Response to Reviewer

Major Comments

Comment 1: For the experimental data, more information should be provided. What is the instrumental set-up? Is only one measurement location used (90 m hub-height of 1 turbine)? Results could differ a lot depending on where these measurements are taken since turbine wakes have great effect on the wind stochastic processes. Also, the difference in resolutions between WRF measurements and actual experimental data can influence the predictions. Please comment on those.

Response:

We thank the reviewer for raising these important points. In response, we have supplemented detailed information regarding the instrumentation setup of the wind farm in Section 2.1. Importantly, there is no resolution difference between the WRF data and the experimental measurements—both have a temporal resolution of 15 minutes. We have rewritten Section 2.1 as follows:

2.1 Data

The target wind farm in this study is an offshore wind farm located in Jiangsu Province, China, which belongs to the northern subtropical monsoon climate zone with flat terrain. Wind speeds are higher in summer and relatively stable in winter. Sea–land breezes alternate markedly, and offshore wind directions vary frequently, predominantly from the east. This study utilized wind farm data from April to August 2023. Meteorological information, including wind speed and direction at hub height, was obtained from a meteorological mast installed within the farm. Power data at the individual turbine and station level were collected via the SCADA system mounted at the turbine nacelles. All data have a temporal resolution of 15 minutes. The installed capacity of the wind farm is 300 MW, comprising 96 Myse 3.0–135 turbines with a rotor diameter of 135 m and a hub height of 90 m. The annual mean wind speed at hub height is 7.3 m/s. Since the forecast wind speed provided by NWP represents the regional wind speed over the wind farm area, and the target variable for prediction is the station-level wind speed, we used the average wind speed of the 96 turbines at the same time (i.e., the station-level wind speed) as the observed value for prediction. This approach also ensures the integrity and continuity of the wind speed data.

Since large-scale offshore wind farms are under complex meteorological conditions, the introduction of the ACI can reflect the meteorological phenomena related to wind speed changes, which can help to better adjust the bias and improve the prediction of future wind speed. Therefore, we added ACI as the quantity of characteristics in the wind speed correction. ACI includes the strength of the East Asian Major Trough (CQ) and the area, strength, ridge line, and west extension ridge point of Subtropical High (GM, GQ, GX, and GD). The CQ is standardized by the height field of 500 hPa of the ERA5 reanalysis data of 110 ~ 145 ° E and 25 ~ 45 ° N. GM, GQ, GX and GD were calculated using the average data of the height field of 500 hPa 00, 06, 12, 18 hours of the ERA5 reanalysis data (Wang et al., 2021).

Comment 2: Motivation on the use of BCMMC, RFE, BO, and RF is missing. Why not other ones? Also, a quantitative comparison with the state of the art for the results achieved is missing.

Response:

Thank you for your insightful comments regarding our work.

BCMMC was selected because it allows a more refined partitioning of meteorological patterns over the offshore wind farm, thereby characterizing wind field features across different time periods. By conducting modal-specific correction, BCMMC effectively reduces systematic errors under specific conditions and enhances the model's adaptability to varying scenarios.

RFE (Recursive Feature Elimination) is employed to perform rational input feature selection, constructing a more efficient and accurate wind speed prediction and correction model while reducing the risk of overfitting.

BO (Bayesian Optimization) and RF (Random Forest) were chosen due to their demonstrated superior performance in hyperparameter optimization and regression prediction, respectively, as reported in previous studies. Their integration enables accurate wind speed correction values.

Considering that the complex hybrid model prediction methods mentioned in the literatures are tailored to specific prediction durations and application scenarios, these hybrid models may not necessarily be applicable to the target wind field of the experiments in this research paper. Therefore, in the subsection 'Comparison experiment' of the results section, we use the popular machine learning methods mentioned in the literature to build hybrid models to predict the wind speed and visualize the prediction performance of this paper's method through the comparison of various error indicators.

Comment 3: Same for lines 88-110 and 111-133: More concise motivation of the paper is required. Please specify more clearly what are the limitations of the existing methods. As you suggest, features such as SLB should be incorporated in the prediction. What is the magnitude of errors due to not incorporating SLB for instance?

Response:

We thank the reviewer for this constructive suggestion. Considering the influence of sea-land breeze (SLB) arising from diurnal variation and weather stability on wind speed, we proposed the BCMMC model for wind speed modal classification. In the ablativity experiment (Section 3.5), we compared and discussed the contribution of the BCMMC model to the overall hybrid model error. Any model that incorporates the BCMMC module achieved strong prediction performance, significantly outperforming other models. This demonstrates that the BCMMC model plays a key role in improving wind speed prediction accuracy. Besides, we have thoroughly revised the motivation section (lines 88-133) to make it more concise and focused, as detailed below.

In recent years, the hybrid model, which integrates various NWP models and predictive modeling techniques, has emerged as the predominant method of prediction when incremental advances in NWP and predictive modeling technologies are insufficient to achieve breakthroughs. With the continuous improvement of the performance of artificial intelligence models, machine learning algorithms are extensively employed in wind speed prediction modeling. Parri and Teeparthi (Parri and Teeparthi, 2024) introduced a hybrid wind speed prediction model (SVMD-TF-QS) that integrates a novel query selection mechanism (QS), continuous variational mode decomposition (SVMD), and a Transformer (TF)-based model to accurately forecast wind speed while minimizing computational load. The hybrid models effectively leveraged the strengths of individual models to improve forecast accuracy and reliability. Despite the unique advantages of deep learning in the processing of complex data, the advantages of machine learning in terms of computational efficiency, interpretability, stability, and convenience make it still worthwhile to pay attention to and apply in wind speed prediction tasks. Lahouar (Lahouar, 2017) implemented hour-ahead wind power prediction using a random forest algorithm, independent of irrelevant inputs and without optimization. Zhu (Zhu et al., 2023) proposed a wind speed behavior prediction method based on multi-feature and multi-scale ensemble learning, which significantly improved the accuracy of wind speed prediction by integrating environmental and background features. Prediction models based on multi-algorithm fusion will become an important development direction in the field of wind speed prediction.

In offshore wind farms, wind speed is influenced by complex meteorological processes, among which sea-land breeze (SLB) plays a critical role due to diurnal temperature contrasts (Shen, 2021). SLB modulates turbulence intensity and wind speed gradients, potentially altering wind-power characteristics.However, to date, few studies have considered the impacts of weather systems, terrain, and day-night alternation on wind speed. In summary, the following problems remain to be solved in the field of wind speed prediction:

(1) The feature factors input to the corrected model for wind speed prediction have significant limitations. Traditional forecast revision models use historical wind speed data as input and have not considered the interactions between meteorological factors. It does not have any feature selection and lacks feature quantities that can indicate the trend of weather stability;

(2) The factors influencing the wind speed prediction correction method are not comprehensive enough. Previous studies have ignored the influence of meteorology and the principles of statistical models. The offshore wind field should consider the interaction between SLB, large-scale circulation, and other weather systems, as well as high and low wind speed values in the models. Due to the randomness of wind speed and the localized nature of meteorological features, wind speed correction requires a variety of models.

Comment 4: In Sect. 3.4. was hyper-parameter tuning carried out for the different models compared? If not, the analysis would not be valid. Please provide the hyper-parameter tuning results as well. Do they correspond to the accuracy observed in other studies in the state of the art that use the same method?

Response:

We thank the reviewer for this important comment. Yes, hyper-parameter tuning was systematically performed for all compared models in Section 3.4. Specifically, we employed Bayesian optimization combined with 10-fold cross-validation on the training dataset, which consists of 11,136 samples (approximately 80% of the total data). The optimal hyper-parameters found for each model are summarized in Table 6 below. These results have been added to the revised manuscript (Section 3.4).

The absolute errors of our baseline models are larger than those reported in some other studies (e.g., Xiong et al., 2023) because of task differences: offshore station-level prediction at 15-min resolution is much more challenging than the settings in many benchmark papers. Notably, Xiong et al. acknowledged that conventional ML models perform poorly under limited meteorological data – which exactly matches our observation. The key point is that our proposed BCRBR-based method reduces rRMSE to 9.4%, outperforming even the VBL method in Xiong et al. (rRMSE = 15.9%). Therefore, our baseline results are reasonable given the task difficulty, and the dramatic improvement of our method is what demonstrates its novelty and effectiveness.

Xiong, X., Zou, R., Sheng, T., Zeng, W., and Ye, X.: An ultra-short-term wind speed correction method based on the fluctuation characteristics of wind speed, Energy, 283: 129012, 2023.

Table 5: The optimal hyper-parameters found for each model.

Model	Key Hyper-parameters (optimal values)
RF	n_estimators=300, max_depth=22, min_samples_split=5, min_samples_leaf=2, max_features='sqrt'
ERT	n_estimators=280, max_depth=24, min_samples_split=4, min_samples_leaf=1, max_features='auto'
DF	n_estimators_rf=200, n_estimators_extra=200, n_trees=100, layer=2, cascade=True
XGBoost	n_estimators=550, max_depth=9, learning_rate=0.045, subsample=0.8, colsample_bytree=0.8, reg_alpha=0.1, reg_lambda=1.0
lightGBM	n_estimators=450, num_leaves=35, max_depth=12, learning_rate=0.04, subsample=0.8, feature_fraction=0.8, reg_alpha=0.05, reg_lambda=0.5
DNN	layers=[128, 64, 32], activation='ReLU', dropout=0.25, batch_size=64, epochs=200, learning_rate=0.0008 (Adam), early stopping patience=15

Comment 5: The input features and labels to predict are hard to follow as they are explained in different sections of the manuscript. I suggest expanding Table 1 with the prediction labels, time and spatial resolutions, the data source, and the forecast time (i.e., 1-hour ahead forecasting).

Response:

We thank the reviewer for this suggestion. Since our prediction target is the station-level wind speed (a point measurement), the WRF outputs at the wind farm location originally have a spatial resolution of 1 km. All meteorological forecast variables were interpolated to the exact longitude and latitude of the wind farm using bilinear interpolation. The timestamps for all data have been synchronized. This information has been added in Section 2.2.2 (WRF model). We have expanded Table 1 to include data source and temporal resolution. The relevant changes are as follows:

2.2.2 WRF model

In this study, the WRF 4.2 model developed by the National Center for Environmental Prediction (NCEP) is used, which has the characteristics of portability, extensibility, high efficiency, multiple nesting and rich parametric scheme design (Skamarock et al., 2019). Combined with the three-layer grid nesting configuration, the prediction region is shown in Figure 3. The number of grids is 150 × 150 90 × 90 and 150 × 180, and the horizontal grid resolutions were 9km, 3km, and 1km, respectively. The center points of the grid were set at 34 ° N and 120 ° E. The system is updated every 12 hours, once at 0:00 UTC and once at 12:00 UTC, with forecasts for the next 7 days. Considering that the time scale of the meteorological station data in the study area is 15min, the time interval of the forecast data from the WRF model is also set to 15 min. The meteorological factors selected for the forecast include wind speed in the 10-meter, 90-meter, 110-meter, and 130-meter wind directions, temperature of 2 meters, relative humidity of 2 meters, surface air pressure, and precipitation. Use the bilinear interpolation method to interpolate the WRFOUT grid-based weather forecast data to the latitude and longitude of the target wind farm.

Table 1: Names of input features and their abbreviations.

Feature Abbreviations	Feature name	Related Information

WS90	90-meter Wind Speed	
T2	2-meter Temperature	
RH2	2-meter Relative Humidity	
PRS2	2-meter Air Pressure	
PRE	Precipitation	Temporal resolution:
WS10	10-meter Wind Speed	15 minutes;
WD10	10-meter Wind Direction	Data source: WRF
WD90	90-meter Wind Direction	model
WS110	110-meter Wind Speed	
WD110	110-meter Wind Direction	
WS130	130-meter Wind Speed	
WD130	130-meter Wind Direction	
CQ	Strength of East Asian Major Trough	Temporal resolution:
GM	Area of Subtropical High	1 day;
GQ	Strength of Subtropical High	Data source:
GD	Westward Extending Ridge Point	Atmospheric
GX	Subtropical High Ridge	Circulation Index

Comment 6: In Sect 3.4. the manuscript comments on the performance of classic methods such as XGB for time-series forecasting. However, the typical data structure used in time-series forecasting by XGB is following an auto-regressive process approach. This is, past measurements are used to predict future ones. I suggest trying this approach or deleting these lines.

Response:

Thank you for your suggestion. We have decided to remove these lines of text, as they may be controversial. The revised Section 3.4 is as follows:

3.4 Comparison experiment

Table 5: The optimal hyper-parameters found for each model.

Model	Key Hyper-parameters (optimal values)
RF	n_estimators=300, max_depth=22, min_samples_split=5, min_samples_leaf=2, max_features='sqrt'
ERT	n_estimators=280, max_depth=24, min_samples_split=4, min_samples_leaf=1, max_features='auto'
DF	n_estimators_rf=200, n_estimators_extra=200, n_trees=100, layer=2, cascade=True

XGBoost	n_estimators=550, max_depth=9, learning_rate=0.045, subsample=0.8, colsample_bytree=0.8, reg_alpha=0.1, reg_lambda=1.0
lightGBM	n_estimators=450, num_leaves=35, max_depth=12, learning_rate=0.04, subsample=0.8, feature_fraction=0.8, reg_alpha=0.05, reg_lambda=0.5
DNN	layers=[128, 64, 32], activation='ReLU', dropout=0.25, batch_size=64, epochs=200, learning_rate=0.0008 (Adam), early stopping patience=15

Table 6: Comparing the performance of the models in the experiment in terms of error metrics.

	RMSE(m/s)	rRMSE(%)	MAE(m/s)	MAPE(%)	FA(%)	R
WRF	2.692	26.21	2.134	79.2	30.2	0.766
BCRBR	0.965	9.4	0.613	25.8	78.4	0.898
RF	2.733	26.6	2.409	124.3	19.1	0.682
ERT	2.369	23.07	1.978	86	27.1	0.745
DF	1.866	18.17	1.464	59.9	42.9	0.738
XGBoost	2.66	25.9	2.234	125.6	22.4	0.632
lightGBM	2.403	23.4	2.135	109.1	19.7	0.775
DNN	2.028	19.75	1.722	94	29	0.22

To comprehensively evaluate the wind speed prediction performance of the BCRBR model, we selected popular machine learning and deep learning methods in the wind power field, such as the RF, ERT, DF, XGBoost, lightGBM, and DNN models, and used the same dataset to predict wind speed for comparison experiments. The optimal hyper-parameters found for each model are summarized in Table 5. Table 6 shows the error metrics of the prediction effects of each model. After comparison, the BCRBR model performed the best in all error metrics and demonstrated good performance in the limited dataset, highlighting its strong competitiveness. The Taylor diagram in Figure 15(a) visually displays the correction effects of each model, with the BCRBR model being closest to the reference point, indicating that its prediction results were closest to the measured values, had the smallest error, and exhibited the best prediction performance.

Comment 7: Regarding the robustness experiment, please give comments on how the trained model behaves in accordance to the SLB, since there is none in a mountain zone.

Response:

Thank you for your suggestion. We have discussed the model's performance at the end of the robustness experiments, as follows:

In the robustness experiment, the overall accuracy of wind speed prediction for the wind farm in Jiangxi Province of China was slightly lower as compared to the offshore wind farm in Jiangsu Province, mainly because the wind farm in Jiangxi Province is a mountainous wind farm with a more complex topography than an offshore wind farm. In intricate terrain, numerous factors affect wind speed, including the drag effect caused by the ruggedness of mountain surfaces on the atmosphere, as well as localized circulations like valley winds and slope winds, stemming from the uneven heating and cooling of mountainous regions.

In the future, the following methods will be considered to enhance the accuracy of wind speed prediction in mountain areas. Incorporating terrain factors and underlying surface parameters, such as terrain height, slope, roughness, etc., as input features in the wind speed prediction model. Increasing the density and quality of observations, particularly in complex topographic regions, to provide a larger sample size for model training and validation.

Comment 8: Please modify the discussion and conclusions sections according to the comments given.

Response:

Thank you for your valuable feedback. We have revised the discussion and conclusion sections based on your comments. Please refer to the revised manuscript for the Discussion section. The Conclusions section is as follows:

4 Conclusions

This study presented a multimodal short- and medium-term wind speed prediction correction approach based on bi-clustering and machine learning, aiming to address the crucial scientific problems of incomplete consideration of influencing factors and limited feature extraction in traditional wind speed prediction. In this paper, the BCRBR model was innovatively constructed, with offshore wind farms as the research object, and the complex influence mechanisms of sea-land breeze and atmospheric circulation on wind speed were thoroughly considered from a meteorological perspective. By introducing bi-clustering strategies and innovative features such as atmospheric circulation indices, precise correction of wind speed predictions was achieved in this study. Compared to the traditional WRF model, the errors of the corrected wind speed predictions were significantly reduced, specifically the following. RMSE, rRMSE, MAE and MAPE all decreased by more than 60%, the wind speed forecast accuracy rate increased from 30.2% to 78.4%, and the correlation coefficient R increased from 0.77 to 0.9.

This research not only offers new thoughts for wind speed prediction in methodology, but also provides data source guarantees to enhance the accuracy of wind power prediction. The research findings have significant theoretical value and practical significance in promoting the large-scale development of wind power and the sustainable development of power systems. The results of comparative experiments demonstrated that the BCRBR model outperforms the prevalent single-model prediction methods in the current literature. The results of the robustness experiments indicated that this method also performed better than the traditional WRF model in the prediction of wind speed in mountain wind farms in terms of various performance indicators, but there was a slight disparity compared to the results in offshore wind farms, which provided an important direction for subsequent improvement.

Future research will focus on the following directions to improve the accuracy of wind speed prediction in mountainous areas:

(1) Integrating terrain factors and surface parameters—such as elevation, slope, and roughness—as input features for wind speed prediction models.

(2) Enhancing the quality of observational data, especially in complex terrain regions, by implementing data quality control protocols to supply more reliable samples for model training and validation.

(3) Refining model parameters and extracting informative features to improve prediction performance under complex terrain conditions, thereby broadening the applicability of the method and supporting efforts to mitigate instability in renewable energy generation.

Minor Comments

Comment 9: Lines 54-72: Please discuss quantitatively WRF errors. This is, provide statistical figures for “significant errors” as presented in line 67.

Response:

Thank you for your valuable feedback. We have provided a quantitative discussion of the WRF error range; please refer to lines 81–87 for details.

Comment 10: Line 45: Please add a reference.

Response:

A reference has been added to line 45.

Comment 11: Line 46: Complex terrain of the ocean may be misleading. Typically, complex terrain is associated to mountain/valley areas.

Response:

We have corrected the statements that could have been misleading to ensure the rigor of academic research.

Comment 12: Please indicate in the introduction the amount of data that will be used, the length of the campaign, etc. Also, what are the coordinates of the wind farms, their names, etc.

Response:

We have provided additional details regarding the data in the introduction. Due to confidentiality agreements with the wind farm, we are unable to provide specific information such as the wind farm's coordinates and name.

Comment 13: Please formulate or expand on the wind speed evaluation index, comparison experiment, robustness experiment, etc.

Response:

We have provided a more detailed explanation of the “wind speed evaluation index,” “comparative experiments,” and “robustness experiments.”

Comment 14: 3 would benefit from the off-shore wind farm coordinates.

Response:

Due to confidentiality agreements with the wind farm, we are unable to provide specific information such as the wind farm's coordinates and name.

Comment 15: Sect 2.1. Data. Please indicate from which up to which day data is available, which measurement instruments are used, the source of ACI, etc.

Response:

We have provided a more detailed explanation of the data in Section 2.1. Data.

Comment 16: 2.2.3. Lines 244-245: Motivation on the usage of BCMMC model is insufficient. You could provide some reference to motivate the good performance of it under similar scenarios.

Response:

References were added to lines 244–245. In Section 2.2.1, we discussed the motivation for using the BCMMC model in some detail, as follows:

2.2.1 Bi-clustered Recursive Bayesian Forest Model

The BCRBR model proposed in this study contains four patterns which are the biclustered meteorological pattern classification model (BCMMC), RFE, Bayesian optimization (BO) and Random Forest (RF) algorithm. First, considering the influence of SLB generated by day and night changes and weather stability on wind speed, the BCMMC model was used for the modal classification of wind speed data and added ACI as input features. According to the division of the historical meteorological environment label and the prediction of the target data set label, the modal matching of the target data set and the historical data set was performed, to reduce the interaction between the extreme values of the wind speed of the input model. Furthermore, to reduce the complexity of the correction model and overfitting to enhance interpretability, the input features of the wind speed correction model were screened using the RFE method. Finally, the RF regression algorithm was chosen for the final correction of wind speed, and the parameters were optimized by the BO algorithm before each model training.

Comment 17: Line 367: There is a typo: “The formula is as follows” two times.

Response:

We have corrected the typo. Only one instance of “The formula is as follows” remains.