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Research Article

Multi-temporal forecasting of wind energy production using artificial intelligence models

Doha Bouabdallaoui [*], Touria Haidi, Mounir Derri, Ishak Hbiak, Mariam El Jaadi

Laboratory LAGES, Ecole Hassania des Travaux Publics (EHTP), Casablanca, 20000, Morocco

Abstract. In response to changing energy demands, electricity suppliers are increasingly turning to sustainable energy sources, with wind power emerging as a promising solution. This study aims to predict wind energy production over four time horizons: hourly, daily, weekly, and monthly, for a 12,300 kW wind farm located in Northamptonshire, UK. We employed three artificial intelligence (AI) techniques: an ensemble of bagged decision trees, artificial neural networks (ANNs), and support vector machines (SVMs). The paper provides a comparative evaluation of AI-based forecasting techniques for wind energy prediction, highlighting differences in model performance across time horizons while emphasizing the strengths and limitations of each method in addressing the temporal variability of wind energy production. The models were tested over various times using important performance measures, such as the correlation coefficient (R), the coefficient of determination (R^2), mean absolute error (MAE), root mean squared error (RMSE), and bias. The results indicate that support vector machines achieve the highest accuracy for medium-term forecasts, with a coefficient of determination of 0.9722 and a mean absolute error of 44.91 kW. Artificial neural networks perform best in short-term forecasting, particularly at the daily level, with a coefficient of determination of 0.948 and a mean absolute error of 36.04 kW. In contrast, long-term predictions exhibit greater variability across models, with the coefficient of determination decreasing to 0.778, reflecting the increased complexity of extended forecasting. The ensemble of bagged decision trees demonstrates strong predictive capability but with slightly higher error margins compared to support vector machines. The obtained results could serve as a reference for selecting the most suitable models based on forecasting objectives and time constraints. Future improvements in forecasting accuracy could happen by combining these models with optimization algorithms, especially for medium- and long-term predictions, where making accurate forecasts is still very difficult.

Keywords: Artificial Neural Networks, Ensemble of bagged decision trees, Machine learning, Renewable Energy, Support Vector Machines, Wind Energy Forecasting.

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1. Introduction

The transition to sustainable energy sources continues rapidly as electricity suppliers strive to meet evolving energy demands (Acikgoz *et al*., 2020; Alghamdi *et al*., 2023; Alvarez *et al*., 2020; Andrade & Bessa, 2017; Haidi & Cheddadi, 2022a; Mat Daut *et al*., 2017; Memarzadeh & Keynia, 2020). Among renewable energy sources, wind power has emerged as a promising alternative due to its significant benefits and its crucial role in moving toward a more sustainable environment (Alghamdi *et al*., 2023; Bouabdallaoui, Haidi, & El Jaadi, 2023; Buturache & Stancu, 2021; Cai *et al*., 2019; Haidi & Cheddadi, 2022b; Idrissi *et al*., 2022; Li *et al*., 2022).

Accurate forecasting of wind energy production is increasingly vital for the continuous operation of modern grid systems (Hassoine *et al*., 2022; Tyass *et al*., 2023). Good forecasting models are important for predicting changes in energy production, which helps improve how the system works and coordinates with other energy sources. (Abedinia *et al*., 2020; Bouabdallaoui, Haidi, Elmariami, *et al*., 2023; Hu *et al*., 2021; Meng *et al*., 2022; J. Zheng *et al*., 2023).

Various papers in the literature apply several approaches, such as statistical analysis, physical modeling, and machine learning techniques, to predict wind power production. For instance, (Jamii *et al*., 2022) suggest an artificial neural network (ANN)-based model that uses meteorological variables such as wind speed, temperature, and air pressure for predicting wind energy output. The study finds ANN to be highly precise and efficient, outperforming other methods like decision trees (DT), regression vector machines (RVM), and kernel ridge regression (KRR).

Other studies have explored different techniques to improve wind energy forecasting. For example, (Taghinezhad & Sheidaei, 2022) look at how using an ANN can help predict how much power a turbine will produce in different wind conditions, and they find that the ANN model, especially the one trained with the Levenberg-Marquardt backpropagation method, gives better results for estimating turbine power curves. Similarly, (You *et al*., 2022) create a short-term wind energy forecasting model that uses support vector machines (SVM) along with a method called CEEMDAN to reduce noise. The enhanced model shows improved precision and convergence, meeting the requirements for safe wind farm operation. Further, (Lian & He, 2022) propose a model that combines wavelet denoising with SVM, refined by the slime mold algorithm, to increase the precision of wind energy predictions. The results validate the method's high predictive accuracy.

[*] Corresponding author(s)
Email: bouabdallaoui.doha@gmail.com (D. Bouabdallaoui)

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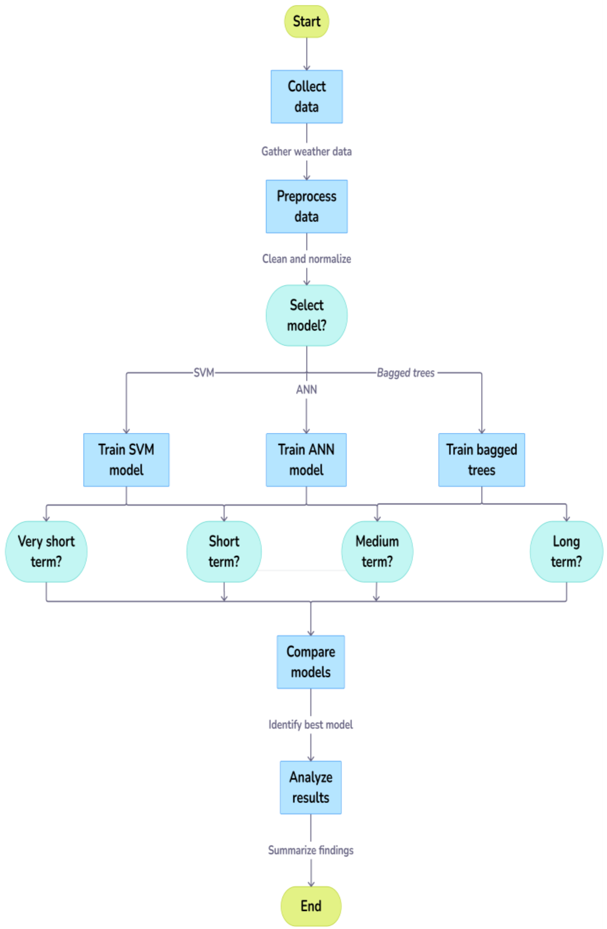


Fig. 1 Flow chart of the study structure

The research by (Torres-Barrán *et al*., 2019) examines how well gradient boosted regression (GBR), extreme gradient boosting (XGB), and random forest regression (RFR) can predict solar radiation and wind power both locally and globally. The research highlights the effectiveness of GBR and XGB as competitive alternatives, particularly for broader geographic wind energy predictions.

The primary goal of this paper is forecasting wind energy output for a 12,300 kW wind farm in Northamptonshire, United Kingdom. Three AI techniques—SVM, ANN, and an ensemble of bagged decision trees—are evaluated across very short, short, medium, and long-term horizons to determine which model offers the highest accuracy in each timeframe. Fig. 1 presents the organizational structure of the paper. This study also seeks to provide a clear comparison of these widely used AI methods, focusing on their performance over different time scales.

2. Methods

The commissioning of the Kelmarsh wind farm in West Northamptonshire, East Midlands, England, UK, took place in 2016. Table 1 lists fundamental information about the park. Wind generator data are recorded by a Supervisory Control and Data Acquisition (SCADA) monitoring system installed on-site. The dataset was published by Cubico Sustainable Investments Ltd. under an open data license, CC-BY-4.0. (Plumley, 2022). The collection of data began in 2016 and continued until the middle of 2021. It contains more than 250 data points. The data

Table 1
Principal information of the wind farm chosen

Name	Kelmarsh wind farm
Status	Operating
Commissioning Year	2016
Installed Capacity	12 kW
Mount type	Onshore
Owner	Blue Energy
Location	West Northampton-shire, East Midlands, England, United Kingdom
Coordination	52.4028, -0.9598

that interest us include time, wind energy (kW), wind speed (m/s), and wind direction (°). To predict wind power production for Kelmarsh Wind Park, three methods were implemented: Support Vector Machine (SVM), Artificial Neural Network (ANN), and an ensemble of bagged decision trees. This choice was made to systematically evaluate different types of models from three learning approaches: neural networks, margin-based learning, and ensemble methods. Rather than focusing on a single class of algorithms, we adopted a comparative approach to assess how each performs across multiple forecasting horizons, from very short-term to long-term. This selection allows for a structured and interpretable evaluation of:

- a connectionist model (ANN),
- a kernel-based margin optimizer (SVM),
- and an ensemble-based decision learner (bagged trees),

Beyond their independent performance, the models themselves serve as decent baselines for the future. Their examination of shortcomings and strengths by forecasting horizon provides a starting point for further development—hybridization, optimization, or comparison to deep models. By bringing each approach's shortcomings and strengths through forecasting horizons into view, the study presents working knowledge with which to inform future model enhancements.

2.1 Data Preprocessing

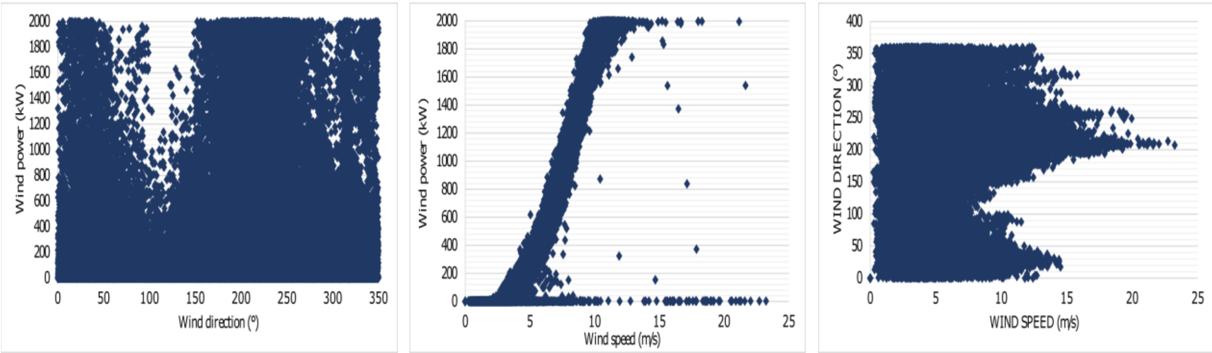
The dataset contains 57,152 time-stamped records collected every 10 minutes from the SCADA system of the Kelmarsh wind farm. Each record includes wind speed (m/s), wind direction (°), and wind power output (kW), along with a timestamp converted into datetime format. The data spans the full year 2020 and January 2021. A data quality assessment revealed no missing values. However, a small number of records with negative wind power values—non-physical under standard operating conditions—were identified and removed:

$$\text{ValidRows} = \{(X_i, Y_i) \mid Y_i > 0,\ X_i \in R^n \text{ et } Y_i \in R\} \qquad (1)$$

$X_i = [X_{1i}, X_{2i}]$ represents the inputs, while Y_i represents the output. Zero values in input or output variables were retained, as they reflect plausible operational scenarios (e.g., calm wind periods or maintenance shutdowns). No outlier filtering was applied beyond this physical consistency check.
Input features were normalized using min–max scaling into the interval [−1,1], using statistics computed from the training subset:

Table 2
Time scale of prediction and their typical utilization

Prediction Horizon	Time Scale	Study time scale	Typical Use
Very Short-Term	Minutes to a few hours (0-6 hours)	1 hour	- Real-time energy management - Grid operation - Supply-demand balancing
Short-Term	Several hours to several days	1 day	- Energy trading - Resource allocation - Maintenance scheduling
Medium-Term	Several days to a few months	1week	- Grid planning - Strategic planning - Capacity expansion - Long-term energy scenarios
Long-Term	Beyond a few months (1 month +)	1month	- Infrastructure investments - Renewable energy project planning - Energy policy development - Assessment of renewable energy targets.



(a) (b) (c)

Fig. 2 (a) Scatter plot of: (a) wind direction Vs wind power, (b) wind speed Vs wind power, (c) wind speed Vs wind direction

$$X_i' = 2 \cdot \frac{X_i - min\,(X)}{max\,(X) - min\,(X)} - 1 \tag{2}$$

This normalization ensures balanced feature contributions and benefits techniques. No additional feature engineering was applied. The two input variables were retained in their original form as the only available meteorological parameters in the SCADA dataset. Wind speed is the primary input for modeling turbine behavior, while wind direction provides additional spatial context. Their joint use ensures a physically interpreted and operationally viable input set.

We conducted the training and internal testing phase using all data from January to December 2020 (52,704 samples), employing time-aware data splits for cross-validation. The models were then externally validated on a hold-out set of 4,465 samples from January 2021, a period excluded from training. This structure allows for assessing model generalization and robustness across multiple forecast horizons: the first hour (very short-term), first day (short-term), first week (medium-term), and full month (long-term). Table 2 provides details on the forecast horizons and the rationale for each period.

For data exploration, graphical representations are provided to illustrate key relationships within the variables. Fig. 2(a) illustrates the relationship between wind speed and energy output. Data follow a nonlinear increasing pattern, typical of turbine power curves: energy generation remains low at low wind speeds, increases rapidly within the operational range, and tends to saturate at high speeds. A Pearson correlation coefficient of 0.93 between wind speed and power further confirms this strong functional relationship, highlighting its dominant predictive role. Fig. 2(b) shows wind direction plotted against power. The absence of a clear trend, supported by a low correlation coefficient of 0.08, indicates that wind direction has limited linear influence on power output. However, it could potentially capture site-specific or directional flow effects, leading to its retention as a complementary feature. Fig. 2(c) illustrates the distribution of wind speed and direction, confirming their near independence (r=0.09) and justifying their use as uncorrelated inputs in the model. Figure 3 provides an overview of the dataset by showing each variable's mean,

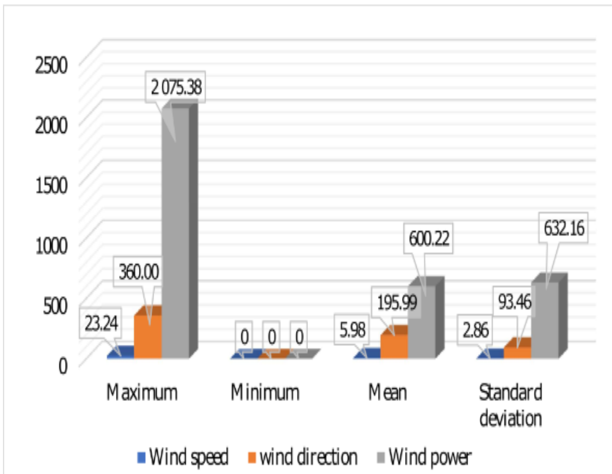


Fig. 3 Statical information about: wind speed (m/s), wind direction (°), and wind power (kW)

Table 3
Hyperparameters of the ANN model used

Hyperparameter	Value
Architecture	One hidden layer with 34 neurons
Hidden Activation	Sigmoid (logsig)
Output Activation	Linear (purelin)
Training Algorithm	Levenberg–Marquardt backpropagation (trainlm) with Bayesian Regularization
Number of Epochs	1000
Early Stopping	After 6 validation failures
Learning Rate	Default (trainlm)
Weight Initialization	Default
Cross-Validation Strategy	5-fold cross-validation on training set
Data Split	80% training, 10% validation, 10% internal test
Hyperparameter Tuning	Grid search on hidden layer size (10–34 neurons)
Selection Metric	Root Mean Squared Error (RMSE) on validation folds

maximum, minimum, and standard deviation. This figure helps assess the overall characteristics and variability within the dataset.

2.2 Artificial Neural Networks (ANNs)

Artificial Neural Networks (ANNs) emulate human brain structure and function as closely as possible. Its structure consists of interlinked nodes in layers. Neurons process input data via weighted connections, incorporating biases and activation functions. The training involves iterating input into the network until it reaches the desired output. Using ANNs to make accurate predictions on new data is becoming more common, showing they can be used in various areas like image recognition, understanding language, and predicting things like wind power (Abedinia & Amjady, 2015; Ateş, 2023; Bouabdallaoui, Haidi, Elmariami, *et al.*, 2023; Cali & Sharma, 2019; Kumar *et al.*, 2020; Tarek *et al.*, 2023; Verma *et al.*, 2023).

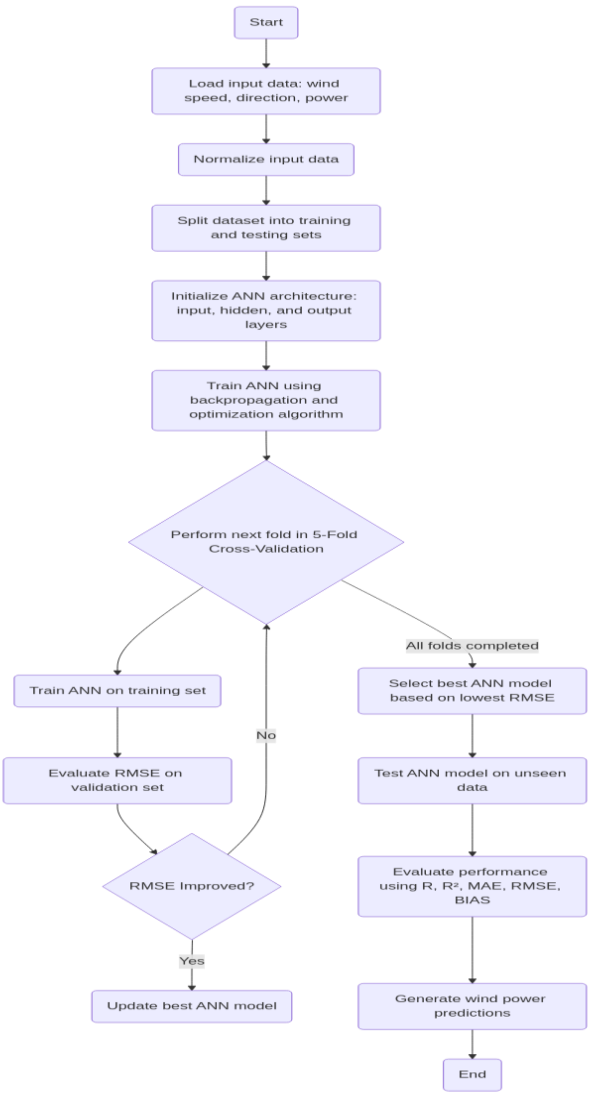


Fig. 4 Flow chart of the ANN model used

This study trained the ANN to forecast wind power output using normalized wind direction and speed. The structure has one hidden layer that uses sigmoid (logsig) activation and a linear (purelin) output layer, which is good for predicting continuous values. We performed training using the Levenberg–Marquardt backpropagation algorithm (trainlm), incorporating Bayesian regularization to prevent overfitting. The learning rate and the remaining optimization parameters remained at their default values, as the training function dictated them. We conducted a grid search to identify the optimal hidden layer neuron count, ensuring the best possible model performance. Trial values used were 10, 20, 30, and 34. The model with 34 neurons possessed the lowest validation root mean squared error (RMSE) during cross-validation.

A 5-fold cross-validation method using training data was used to assess how well the model performs and to confirm that it works consistently across different groups. The best configuration was selected based on the lowest validation RMSE. This method provides a robust estimation of model performance and reduces sensitivity to data splits. We allowed a maximum of 1000 training epochs and activated early stopping after six consecutive validation failures. Prior to training, we removed constant input columns and initialized network weights using the training function's default method. Fig. 4 provides a schematic of the ANN training process, while Table 3 summarizes all architectural and training parameters.

2.3 Support Vector Machines (SVMs)

Supervised machine learning algorithms named Support Vector Machines (SVM) operate mainly through classification and regression applications. The regression model variant of SVM uses input factors as inputs to predict outputs from variables. When applied to regression analysis, as this study demonstrates, the SVM devises predictions regarding a variable's outcome using provided input variables. The SVM regression model finds the best position for a hyperplane by using training data, which helps it make predictions that are as close as possible to actual results. In SVM regression, the hyperplane represents the optimal boundary or decision surface computed by the algorithm to minimize forecasting errors. It determines the predicted output based on the input features. Initially, the

Table 4
Hyperparameters of SVM model used

Hyperparameter	**Value / Description**
Kernel Function	Gaussian (RBF)
Kernel Scale (σ)	Grid search: values in [0.1, 10]; optimal = 1.4
Regularization Parameter (C)	Grid search: values in [0.01, 100]; optimal = 6.161
Standardization	Yes (zero mean, unit variance)
Training Algorithm	Sequential Minimal Optimization (SMO)
Number of Iterations	12,999
Bias Term	1006
Cross-Validation	5-fold, used during grid search
Model Selection Criterion	Root Mean Squared Error (RMSE) on validation folds

support vectors select the data points closest to the hyperplane to initiate the model-building process, as outlined in the works of (Gu *et al.*, 2021; Khosravi *et al.*, 2018; Kuriakose *et al.*, 2020; Pinto *et al.*, 2014, p. 202320; Wang *et al.*, 2023; Yuan *et al.*, 2015; Y. Zheng *et al.*, 2023).

In this study, the SVM was used to predict wind power with a Gaussian (RBF) kernel, chosen because it can effectively handle complex patterns in weather data. Prior to training, input

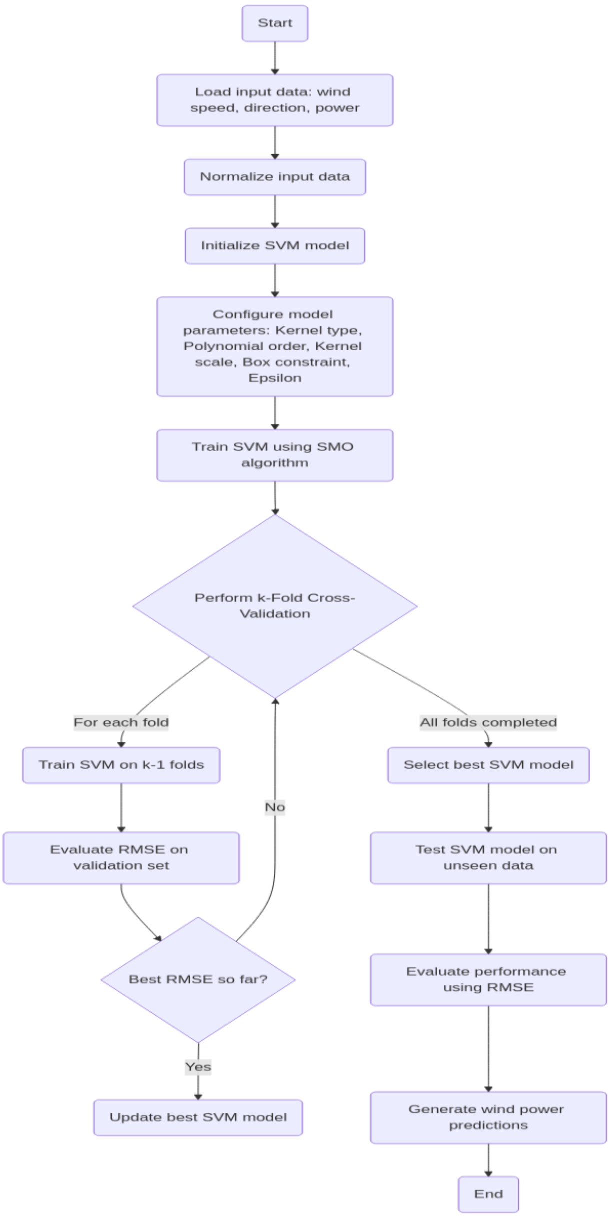


Fig. 5 Flow chart of the SVM model used

features were standardized to zero mean and unit variance, a common practice that improves kernel efficiency and convergence behavior.

To maximize model accuracy, a grid search was conducted to tune the following hyperparameters:

- Box Constraint (C): This parameter regulates the trade-off between training error and model complexity. We explored values from 0.01 to 100 on a logarithmic scale.
- Kernel Scale (σ): This parameter determines how wide the Gaussian kernel function is in SVM, influencing how well the model picks up on small changes and nonlinear patterns in the input data. We tested values between 0.1 and 10.

Each parameter pair was evaluated through 5-fold cross-validation on the training data. This validation strategy was selected for its balance between statistical reliability and computational efficiency. It ensures that all samples contribute to both training and validation, reducing the risk of overfitting. The optimal hyperparameter combination was selected based on the lowest average root mean squared error (RMSE) across the folds.

The final model was trained using the Sequential Minimal Optimization (SMO) algorithm. It converged after 12,999 iterations, with a resulting bias term of 1006 and a small weight vector norm (1.8974e-05), consistent with the support vector framework. Table 4 presents the hyperparameters. Fig. 5 illustrates the SVM modeling process used in this study.

2.3 Ensemble of bagged decision trees

The ensemble of bagged decision trees operates in a coherent way to enhance the accuracy and reliability of the regression task. Various decision trees, trained on different subsets of training data generated by bootstrap sampling with replacement, form the basis of this method. Each decision tree learns the models and relationships of the inputs and from its subset separately. During prediction, the ensemble averages each individual tree's predictions, most often by taking an average, to provide a more accurate and stable prediction. This technique helps in overcoming overfitting, which is a problem that is often encountered with individual decision trees, as diversity is introduced into the learning process (Alghamdi *et al.*, 2023; Khan *et al.*, 2021).

In this case, bagging was selected for its ability to improve prediction reliability while maintaining interpretability and low model complexity. Each tree receives the full set of input features—normalized wind speed and direction—and learns independently from its bootstrapped data. The ensemble prediction aggregates the individual outputs, yielding a smoother and more generalizable forecast of wind power.

The model was configured with 30 learning cycles, meaning 30 individual decision trees were trained. The minimum leaf size was set to 8, which controls the granularity of splits in each tree

Table 5
Hyperparameters of the ensemble of bagged decision trees model used

Hyperparameter	Value
Ensemble Method	Bagging (bootstrap aggregating)
Number of Trees	30 learning cycles
Bootstrap Sampling	Enabled (sampling with replacement)
Minimum Leaf Size	8
Feature Sampling	None (all features used at each split)
Final Prediction	Average of individual tree outputs
Implementation	MATLAB's "Bag" method

and prevents overfitting on small data partitions. The ensemble was trained using MATLAB's standard "bag" method, which implements bootstrap sampling with replacement. Hyperparameters were selected empirically to balance performance and model simplicity.

From a methodological perspective, the choice of bagging over more complex ensemble methods such as boosting or random forests was deliberate. Boosting relies on sequential learning and is sensitive to noise and hyperparameter settings, which may complicate comparisons in multi-model studies. Random forests introduce feature subsampling at each split, which provides little benefit in our case due to the limited number of input features. In contrast to it, bagging is a controlled ensemble technique, sufficiently appropriate for low-dimensional input spaces and insensitive to different training runs. This characteristic makes bagged trees a robust baseline for comparing against other learning paradigms such as kernel-based (SVM) and neural models (ANN). The structure of the bagging workflow is illustrated in Fig. 6. Table 5 shows hyperparameters used.

2.5. Evaluation metrics

The effectiveness of machine learning techniques is evaluated using various metrics in wind energy forecasting. These metrics shed light on how accurate and trustworthy projections are. The present study's key evaluation criteria are as follows:

The coefficient of correlation (R), commonly known as Pearson's correlation coefficient, quantifies the linear relationship and the variance in the dependent variable (y) that is predictable from the independent variable (x). The scale runs from -1 to 1, where 1 represents a fully positive connection.

$$R = \sum(xi-\bar{x})(yi-\bar{y}) \Big/ \sum(xi-\bar{x})^2(yi-\bar{y})^2 \qquad (3)$$

The coefficient of determination (R^2) quantifies how closely expected values (y) match observed values (yi). It denotes the percentage of the variance in the dependent variable explained by the independent variable.

$$R^2 = \sum(yi-\hat{y}i)^2 \Big/ \sum(yi-\bar{y})^2 \qquad (4)$$

The metric represents the mean absolute difference (MAE) between the expected ($\hat{y}$i) and observed (yi) values. It offers an indication of the typical error magnitude.

$$MAE = {}^{1}\!/_{n} \sum |yi-\hat{y}i| \qquad (5)$$

The Root Mean Squared Error (RMSE) is a measure of the average magnitude of residuals, which are the disparities between observed and anticipated values. Large mistakes are penalized more severely than MAE.

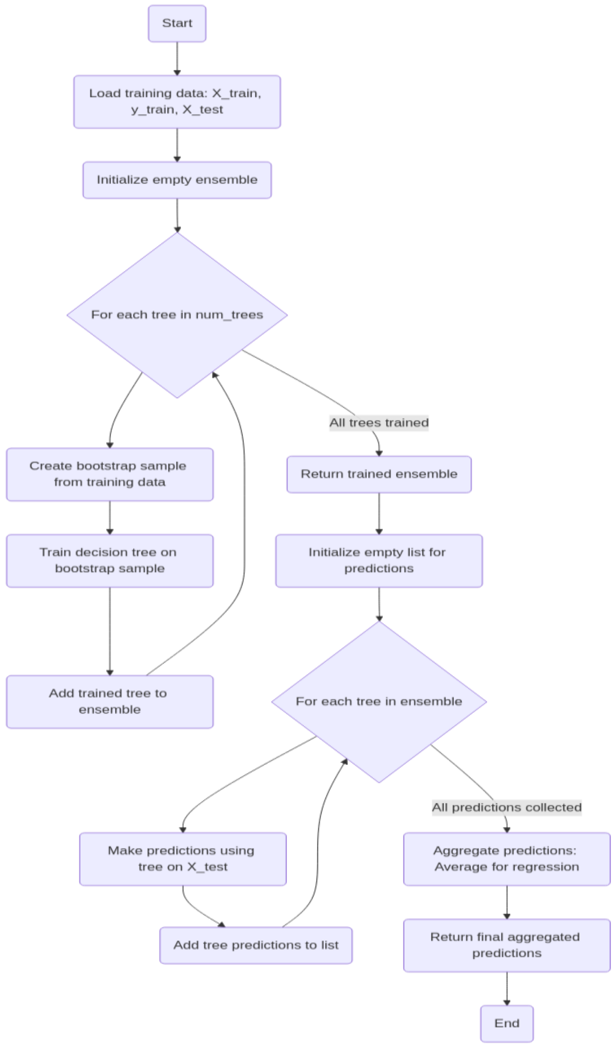


Fig. 6 Flow chart of the ensemble of bagged decision trees model used

$$RMSE = \sqrt{\sum(yi-\hat{y}i)^2 /_{n}} \qquad (6)$$

When comparing predictions to observed values, bias is the average propensity of the predictions to be higher or lower. Predictions are generally too high when there is a positive bias, and vice versa.

$$BIAS = {}^{1}\!/_{n} \sum(yi-\hat{y}i) \qquad (7)$$

4. Results and Discussion

4.1 Long-term prediction results

The three predictive techniques, SVMs, ensemble of bagged decision trees, and ANNs, are compared in terms of performance utilizing important criteria for long-term wind power prediction on a one-month horizon. Fig. 7 presents the scatter plot of expected output vs. actual values in the long-term horizon of each method. The coefficient of determination and the correlation coefficient indicate moderate linear links between the actual and forecast wind power outputs using all available methodologies. Despite not being particularly high (for R: SVM = 0.890, ensemble of bagged trees = 0.889, ANN =

Table 6
Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) with Confidence Intervals (monthly horizon)

Model	MAE	95% CI (MAE)	RMSE	95% CI (RMSE)
ANN	100.95	[92.95, 109.14]	287.09	[268.52, 304.65]
Bagged Trees	101.29	[93.15, 109.49]	286.99	[268.48, 304.89]
SVM	102.02	[94.68, 110.04]	285.80	[267.51, 303.99]

Table 7
Wilcoxon Test Results (monthly horizon)

Comparison	Test Statistic (MAE)	p-value (MAE)	Test Statistic (RMSE)	p-value (RMSE)
ANN vs Bagged Trees	4721,622	0.0022	4779,213	0.0168
ANN vs SVM	4518,422	6.01e-08	4707,796	0.0013
Bagged Trees vs SVM	4690,291	0.0006	4785,939	0.0207

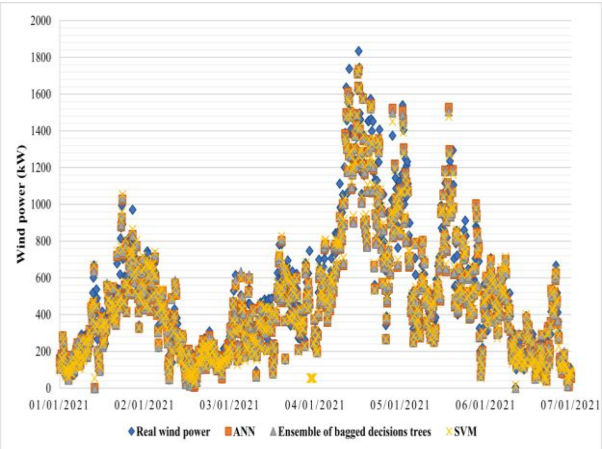


Fig. 7 Scatter plot of predicted values against real values in long term

0.889; for R^2: SVM SVM= 0.778, ensemble of bagged trees = 0.776, ANN = 0.776). These measurements nonetheless show a useful degree of reliability. When examining the mean absolute error (MAE), the ANN approach has the lowest average error (ANN = 100.925), suggesting more accurate wind power forecasts. SVM and ensemble of bagged decision trees approaches trail closely behind, showing marginally higher MAE values while retaining respectable precision (SVM = 101.995, ensemble of bagged trees = 101.271). The effectiveness of SVM is shown by the Root Mean Squared Error (RMSE), which has the lowest total errors when looking at both the amount and direction of mistakes (SVM = 285.766) compared to the ensemble of bagged trees (286.960) and ANN (287.058). The RMSE statistic highlights SVM's effectiveness in reducing mistakes even while it doesn't reach large levels. The systematic propensity to overestimate or underestimate, measured by bias values, is comparatively constant across all techniques. When compared to SVM, the bias for both the ANN and ensemble of bagged decision tree approaches is marginally smaller, suggesting that the various models' prediction abilities are well distributed (SVM = 39.587, ensemble of bagged trees = 38.192, ANN = 38.033).

To check if the differences in forecasting performance between the ANN, Ensemble (Bagged Trees), and SVM models are meaningful, we used two methods: Confidence Intervals (CI) and Wilcoxon Signed-Rank Tests. Confidence intervals (CI) are a statistical tool used to estimate the uncertainty around a performance metric, in this case, the Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE). A 95% confidence interval indicates the range of values within which the true performance metric is likely to lie, with 95% certainty. These intervals were calculated using the bootstrap method (with 1000 resamples), providing a robust estimate of the variability and precision of the performance metrics (Cumming, 2013). Wilcoxon signed-rank tests are non-parametric statistical tests used to assess whether the differences between paired observations—in this context, the prediction errors (absolute and squared errors) of two different models—are statistically significant. A p-value less than 0.05 indicates that the observed differences in performance metrics are unlikely to be due to chance, thus confirming a genuine difference in predictive performance between the compared models (Taheri & Hesamian, 2013). Tables 6 and 7 summarize the results.

The statistical validation confirms that the differences in MAE and RMSE among the models are statistically meaningful. Specifically, ANN significantly outperforms both the ensemble of bagged trees and SVM models in terms of MAE, with particularly strong significance observed against SVM. For RMSE, the differences are still statistically significant, showing that ANN, ensemble of bagged trees, and SVM models have different forecasting abilities. Although confidence intervals overlap slightly, the statistical tests highlight clear systematic differences between these methods for monthly wind power forecasting. These statistical findings demonstrate that the differences in performance are not merely because of random variation but represent genuine differences in the forecasting capabilities of each modeling approach.

4.2 Medium-term prediction results

Using the same measures, the approaches are contrasted in medium-term wind power forecast over a one-week horizon. Fig. 8 displays the scatter plot of the method's expected output against actual values. Strong positive correlations are seen in all three approaches, suggesting that the techniques adequately represent the overall patterns in the data. The best R value is obtained using SVM, suggesting a more precise linear fit. The percentage of variation explained by the models is further quantified by R^2. Because of its higher R^2 value, SVM appears to offer a more accurate depiction of the variability in the wind power data (for R: SVM = 0.9879, ensemble of bagged trees = 0.9876, ANN = 0.9872; for R^2: SVM = 0.9722, ensemble of bagged trees = 0.9696, ANN = 0.9681). In terms of statistical notation, MAE stands for mean absolute error between expected and observed values. With its lowest MAE (ensemble of bagged trees = 44.91), the ensemble of bagged decision trees provides outputs that are, on average, closest to the real values. When it comes to minimizing absolute mistakes, an ensemble of bagged decision trees is a better option since it suggests that it

Table 8
Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) with 95% Confidence Intervals (weekly horizon)

Model	MAE	95% CI (MAE)	RMSE	95% CI (RMSE)
ANN	7.52	[4.67, 10.50]	9.35	[5.56, 11.97]
Bagged Trees	25.42	[20.22, 30.65]	28.14	[22.55, 33.42]
SVM	5.13	[3.17, 7.07]	6.70	[4.02, 9.04]

Table 9
Wilcoxon Signed-Rank Test Results (weekly horizon)

Comparison	Test Statistic (MAE)	p-value (MAE)	Test Statistic (RMSE)	p-value (RMSE)
ANN vs .Bagged Trees	215347.0	0.000089	201864.0	0.00000007
ANN vs. SVM	235282.0	0.0814	218047.0	0.00029
Bagged Trees vs .SVM	245192.0	0.5084	230750.0	0.0253

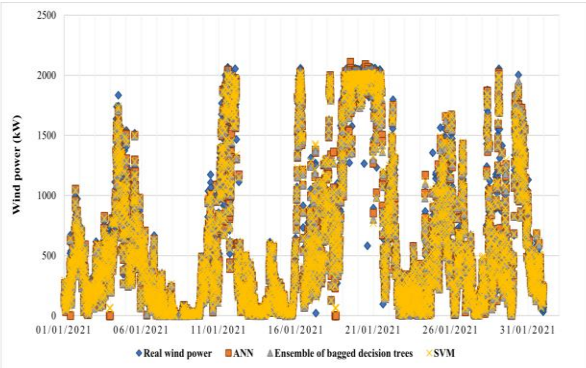


Fig. 8 Scatter plot of predicted values against real values in medium term

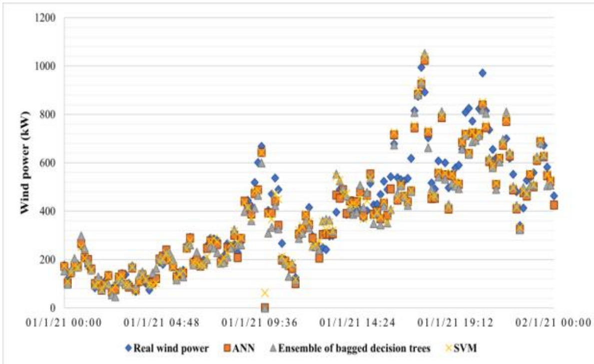


Fig. 9 Scatter plot of predicted values against real values in short term

is more accurate in terms of size. The MAE of SVM and ANN models are close (SVM=45.79, ANN=45.06), indicating equivalent accuracy. The SVM method has the lowest RMSE (SVM = 59.94), indicating that its average predictions are more in line with the real values. Lower RMSE values (ensemble of bagged trees = 62.70, ANN = 64.19) demonstrate better overall prediction accuracy. For every approach, the BIAS values are negative, indicating a consistent tendency to underestimate. As the SVM model has the lowest negative BIAS, it is likely to estimate wind power more accurately. To evaluate the statistical relevance of observed between-model variations in performance, we computed 95% confidence intervals for both MAE and RMSE using bootstrap resampling and performed pairwise Wilcoxon signed-rank tests. Tables 8 and 9 present the outcomes.

These results indicate that both ANN and SVM significantly outperform the ensemble of bagged trees across most error metrics. The performance difference between ANN and SVM is less pronounced: while the RMSE difference is statistically significant in favor of SVM, the MAE difference does not reach significance. This suggests that both ANN and SVM are suitable choices for weekly wind power forecasting, with SVM exhibiting a marginal edge in terms of error magnitude.

4.3 Short-term prediction results

When comparing the performance measures for predicting wind power across a daily time span for the three artificial intelligence methodologies, the high R-values for all methods suggest that the models capture the overall trends in wind power well, with ANN displaying a slightly stronger correlation (SVM = 0.975, ensemble of bagged trees = 0.965, ANN = 0.978). The impressive R^2 values of all the approaches highlight their capacity to forecast and explain fluctuations in wind power (SVM = 0.946, ensemble of bagged trees = 0.921, ANN = 0.948). Once more, ANN is superior in this regard. Comparable and lower MAE values are shown by SVM and ANN, beating the ensemble approach (SVM = 36.65, ensemble of bagged trees =

Table 10
Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) with Confidence Intervals (daily horizon)

Model	MAE	95% CI (MAE)	RMSE	95% CI (RMSE)
ANN	7.55	[3.96, 11.86]	9.24	[4.14, 11.79]
Ensemble	24.91	[16.28, 33.64]	27.45	[16.66, 33.72]
SVM	5.20	[2.56, 7.63]	6.36	[2.53, 7.92]

Table 11
Wilcoxon Test Results (daily horizon)

Comparison	Test Statistic (MAE)	p-value (MAE)	Test Statistic (RMSE)	p-value (RMSE)
ANN vs Ensemble	0.0	0.0156	0.0	0.0156
ANN vs SVM	6.0	0.219	6.0	0.219
Ensemble vs SVM	1.0	0.0313	1.0	0.0313

47.47, ANN = 36.04). From this, it may be inferred that SVM and ANN offer generally more precise predictions. With a greater RMSE than the ensemble technique, ANN gets the lowest , closely followed by SVM (SVM = 52.79, ensemble of bagged trees = 63.87, ANN = 51.70). Comparing SVM and ANN to the ensemble, the results imply that both provide greater precision. SVM has the least bias, followed by ANN and the ensemble method. The negative values indicate a tendency to underestimate wind power, with SVM being the least biased (SVM = -13.86, ensemble of bagged trees = -21.22, ANN = -19.07). Figure 9 shows the scatter plot of the method's expected output against actual values. To ensure these observed differences are not due to random variation, Wilcoxon signed-rank tests and confidence intervals for MAE and RMSE were applied. Tables 10 and 11 summarize the results.

The statistical validation confirms that the differences in MAE and RMSE among the models are meaningful. In particular, SVM significantly outperforms the ensemble method, and ANN also shows advantages over the ensemble. The close performance of ANN and SVM indicates they are both reliable for weekly wind power forecasting, with slight differences that favor ANN in this specific scenario.

4.4 Very short-term prediction results

The following insights are revealed by the hourly wind power forecast results: There is a significant linear relationship between the prediction output and real data, as approved by the R-values (SVM = 0.986, ANN = 0.981, ensemble of bagged trees = 0.880). The ensemble approach, on the other hand, shows a lower R, which may indicate a possible divergence from linearity or systemic inaccuracies in the forecasts. The high R^2 values (SVM = 0.995, ANN = 0.995, ensemble of bagged trees = 0.976) indicate that all methods are very good at explaining the changes in hourly wind power. The values are true for all methods. High R-values indicate an excellent explanatory ability to capture the variation in the hourly wind power. All approaches yield consistent values. Low MAE values demonstrate accurate forecasts. SVM and ANN have lower MAE values than the ensemble technique, which means they are more accurate (SVM = 3.465, ANN = 4.431, ensemble of bagged trees = 13.533). The RMSE values (SVM = 4.847, ANN = 5.599, ensemble of bagged trees = 14.013) demonstrate the accuracy of the forecasts. Once more, ANN and SVM show reduced RMSE, suggesting more precise predictions in comparison to the ensemble approach. Systematic mistakes are present, as shown by BIAS readings (SVM = -2.433, ANN = -0.457, and ensemble of bagged trees = 1.417). When compared to SVM and ANN, the ensemble approach shows a positive BIAS, indicating a propensity to overestimate wind power. The scatter

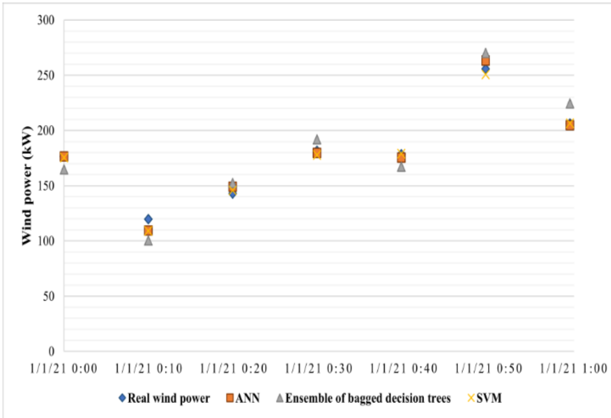


Fig. 10 Scatter plot of predicted values against real values in the very short term

plot of the method's expected output against actual values is shown in Fig. 10. The significance of these differences was assessed through Wilcoxon signed-rank tests and confidence intervals for MAE and RMSE. Results presented in Tables 12 and 13 confirm that the performance differences are not due to random variation.

The SVM model consistently shows the lowest MAE and RMSE values with narrow confidence intervals, highlighting its superior predictive performance. The Wilcoxon tests support the finding of those variations as being statistically significant, especially when comparing the ensemble method to the other models. While ANN and SVM exhibit closer accuracy, the SVM model remains the most robust and reliable choice to predict very short-term hourly wind energy.

To better understand the strengths and weaknesses of each forecasting model across various time horizons, it is essential to analyze key performance metrics. According to (Miettinen *et al.*, 2020), metrics such as MAE, RMSE, and BIAS are critical indicators in evaluating forecasting accuracy. Fig. 11 illustrates the distribution of these metrics across the three forecasting methods.

The MAE histogram reveals that SVM achieves lower error values predominantly at medium-term horizons, confirming its robustness to moderate fluctuations. The ANN model shows low MAE at short time frames, but the error varies more as the time frames get longer, which matches what (Ahmadi *et al.*, 2020; Soman *et al.*, 2010) found. Bagged trees present the highest dispersion of errors, indicating declining accuracy as the forecast duration increases. The RMSE distributions highlight that SVM performs well, especially when dealing with larger errors in short- and medium-term forecasts, which matches what (Heinermann & Kramer, 2014) found. The ANN model

Table 12
Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) with Confidence Intervals (hourly horizon)

Model	MAE	95% CI (MAE)	RMSE	95% CI (RMSE)
ANN	4.43	[2.08, 7.04]	5.60	[1.94, 6.93]
Ensemble	13.53	[10.98, 16.24]	14.01	[11.08, 16.32]
SVM	3.47	[1.28, 6.29]	4.85	[1.30, 6.24]

Table 13
Wilcoxon Test Results (hourly horizon)

Comparison	Test Statistic (MAE)	p-value (MAE)	Test Statistic (RMSE)	p-value (RMSE)
ANN vs. Ensemble	0.0	0.0156	0.0	0.0156
ANN vs. SVM	7.0	0.297	7.0	0.297
Ensemble vs. SVM	0.0	0.0156	0.0	0.0156

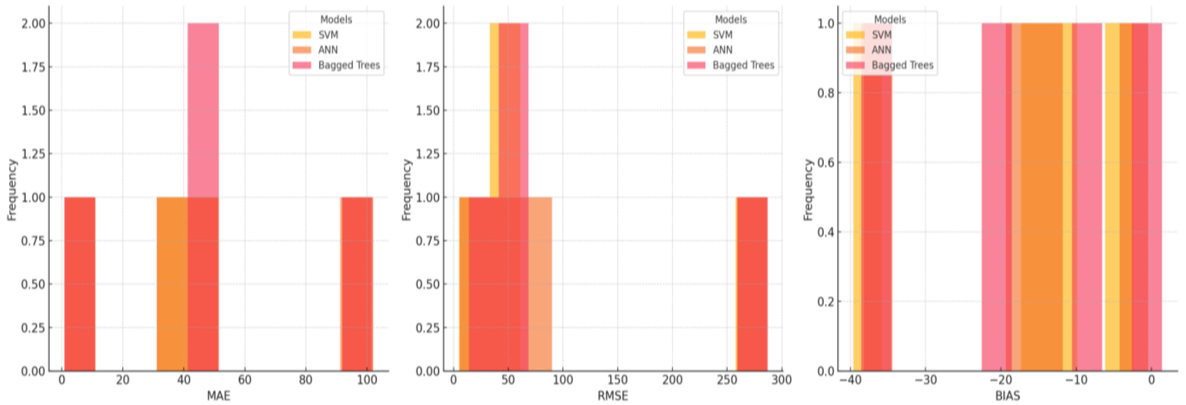


Fig.11 Histograms of the distribution of key evaluation metrics: MAE, RMSE, and BIAS for the predictive models

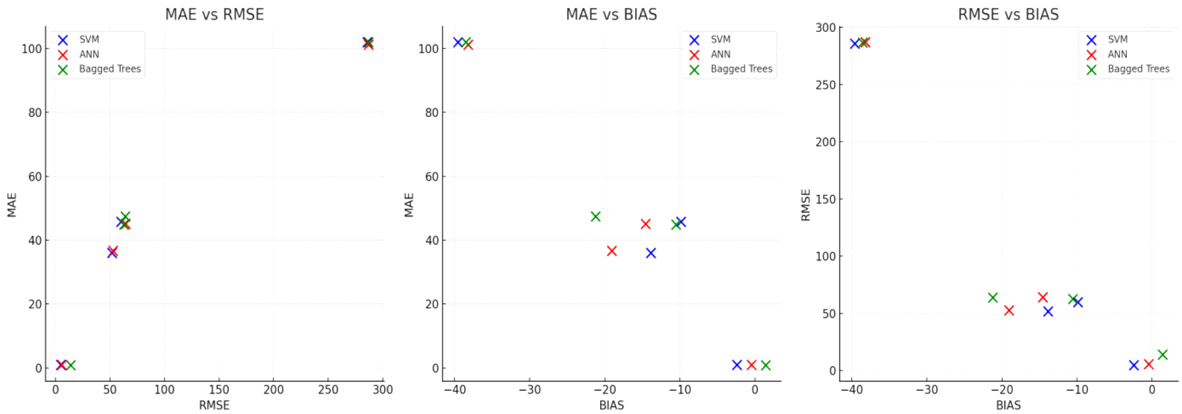


Fig.12 Scatter plots illustrating the relationships between key evaluation metrics: MAE, RMSE, and BIAS of the predictive models

shows higher sensitivity to substantial forecast deviations, especially beyond medium-term horizons. Bagged trees exhibit distinct clusters at higher RMSE values (~300), underscoring their limited reliability at extended horizons. BIAS analysis indicates that all three models consistently produce slightly negative forecasts (underestimation). SVM and ANN display moderate negative bias (-10 to -20), whereas bagged trees demonstrate a more pronounced negative bias (up to -40), particularly at longer horizons.

The scatter plots in Fig. 12 comprehensively visualize these error dynamics. Optimal forecasting performance corresponds to low MAE, low RMSE, and minimal bias. SVM and ANN predominantly occupy this optimal space, particularly at short- and medium-term horizons. In contrast, bagged trees struggle with higher prediction errors and substantial bias, increasingly evident as the forecast horizon lengthens.

The models' predictive capability, quantified by R^2, further elucidates performance differences across forecast horizons. At very short horizons, all models achieve high precision (R^2 close to 1). Performance divergence becomes noticeable at short-term horizons, where bagged trees begin to degrade markedly ($R^2 < 0.85$), whereas SVM and ANN remain above 0.90. This divergence further accentuates at medium- and long-term horizons, with SVM and ANN maintaining R^2 values around 0.75–0.80, compared to bagged trees' significantly reduced R^2 (~0.50–0.75).These differences can be accounted for in terms of the intrinsic trade-offs between model complexity and regularization. ANN models are highly flexible, which makes them well-suited to modeling short-term nonlinear dependencies but prone to overfitting at longer horizons. SVM finds a good middle ground between being complicated and being able to apply to different situations by using its margin-based regularization, which helps it handle uncertainty and changes over time for medium-term predictions. Trees that are combined together can reduce errors by averaging, but they struggle to capture complex time-related patterns, leading to significant errors over long periods. It's important to understand that the model's performance is limited by the data from SCADA measurements, which only includes wind direction and speed. This data is not enough for real-time forecasting because it doesn't cover other important weather factors like changes in atmospheric pressure or temperature differences. These unmodeled variables would be significant sources of forecast errors observed at longer horizons. Moreover, this study focuses exclusively on data from a single wind farm. Although this work provides controlled comparability, direct generalization to other sites is not guaranteed without further validation. Nonetheless, it is reasonable to expect comparable performance on wind farms exhibiting similar meteorological and operational characteristics, provided model hyperparameters are appropriately tuned.

Fig. 13 synthesizes these insights visually through a radar chart, clearly depicting model performance across forecasting horizons. While all models perform similarly in the very short term, SVM and ANN show better adaptability and consistent predictions as the time frames get longer, highlighting their strength in handling complex data and changing time patterns.

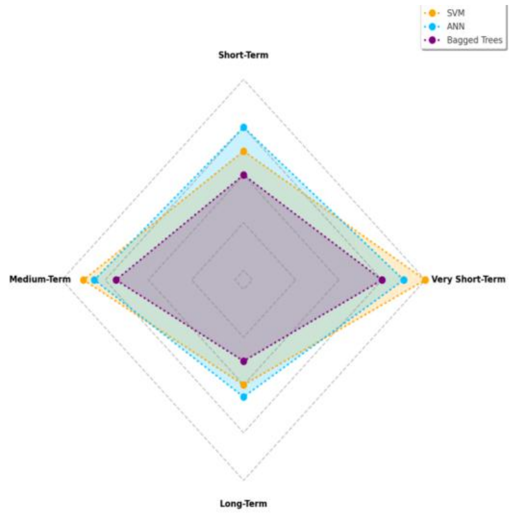


Fig.13 Radar chart of forecasting model performance across the four time horizons

Overall, the comparison shows that ANN and SVM are better at predicting wind energy over multiple time periods, performing significantly better than bagged decision trees for complex, long-term forecasts.

6. Conclusion

This research looked at how well three machine learning models—Support Vector Machine (SVM), Artificial Neural Network (ANN), and a group of bagged decision trees—could predict wind power generation at the Kelmarsh wind farm in the UK. Based on the observations of wind speed and direction collected by the site's SCADA system, forecasts were issued for different time horizons: one hour, one day, one week, and one month. With this systematic protocol, it was possible to make a systematic comparison of the predictability of each model, which provided information on their accuracy and reliability under varying temporal scales. The SVM model showed better prediction results, especially for short- and medium-term forecasts, with very high accuracy scores (R^2 = 0.9949 for hourly predictions, MAE = 3.47 for weekly predictions). This is because it has its own margin-based learning mechanism that can effectively balance model complexity and generalization capability. The ANN model also showed strong performance, particularly for short-term predictions (R^2 = 0.9808 for hour-ahead forecasts), indicating its ability to recognize complex, small time patterns. However, as the forecast period got longer, the model's performance dropped, showing it was sensitive to changes and might have been too closely fitted to the training data, highlighting the need for careful adjustment of its settings and controls. The bagged decision trees model showed consistent performance at very short forecasting horizons but exhibited decreasing accuracy as the prediction horizon increased. The inherent structural vulnerabilities of tree ensembles, such as their limited capacity to handle high-order nonlinearities and long-term temporal relationships, explain this decline. These results indicate that there are important compromises between variance and bias, highlighting the importance of carefully setting up and adjusting models for different forecasting time frames. This study, based solely on wind speed and direction, demonstrates the basic accuracy of the machine learning methods selected to predict wind power. This study's methods and results can be applied to other wind farms with similar technology and weather, as long as the model settings are adjusted properly. Future research could improve forecasting abilities by looking into mixed modeling techniques, such as combining ANN with statistical methods or mixing ensemble learning with deep learning. Also, adding weather data and information from nearby weather stations could improve how well the model works, especially for longer-term forecasts.

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