_2 - e\_3 \tag{3}$$

$$e\_c = e\_3 - e\_4 \tag{4}$$

$$e\_f\_m = e\_4 \tag{5}$$

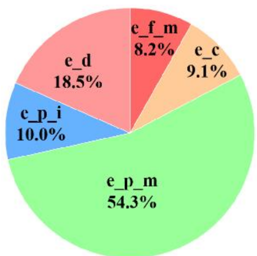

Figure 10: Error decoupling result

4. Conclusion

This paper proposes a systematic error evaluation and uncertainty quantification metric system and implements the decoupling of day-ahead wind power forecasting errors. This system can provide more detailed information for model improvement, allowing for the formulation of targeted improvement strategies.

References

[1] Yan Jie, Corinna Moehrlen, Tuhfe Goecmen, Mark Kelly, Arne Wessel, Gregor Giebel. Uncovering wind power forecasting uncertainty sources and their the whole chain. *RENEWABLE & SUSTAINABLE ENERGY REVIEWS* 2022;165.