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Machine learning-based wind speed prediction using random forest: a cross-validated analysis for renewable energy applications

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Abstract

Wind speed prediction plays a crucial role in renewable energy planning and optimization. This study presents a comprehensive analysis of wind speed forecasting using Random Forest (RF) models. RF with 5-fold cross-validation, using a time-based splitting strategy to ensure temporal dependencies were preserved, enhancing model stability and reliability. The research utilized wind speed data collected throughout 2023 at the Bowen Abbot facility. The model demonstrated robust performance across multiple evaluation metrics, achieving an average R^2 score of 0.9155 (±0.0035) through 5-fold cross-validation. Error analysis revealed consistent performance across training, testing, and validation sets, with root mean square errors (RMSE) of 0.6624 (±0.0098) m/s. Feature importance analysis revealed that the 3-hour rolling mean wind speed was the most influential predictor, accounting for 89.84% of the model's predictive power, followed by 1-hour (2.59%) and 3-hour (2.57%) lagged wind speeds. This hierarchical importance of temporal features suggests that recent wind patterns are crucial for accurate predictions. The error distribution analysis showed approximately normal distributions with slight deviations in the tails, particularly in the validation set (kurtosis: 5.2146). Key findings indicate that the model maintains high prediction accuracy across different temporal scales, with mean absolute errors (MAE) averaging 0.4998 (±0.0098) m/s. The model's stability across different data partitions suggests its reliability for operational deployment. These results demonstrate the potential of RF algorithms for accurate wind speed forecasting in renewable energy applications, providing a valuable tool for wind power generation planning and management. The study's findings contribute to the growing body of research on machine learning applications in renewable energy, offering insights into model performance evaluation and error analysis methodologies for wind speed prediction systems.

1. Introduction

Accurate wind speed prediction is undeniably crucial for the effective planning and optimization of renewable energy systems (Adnan et al., 2019; Demirtop & Sevli, 2024). The inherent intermittency and unpredictable nature of wind resources necessitate the development of sophisticated forecasting models. These models are essential for ensuring grid stability, optimizing energy production, and facilitating the seamless integration of wind power into the broader energy mix [4–6]. Traditional forecasting methods, often rooted in statistical time series analysis or simpler physical models, frequently struggle to capture the intricate, non-linear dynamics inherent in wind speed data[6–8]. This limitation has fueled extensive research into the application of ML techniques, offering the potential for significant improvements in both the accuracy and reliability of wind speed forecasts [9]. This study delves into this crucial area by investigating the application of RF regression models, enhanced with robust cross-validation techniques, for accurate and reliable wind speed prediction.

The escalating global reliance on renewable energy sources, particularly wind power, has underscored the critical importance of precise wind speed prediction. Accurate forecasts are not merely desirable; they are essential for a wide range of applications within wind energy management, impacting both operational efficiency and economic viability. These applications include, but are not limited to:

Grid Integration and Stability: The unpredictable nature of wind power generation poses a significant challenge to grid stability. Accurate forecasts of wind power output fluctuations are crucial for maintaining grid balance, preventing disruptions, and ensuring the reliable supply of electricity [4]. Without accurate predictions, grid operators face the risk of power outages, frequency deviations, and voltage instability, potentially leading to significant economic losses and societal disruption. The ability to anticipate variations in wind power generation allows for proactive adjustments to the energy supply, integrating other energy sources seamlessly to compensate for fluctuations [10].

Resource Assessment and Wind Farm Siting: Before investing in the construction of a new wind farm, a thorough assessment of the wind resource potential is paramount. This involves gathering and analyzing wind speed data over extended periods to determine the average wind speed, its variability, and the overall energy yield. Accurate wind speed data is the cornerstone of this assessment, guiding decisions about the optimal location, size, and design of the wind farm [11]. Underestimating wind resource potential can lead to undersized projects; while overestimating it can result in economically unviable investments.

Economic Dispatch and Energy Trading: Precise wind speed forecasts are vital for optimizing energy dispatch strategies, ensuring that wind power is integrated efficiently into the electricity market. Accurate predictions enable power producers and traders to make informed decisions about energy production, storage, and trading, maximizing profitability while minimizing costs [12]. The ability to anticipate changes in wind power output allows for more effective scheduling of other generation units, reducing reliance on expensive peaking plants and optimizing overall system efficiency. This also facilitates effective participation in energy markets, optimizing revenue streams and minimizing financial risk.

Operational Planning and Maintenance: Wind turbine operations and maintenance are significantly influenced by wind speed predictions. Accurate forecasts allow for proactive scheduling of maintenance activities, minimizing downtime and maximizing the operational lifespan of wind turbines [10, 12]. Forecasting extreme weather events such as high winds or icing allows for timely preventative measures, reducing the risk of damage and costly repairs. This proactive approach minimizes disruptions to energy generation and reduces overall operational costs.

The limitations of traditional forecasting methods have propelled significant research into the application of ML algorithms for wind speed prediction. Several ML algorithms have been explored, each possessing unique strengths and limitations that make them suitable for specific applications or datasets. These include:

Support Vector Regression (SVR): SVR models are particularly well-suited for handling high-dimensional data and capturing non-linear relationships. Their ability to effectively model complex patterns in wind speed data makes them a popular choice for wind speed forecasting. However, the computational cost of training SVR models can be high, especially for large datasets. Careful selection of kernel functions and hyperparameters is also crucial for optimal performance [13].

Artificial Neural Networks (ANNs): ANNs, particularly deep learning architectures such as Long Short-Term Memory (LSTM) networks, have demonstrated remarkable capabilities in capturing temporal dependencies in wind speed data [14]. LSTMs are especially effective in handling time series data with long-range dependencies, making them well-suited for predicting wind speed over extended periods. However, ANNs can be computationally intensive to train and require significant amounts of data for optimal performance. Overfitting can also be a concern if the model is not properly regularized [15].

RF: RF models are ensemble methods that combine multiple decision trees to improve prediction accuracy and robustness [16, 17]. Their inherent ability to handle non-linear relationships, high dimensionality, and noisy data makes them a strong contender for wind speed forecasting. RF models are relatively less prone to overfitting compared to other ML algorithms, and their computational cost is generally moderate.

Other Notable Techniques: A diverse range of other ML algorithms have been applied to wind speed forecasting with varying degrees of success. These include Gradient Boosting Regressors [18], which are known for their high accuracy and efficiency; Extreme Learning Machines [19], which are particularly fast to train; and Gaussian Process Regression [20], which provides probabilistic predictions along with point estimates. The choice of the most appropriate algorithm depends on factors such as data characteristics, computational resources, and the desired level of interpretability.

While previous studies have demonstrated the potential of various ML models for wind speed prediction, several research gaps remain. There is a need for more comprehensive analyses of specific algorithms under diverse conditions and data characteristics. This study directly addresses these gaps by focusing on the performance of RF regression models, enhanced by the rigorous application of cross-validation techniques. The specific objectives are:

i. To evaluate the performance of RF in predicting wind speed data, using a diverse range of performance metrics. This evaluation will extend beyond simple accuracy measures, exploring the model's behavior across different temporal scales and data subsets.

ii. To assess the model's stability and generalizability using robust cross-validation techniques. This will provide insights into the model's ability to generalize to unseen data, crucial for real-world applications. The results will help determine the reliability and robustness of the model under various conditions.

iii. To conduct a thorough analysis of the model's prediction errors, investigating their distribution and identifying potential sources of error. This detailed analysis will illuminate areas for potential model improvement and provide valuable insights into the limitations of the approach.

iv. To demonstrate the practical applicability of the RF model for real-world renewable energy applications. This will involve a discussion of the model's potential for integration into existing wind energy management systems and its implications for operational efficiency and economic decision-making.

2. Study Area and Data

The study focuses on Abbot Point (Bowen), Queensland, Australia, a coastal region known for its dynamic environmental conditions. The geographical location of Abbot Point is shown in Figure 1.

Figure 1. Study area

Abbot Point's coastal location is particularly vulnerable to wind-related hazards such as coastal erosion and storm waves, and therefore, requires accurate wind speed prediction for effective coastal management practices. The regional dynamic nature of wind patterns provides a suitable case study to evaluate the performance of ML models in predicting wind speed. The meteorological data used in this study were obtained from a weather station located at Abbot Point (Bowen). Hourly meteorological data were collected continuously from January 1, 2023 to December 31, 2023, providing a comprehensive dataset for model training and evaluation (Figure 2). The time series of wind speed data, shown in Figure 2, illustrates the variability in wind patterns over the study period. The parameters are given in tabular form (

Table *1*).

Table 1. Summary statistics of wind speed (m/s) for the training, validation, and test datasets, including count, mean, standard deviation, minimum, quartiles (25%, 50%, 75%), and maximum values.

Metric	Training	Validation	Test
Samples	5278	876	876
Mean (m/s)	5.13	5.04	4.98
Std Dev (m/s)	2.25	2.35	2.28
Min (m/s)	0	0	0.1
25% (m/s)	3.6	3.3	3.3
50% (Median) (m/s)	5.2	5	5
75% (m/s)	6.8	6.88	6.7
Max (m/s)	11.6	11.9	11.5

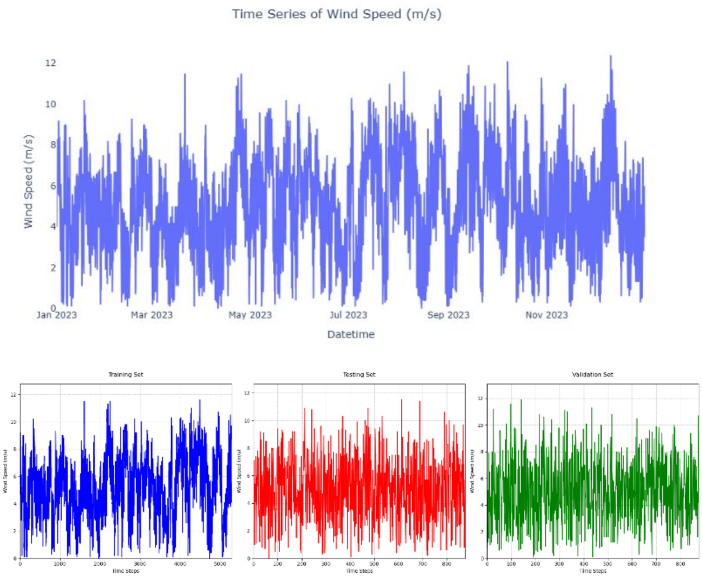


Figure 2. Time series of wind speed alongside its training, testing, and validation samples.

Data preprocessing is a crucial step to ensure the quality and reliability of the dataset. This step includes cleaning the data, designing relevant features, and dividing the dataset into training and testing sets, which are necessary for the effective development of ML models (Li et al., 2024). The collected dataset was examined for missing values, outliers, and inconsistencies to ensure data quality [22].

Features were selected based on their established correlation with wind speed and their potential to enhance the accuracy of ML models. New features were created to enrich the dataset, resulting in a shape of (7541, 13). The new columns were calculated using the following equations:

Lag Features Formula: $X_{lag}(t) = X(t-n)$ (1)

where: $X(t)$ is the wind speed at time t

n is the lag period (1 h, 3 h, 6 h, 12 h, 24 h)

Rolling Mean Features Formula:

$$X_{\text{rolling}}(t) = \frac{1}{n}\sum_{i=0}^{n-1} X(t-i) \quad (2)$$

n is the window size (3 h, 6 h, 12 h, 24 h)

$X(t-i)$ is the wind speed at time t-i

Feature Importance Calculation: RF algorithm calculates feature importance using the Mean Decrease in Impurity (MDI) formula:

$$\text{FI(feature)} = \frac{\sum_{t\text{ nodes}} w_t \Delta i(s_t,t)}{\sum_{t\text{ nodes}} w_t} \quad (3)$$

w_t is the weighted number of samples reaching node t $\Delta i(s_t,t)$ is the decrease in impurity at node t

s_t is the split at node t.

The newly created features are presented in Table 2 and visually represented as a time series in Figure 4. Figure 3 illustrates the temporal evolution of key engineered features derived from the wind speed data, such as the 3-hour rolling mean wind speed (Wind_Speed_Rolling_Mean_3h), 1-hour lagged wind speed (Wind_Speed_Lag_1h), 3-hour lagged wind speed (Wind_Speed_Lag_3h), and others listed in Table 2. Each subplot displays the feature's variability over the study period (January 2022 to December 2023), highlighting short-term trends, immediate past conditions, and cyclical patterns.

The use of specific lag periods and rolling windows is crucial for capturing both short-term fluctuations and daily cycles in time-series data. The selection of 1-hour, 3-hour, 6-hour, 12-hour, and 24-hour lag periods, along with 3-hour, 6-hour, 12-hour, and 24-hour rolling windows, allows for a comprehensive analysis of temporal dependencies. These intervals are chosen to align with the hourly of the dataset and are informed by prior studies [23].

Table 2. Created new features to improve model performance

Feature	Explanation
Wind_Speed_Rolling_Mean_3h	Average wind speed over the previous 3 hours, providing short-term trend information
Wind_Speed_Lag_1h	Wind speed value from exactly 1 hour ago, capturing immediate past conditions
Wind_Speed_Lag_3h	Wind speed value from exactly 3 hours ago, showing medium-term past conditions
Wind_Speed_Rolling_Mean_6h	Average wind speed over the previous 6 hours, showing longer trend patterns
Wind_Speed_Lag_24h	Wind speed value from exactly 24 hours ago, capturing daily cyclical patterns
Wind_Speed_Rolling_Mean_12h	Average wind speed over the previous 12 hours, showing half-day trends
Wind_Speed_Rolling_Mean_24h	Average wind speed over the previous 24 hours, showing full-day patterns
Wind_Speed_Lag_6h	Wind speed value from exactly 6 hours ago, showing quarter-day past conditions
Wind_Speed_Lag_12h	Wind speed value from exactly 12 hours ago, showing half-day past conditions

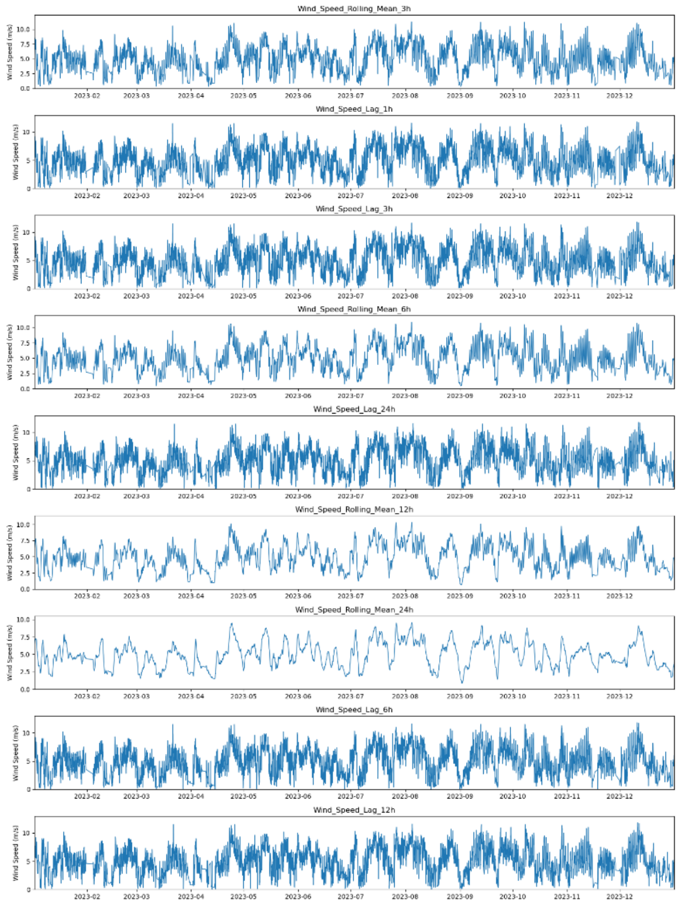


Figure 3. Time series of generated features.

The preprocessed dataset, then, was split into training and testing sets to evaluate the performance of ML models and assess their generalization abilities. In splitting 70%, 15%, 15% of the data was allocated for training, testing, and validation as suggested by [24] (see Figure 4 and Figure *5*). This approach helps prevent data leakage and ensures that the performance of the model on the test set is a reliable indicator. The 5-fold cross-validation was performed using a time-based splitting strategy to ensure that temporal dependencies were preserved during model evaluation, reflecting the sequential nature of the wind speed data.

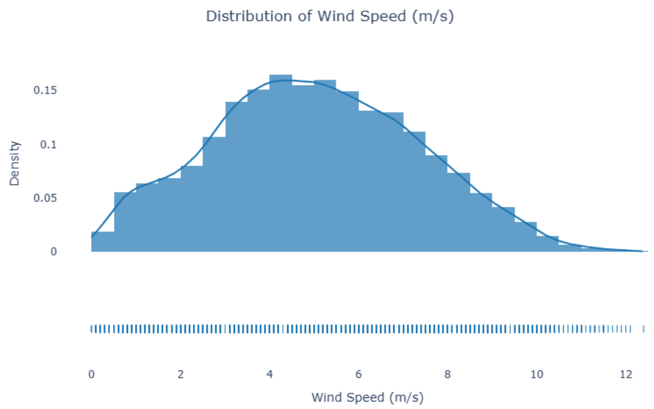


Figure 4. Distribution of the full dataset

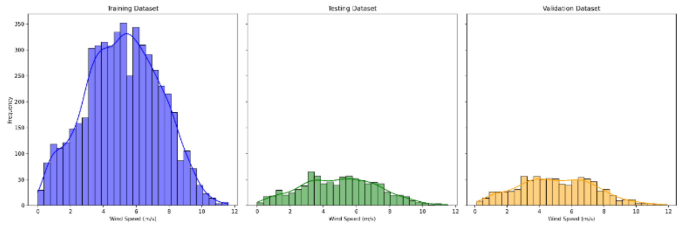


Figure 5. Distribution of training, validation, and test datasets

Data quality control measures identified minimal missing values in the dataset, with only 4 missing entries each in wind speed and direction measurements, and single missing values in temperature, humidity, and pressure readings, representing less than 0.05% of the total dataset. These gaps were addressed through appropriate interpolation techniques to maintain data continuity.

The temporal of hourly measurements provides sufficient granularity for detailed wind pattern analysis while maintaining manageable computational requirements for ML applications. The dataset's comprehensive coverage of a full annual cycle ensures that seasonal variations and patterns are fully captured in the analysis.

The analysis was performed using Python programming software, utilizing libraries such as scikit-learn for model implementation, evaluation, and hyperparameter tuning, pandas for data manipulation, and matplotlib for visualization. Jupyter Notebook served as the interactive environment for coding, data exploration, model development, and visualization of results.

The performance of each trained model was evaluated on the test and validation dataset the following metrics:

1. Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (O_i - P_i)^2} \tag{4}$$

where O_i and P_i are the observed and predicted values, respectively, and α is the number of data points.

2. Mean Absolute Error (MAE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |O_i - P_i| \tag{5}$$

3. Nash-Sutcliffe Efficiency (NSE):

$$NSE = 1 = \frac{\sum_{i=1}^{n} (O_i - P_i)^2}{\sum_{i=1}^{n} (O_i - \bar{O})^2} \tag{6}$$

where $\bar{O}$ is the mean of the abcerved values.

4. Coefficient of Determination (R^2):

$$R^2 = \frac{\left(\sum_{i=1}^{n} (O_i - \bar{O})(P_i - \bar{P})\right)^2}{\sum_{i=1}^{n} (O_i - \bar{O})^2 \sum_{i=1}^{n} (P_i - \bar{P})^2} \tag{7}$$

(8)

where $\bar{P}$ is the mean of the predicted values.

5. Kling-Gupta Efficiency (KGE):

$$KGE - 1 - \sqrt{(r-1)^2 + (\alpha - 1)^2 + (\beta - 1)^2} \tag{8}$$

where:

- r is the Pearson corrolation coefficient between observed and predicted values.
- $\alpha = \frac{\sigma i}{\sigma_0}$ is the variability ratio (σ denotes standard deviation).
- $\beta = \frac{\bar{P}}{\bar{O}}$ is the tias ratio.

6.Percentage Bias (PBIAS):

$$PBIAS = 100 \times \frac{\sum_{i-1}^{n} (O_i - P_i)}{\sum_{i-1}^{n} O_i} \tag{9}$$

7. KGE Bias Component (KGE_{Bias}):

$$KGE_{\text{Bias}} = |\beta - 1| \tag{10}$$

where β is as defined in the KGE formula.

8. PBIAS Error Component:

$$PBIAS_{\text{Error}} = \sqrt{\sum_{i=1}^{n} (P_i - O_i)^2} \tag{11}$$

3. Results

RF model demonstrated robust performance in predicting wind speed, as evidenced by the evaluation metrics across training, testing, and validation datasets. The model achieved an average R^2 score of 0.9155 (±0.0035) during 5-fold cross-validation, indicating a strong correlation between observed and predicted values. The RMSE values across the datasets were consistent, with an average of 0.6624 (±0.0098) m/s, highlighting the model's accuracy in capturing wind speed variations.

Table 3 presents the detailed results for each fold of the 5-fold cross-validation. The RMSE values ranged from 0.6452 m/s (Fold 2) to 0.6731 m/s (Fold 4), demonstrating minor variability and reinforcing the reliability of the model's predictions. Similarly, the R^2 scores remained consistently high across the folds, varying between 0.9106 (Fold 4) and 0.9211 (Fold 2), which reflects the model's strong predictive capability. Additionally, the Mean Absolute Error (MAE) values were uniformly low, with the smallest error of 0.4840 (Fold 2) and the largest of 0.5105 (Fold 4), further validating the model's ability to minimize discrepancies between observed and predicted values.

These metrics collectively emphasize RF model's robustness and precision. Notably, the slight variations among the folds suggest the model is well-generalized and resilient to different subsets of the data. The consistently high R^2 scores and low error values across all folds underscore its effectiveness in capturing wind speed dynamics, making it a reliable tool for wind speed prediction.

Table 3. Cross-validation performance metrics for the RF model

Fold	RMSE	R^2	MAE
Fold 1	0.6617	0.9143	0.5097
Fold 2	0.6452	0.9211	0.4840
Fold 3	0.6705	0.9168	0.4991
Fold 4	0.6731	0.9106	0.5105
Fold 5	0.6617	0.9144	0.4956

Figure 6 and Table 4 provide complementary insights into the relative importance of features in predicting wind speed, emphasizing the dominance of short-term trends.

Figure 6 highlights the Wind_Speed_Rolling_Mean_3h as the most significant feature, with an importance score (IS) of 0.8984, far surpassing all other predictors. This result underscores the model's reliance on short-term wind speed variations, indicating that averaging wind speeds over the past three hours provides critical information for accurate predictions. In contrast, features such as Wind_Speed_Lag_1h (0.0259) and Wind_Speed_Lag_3h (0.0257) have a minimal impact, suggesting that individual lagged wind speed values carry less predictive weight compared to aggregated short-term trends.

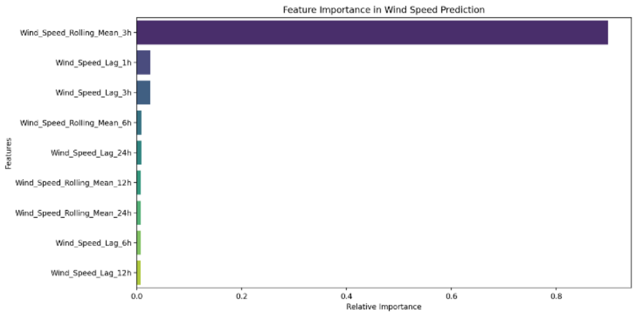


Figure 6. Feature importance visualization

This pattern is consistent with the model's evaluation metrics. The low RMSE and high R^2 indicate that the model effectively captures the variability in wind speed using features that focus on short-term aggregated trends rather than individual lagged values or longer-term averages. For instance, the negligible importance of Wind_Speed_Rolling_Mean_12h and Wind_Speed_Rolling_Mean_24h suggests that smoothing over extended periods does not contribute significantly to predicting immediate wind speed fluctuations.

The alignment between feature importance and model performance reinforces the critical role of short-term aggregated features, such as Wind_Speed_Rolling_Mean_3h, in driving the accuracy and reliability of the RF model. These findings highlight the need to prioritize such features in future wind speed prediction frameworks, ensuring that models are both efficient and focused on the most informative predictors.

Table 4. Feature importance summary

Feature	IS	Summary
Rolling_Mean _3h	0.8984	Highly significant for short-term wind trends
Lag_1h	0.0259	Minimal impact, captures immediate past conditions
Lag_3h	0.0257	Minimal impact, captures medium-term past conditions
Rolling_Mean _6h	0.0093	Negligible impact, smooths short-term fluctuations
Lag_24h	0.0090	Negligible impact, captures daily cyclical patterns
Rolling_Mean _12h	0.0081	Negligible impact, smooths half-day trends
Rolling_Mean _24h	0.0081	Negligible impact, smooths full-day trends
Lag_6h	0.0079	Negligible impact, captures quarter-day past conditions
Lag_12h	0.00 78	Negligible impact, captures half-day past conditions

In Table 5, the model's performance metrics for the testing and validation datasets further validate these findings. The Root Mean Squared Error (RMSE) values of 0.6382 and 0.6211, and Mean Absolute Error (MAE) values of 0.4742 and 0.4481, indicate that the model consistently produces low prediction errors. Additionally, the Nash-Sutcliffe Efficiency (NSE) and R^2 values, both exceeding 0.91, confirm the strong correlation between observed and predicted values. The Kling-Gupta Efficiency (KGE) scores of 0.948 (testing) and 0.9382 (validation) underscore the model's excellent predictive capability.

The Percent Bias (PBIAS) and Kling-Gupta Bias (KGEBias) values, close to zero, further confirm the absence of systematic over- or underestimation. The low PBIAS error percentages of 21.4643 (testing) and 20.8963 (validation) demonstrate the model's reliability even under dynamic conditions.

Table 5. Performance metrics comparison: test set vs. validation set

Metric	Test Set	Validation Set
RMSE	0.6382	0.6211
MAE	0.4742	0.4481
NSE	0.9292	0.9175

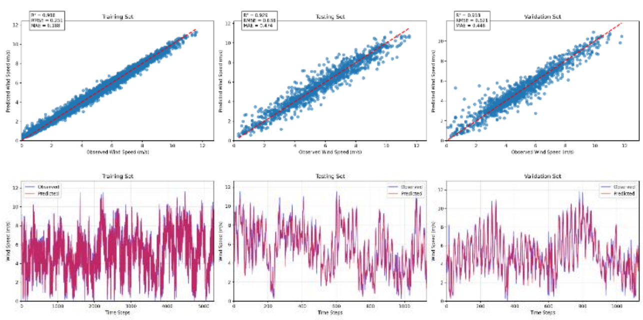
R^2	0.9292	0.9175
KGE	0.948	0.9382
PBIAS	0.0031	-0.0426
KGE_{Bias}	0	0.0004
$PBIAS_{Error}$	21.4643	20.8963

The predictive capability of RF model is further evaluated using scatter plots, residual plots, and time series comparisons, as shown in Figure 7. These visualizations provide additional evidence of the model's strong performance in predicting wind speed across the training, testing, and validation datasets.

The scatter plots in the first row of Figure 7 demonstrate the relationship between observed and predicted wind speed values for the training, testing, and validation datasets. The close alignment of data points with the 1:1 line indicates the model's ability to accurately capture the variability in wind speed. The minor deviations observed in the validation dataset reflect the challenges of generalizing to unseen data, yet the results remain consistent with the metrics presented in Table 5 , such as the high R^2 values of **0.9292** and **0.9175** for the testing and validation sets, respectively.

The second row of Figure 7 presents the residual plots for the three datasets, showcasing the differences between observed and predicted values. The residuals are centred around zero, with no apparent patterns, confirming the model's ability to minimize systematic bias. The narrow range of residuals in the testing and validation sets aligns with the low RMSE values of **0.6382** and **0.6211**, as detailed in Table 5, reinforcing the model's accuracy.

The time series plots in the third and fourth rows of Figure 7 provide a direct comparison of observed and predicted wind speed values over time for the testing and validation datasets. The high degree of overlap between the observed (blue) and predicted (red) lines highlights the model's effectiveness in capturing temporal patterns and short-term fluctuations. This is consistent with the findings in Figure 6, where the feature importance analysis identified short-term aggregated features, such as **Wind_Speed_Rolling_Mean_3h**, as the most significant contributors to the model's performance.



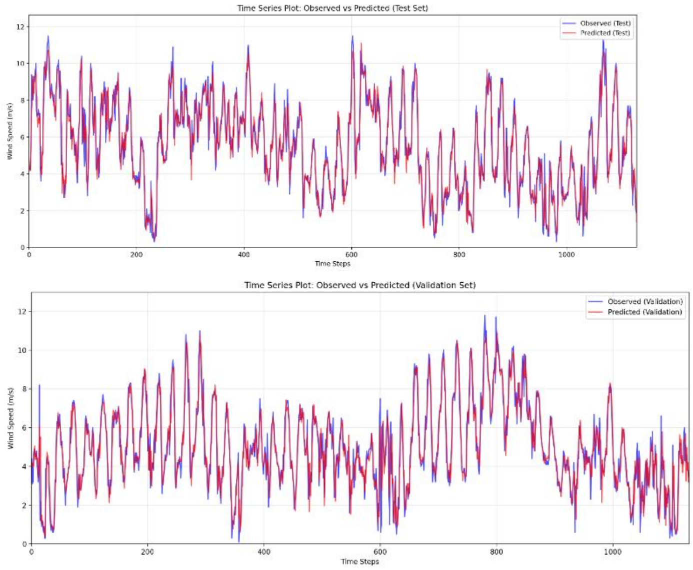


Figure 7. Model performance visualization, including scatter plots (top row), residual plots (middle row), and time series plots (bottom rows) for the training, testing, and validation datasets.

The performance of RF model was further assessed using error distributions and quantile-quantile (Q-Q) plots, as shown in Figure 8 and Figure *9*, respectively. These visualizations provide insight into the residual behavior across the training, testing, and validation datasets. They also confirmed the model's reliability and accuracy, as shown in Table 5, which summarizes the key evaluation metrics for the testing and validation datasets. Error analysis revealed that the distributions of residuals were approximately normal, with slight deviations in the tails, particularly in the validation set. Specifically, the validation set exhibited a kurtosis value of 5.2146, indicating a leptokurtic distribution with heavier tails and a sharper peak compared to a normal distribution (which has a kurtosis of 3). This suggests that the model occasionally produces larger prediction errors for extreme wind speed values in the validation data, reflecting potential challenges in capturing rare or outlier events. Despite this, the overall symmetry and near-normal behaviour of the residuals support the model's robustness for practical applications.

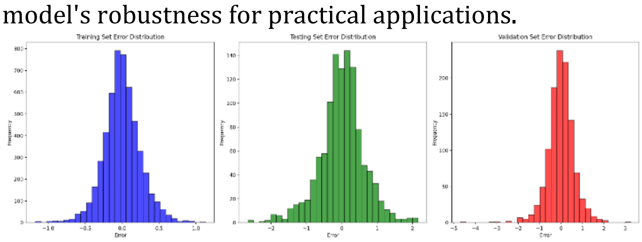


Figure 8. Error distribution histograms for the training, testing, and validation datasets.

The histograms in Figure 8 illustrate the error distribution for the training, testing, and validation datasets. The residuals exhibit a near-Gaussian distribution centered around zero for all datasets, indicating that the model effectively minimizes systematic bias. The narrower spread in the training set errors suggests strong learning during model training, while the slightly broader spreads in the testing and validation sets reflect the model's generalization capability. The validation set errors remain tightly distributed, demonstrating the model's consistency in predicting unseen data.

The Shapiro-Wilk test confirmed these observations, with p-values below 0.05, suggesting modest departures from normality. Q-Q plots showed good alignment with the theoretical normal distribution in the central ranges, supporting the reliability of the model's predictions.

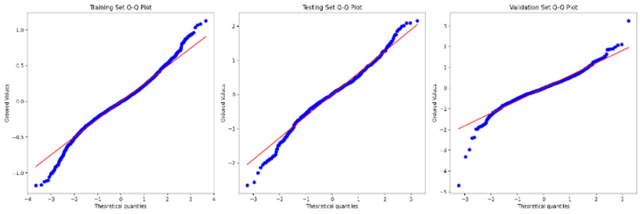


Figure 9. Quantile-quantile (Q-Q) plots for the training, testing, and validation datasets.

The analysis shows that the prediction errors across all three sets—training, testing, and validation—follow a roughly bell-shaped pattern, with the errors centered near zero, indicating unbiased predictions. The errors' average is almost zero for all sets, but the variability (standard deviation) is larger for the testing and validation sets than for the training set. Additionally, the validation set has the most pronounced heavy tails, meaning more extreme values, and it shows a slight skew to the left.

The Q-Q plots support these findings, showing good alignment with a normal distribution overall, though there are some deviations at the edges (tails), especially for the validation set. These characteristics suggest that while the errors aren't perfectly distributed, they are symmetrical and well-behaved enough for practical purposes. The higher variability in the testing and validation sets hints at some overfitting during training, but it's not a significant issue.

The model's performance was consistent across different temporal scales, with mean absolute errors (MAE) averaging 0.4998 (±0.0098) m/s. These findings underscore the model's potential for operational deployment in wind energy applications, where accurate and stable wind speed predictions are critical for optimizing power generation and grid integration.

The results also highlight the importance of comprehensive error analysis and cross-validation in evaluating ML models for renewable energy applications. By identifying potential biases and assessing model stability, this study provides a framework for developing reliable wind speed prediction systems.

4. Discussion

This study presents a comprehensive evaluation of RF models for wind speed forecasting, utilizing a year's worth of data from the Bowen Abbot facility in Queensland, Australia. The results demonstrate the model's robust performance across multiple evaluation metrics and its potential for operational deployment in renewable energy applications. However, several key aspects warrant further discussion.

RF model achieved a high average R^2 score of 0.9155 (±0.0035) across five-fold cross-validation, indicating a strong predictive capability. This is consistent with other studies highlighting the effectiveness of RF for wind speed prediction [25–27]. The low RMSE values (average 0.6624 (±0.0098) m/s) and MAE values (average 0.4998 (±0.0098) m/s) further confirm the model's accuracy in capturing wind speed variations. The consistent performance across training, testing, and validation sets suggests good generalizability, a crucial aspect for real-world applications. This contrasts with some studies that report challenges in generalizing ML models to unseen data [28], emphasizing the importance of the cross-validation methodology employed here. The stability observed across different data partitions supports the model's reliability for operational deployment in wind energy management systems.

The relatively small standard deviations observed in the cross-validation metrics (0.0035 for R^2, 0.0098 for RMSE, and 0.0098 for MAE) indicate the model's robustness and resilience to different data subsets. This suggests that the model is not overly sensitive to the specific data partitions used for training and testing, further enhancing its reliability for real-world applications. This finding aligns with the inherent robustness of RF algorithms, which are known for their ability to handle noisy data and avoid overfitting [29, 30].

The feature importance analysis revealed a clear hierarchical structure, with the 3-hour rolling mean wind speed being the most influential predictor (89.84% importance). This dominance of short-term temporal features suggests that recent wind patterns are crucial for accurate predictions. This finding is consistent with the observation that wind speed exhibits short-term dependencies [31], and highlights the importance of incorporating appropriately aggregated temporal features in wind speed prediction models. The relatively low importance of longer-term lagged wind speeds (e.g., 12-hour and 24-hour lags) suggests that longer-term cyclical patterns are less relevant for short-term predictions.

The focus on short-term trends (3-hour rolling mean) is a significant finding, potentially offering valuable insights for model simplification and optimization. Future research could explore the impact of different aggregation window sizes and investigate the optimal balance between short-term and long-term temporal features. Furthermore, exploring the inclusion of other meteorological variables (e.g., temperature, humidity, pressure) [32, 33] could further enhance predictive accuracy. The current study's reliance on wind speed data alone limits the model's potential to capture the influence of other factors that might affect wind speed patterns.

The error distribution analysis showed approximately normal distributions with slight deviations in the tails, particularly in the validation set (kurtosis: 5.2146).While the near-normality of the residuals suggests that the model is largely unbiased, the heavier tails in the validation set indicate the presence of some outliers or extreme values. These deviations could be due to unforeseen weather events or other unmodeled factors. Further investigation into these outliers might reveal additional insights into the model's limitations and potential areas for improvement. The application of more robust statistical tests to assess normality, such as the Shapiro-Wilk test, would provide a more rigorous assessment of the error distribution's conformity to a Gaussian model.

The near-normal distribution of errors suggests that the RF model is well-suited to capturing the stochastic nature of wind speed. However, the slight deviations from normality, particularly in the tails of the validation set's error distribution, warrant further investigation. Techniques to address these deviations, such as employing robust regression methods or incorporating error correction mechanisms [34, 35], could be explored in future studies to improve prediction accuracy and reliability, especially for extreme wind events. Furthermore, a more detailed analysis of the residuals, potentially using techniques like residual plots and autocorrelation functions, could provide additional insights into the model's performance and potential sources of error.

5. Conclusion

This study provides a comprehensive investigation into the effectiveness of RF for wind speed forecasting, utilizing a substantial dataset of hourly observations over one year from the Bowen Abbot Point facility in Queensland, Australia. The findings highlight the model's strong predictive performance, its capacity for generalization, and its potential for practical applications in renewable energy systems.

RF model exhibited exceptional accuracy, demonstrating consistent and reliable performance across training, testing, and validation datasets. Metrics such as R^2, RMSE, and MAE showcased its robustness and suitability for operational use in wind energy management. The model's high accuracy and stability make it suitable for real-time wind energy management, such as optimizing energy dispatch strategies and improving grid stability through reliable wind power forecasts. These capabilities can enhance economic dispatch in energy trading and support proactive maintenance scheduling, maximizing operational efficiency and economic viability. Additionally, the feature importance analysis revealed a significant emphasis on short-term temporal features, underlining the critical role of recent wind patterns in enhancing prediction accuracy.

As the renewable energy landscape evolves, future wind speed prediction methodologies are expected to shift from traditional onshore approaches to techniques specific to offshore environments. Offshore wind turbines, especially floating facilities, operate under unique meteorological conditions that require the development of innovative prediction models that can accurately predict wind behavior in coastal and offshore regions. In order to improve these prediction methods in the future, it will be important to focus on both accuracy and computational efficiency in a balanced manner in the light of methodological approaches mentioned in this paper.

Further research could focus on optimizing data preprocessing techniques and feature selection methods specifically tailored to wind speed data. For example, temperature gradients integration between land and water surfaces generates local wind patterns, such as sea breezes, could improve the ability of models to capture coastal wind dynamics.

This study used only wind speed data, potentially missing effects from variables like temperature or pressure, and focused on one coastal site, which may not reflect all wind conditions.

Finally, future research should focus on developing user-friendly tools and interfaces that integrate these advanced models and provide accessible wind speed estimates for coastal stakeholders. Empowering stakeholders with accurate and practical tools enable informed decision making for effective risk management and planning [36–42].

Author contributions

Ahmet Durap: Writing-Original draft preparation, Conceptualization, Methodology, Software, Data curation, Software, Validation, Visualization, Investigation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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