Artificial Intelligence Review (2025) 58:191
https://doi.org/10.1007/s10462-025-11191-0

Sustainable AI-driven wind energy forecasting: advancing zero-carbon cities and environmental computation

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Accepted: 6 March 2025 / Published online: 29 March 2025

Abstract

Accurate forecasting of wind speed and power is transforming renewable wind farm management, facilitating efficient energy supply for smart and zero-energy cities. This paper introduces a novel low-carbon Sustainable AI-Driven Wind Energy Forecasting System (SAI-WEFS) developed from a promising real-world case study in MENA region. The SAI-WEFS evaluates twelve machine learning algorithms, utilizing both single and ensemble models for forecasting wind speed (WSF) and wind power (WPF) across multiple timeframes (10 min, 30 min, 6 h, 24 h, and 36 h). The system integrates multi-time horizon predictions, where the WSF output is input for the WPF model. The environmental impact of each algorithm is assessed based on CO_2 emissions for each computational hour. Predictive accuracy is assessed using mean square error (MSE) and mean absolute percentage error (MAPE). Results indicate that ensemble algorithms consistently outperform single ML models, with tree-based models demonstrating a lower environmental impact, emitting approximately 60 g of CO_2 per computational hour compared to deep learning models, which emit up to 500 g per hour. This system enhances the Urban Energy Supply Decarbonization Framework (UESDF) by predicting the Urban Carbon Emission Index (UCEI) to illustrate the Urban Carbon Transition Curve.

Keywords Sustainable artificial intelligence · Green algorithms · Wind energy forecasting · Sustainability · Urban deep decarbonization · Zero-energy city

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Abbreviations

BP	Backpropagation
CART	Classification and Regression Trees
CI	Computational intelligence
GHG	Greenhouse gas
IoTs	Internet of Things
KW	Kilowatts
MA	Moving average
MAPE	Mean absolute percentage error
MB	Megabyte
ML	Machine learning
MLP	Multi-layer perceptron
MRA	Multiple regression analysis
MSE	Mean square error
MW	Megawatts
NW	Northwest
NWP	Numerical weather prediction
RBF	Radial base function
RF	Random Forest
S	Seconds
SAI	Sustainable Artificial Intelligence
SAI-WEFS	Sustainable AI-Driven Wind Energy Forecasting System
UESDF	Urban Energy Supply Decarbonization Framework
UCEI	Urban Carbon Emission Index
UCTC	Urban Carbon Transition Curve
VSTWPF	Very short-term wind power forecasting (KW/turbine)
VSTWSF	Very short-term wind speed forecasting (m/s)
WPF	Wind power forecasting (KW/turbine)
WSF	Wind speed forecasting (m/s)
XGBoost	Extreme gradient boosting
$\widehat{y}_i$	Predicted output
y_i	Actual output
b	Bias vector
f (.)	Activation function
F	Regression trees space
fk	Independent tree structure
K	Additive function
L	The differentiable convex cost function
W	Weight matrix
x	Independent variables
Y	Output vector
W	Weight matrix
Ω	Regularization term
ξ	Slack variable

1 Introduction

1.1 Wind energy supply for zero-carbon cities

Urban areas contribute significantly to global greenhouse gas emissions, with 75% of greenhouse gases (GHG) or CO_2 equivalent ($CO_{2\ eq}$) emissions. By 2050, 68% of the world's population will live in cities, further increasing emissions. Smart cities leverage IoT, Big Data, and AI to optimize resources for urban sustainability. However, achieving net zero requires major structural changes, including cutting GHG emissions by 80% or more by 2050, while zero-carbon cities focus on using renewable energy and reducing all emissions (Wang et al. 2023; Seto et al. 2021; Darwish 2025). This includes transitioning to a net-zero carbon electricity grid and electrifying key sectors such as transportation, heating, and cooking. Additionally, carbon valorisation converts captured CO_2 into industrial goods. Achieving this transformation requires investment in green technologies and renewable energy, aiming to cut emissions by 80–100% by 2050, creating sustainable, smart and net-zero cities (Ramaswami et al. 2021; Song et al. 2024).

Wind energy is crucial for providing a sustainable and clean source of power and mitigating climate change. Globally, about 60 Gigawatts (GW) of wind power capacity has been added during 2024, reaching 900 GW in 2024 (Song et al. 2024; Portocarrero Mendoza 2024). However, the nature of wind as an interrupted energy resource makes wind energy an unpredictable energy source (Piazza et al. 2020; Elmousalami 2021a). Wind energy has yet to reach its full potential and cannot consistently deliver power at specific times (Yaghoubirad et al. 2023; Karijadi et al. 2023). Computational models predict future wind speeds using historical data and meteorological conditions, which are then used to estimate wind power generation. Accurate forecasting is essential for optimizing performance and integrating wind energy into power grids, with predictions varying by time scale to serve different operational needs, from real-time balance to maintenance planning (Breslow and Sailor 2002; Wu et al. 2022a). Therefore, achieving highly accurate wind energy forecasting is essential for optimizing the operation and management of any wind farm station, as shown in Fig. 1 (Hu et al. 2021; Qian et al. 2019).

Fig. 1 Wind speed and power forecasting time scale

1.2 Sustainable artificial intelligence (SAI)

The development and application of AI technologies raise concerns about their environmental footprint SAI emerges as a response, aiming to minimize this impact through a two-fold approach. Firstly, it focuses on developing and utilizing more environmentally friendly AI systems. Secondly, it leverages the power of AI to address environmental challenges directly (Elmousalami et al. 2024a; Wynsberghe 2021). The environmental cost of AI stems from the significant energy consumption associated with training and running complex models. SAI practices aim to mitigate this impact by exploring energy-efficient hardware and algorithms. Techniques such as parameter reduction in models and the utilization of pre-trained models can further decrease the energy footprint. Additionally, data collection and storage can have environmental consequences. SAI promotes responsible data management practices to minimize the environmental impact associated with this stage of the AI lifecycle (Wu et al. 2022b; Wilson and Velden 2022).

Beyond efficiency, SAI recognizes the potential of AI as a powerful tool for environmental problem-solving. AI can be harnessed to optimize resource management, including water and energy use. In agriculture, AI-powered systems can analyse data to identify areas of water waste and optimize irrigation practices. Similarly, in urban environments, SAI can contribute to optimizing energy use in buildings and even assist with developing and implementing renewable energy solutions. By leveraging AI's analytical capabilities, researchers can advance climate change research and prediction, further supporting the pursuit of environmental sustainability (Elmousalami et al. 2024a; Wynsberghe 2021; Wu et al. 2022b; Dhayal et al. 2025).

1.3 Research gaps and problems

The review of related work highlights key research gaps in the evaluation of AI-based wind energy prediction models. While numerous studies have focused on wind speed and power forecasting, sustainable AI approaches and the comparison of different algorithms across various time horizons have been underexplored. For instance, previous work such as in Lydia et al. (2024) and Liao et al. (2022) has primarily emphasized wind speed and power prediction using AI models without addressing sustainability aspects or varying prediction horizons. Similarly, Sun et al. (2024) and Cakiroglu et al. (2024) focused on wind power prediction and did not compare AI models or consider different time frames. Moreover, the research conducted in Zhang et al. (2024a) incorporated data enhancement techniques and did not include a focus on sustainable AI approaches. In contrast, the present study bridges these gaps by providing a thorough assessment of AI algorithms for wind speed and power prediction, emphasizing sustainable AI practices while considering various forecasting time horizons as in Table 1.

1.4 Research objectives

This paper addresses the transition to renewable energy in smart cities by focusing on wind energy optimization through advanced forecasting techniques. The research outlines four key objectives:

Table 1 Evaluation of the related work

References	Key objective	Year	Aspects				
			Sustainable AI	Wind speed prediction	Wind power prediction	AI models comparison	Different time horizons
Lydia et al. (2024)	Wind energy prediction algorithms	2024	×	√	√	√	×
Liao et al. (2022)	Hybrid Short-term wind power prediction	2024	×	√	√	√	×
Sun et al. (2024)	Offshore wind power turbine forecasting	2024	×	×	√	×	√
Cakiroglu et al. (2024)	Wind turbine power prediction	2024	×	×	√	√	×
Zhang et al. (2024a)	Data augmentation for wind power forecasting	2024	×	√	√	√	×
This paper	An extensive assessment of Green AI models for wind speed and power forecasting	2024	√	√	√	√	√

(1) Performance Evaluation of AI Models: A comparative analysis of twelve ML and DL models is conducted for multi-step WSF and WPF. The study examines ensemble methods, scalable boosting machines, Random Forests, and other ML models to establish a comprehensive benchmark for accuracy and reliability in forecasting.
(2) Environmental Impact Assessment: Beyond traditional metrics such as MAPE and MSE, the environmental cost of AI algorithms is evaluated by quantifying CO_2 emissions per computational hour. This dual-criteria approach aims to identify models that balance high predictive accuracy with minimal carbon footprint.
(3) Development of SAI-WEFS: An integrated Sustainable AI-Driven Wind Energy Forecasting System (SAI-WEFS) is proposed to enhance wind speed and power prediction capabilities, prioritizing both precision and computational efficiency.
(4) Integration into Urban Decarbonization Frameworks: The SAI-WEFS is incorporated into an Urban Energy Supply Decarbonization Framework (UESDF) to quantify the Urban Carbon Emission Index (UCEI) and visualize the Urban Carbon Transition Curve (UCTC). This integration supports data-driven strategies for reducing urban carbon emissions and advancing zero-energy city goals.

The study aims the synergy between AI-driven forecasting, environmental sustainability, and urban energy planning, offering actionable insights for optimizing wind energy systems while minimizing ecological impacts.

2 Literature review

Due to the depletion of fossil fuels, wind turbines are becoming a key alternative for energy generation. In addition, the wind's nonstationary nature challenges traditional forecasting methods, leading to risks for power system operations. Methods such as eXtreme Gradient Boosting (XGBOOST), Multi-Layer Perceptron (MLP) with Bayesian Optimization (BO), and Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) were tested, with the Ensemble method achieving a mean square error (MSE) of 7.2 in 45 s and CNN-LSTM achieving an MSE of 6.8 in 450 s. These results highlight wind power's potential as a reliable and sustainable energy source (Malakouti et al. 2024). Several studies introduce machine learning techniques, including extremely randomized trees, light gradient boosting machines, ensemble methods, and CNN-LSTM, to enhance wind power prediction accuracy. CNN-LSTM achieved the lowest MSE, while ensemble methods offered reliable results with faster computational performance (Malakouti et al. 2022).

A study at a Texas wind farm found that Random Forest (RF) outperformed other algorithms like K-Neighbors in predicting turbine output, highlighting a trade-off between speed and accuracy in forecasting (Malakouti 2023a). Another analysis of 850,660 data points identified Extra Tree as the best-performing model for turbine production predictions, emphasizing the need for advanced ML techniques in renewable energy (Malakouti 2023b). Additionally, a hybrid ensemble of LightGBM and Extra Trees achieved superior accuracy in wind speed prediction at Basel Airport, demonstrating the potential of ensemble methods in wind energy forecasting (Malakouti and Ghiasi 2022). These studies underscore ML's critical role in optimizing wind energy forecasting for sustainable energy transitions.

Researchers have long focused on renewable energy, studying ways to utilize, collect, manage, and improve its efficiency. The Sotavento wind farm in Galicia, Spain, a 17.56 MW facility with 24 turbines, utilized iterative "babysitting" hyperparameter optimization and tenfold cross-validation to refine machine learning models such as LightGBM, Gradient Boosting, RF, and K-neighbors, ensuring robust wind energy forecasting (Malakouti 2023c). In parallel, a study in Turkey applied the Light Gradient Boosting Machine (LightGBM) with grid search hyperparameter tuning, achieving exceptional accuracy in wind speed ($R^2 = 0.98$ after 25 s) and turbine power output ($R^2 = 1.0$ after 90 s) predictions, validated through root mean square error (RMSE) and R^2 metrics (Malakouti 2023d). These efforts underscore the pivotal role of machine learning in advancing wind energy systems, enabling rapid, precise forecasting to accelerate the global transition from fossil fuels to renewables amid escalating climate challenges.

3 Machine learning models

3.1 Single ML models

Single machine learning algorithms are individual ML models that are trained and executed on a single machine or processor. These algorithms can range from simple linear regression to more complex neural networks. Multiple Layer Perceptrons (MLP) are a type of artificial neural network consisting of interconnected layers of neurons as in Fig. 2. Each neuron receives inputs, applies a weighted sum and activation function, and produces an output. MLPs can learn complex patterns and are widely used for tasks like classification and regression (Hopfield 1982; Siddique and Adeli 2013; Elmousalami and Hassanien 2003).

Support Vector Machines (SVMs) are supervised learning algorithms employed for both classification and regression tasks. They operate by identifying a hyperplane that best separates data into distinct classes, aiming to maximize the margin between these classes, which

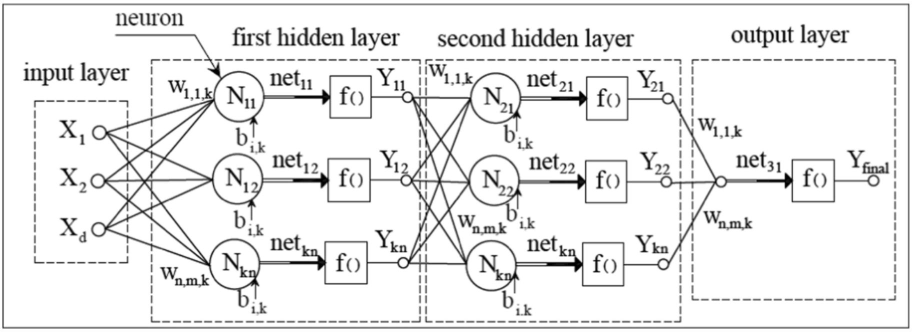


Fig. 2 Multilayer perceptron network (MLP) (Elmousalami 2020)

enhances their robustness to noise and outliers. SVMs are particularly effective when dealing with high-dimensional data (Elmousalami and Sakr 2024a; Elmousalami et al. 2024b).

Regression algorithms predict continuous numerical values based on input features. Linear regression establishes a linear relationship between inputs and outputs, whereas nonlinear regression techniques, such as polynomial regression or decision trees, can model more complex relationships. These regression methods are extensively applied across various fields, including finance, economics, and engineering (Elmousalami et al. 2021; Elmousalami and Sakr 2024b; Elmousalami 2021b).

Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are designed to process sequential data, like time series or natural language. They feature feedback connections that allow them to maintain information about previous inputs. LSTMs, a specialized type of RNN, utilize "gates" to regulate the flow of information, making them more adept at learning long-term dependencies. Both RNNs and LSTMs are commonly used for tasks such as language modelling, and speech recognition (Elmousalami et al. 2024c; Alnaser et al. 2024).

3.2 Ensemble machine learning

Ensemble machine learning techniques integrate multiple models to enhance predictive performance by combining their strengths. Bagging, or Bootstrap Aggregating, involves generating multiple subsets of the original dataset through sampling with replacement. Each subset trains a separate model, and their predictions are aggregated, typically by averaging for regression tasks or voting for classification, to produce a result. This approach aims to reduce variance and prevent overfitting, leading to more robust models.

RFs extend the Bagging concept by employing decision trees as base learners and introducing additional randomness during model construction. At each node, a random subset of features is considered for splitting, which decorrelates the trees and enhances the ensemble's generalization ability. Boosting, on the other hand, is a sequential technique that focuses on correcting the errors of prior models. Each new model is trained to address the shortcomings of its predecessors, often by giving more weight to misclassified instances. This iterative process aims to convert weak learners into a strong composite model, improving overall accuracy (Fig. 3).

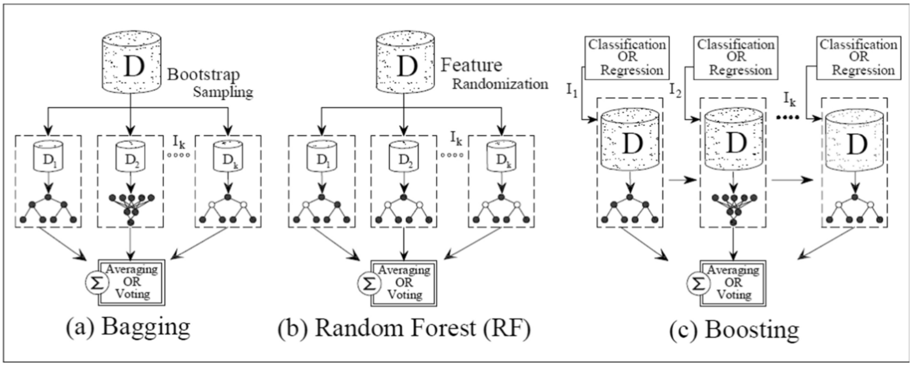


Fig. 3 Ensemble machine learning: **a** bagging, **b** RF, and **c** boosting (Elmousalami 2020)

4 Research methodology

The research methodology incorporates ML techniques and CO_2 emissions evaluation. The process begins with data collection from anemometers, followed by thorough pre-processing steps including cleaning, normalization, and structuring. The data is then split into training (70%) and testing sets (15%), with a separate validation set used for hyperparameter optimization. ML models have been trained using K-folds cross-validation (15%). The trained model is then used to predict wind speed and power (WSF and WPF). The predicted values are fed into a CO_2 emissions evaluation module to assess the potential environmental impact. The entire process iterates, optimizing hyperparameters through a hyperparameter optimization technique such as Bayesian optimization, until desired conditions are met, leading to the development of an optimal machine learning model for wind speed and power prediction and CO_2 emissions evaluation as in Fig. 4. Therefore, the predictive algorithms are selected with a dual focus on maximizing forecast accuracy and minimizing CO_2 emissions, reflecting a sustainable AI methodology.

5 ML application

5.1 Gabal El-Zayt wind farm dataset

The onshore Gabal El-Zayt wind farm (200 MW) in Egypt has been selected as the data source for the developed models. The Gulf of Suez and the Gulf of Aqaba are highly promising areas for offshore and onshore wind energy farms as in Fig. 5. The dataset used in this study consists of wind speed and power measurements collected from Gamesa G80-2.0 wind turbines, each with a capacity of 2 MW (Elmousalami et al. 2021; Fukutomi 2024; Samanvitha et al. 2025). Wind speed data was measured using anemometers, which provide precise, real-time measurements essential for accurate forecasting. Input parameters such as "hour" are only relevant for very short-term wind speed and power predictions (VSTWSP and VSTWPP), as they capture intra-day variations critical for forecasts within one hour. However, for predictions beyond one hour, the "hour" parameter loses significance,

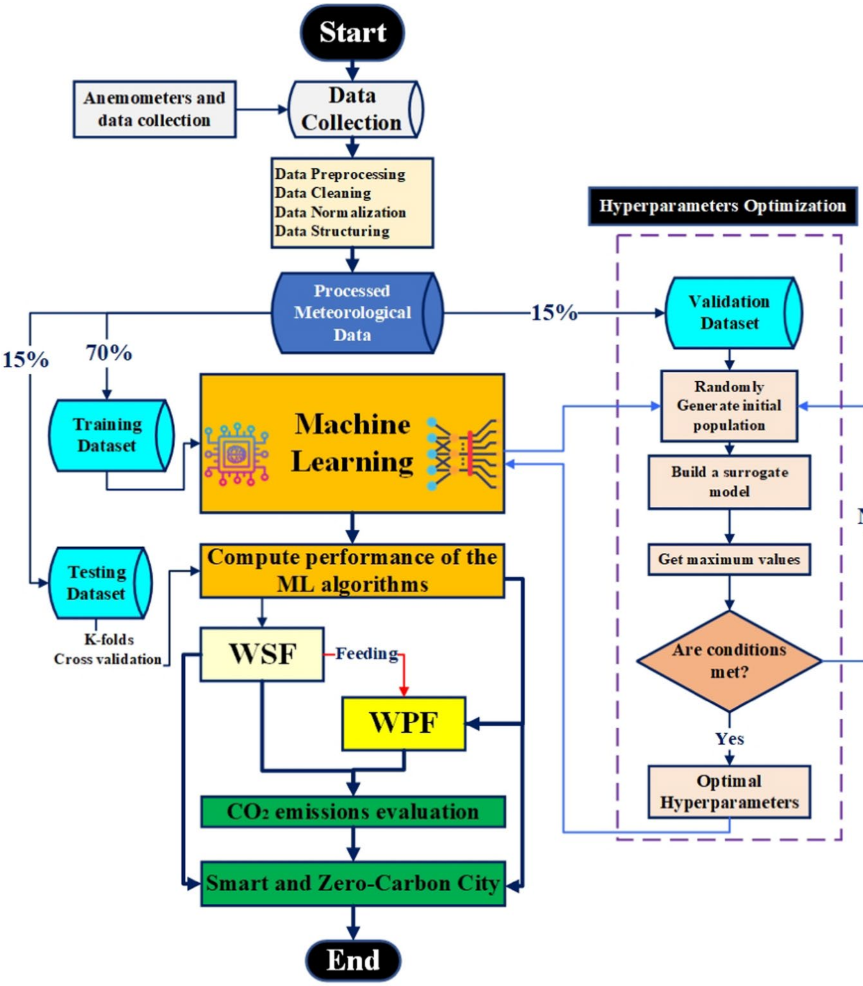


Fig. 4 Wind energy forecasting integration methodology

as larger time intervals (e.g., "day" or "36 h") become more relevant for capturing broader temporal patterns that influence wind speed and power.

The dataset used for wind speed and power forecasting includes several critical parameters influencing turbine performance. Height (P_1) refers to the altitude of the turbine hub in meters, significantly affecting wind speed due to wind profile variations at different altitudes. Windvane (P_2) measures the wind direction in degrees, which is crucial for optimizing turbine alignment and maximizing energy capture. Atmospheric temperature (P_3), recorded at hub height, impacts air density and, subsequently, wind power potential. Humidity (P_4) indicates the relative amount of water vapor in the air, which can influence atmospheric conditions and, in turn, affect wind dynamics. Atmospheric pressure (P_5), measured in hectopascals (hPa), is essential for understanding the air density and the behaviour of wind flows around the turbine. Temporal parameters such as Month (P_6) and Hour (P_7) are

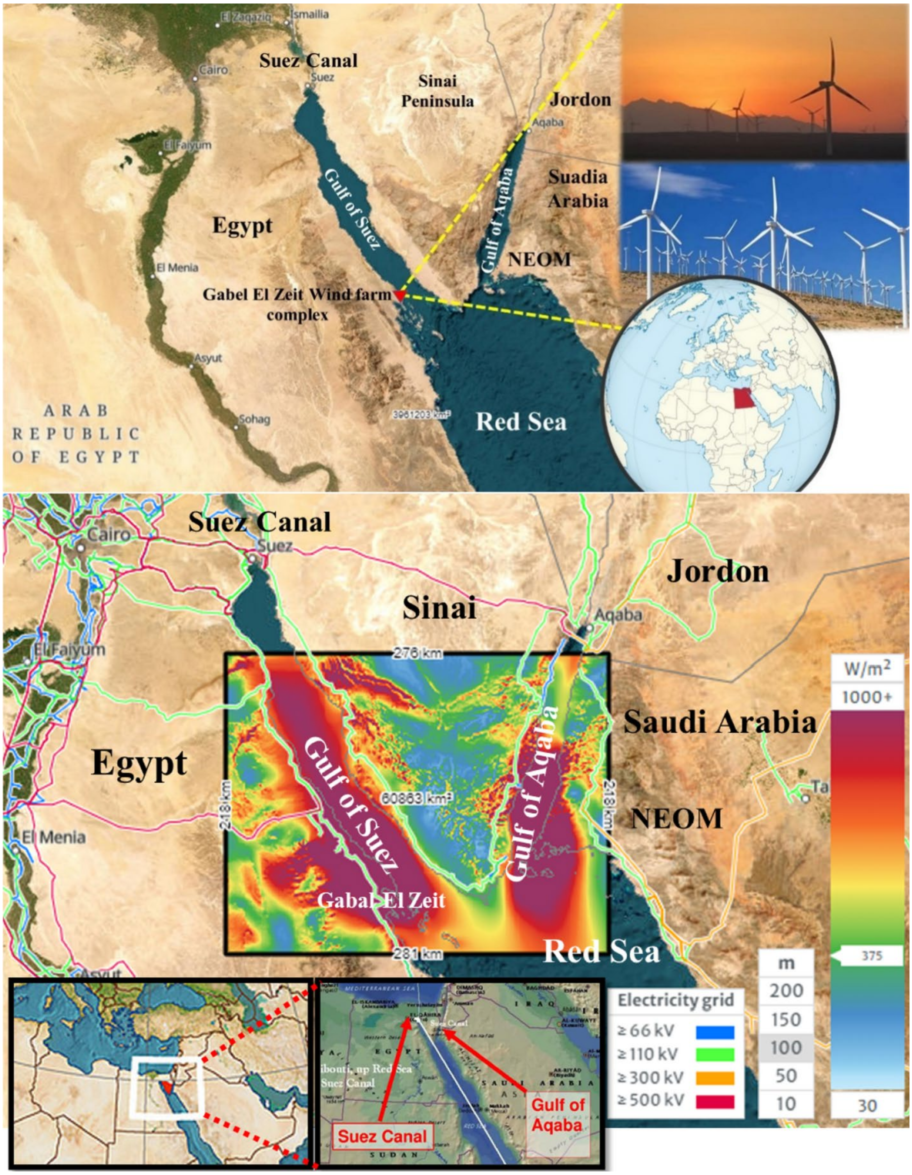


Fig. 5 The strategic location of the Gabel El Zeit wind station that extends onshore and offshore of 60,863 km^2

useful for capturing seasonal and short-term variations in wind patterns, where month is crucial for longer-term trends, and hour is primarily relevant for very short-term predictions of less than one hour. Wind speed (P_8), measured in meters per second, is directly linked to Wind Power (P_9), measured in watts per square meter, as wind power is a function of wind speed cubed.

The interrelationship among these parameters helps create accurate forecasting models for wind energy generation. The absence of data for June, July, and August in the dataset is due to significant issues related to data quality during these months. Upon reviewing the raw data, it was found that a substantial portion contained missing or illogical values, such as abrupt wind speed or anomalies this is due to turbine maintenance and bird immigrations where the whole station stops to save birds (Hilgerloh et al. 2011). As part of the pre-processing step, this data was excluded to ensure the integrity and reliability of the forecasting models (Table 2).

5.2 Machine learning development

For the prediction of very short-term wind speed (VSTWSF), seven data predictors were selected as inputs for twelve machine learning models, with a dataset comprising seven independent variables and one dependent variable (VSTWSF). Models employed included Decision Tree (DT) using CART as a continuous tree, Support Vector Machines (SVM) with an RBF kernel, and deep neural networks (ANNs and RNNs with LSTM). The deep learning models used three hidden layers, each containing 100 neurons. Additionally, linear,

Table 2 The models' parameters description

Notation	Name	Description	Unit
P_1	Height	Height or altitude of turbine hub	Meters
P_2	Windvane	The main direction the wind is blowing	Degrees
P_3	Atmospheric temperature	A measure of temperature at the levels of the Height parameter. It is governed by many factors, including incoming solar radiation, humidity, and altitude	Degrees celsius
P_4	Humidity	Relative humidity which measures water vapor, is relative to the temperature of the air	%
P_5	Atmospheric pressure	the pressure within the atmosphere of the wind farm recording station	Hectopascals (hPa)
P_6	Month	Calendar month of meteorological data recording (1 to 12 format)	Each
P_7	Hour	Hour of the recording day (24-h format) for very short predictions	Each
P_8	Wind Speed	Measured wind speed	Meters per second (m/s)
P_9	Wind Power	Measured wind power	Watts per square meter (W/m^2)

and polynomial regression models were applied, while ensemble learning techniques such as RF, and XGBoost were used to enhance performance.

The dataset for VSTWPF utilized the same predictors as VSTWSF, with an additional VSTWSF model integrated as an input, making a total of eight predictors. The structure of the deep neural network for VSTWPF also included three hidden layers of 100 neurons each, resulting in a model with 309 neurons. The integration of wind speed and power prediction models followed a similar process, where evaluation and validation techniques were applied to select the most optimal algorithms for VSTWSF and VSTWPF. All machine learning models were implemented using Python programming.

5.3 Hyperparameters optimization

Hyperparameter tuning is a very important step for the majority of machine learning (ML) methods (Elmousalami and Sakr 2024a; Elmousalami et al. 2024d; Sonmez and Uysal 2021). This study conducts Bayesian optimization to select the optimal hyperparameters based on the validation data set using Eqs. (1) and (2).

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_i - \widehat{y}_i|}{\widehat{y}_i} \times 100 \tag{1}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}[y_i - \widehat{y}_i]^2 \tag{2}$$

The Bayesian optimization algorithm is a method for optimizing hyperparameters in machine learning models by utilizing principles from Bayesian statistics. Initially, a population generation (Gen = 0.0) is generated with random hyperparameter configurations. This population undergoes evaluation based on prediction errors such as MAPE or MSE. The algorithm then computes a weight vector to update the hyperparameters iteratively, aiming to minimize the error. The process involves updating the generation count (Gen = Gen + 1).

The ANN model comprises three layers, each containing ten neurons with ReLU activation functions; polynomial regression is applied as a second-order polynomial; tree-based models utilize an ensemble of 20 trees with MSE as the splitting criterion; SVM employs an RBF kernel with a gamma parameter, running up to 10,000 iterations.The R-squared (R^2: coefficient of determination) is as Eq. (3):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i - \widehat{y}_i\right)^2}{\sum_{i=1}^{n}\left(y_i - \overline{y}_i\right)^2}, \quad 0 \le R^2 \le 1 \tag{3}$$

R^2 represents how well the algorithm fits the data. Adjusted R-squared R^{*2} is calculated using Eq. (4).

$$R^{*2} = R^2 - \frac{\left(1 - R^2\right)K}{n - (K+1)} \tag{4}$$

6 Results and analysis

6.1 WSF results

The performance of various ML models, including both individual and ensemble methods, for wind speed forecasting as the VSTWSP model is presented in Fig. 6. Models were evaluated using four metrics: MAPE, MSE, R^2, and R^{*2}. Among the ensemble models, Extra Trees exhibited the best performance with a low MAPE (3.485%), MSE (0.254), and a high R^2 value (0.994), indicating strong predictive accuracy. In comparison, single models such as Decision Trees (DT) performed relatively reliably with slightly higher MAPE and MSE. Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) had a significantly higher MAPE (10.7%) and lower R^2 (0.97), reflecting weaker performance than tree-based ensemble models. Simple models such as Polynomial Regression and Linear Regression showed the poorest performance, with MAPE values above 20% and R^2 values below 0.7. Deep Neural Networks (DNNs) exhibited poor predictive accuracy, with a MAPE of 42.34% and an R^2 of only 0.264.

For the 30-min time scale, Decision Trees (DT) demonstrated the best overall performance with a MAPE of 7.82%, a low MSE of 1.3, and an R^2 of 0.994, indicating high predictive accuracy. Extra Trees and Bagging performed well, with MAPE values of 8.635% and 11.439%, respectively, and R^2 values close to 0.997. In contrast, RNN and LSTM, a deep learning model, showed higher MAPE (12.6%) and maintained good accuracy, with an R^2 of 0.993. RF had moderate performance (MAPE of 13.484%), while ensemble models such as SGB and XGBoost performed poorly compared to tree-based models, with MAPE values of 11.8% and 22.231%, respectively, and lower R^2 values. The poorest performers were Polynomial Regression, DNNs, and Support Vector Machines (SVM), which had significantly higher MAPE values (above 33%) and R^2 values below 0.7, indicating low predictive accuracy. AdaBoost showed the highest MAPE (55.6%) and low R^2 (0.37), making it one of the least effective models for this 30-min horizon forecasting task as in Fig. 7.

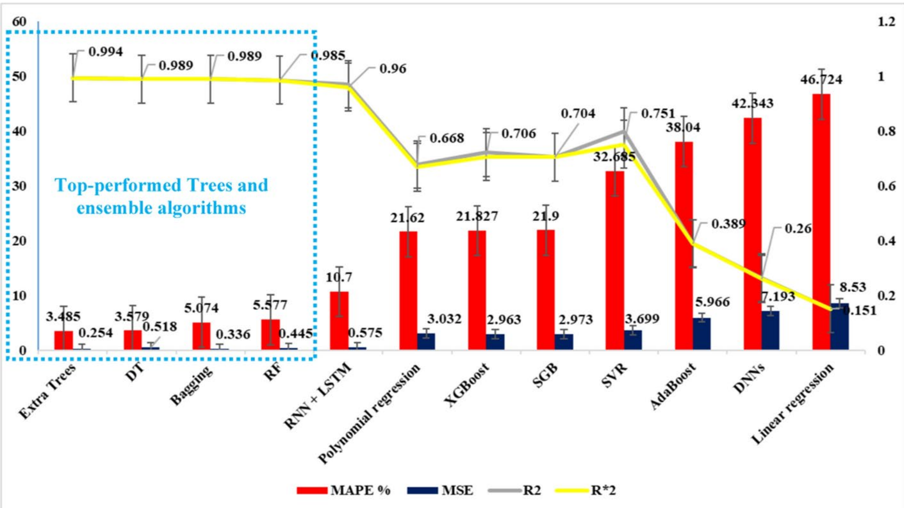


Fig. 6 Results of ML models for VSTWSF 10 min (10 M)

For the 6-h ahead time scale, DT and Bagging demonstrated strong predictive accuracy with MAPE values of 4.103% and 4.171%, respectively, and high R^2 values (both around 0.99). Extra Trees performed well with slightly higher MAPE (4.643%) and MSE, while RF followed with moderate performance (MAPE of 4.975%). In contrast, deep learning models such as RNN and LSTM had a much higher MAPE of 11.6% and lower R^2 (0.913), indicating poorer predictive capability. Ensemble models such as XGBoost and SGB showed significantly higher MAPE values (above 26%) and lower R^2, indicating weaker accuracy. Simple models such as SVM, Polynomial Regression, and Linear Regression performed the worst, with MAPE values exceeding 30% and R^2 values below 0.7. Deep Neural Networks (DNNs) had the lowest performance, with a MAPE of 38.55% and an R^2 of 0.196, indicating that deep learning approaches were less effective for this 6-h prediction horizon compared to tree-based ensemble models as in Fig. 8.

For the 24-h ahead time scale, the Extra Trees ensemble method demonstrated the best performance with a MAPE of 4.645% and an R^2 of 0.948, showing high predictive accuracy. DT and Random Forest Regression (RFR) followed closely, with MAPE values of 5.179% and 6.502%, respectively, and similarly high R^2 values. The performance of Bagging, another ensemble method, was on par with other top models, with a MAPE of 6.538%, slightly higher than DT, and still achieving a respectable R^2 of 0.951. In contrast, the RNN + LSTM deep learning model exhibited a higher MAPE of 9.3%, though it maintained a relatively strong R^2 of 0.902. The ensemble methods SGB and XGBoost showed poorer performance with MAPE values above 15%, indicating less accuracy over the 24-h horizon. Polynomial Regression, while maintaining some accuracy (MAPE of 17.142%), still lagged behind the top ensemble methods. Adaboost, SVM, and DNNs demonstrated the weakest predictive accuracy, with MAPE values ranging from 25% to nearly 45%. These models exhibited significantly lower R^2 values, indicating they were not well-suited for long-term forecasting over a 24-h time horizon as in Fig. 9.

For the 36-h ahead time scale, the Extra Trees ensemble method again shows the best predictive performance, with a MAPE of 9.148% and an R^2 of 0.948, closely followed by DT and Bagging, which performed well with MAPE values of 9.209% and 9.222%, respectively, and high R^2 values above 0.94. RF performed similarly, with a slightly higher MAPE

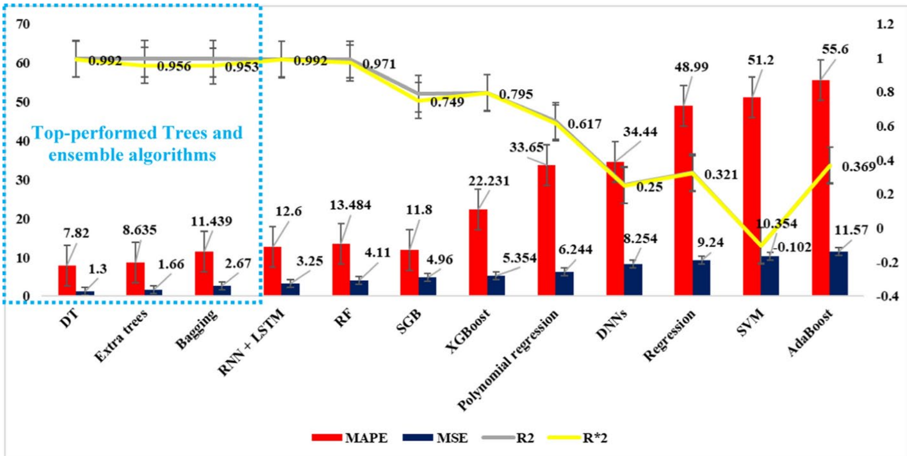


Fig. 7 ML results for 30 min ahead of WSF

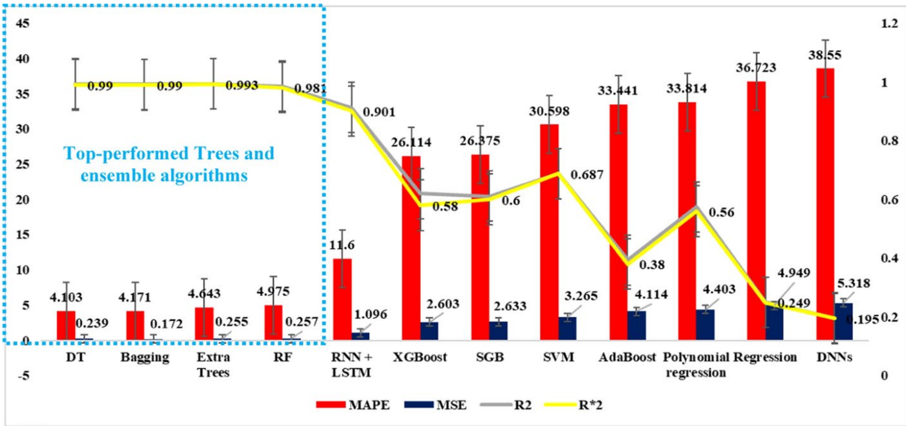


Fig. 8 ML results for 6 h ahead of WSF

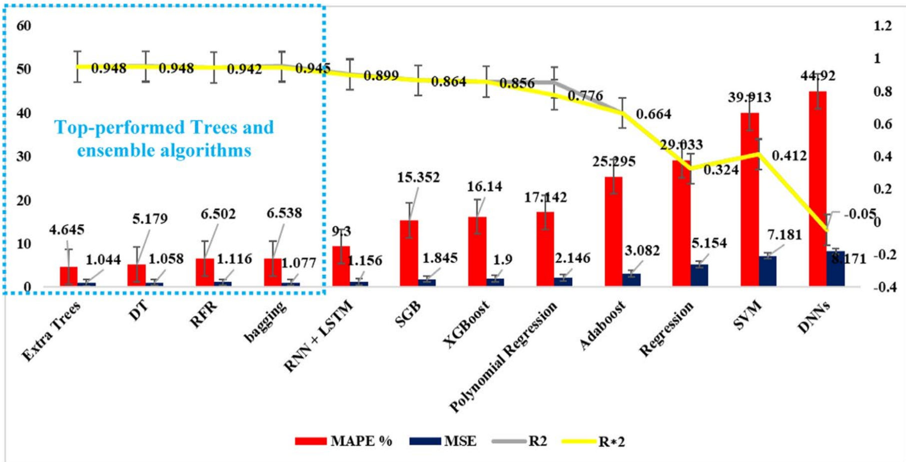


Fig. 9 ML results for 24 h ahead of WSF

of 9.642%. The RNN + LSTM model, a deep learning approach, showed a higher MAPE of 15.3%, indicating less accurate predictions compared to ensemble models. Its R^2 of 0.78 reflects reasonable performance with room for improvement over the 36-h horizon. Models such as SGB, XGBoost, and SVM displayed significantly worse performance, with MAPE values exceeding 30% and lower R^2 values, indicating poor suitability for longer-term forecasting. Polynomial Regression, AdaBoost, and Regression models performed the worst, with MAPE values ranging from 46 to 50%, showing limited forecasting ability over a 36-h time horizon. The low R^2 values for these models underscore their limited predictive capability, with DNNs showing the poorest overall performance at 50.083% MAPE as in Fig. 10.

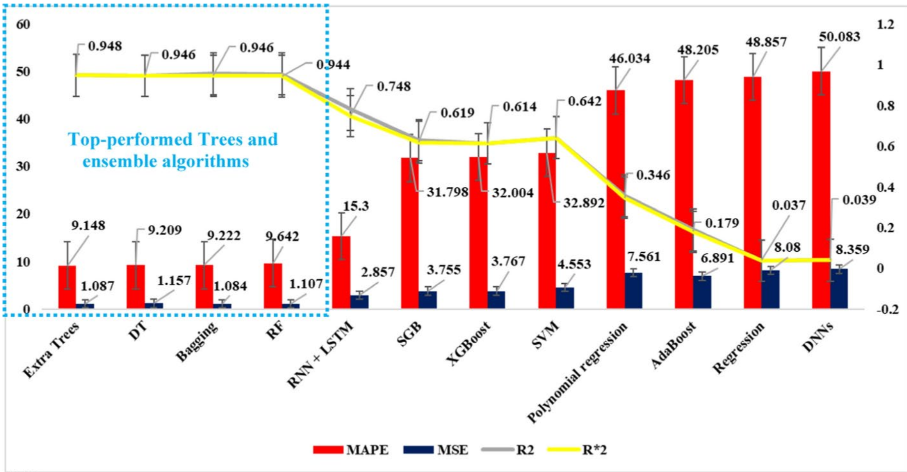


Fig. 10 ML results for 36 h ahead of WSF

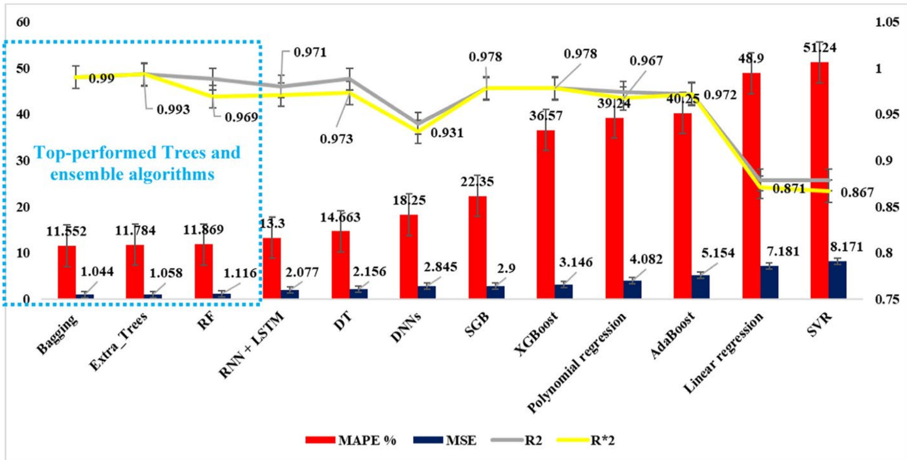


Fig. 11 Results of ML models for VSTWPF (10 M)

6.2 WPF results

The performance of various ML models for wind power forecasting (WPF) as the VST-WPF model was presented using metrics such as MAPE (%), MSE, R^2, and adjusted R^2 as in Fig. 11. Bagging, an ensemble method, showed the best performance with a MAPE of 11.552%, MSE of 10,945.686, and an R^2 of 0.99, indicating high predictive accuracy. Extra Trees and RF closely followed, with MAPE values of 11.784% and 11.869%, respectively, and R^2 values above 0.98, demonstrating their strong prediction ability. Among single models, RNN and LSTM had a moderate MAPE of 13.3% and an R^2 of 0.98, performing better than DT, which had a MAPE of 14.663%. Deep learning models such as DNNs performed worse, with a much higher MAPE of 37.47% and a lower R^2 of 0.94, indicating lower accuracy for wind power prediction. Ensemble methods such as SGB and XGBoost displayed poorer performance compared to Bagging and extra trees, with MAPE values exceeding 41%, though their R^2 values (around 0.978) were still relatively high. Polynomial Regression, AdaBoost, Linear Regression, and SVR models showed the weakest performances as in Fig. 11.

For a 30-min WPP, Bagging, an ensemble method, shows the best performance with a low MAPE of 4.12% and an MSE of 2.126, achieving an R^2 of 0.969, making it the most accurate model. Extra Trees and RF performed well, with MAPE values of 4.151% and 4.183%, respectively, and R^2 values close to 0.96, indicating strong predictive abilities. On the other hand, models such as DT, XGBoost, and SGB, all ensemble methods, had higher MAPEs around 9.664% to 10.478%, suggesting lower prediction accuracy compared to the top performers, though their R^2 values remained reasonably high (above 0.93). RNN and LSTM, a deep learning model, showed a significantly higher MAPE of 18.3%, indicating lower accuracy, while Polynomial Regression and DNNs performed poorly with MAPE values exceeding 39%. AdaBoost and Regression models showed MAPE values around 44.9% and 48.99%, respectively. As a result, these algorithms are less suitable for this short-term forecasting task. Lastly, SVM performed the worst with an extremely low R^2 value close to zero, indicating near-random predictions as in Fig. 12.

For the 6-h WPP, the best-performing models are ensemble methods, particularly Bagging and Extra Trees, with MAPE values of 4.116% and 4.144% respectively, and high R^2 values (0.971 and 0.961), indicating accurate predictions. RF also performs well with a MAPE of 4.2% and R^2 of 0.96. Single models such as DT achieve moderate accuracy, with a MAPE of 4.335% and an R^2 of 0.943. However, the performance drops for other ensemble models such as XGBoost and SGB, which both exhibit MAPE values above 7% and lower R^2 scores (0.941 and 0.935), signaling reduced accuracy compared to top-performing models. Deep learning models such as RNN LSTM and DNNs show higher MAPE (11.8% and 33.65%) and larger MSE values, indicating less precise predictions over this forecast horizon. Polynomial Regression, AdaBoost, and SVM demonstrate poor performance, with high

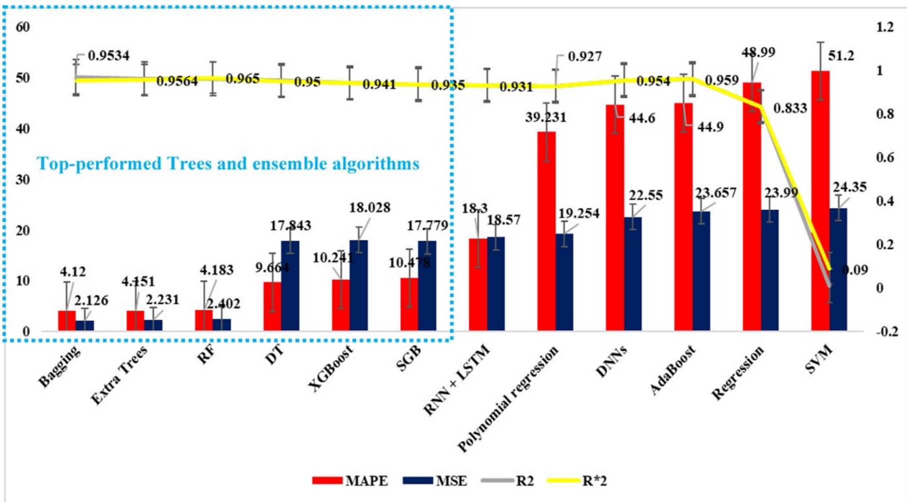


Fig. 12 ML results for 30 min ahead WPF

MAPE values (over 22%) and significantly lower R^2, suggesting they are unsuitable for 6-h WPP. SVM performs the worst, with a MAPE of 51.2% and an R^2 of just 0.1, reflecting minimal predictive accuracy as in Fig. 13.

For a 24-h forecast horizon, ensemble models, particularly Bagging and Extra Trees, achieved the best results with MAPE values of 4.72% and 4.727%, respectively, and R^2 values of 0.977 and 0.971, indicating high accuracy. RF performed with a MAPE of 4.79% and an R^2 of 0.965. Single models such as DT showed good accuracy with a MAPE of 5.163% and an R^2 of 0.96, making it competitive with ensemble models. However, other ensemble methods such as XGBoost and SGB performed less satisfactorily, with higher MAPE values (5.278% and 5.345%) and lower R^2 scores, particularly SGB with an R^2 of 0.721. Deep learning models such as LSTM and DNNs had significantly higher MAPE values (15.8% and 33.6%), reflecting reduced accuracy over this longer forecast horizon. Polynomial regression and AdaBoost performed poorly, with MAPE values over 28%, while SVM had the worst performance with a MAPE of 49.254% and an R^2 of 0.151, making it unsuitable for 24-h predictions as in Fig. 14.

For the 36-h wind power prediction (WPP), the evaluation of various machine learning models reveals their performance based on metrics such as MAPE, MSE, R^2, and adjusted R^2. Bagging, Extra Trees, and RF emerge as the top-performing ensemble methods, with MAPE values of 4.138%, 4.156%, and 4.232% respectively, and all achieving an R^2 of 0.965. This indicates that these models are highly effective at making accurate predictions for wind power output 36 h ahead. In addition, DT demonstrates strong performance with a similar MAPE of 4.445% and an R^2 of 0.965, indicating reliable forecasting capability. XGBoost, RNN, and LSTM provide competitive results with MAPE values of 5.737% and 5.853% respectively.

In contrast, other models such as SGB, Polynomial Regression, and DNNs show poorer performance. Specifically, SGB exhibits a lower R^2 of 0.811, and DNNs have an exceptionally high MAPE of 74.278%, indicating significant inaccuracies in predictions. AdaBoost, Regression, and SVM perform the worst, with MAPE values exceeding 77% and very low

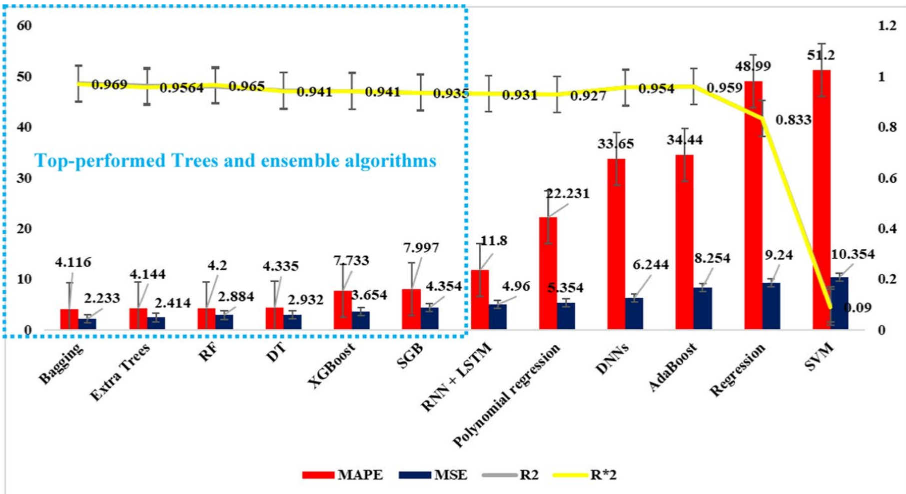


Fig. 13 ML results for 6 h ahead WPF

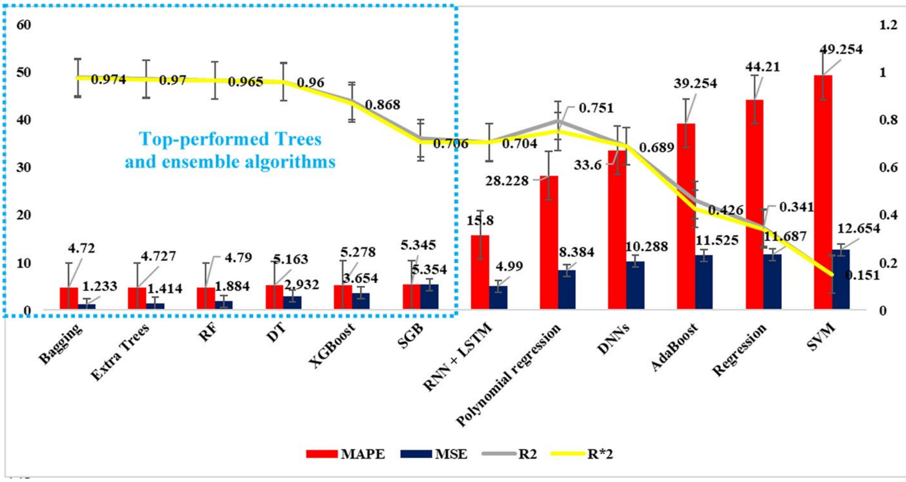


Fig. 14 ML results for 24 h ahead WPF

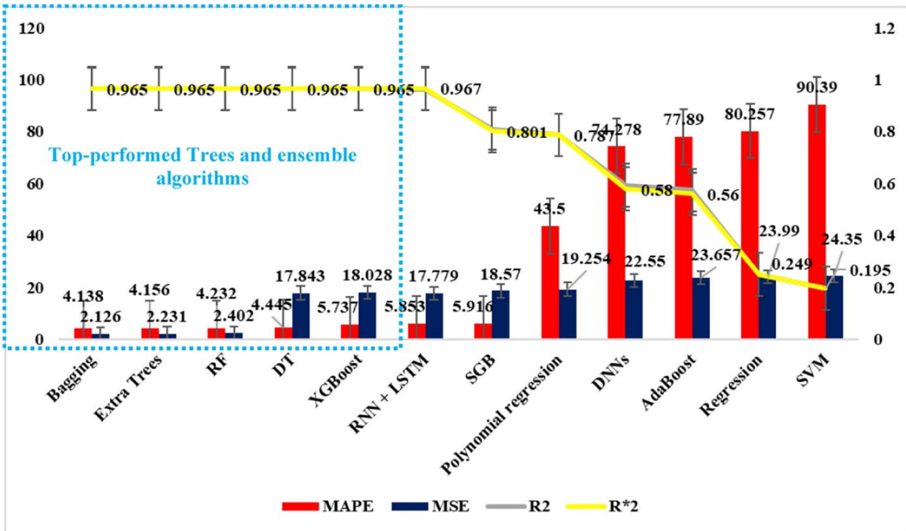


Fig. 15 ML results for 36 h ahead WPF

R^2 scores, indicating these models are not suitable for 36-h WPP tasks. The overall analysis suggests that ensemble methods, particularly Bagging and Extra Trees, provide the most reliable and accurate predictions for wind power forecasting over 36 h as in Fig. 15.

Figures 16A and 17 illustrate the efficacy of the Extra Trees model in predicting VST-WSP, with a majority of the forecasted values aligning closely with observed wind speeds. Similarly, Figs. 16B and 18 demonstrate the Bagging model's capability in forecasting VSTWPP, where the predicted values closely correspond to actual measurements with minimal deviations. Figure 19 presents the application of the Extra Trees model, utilizing

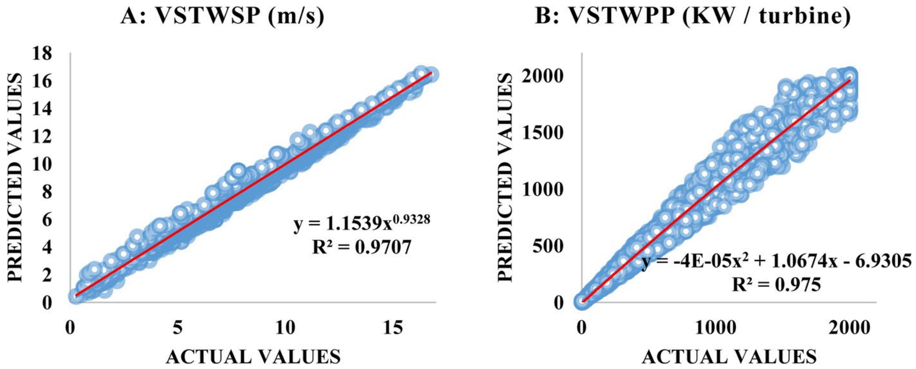


Fig. 16 Predicted and actual values of the developed models

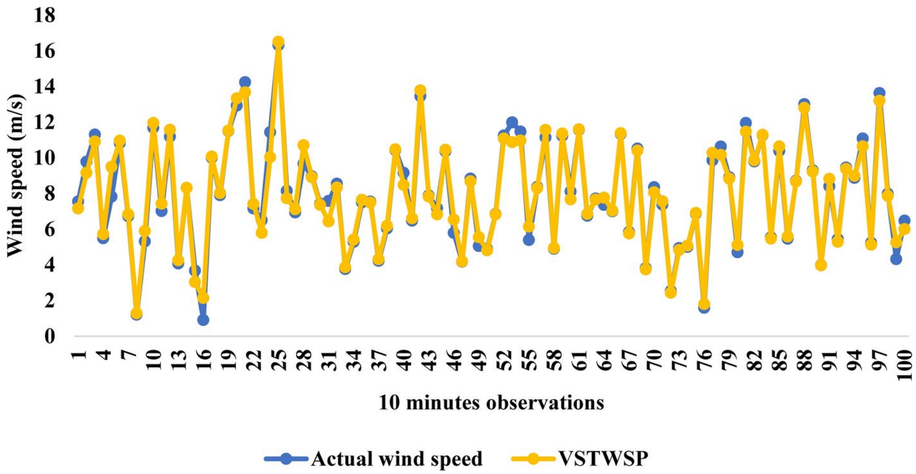


Fig. 17 Actual wind speed against VSTWSP

meteorological data collected every 10 min, to forecast wind speed 36 h ahead, achieving a MAPE of 12.3% and an MSE of 2.21, indicating its reliability for wind speed forecasting. In parallel, the Bagging model forecasted wind power 36 h in advance with a MAPE of 32.53% and a RMSE of 413 kW. Despite these variances in accuracy, Fig. 20 confirms that the Bagging ensemble model effectively captures wind speed trends over 36 h, underscoring its robustness in wind power forecasting.

In the context of this study, "36 h ahead" refers to a single prediction made 36 h in advance. This means that the forecasting models are tasked with predicting wind speed and power for a specific point in time 36 h after the current observation. The prediction is not continuously updated at regular intervals throughout the 36 h. The performance of the Extra Trees model for 36 h ahead of WSP shown in Fig. 20 reveals reliable performance, despite some deviations from the actual wind speed, the model's overall accuracy remains within acceptable limits. Based on the accuracy metrics MAPE of 9.148%, MSE of 1.087, and an R^2 value of 0.948 the deviations are reasonable and fall within an acceptable range

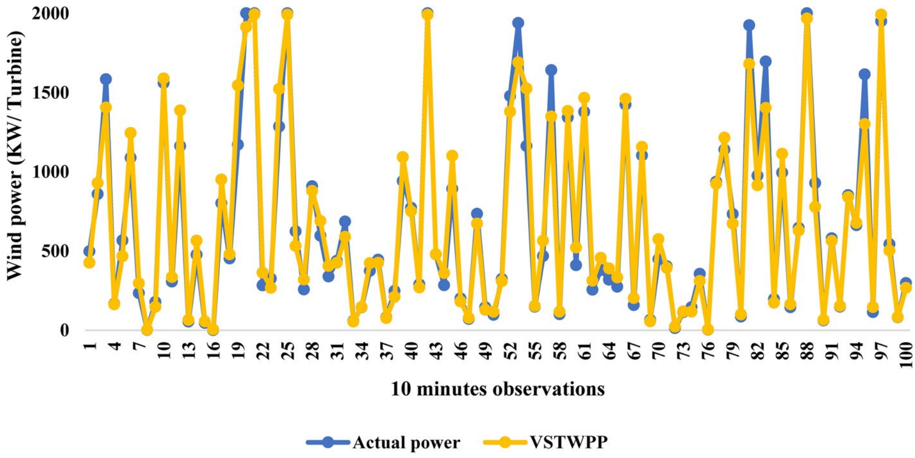


Fig. 18 Actual power against VSTWPP

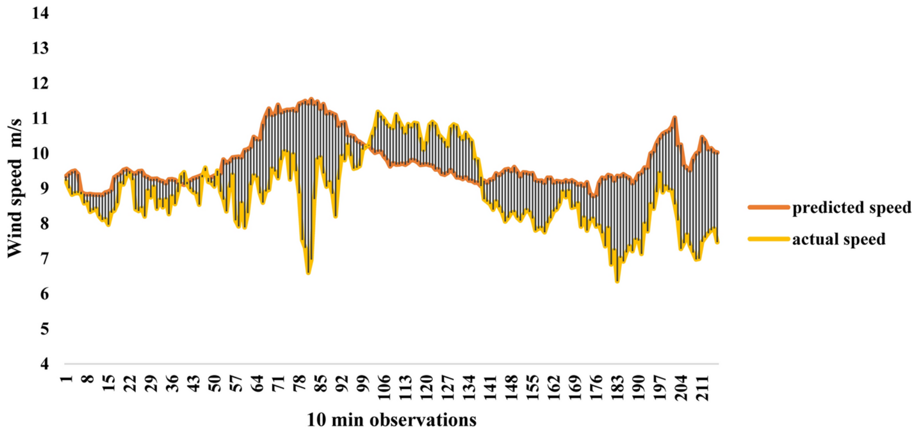


Fig. 19 Performance of Extra tree models for 36 h ahead of WSP

for machine learning models. These values demonstrate that the model maintains high predictive accuracy, with the R^2 of 0.948 indicating a strong correlation between the predicted and actual values. Therefore, while the model occasionally misses rapid changes, its performance is still reliable for practical applications. The results indicate a decline in predictive accuracy for wind speed and wind power as the forecasting time frame increases. This suggests that shorter time horizons yield more accurate predictions, while longer time intervals tend to introduce greater uncertainty and variability, reducing the model's overall precision.

6.3 Sustainable AI assessment

The environmental impact is measured in terms of carbon dioxide equivalent (CO_2e) emissions produced during training and execution on a computer system. Standardized CO_2e emissions per computational hour were calculated, revealing linear regression as the most

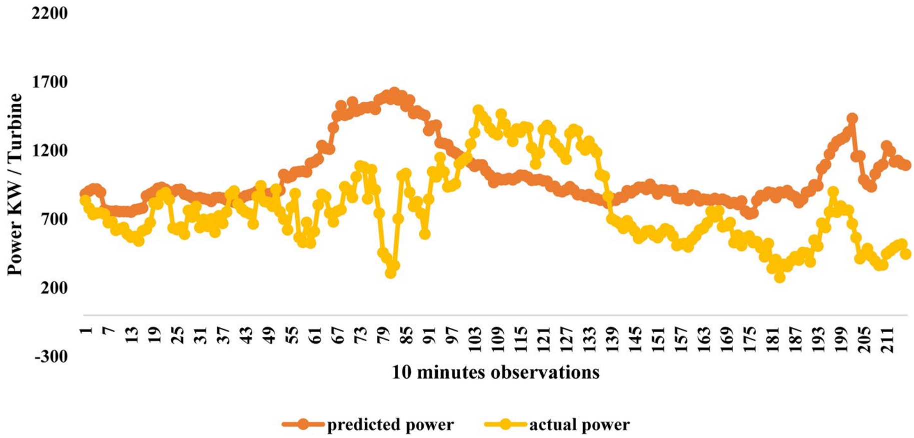


Fig. 20 Performance of the Bagging model for 36 h ahead of WPP

environmentally friendly option and ANNs and DNNs as the least. This highlights the need to consider both an algorithm's accuracy and its environmental impact when choosing a model for a particular computational task (Rashid et al. 2024; Cruz et al. 2024). Furthermore, an equation was presented that calculates total CO_2e emissions based on the number of times the algorithm is run and the CO_2e emissions associated with each iteration. This formula emphasizes that the environmental impact depends on how often the algorithm is used and how much CO_2e each use generates (Elmousalami et al. 2024a; Samanvitha et al. 2025). The number of times the algorithm is run is itself influenced by the number of people using the code and how frequently each user executes it (Elmousalami et al. 2024a; Ahmad et al. 2023). Therefore, this paper highlights the importance of considering the environmental footprint of algorithms alongside their performance when making choices in computational tasks as in Eq. (5).

$$E_{total} = (N_u \times T_u) \times E_t \tag{5}$$

The equation relates the CO_2 emissions of a computational system to the number of users and their computational activities where E_{total}: This represents the total amount of CO_2 emissions generated in grams (g) by the entire system (g). N_u: This signifies the total number of users interacting with the system. T_u: This denotes the computational time in hours per user. E_t: This represents the CO_2 emissions of each computational hour within the system. The equation itself suggests a linear relationship between these variables. It implies that the total CO_2 emissions (E_{total}) increase proportionally with the number of users (N_u) and the computational time per user (T_u). Additionally, the CO_2 emissions per trial (E_t) contribute directly to the overall emissions. This equation could be helpful for:

1. Estimating CO_2 footprint: By knowing the number of users, their computational demands, and the emissions per trial, researchers can estimate the total CO_2 footprint of the system.
2. Optimizing efficiency: By analyzing the equation, researchers can identify ways to reduce CO_2 emissions. This could involve strategies such as reducing the computational

time per user (T_u) or lowering the emissions per trial (E_t) through energy-efficient hardware or software optimization.

Figure 21 illustrates the average CO_{2e} emissions for each algorithm where Table 3 displayed environmental evaluation for each computational model. This bar chart depicts the varying environmental impact, measured in grams of CO_2 emissions per hour, incurred during the training process of machine learning algorithms. There is a clear distinction between algorithms based on their CO_2 footprint. Deep Neural Networks (DNNs) and RNN + LSTM algorithms, situated on the far right of the chart, exhibit the highest CO_2 emissions, exceeding 400 g per hour. This can be attributed to their intricate structures necessitating substantial computational power, delivered by data centres with potentially high energy demands. Conversely, algorithms such as DT and Linear/Logistic Regression, positioned furthest to the left, generate the lowest CO_2 emissions, falling below 100 g per hour due to their less complex nature, requiring minimal computational resources during training. As a result, the selection of a machine learning algorithm significantly influences its environmental impact. Opting for algorithms with lower computational demands, such as decision trees or linear regression models, can considerably reduce CO_2 emissions associated with the training process, promoting a more sustainable approach to artificial intelligence. This paper set 150 CO_2 grams per computational hour to define green algorithms that will be included in the final wind energy forecasting system.

Figure 21 was generated using the CodeCarbon Python library, which tracks and estimates the average CO_2 emissions produced by different machine learning algorithms during their training and prediction processes. Each bar in the chart represents the average CO_2 emissions (measured in grams) for the respective algorithm across multiple time horizons. Algorithms such as DNNs, XGBoost, and RNN + LSTM show significantly higher emissions compared to simpler models such as linear regression and decision trees. This analysis highlights the environmental cost associated with the computational intensity of each

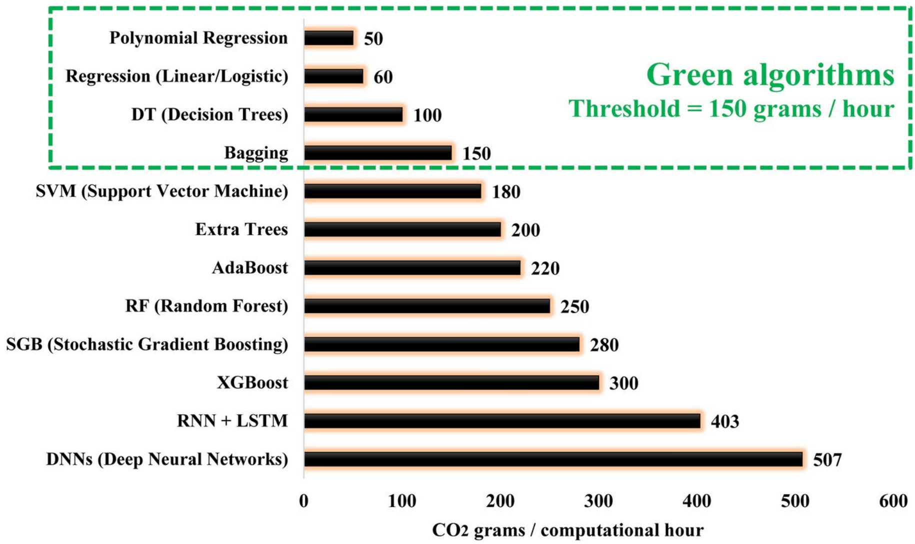


Fig. 21 Average CO_2 emissions per Computational hour (E_t)

Table 3 Environmental categorization for each model

Algorithm	CO_2 emission impact	Causes of CO_2 emissions
DNNs (deep neural networks)	High	Training requires significant computational power, on large server farms with high energy consumption (Rashid et al. 2024; Cruz et al. 2024)
RNN + LSTM	High	Similar to DNNs, it requires significant computational power for training (Rashid et al. 2024; Munyasya and Chileshe 2018)
XGBoost	High	Training can be computationally expensive and generally less demanding than DNNs or LSTMs (Tornede et al. 2023)
SGB (stochastic gradient boosting)	Medium	Similar to XGBoost, training requires moderate computational power (Verdecchia et al. 2023)
RF (Random Forest)	Medium	Training typically demands less computational power than DNNs and LSTMs (Rashid et al. 2024; Munyasya and Chileshe 2018)
AdaBoost	Medium	Similar to RF, training has moderate computational needs (Sev 2009)
Extra Trees	Medium	Similar to RF and AdaBoost, training is computationally moderate (Rashid et al. 2024; Cruz et al. 2024)
SVM (Support Vector Machine)	Medium	Training can be computationally expensive for large datasets, and generally less demanding than DNNs and LSTMs (Elmousalami et al. 2024a; Ahmad et al. 2023)
Bagging	Low = green algorithm	Computational cost depends on the base learner and number of models and typically falls in the medium range (Rashid et al. 2024; Munyasya and Chileshe 2018)
DT (Decision Trees)	Low = green algorithm	Training decision trees are usually less computationally expensive compared to other algorithms (Elmousalami et al. 2024a; Ahmad et al. 2023)
Regression (Linear/Logistic)	Low = green algorithm	These algorithms require relatively low computational power for training (Rashid et al. 2024; Cruz et al. 2024)
Polynomial Regression	Low = green algorithm	Similar to linear and logistic regression, training demands minimal computational resources(Elmousalami et al. 2024a; Ahmad et al. 2023)

algorithm, which is a key factor to consider when optimizing both model performance and sustainability in wind speed and power forecasting tasks (Table 3).

6.4 Sensitivity analysis

Sensitivity analysis in wind energy prediction evaluates the impact of individual predictors (e.g., wind speed, temperature, pressure) on the forecasting model's output. Systematic variation of these inputs helps identify the most influential factors that drive prediction accuracy. This process enhances model reliability and guides improvements in forecasting systems. Figure 22 presents the results of a sensitivity analysis conducted across different time scales (10 min, 30 min, 6 h, 24 h, and 36 h) for wind speed forecasting models. Each bar in the chart represents the F-score for different parameters (P_1 to P_7), illustrating the contribution of each input feature to the model's predictive performance at various time intervals. The F-scores are higher for certain parameters, such as P5 (atmospheric pressure) and P6 (month), especially at longer time scales such as 24 h and 36 h, indicating that these features significantly impact the model's performance in medium- and long-term predictions. This trend suggests that atmospheric pressure and monthly variations are more critical in predicting wind speed when forecasting further into the future. In contrast, the

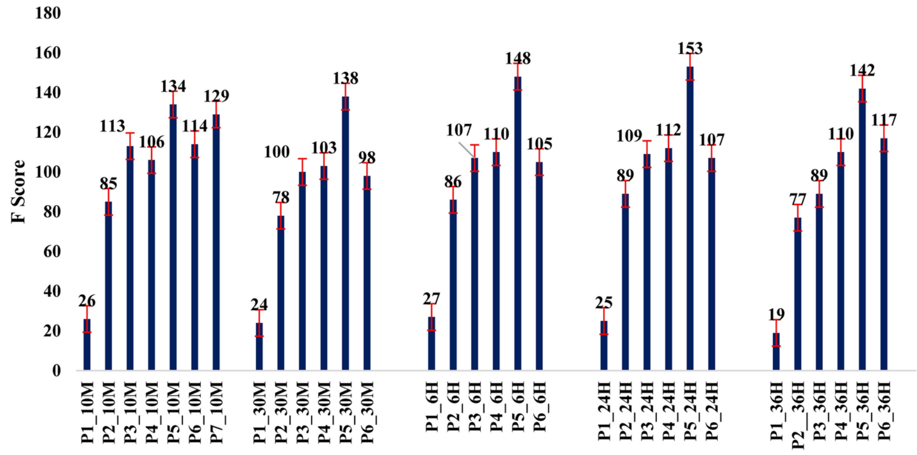


Fig. 22 Sensitivity analysis for WSP

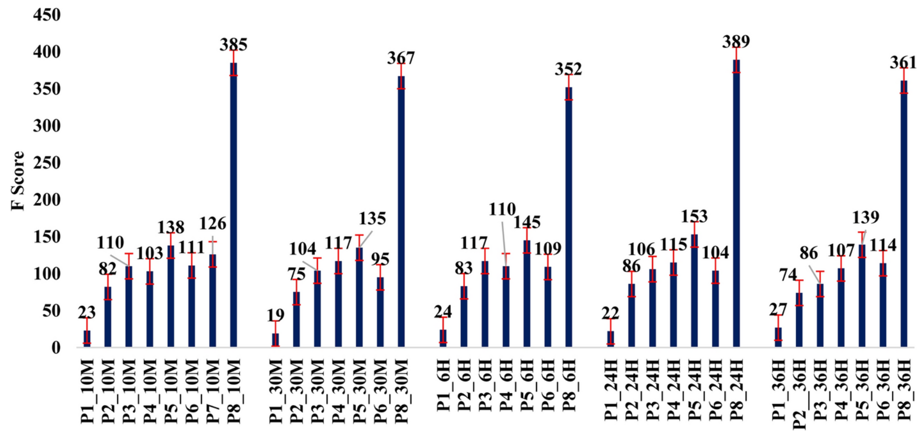


Fig. 23 Sensitivity analysis for WPP

importance of parameters such as P_1 (height) and P_2 (wind vane) fluctuates across different time scales, with their highest F-scores occurring at shorter intervals such as 10 min and 6 h. These features are more influential for very short-term predictions because immediate wind direction and the turbine's height affect short-term variations in wind speed.

Figure 23 illustrates a sensitivity analysis of various parameters affecting wind power forecasting, conducted across different time scales. The analysis shows that wind speed (P_8) has the most significant impact across all time scales, with F-scores peaking at 385 for the 10-min model and 389 for the 24-h model. Other parameters such as the hour (P_7) and atmospheric temperature (P_3) show considerable influence, though to a lesser extent compared to wind speed. The F-scores for these parameters are highest at shorter time scales and gradually reduce at longer ones. Parameters such as humidity (P_4), atmospheric pressure (P_5), and wind vane (P_2) have relatively lower F-scores, indicating a lesser impact on the forecasting models. This analysis provides valuable insights into the contribution of different meteorological factors in wind power prediction across multiple time horizons.

7 Key contributions and discussion

7.1 Sustainable AI-Driven Wind Energy Forecasting System (SAI-WEFS)

SAI-WEFS is an advanced forecasting tool that leverages artificial intelligence to predict wind energy generation while minimizing environmental and computational impacts. SAI-WEFS integrates sustainable AI practices to optimize energy forecasting across multiple time scales, contributing to the development of zero-carbon energy cities. The selection of predictive algorithms is based on forecasting precision and minimizing CO_2 emissions during computational processes (less than 150 CO_2 g/computational hour), promoting eco-friendly energy forecasting. SAI-WEFS is designed to enhance WPF and WSF to support a zero-carbon city's energy supply, aligning with deep decarbonization goals. The system begins with real-time data (RTD) inputs, which feed into decision tree (DT) models for WSF. The DT models operate at various time intervals: 10 min, 30 min, 6 h, 24 h, and 36 h. DT are selected due to low computational carbon emissions, their ability to handle large datasets, and their robustness in identifying patterns between wind-related variables and their corresponding outcomes. This multi-timescale forecasting ensures that both short-term fluctuations and longer-term trends in wind speed are accurately captured, providing reliable input for subsequent stages of energy planning as in Fig. 24.

Once the WSF results are obtained, the system transitions into the wind power forecasting (WPF) phase. The WPF process uses bagging techniques an ensemble machine learning method designed to improve the accuracy and stability of predictions by reducing variance. Bagging works by combining the outputs of multiple decision trees, thereby increasing the reliability of the wind power forecast at various time intervals (10 min, 30 min, 6 h, 24 h, and 36 h). This multi-layered forecasting structure allows the model to account for the dynamic and unpredictable nature of wind, leading to more accurate energy predictions. The use of Bagging in WPF is critical, as it helps smooth out forecast errors that could arise from extreme weather variability, ensuring that the energy supply predictions are accurate low computational carbon, and resilient to outliers and anomalies in wind patterns.

SAI-WEFS integrates WSF and WPF results to form a holistic forecasting system aimed at providing a continuous, accurate prediction of wind-based energy supply. This system feeds into the energy supply chain of a zero-carbon city, helping to maintain a carbon–neutral energy supply by minimizing dependency on fossil fuels. By predicting energy generation more precisely, the system reduces the need for backup fossil fuel energy sources, aligning with deep decarbonization strategies that seek to cut emissions by 80% or more by 2050 (Seto et al. 2021; Ramaswami et al. 2021). This holistic and multi-level forecasting system offers a sustainable solution for urban energy management, supporting the transition to clean, renewable energy systems in cities.

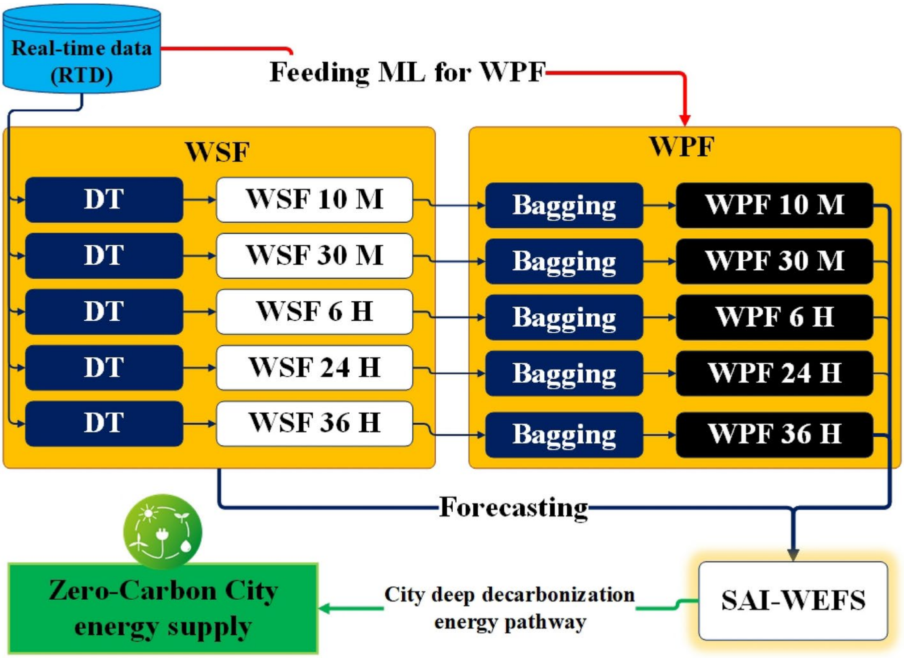
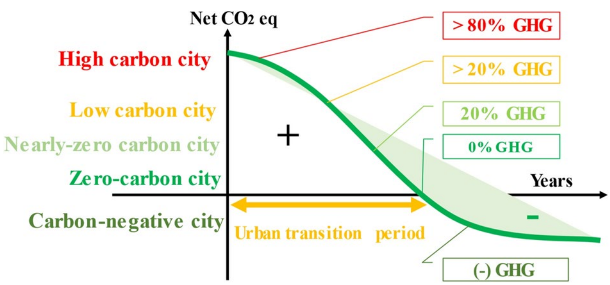


Fig. 24 Architecture of Sustainable AI-Driven Wind Energy Forecasting System (SAI-WEFS)

Fig. 25 Urban Carbon Transition Curve (UCTC)



7.2 Urban Energy Supply Decarbonization Framework (UESDF)

SAI-WEFS, UCTC, and UCEI are key pillars of UESDF. The UCTC depicted in Fig. 25 illustrates the progressive reduction of net CO_2 equivalent ($CO_{2\ eq}$) emissions in cities over time, marking the shift from high-carbon cities to carbon-negative cities. The curve identifies different stages of urban carbon reduction, beginning with high-carbon cities emitting more than 80% GHG and transitioning through low-carbon, nearly-zero carbons, and zero-carbon cities, ultimately reaching carbon-negative cities where GHG emissions are less than zero (net GHG absorption). The "Urban Transition Period" indicates the number of years needed to reach to zero-carbon city (Seto et al. 2021; Ramaswami et al. 2021; Elmousalami and Mohamed 2022). UCTC is highly relevant to SAI-WEFS, as wind energy forecasting has a critical impact on reducing urban carbon footprints by enabling efficient renewable energy integration. SAI-WEFS, through accurate and sustainable AI-based predictions, supports cities in transitioning along UCTC by optimizing wind energy generation, helping reduce reliance on carbon-intensive energy sources, and contributing to the shift toward zero-carbon and carbon-negative city statuses (Elmousalami and Mohamed 2022; Kılkış 2021; Becchio et al. 2016).

The UCEI is a metric designed to assess and compare the carbon footprint of urban areas relative to a predefined baseline. It quantifies the net carbon emissions produced within a city by considering both the emissions generated (e.g., from transportation, industry, and energy production) and the emissions absorbed (e.g., by green spaces and carbon capture systems). The UCEI is defined by the Eq. (6):

$$\text{UCEI} = \frac{\text{Urban Net } CO_{2\ eq}}{\text{Urban } CO_{2\ eq} \text{ baseline}} = \frac{CO_{2\ eq} \text{ produced } - CO_{2\ eq} \text{ absorbed}}{\text{Urban } CO_{2\ eq} \text{ baseline}} \tag{6}$$

In this equation, the numerator represents the difference between the total carbon dioxide equivalent ($CO_{2\ eq}$) produced and the amount absorbed within the urban area. The denominator, the urban $CO_{2\ eq}$ baseline, refers to a reference level of carbon emissions typically derived from historical data or industry standards. The resulting index provides a standardized measure to evaluate how effectively a city is reducing its net carbon emissions compared to its baseline, making it a valuable tool for tracking progress toward carbon neutrality and sustainability goals (Seto et al. 2021; Zhang et al. 2024b).

Figure 26 illustrates the UESDF, which integrates green wind energy decarbonization strategies to achieve net-zero carbon cities. Central to UESDF is the SAI-WEFS, which uses real-time computing (RTC) and real-time data (RTD) to forecast wind energy production accurately. These forecasts provide insights and analysis for managing electricity supply for smart and zero-energy cities. By optimizing wind energy production, SAI-WEFS ensures a steady and sustainable supply of renewable energy, helping to reduce urban carbon emissions. The integration of the Internet of Things (IoTs) and data collection agents within

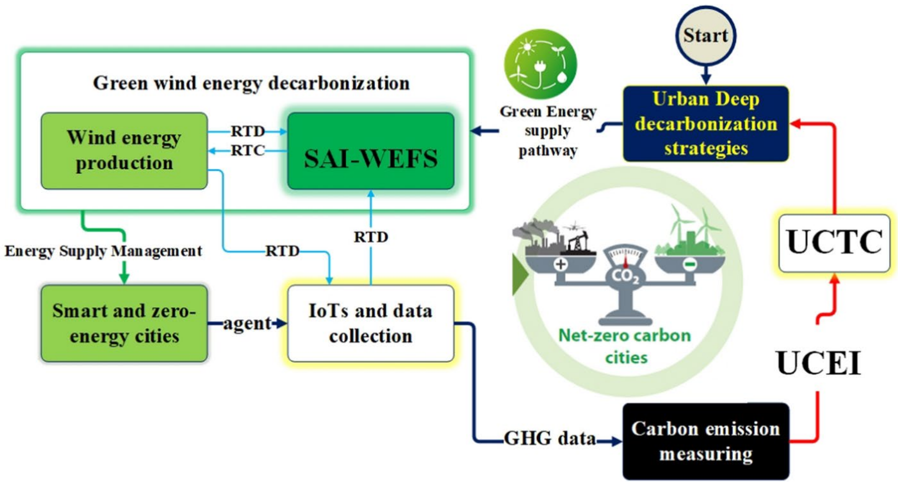


Fig. 26 Urban Energy Supply Decarbonization Framework (UESDF)

the framework further supports real-time monitoring and data-driven decision-making, enabling cities to manage their energy supply more efficiently.

The UCEI and the UCTC serve as performance metrics within the UESDF. UCEI is used to measure and track urban carbon emissions, providing a baseline for cities' emissions and enabling monitoring of progress towards decarbonization. UCTC, on the other hand, visualizes the urban transition from high-carbon to low- or zero-carbon cities, illustrating the reduction in GHG emissions over time. The integration of carbon emission measuring systems and GHG data collection, facilitated by IoTs, provides continuous feedback on urban decarbonization efforts. This data feedback supports urban deep decarbonization strategies, which are foundational to initiating the framework and driving the transition toward net-zero carbon cities, as visualized in the UCTC. Together, SAI-WEFS, UCEI, and UCTC offer a comprehensive approach to managing urban energy supply, forecasting, and carbon reduction.

7.3 Contribution to sustainability

The SAI-WEFS significantly advances sustainable energy management, directly contributing to the United Nations' Sustainable Development Goals (SDGs). By enhancing the precision of wind speed and power forecasts, SAI-WEFS optimizes wind farm operations, minimizes energy wastage, and facilitates the seamless integration of renewable energy into smart and zero-energy cities, thereby supporting SDG 7 (Affordable and Clean Energy). This optimization is crucial for balancing energy supply and demand, reducing reliance on fossil fuels, and promoting cleaner energy alternatives.

Moreover, SAI-WEFS's evaluation of CO_2 emissions associated with various algorithms aligns with SDG 13 (Climate Action), as it seeks to minimize the environmental footprint of computational processes. By integrating the UCEI and UCTC, the system provides valuable metrics for assessing and guiding urban decarbonization efforts. These tools enable city planners and policymakers to monitor progress, identify areas for improvement, and implement strategies that drive the transition toward sustainable, low-carbon urban environments. Collectively, these contributions underscore SAI-WEFS's role in advancing global sustainability initiatives and fostering resilient, eco-friendly communities (Table 4).

8 Conclusion

In conclusion, this study introduces the SAI-WEFS, which leverages ensemble machine learning algorithms to enhance the accuracy of wind speed and power predictions across various time horizons. The integration of wind speed forecasts into wind power predictions has been demonstrated to optimize renewable energy management, thereby supporting the development of smart, zero-carbon cities. Through sensitivity analysis, key predictors such as air pressure, wind vane, and humidity were identified as critical factors influencing forecasting accuracy.

The findings from this research offer actionable insights for industry practitioners and policymakers aiming to advance renewable energy integration and ensure grid stability. By adopting the SAI-WEFS framework, stakeholders can improve operational efficiency and contribute to the broader goal of sustainable urban development. Future research should

Table 4 SDGs and sustainable AI for wind energy prediction

SDGs	Contributions
	Sustainable AI for wind speed and power prediction directly contributes to this goal by: 1. Increasing the efficiency and accuracy of wind farm operation 2. Integrating more renewable energy sources into the grid 3. Reducing greenhouse gas emissions and fossil fuel reliance
	AI for wind prediction fosters innovation in the renewable energy sector It leads to: 1. Development of more advanced wind turbine technologies 2. Improved infrastructure for integrating renewable energy into the grid 3. Creation of new jobs in the clean energy sector
	AI for wind energy prediction improves infrastructure resilience and sustainability, contributing to the development of sustainable communities, smart and zero-carbon cities
	By improving wind energy prediction, AI helps to: 1. Reduce greenhouse gas emissions from the power sector 2. Mitigate climate change impacts 3. Promote a transition to a low-carbon economy
	AI for wind energy prediction facilitates knowledge transfer and skill development, encouraging collaboration and partnerships in sustainable project management

focus on integrating additional environmental variables and assessing the scalability of predictive models across diverse regions and climatic conditions to further enhance the robustness of wind energy forecasting systems.

The recommendations of the paper are as follows.

(1) The algorithms should be selected with a dual focus on maximizing forecast accuracy and minimizing CO_2 emissions, reflecting a sustainable AI methodology.
(2) Tree and ensemble models could produce higher accuracy and less CO_2 than single and deep learning algorithms. Tree-based models emit around 150 g of CO_2 per computational hour, significantly less than deep learning models, which emit up to 500 g.
(3) Integration of wind speed into the wind power forecasting model will increase predictive accuracy.
(4) The SAI-WEFS strengthens the UESDF.
(5) SAI-WEFS provides tools for calculating the UCEI and visualizing the UCTC, supporting efforts in urban energy decarbonization.

(6) Comparing several machine learning algorithms is very practical in selecting the optimal predictive algorithms.
(7) Sensitivity analysis is significant to explore the most significant predictors.

8.1 Limitation

A limitation of the current study is the wind power predictions were made for a single Gamesa G80-2.0 turbine. Additionally, the study does not account for the wake effect, a phenomenon where turbines positioned downwind experience reduced wind speed due to the interference caused by upstream turbines. This could affect the accuracy of power predictions when multiple turbines are involved, as the wake effect can lead to significant variations in wind flow and energy output between turbines. On the other hand, studying a single Gamesa G80-2.0 turbine offers several key benefits. First, it allows for a highly controlled environment where the complexities introduced by multiple turbines, such as the wake effect, can be excluded, leading to more precise insights into the performance of the algorithms. This focus enables a clearer evaluation of the relationship between meteorological conditions and wind power output without interference from external variables. Additionally, analysing a single turbine reduces computational complexity, facilitating a more detailed exploration of the forecasting methods and their environmental impacts, which can then serve as a foundation for scaling the study to larger wind farms.

The lack of comparisons with previous studies in the results is due to the uniqueness of the case study and dataset. The wind speed and power data were collected specifically from Gamesa G80-2.0 turbines at the Gabal El-Zayt wind farm, with meteorological conditions unique to this location. These specific factors, combined with the tailored algorithms and forecasting time horizons used, make direct comparisons with prior work difficult, as other studies often involve different turbine models, geographic settings, or meteorological inputs. This uniqueness limits the applicability of existing benchmarks, thus explaining the absence of comparative results in this study.

8.2 Future research

Future research should explicitly address the wake effect when predicting wind speed and power for wind farms with multiple turbines. By incorporating models that simulate turbine interactions and wake dynamics, predictions can be refined to account for the impact of upstream turbines on downstream ones. Moreover, future studies should extend the forecasting system to cover the entire wind farm, considering each turbine's position and operational conditions. This research direction will enhance the model's accuracy for large-scale energy prediction and support more precise decision-making for wind farm management and optimization.

Future research should address the limitations posed by the uniqueness of this case study by conducting comparative analyses using more generalized datasets from diverse geographic locations and turbine models. Expanding the study to include different wind farms, varying meteorological conditions, and alternative turbine technologies would allow for benchmarking the SAI-WEFS against other studies. Additionally, exploring the performance of the system across different climates and integrating data from hybrid renewable energy sources could provide a broader validation of its predictive capabilities. Incorporating standardized evaluation frameworks and collaborating with international research initiatives could further enhance the generalizability and applicability of the findings, paving the way for more robust comparisons in future studies.

Future research should focus on minimizing the decline in predictive accuracy over longer time horizons by improving model robustness and addressing the increasing uncertainty inherent in extended forecasts. This could be achieved by integrating advanced ensemble learning techniques with hybrid models that combine machine learning (ML) and deep learning (DL) approaches. Additionally, incorporating real-time data assimilation, where live meteorological inputs continuously refine the model, could help reduce deviations in long-term predictions. Exploring the use of transfer learning, where knowledge from short-term forecasts is leveraged to enhance long-term predictions and developing uncertainty quantification methods may also improve forecast reliability over extended periods.

Acknowledgements The collected data of metrological data and the actual measurements of wind speed and wind power at Gabal El-Zayt station (200 MW) have been provided by the New and Renewable Energy Authority (NREA) in Egypt. Special thanks to Engineer [Hazem Ahmed Abd Elmaksoud] for helping and providing data about Gabal El-Zayt station (200 MW).

Author contributions Haytham Elmousalami led the conceptualization, methodology development, data collection, and Python code implementation and was the primary author responsible for drafting, visualizing, and writing the manuscript. Aljawharah A. Alnaser contributed to the conceptualization of sustainable smart cities and provided critical revisions and improvements to the manuscript. Felix Kin Peng Hui reviewed the paper and offered practical insights, enhancing its relevance and clarity. All authors have read and approved the final version of the manuscript.

Funding Open Access funding enabled and organized by CAUL and its Member Institutions
The authors extend their appreciation to the Researchers Supporting Project number (RSPD2025R590), King Saud University, Riyadh, Saudi Arabia.

Data availability The data is available in the following repository: https://github.com/HaythamElmousalami/Wind-Energy-and-Machine-learning.

Declarations

Conflict of interest There is no conflict of interest among the authors.

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