

Article

Empowering Wind Energy Output Optimization: Comparative Assessment of Hybrid Artificial Intelligence Models Towards Wind Speed Forecasting Accuracy

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Abstract

Wind power forecasting is essential for the reliable and efficient operation of wind farms based on power grids, which is significantly important for stakeholders like wind farm owners, power pools, and power traders. Wind power prediction is also crucial for optimal power dispatch, grid security, and minimizing generation curtailment at wind farms. Hence, an accurate methodology for the power production of wind farms is needed for identifying long-term operational performance, failure detection, and ensuring grid integration. The present study proposes a hybrid machine learning (ML) approach that combines the strengths of random forest regression (RFR), artificial neural network (ANN), and support vector regression (SVR), using linear regression (LR) as a meta-model for wind speed forecasting. This modeling approach was trained, validated, and tested on 87,600 hourly data points across 10 variables from high-wind potential sites in the Kingdom of Saudi Arabia: Damat Al Jandal, Taif, Abha, East Coast, and Red Sea. The key findings suggest that the hybrid RFR + ANN + SVR model performed better than individual models, including the simple persistence model, achieving R^2 scores up to 95.3 in testing, with train-test performance loss of less than 5% across all scenarios. The mean bias error (MBE) stayed within ± 0.17 m/s, and the relative root mean square error (RRMSE) stayed below 15%. The hybrid model outperformed the metric-site standalone models and persistence model. Through feature importance analysis, this study also finds that temperature, relative humidity, and cyclical time-encoded features are the most important inputs. For offshore sites, thermal features like pressure and dew point were found to be more important. Due to its demonstrated superior performance across metric-site combinations, this hybrid framework is adaptable to other wind regions with intermittent renewables, with implications for reliable renewable energy integration and grid load stability.

Keywords: wind energy forecasting; artificial intelligence; random forest regression; sensitivity and adaptability analyses; renewable energy



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1. Introduction

The global shift towards low-carbon and sustainable energy systems has made renewable energy a fundamental element for present and future energy projects. It is projected that by 2040, energy from renewables will be the largest source of generated electricity [1]. However, currently, the generation capacity of renewable energy technologies is not enough to meet global power demands. Any natural resource that can be transformed into a clean form of useful energy, such as solar energy in the form of heat and light, hydro, biomass, and wind, among other resources, is considered a renewable energy source. Among renewables, wind energy has proven itself to be a more feasible system due to its comparative cost-effectiveness and sustainability [2–4]. The Kingdom of Saudi Arabia (KSA), in its efforts to reduce dependency on fossil fuels, has set an agenda to increase its renewable power generation capacity to 50% by 2030 [5]. KSA also launched a wind energy program in 2018, inspired by its high wind energy potential across diverse sites within the Kingdom. According to a study by AlQdah et al., the long beaches along the coastlines can produce up to 200 gigawatts, or more, of wind power at a capacity factor of 32.5% [6].

Accurate wind speed prediction is a major necessity for the dispatching and economic scheduling of wind power [7] in order to reduce the overreliance on fossil fuels, enhance the integration of wind power into existing power infrastructure, and optimize power production, especially in regions with massive wind potential like KSA. Machine learning (ML) methods have gained popularity in recent times when it comes to the accurate prediction of wind speed [8]. But due to its intermittent nature, which is caused by its dependence on certain meteorological factors (atmospheric conditions) that are difficult to predict, the traditional methods have become less efficient in making high-precision predictions.

Before ML models emerged, statistical models were used to make predictions. The deep learning model (DLM), for instance, has gained attention as a wind speed prediction tool due to its ability to handle large datasets with greater precision [9,10]. However, all classical models (statistical, ML, and DLM) have their individual limitations, and this has further urged researchers to explore the combination of these individual models into hybrids, leveraging their individual strengths to make high-precision forecasts [11]. A study by Shen et al. showed greater stability and higher precision for hybrid models in wind speed prediction [12]. While recent advances have often focused on deep learning models like TCN, TFT, LSTM, transformer-based, and informer-based, these are often associated with increased computational complexity and require larger training data and computationally heavy hyperparameter optimization [13].

In this study, we propose a novel ensemble (hybrid) ML approach to improve wind speed prediction accuracy in five hot zones in KSA—both onshore and offshore. A key innovation in this work is the incorporation of cyclical time encoding, using time-related features such as hour, day, and month which influence wind speed data observation but are often treated as linear variables, failing to account for their cyclical nature. From a temporal perspective, moving from 23:00 to 00:00 represents a one-hour change that can significantly impact wind behavior. Conventional models might incorrectly interpret these as distant values, whereas they are actually adjacent points in a continuous cycle. This problem is resolved by transforming time-based features into sinusoidal and cosine components. The proposed hybrid framework integrates ANN, SVR, and RFR as a DR meta-model to minimize model-specific biases. This framework is validated across five different meteorological wind-resource regions. The hybridization of ANN–SVR–RFR and LR as a meta-model has not been reported yet within the body of the literature. The proposed hybrid architecture contributes a heterogeneous, meteorologically aware stacking framework that improves robustness through complementary learning and cyclical

temporal representation. An overview of existing investigations on data-driven wind power forecasting is highlighted in Table 1.

Table 1. Summary of related works in data-driven wind power forecasting.

Study	ML Models Employed	Data Characteristics (DP = Data Period, LOC = Location, SO = Source, RES = Resolution)	Performance Metrics	Hybrid Model Comparison	CTE
[14]	ANNs, RNNs, CNN, LSTM Hybrid: ANN–RNN–CNN–LSTM	DP: 1 January–31 December 2018 SO: SCADA database, NASA LOC: Northwest part of Turkey	R^2 , MAE, MSE, RMSE	LSTM outperformed other models; $R^2 = 0.9574$, MAE = 0.0209, MSE = 0.0038, and RMSE = 0.0614.	No
[15]	RFR, SVR, LASSO, kNN, xGBoost	RES: Hourly DP: 5 years LOC: Turkey (Nigde, Cesme, Mamak, Bozcaada, and Silivri)	R^2 , MAE, RMSE	RF is the best algorithm with $R^2 = 0.995$, and MAE = 7.048.	No
[16]	RFR, ANN, DNN, XGB	DP: 2018–2019	MAPE, RMSE	XGB model with MAPE = 26.7% and RMSE = 412 MW. ANN with MAPE = 13.6% and RMSE = 6481 MW was best for daily sums.	No
[17]	RFR, GBM, kNN	SO: SCADA data DP: 1 year	MAE, MSE, MAPE, RMSE, R^2	GBM with a MAE = 0.0277, MAPE = 0.3310, RMSE = 0.0672, MSE = 0.0045, and $R^2 = 0.9651$	No
[18]	RFR, GBR, XGB	SO: ECMWF		Both RFR and XGB outperform SVR, but GBR falls slightly behind.	No
[19]	kNN, RFR, SVR, LR.	SO: NASA Power	R^2	The proposed hybrid model, combining KNN, SVR, RF, and LR, achieved training $R^2 = 0.99$ and testing = 0.94.	No
[20]	DTR, GBR, RFR, SVR, LR	SO: Weather Station LO: Saudi Arabia (Makkah) DP: 1 January 2015, to 31 July 2018	MSE, R^2 , RMSE	DTR achieved $R^2 = 0.994$, MAE = 0.025, MSE = 0.273, and RMSE = 0.522.	No
[22]	ARIMA, RBF–NN, Elman–NN, RVM, LSTM	LOC: Spain (Sotavento) DP: 1 January 2020, to 28 February 2021.	APE, MAPE, RSME, PCC	Proposed model improved by 52.84% compared to the standalone models.	No

Table 1. Cont.

Study	ML Models Employed	Data Characteristics (DP = Data Period, LOC = Location, SO = Source, RES = Resolution)	Performance Metrics	Hybrid Model Comparison	CTE
[21]	LGB, GPR	LOC: USA DP: 1 January 2013 to 1 January 2014 RES: Hourly	R^2 , RMSE, MAPE	Hybrid LGB–GPR outperformed SVR, LR, RF, ANN, LSTM, LGB, and GPR with an R^2 of 0.954.	No
[23]	RF, SVM, BP, LSTM, GRU, BiLSTM, VMD–CNN–GRU, EEMD–Tent–ISSA–LSSVM, LOFVT–INGO–OVMD–LSSVR	DP: 1 January 2019 to 31 December 2020 RES: 15 min	R^2 , MSE, MAE, MAPE	The proposed LOFVT–INGO–OVMD–LSSVR achieved $R^2 = 0.9998$, MSE = 0.0244, MAE = 0.1073, and MAPE = 0.3587.	No
[24]	Hybrid: VMD + LSTM	LOC: KSA DP: 2017–2019 RES: Hourly SO: NSRDB	MAE, RMSE, MAPE, FS	FS compared to baseline models: MAE: 61% and 74% RMSE: 64% and 72% MAPE: 59% and 68%	Partially
[25]	ESN, Persistence Forecasting, ARIMA, FRK	LOC: KSA (Gulf of Aqaba) DP: 2013–2016 RES: Hourly SO: Weather Research and Forecasting model (WRF); meteorological mast data	MSE	Proposed ESN achieved 11% improvement in 2 h-ahead forecasted power. 9% improvement over ARIMA; 11% improvement over persistence.	No
[26]	ANN	LOC: KSA (Qaisumah) DP: 1970–1982 RES: Hourly	MSE, MAPE	No comparative performance analysis reported.	No
[27]	CNN, MLP, SVM, GNB	LOC: KSA (Yanbu) RES: Hourly (2 years) SO: Weather Online service	MAE, Test Accuracy	N/A	No
[28]	ANNs, Feed-forward neural network model (standalone)	LOC: KSA SO: KACARE and meteorological stations	RMSE	60–40% split achieved the lowest RMSE (0.4262) and highest R^2 of 0.9798.	No
[29]	kNN, RFR, SVR, Holt–Winters Method; ARIMA	LOC: KSA (Yanbu) DP: 1970–1982 RES: Hourly	MAPE, sMAPE, MAE, MASE	SVR and RF outperformed kNN; ML algorithms outperformed statistical methods (Holt–Winters, ARIMA).	No

Table 1. Cont.

Study	ML Models Employed	Data Characteristics (DP = Data Period, LOC = Location, SO = Source, RES = Resolution)	Performance Metrics	Hybrid Model Comparison	CTE
[30]	ANNs, Feed-forward neural network model, SVM, RFR	LOC: KSA (Jeddah, Riyadh, Taif, Afif) DP: May 2013 to July 2016 RES: Hourly SO: KACARE	RMSE, R ²	RFR (RMSE = 0.5543) performed slightly better than ANN (RMSE = 0.6109) and others.	No
[31]	Hybrid model: 1D CNN+ BiLSTM	LOC: KSA DP: March 2017 to March 2018 RES: 10 min SO: Wind Data Station	MAE, MSE, MAPE	CNN-BLSTM cuts errors by ~20–32% vs. baseline.	No
[32]	Hybrid: WPD + SAM + BiLSTM; LSTM, BiLSTM, TCN	LOC: KSA (Al-Jouf region) DP: 1 January 2018–30 December 2022 RES: Hourly Source: KAPSARC	MAE, RMSE, R ²	WPD-SAM-BiLSTM model outperformed 27 other models, including individual DL models and hybrid models with different decomposition methods.	No
This Study	Base Models; RFR, ANN, SVR Hybrid Model; RFR-ANN-SVR- LR	LOC: KSA (Damat Al Jandal, Abha, Taif, Offshore East Coast, Offshore Red Sea) DP: 1 January 2023–31 December 2023 RES: Hourly SO: NASA Power	MAE, RMSE, MBE, RRMSE, MAPE, R ²	Proposed RFR-ANN-SVR-LR model maintained near-zero bias (MBE $\pm$ 0.07 m/s) and low RRMSE (<12.5%) across all locations.	Yes

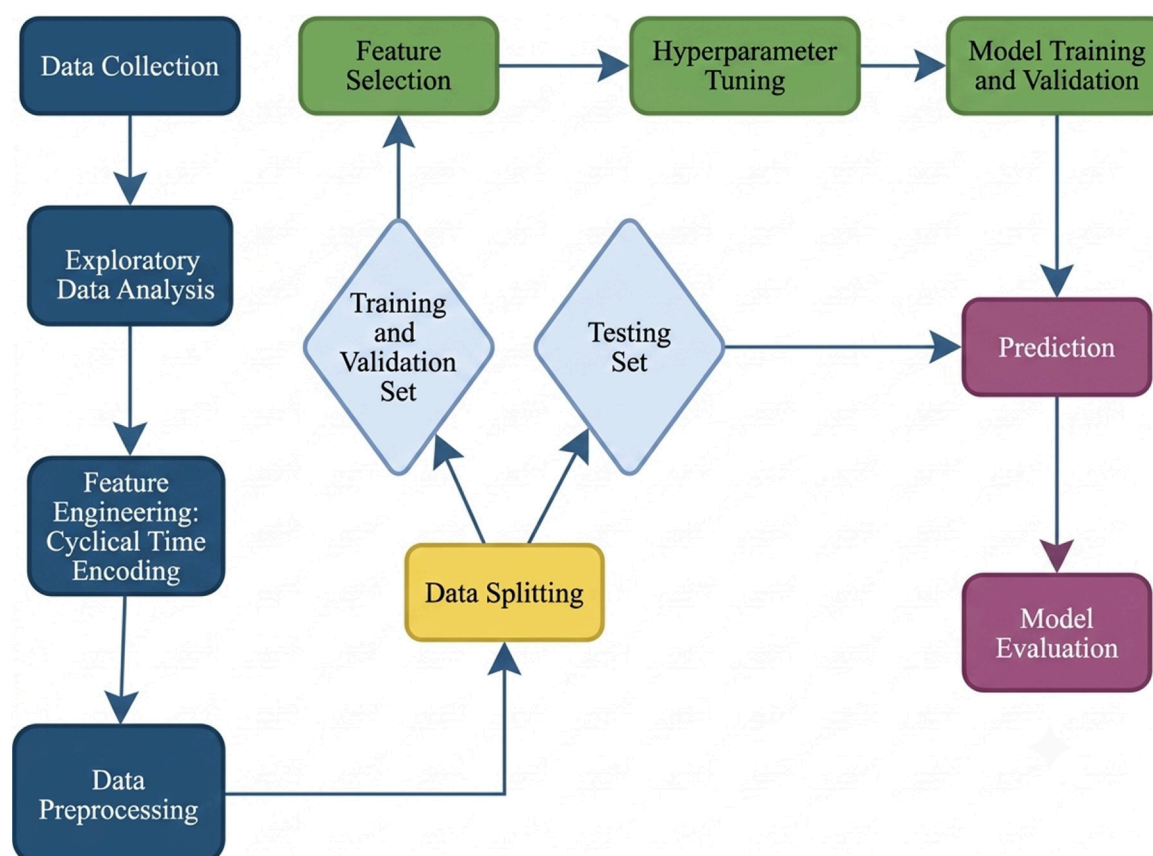
2. Research Methodology

This study identified five high-potential wind energy project sites in KSA through extensive research (see Table 2). A thorough assessment of these locations was conducted to evaluate their wind energy potential, including geographic and meteorological characteristics. The present study involved data collection, data preprocessing, and data analysis to determine tendencies in wind speed datasets for the selected sites. In order to achieve the required results, data preprocessing was carried out before modeling. Additionally, temporal features such as month, hour, and day were represented in their cyclical nature with the help of the Cyclical Trigonometric Encoding (CTE) technique. The data were categorized into three datasets: one each for training (80%), validation (10%), and testing (10%). The most useful variables for the ML model were separated with the help of feature selection. Hyperparameter tuning was employed to identify the optimal hyperparameters for each model. From here, model training and validation were carried out, followed by evaluation according to six key metrics. Figure 1 shows the workflow of the methodology used for the present study.

Table 2. Geographical overview of selected sites.

Site	Type	Latitude (°N)	Longitude (°E)	Altitude (m)	Criteria	Reference
Damat Al-Jandal	Onshore	29.98	39.70	~622	Hosts the largest onshore wind farm in Saudi Arabia	ACWA Power, n.d
Taif	Onshore	21.27	40.42	~1674	High-potential region	ACWA Power, n.d.; [33]
Abha	Onshore	18.25	42.50	~2230	High long-term wind speed trend	[34]
East Coast	Offshore	~26.00	~50.00	~0	Offshore wind energy potential	[35]
Red Sea	Offshore	~23.50	~38.00	~0	Offshore zone with untapped wind resources	[36]

Source: World topographic map.

**Figure 1.** Flowchart of methodology of present study.

2.1. Meteorological Assessment

KSA is known globally for its vast fossil fuel reserves. This enables them to produce energy at lower rates to meet their demand [37]. However, the nation's vision of diversifying its energy supply has led to numerous research studies in the renewable energy space, especially in wind energy [38]. Mas'ud et al. [37] show potential wind sites in western KSA around areas like Al Bahah, Taif, and the Red Sea coastline. These regions have productivity in the summer season. Based on their model projections, it can be seen that the wind energy will remain feasible into the mid-21st century and therefore will be a great contributor in the nation's energy diversification efforts [33].

Mean wind speed distribution in KSA, like any other place, varies across regions as a result of geographical locations and seasonal parameters. Salah et al. [38] show a granular examination of wind power potential in KSA, using data from 12 meteorological stations to analyze site-specific feasibility. Important wind parameters such as Weibull parameters, power density, and wind speed distribution were estimated at heights of 10 m and 100 m using several estimation approaches including least square, moment, and maximum likelihood to determine energy production [39].

Baseer et al. [33] conducted a wind resource assessment in Jubail (the largest industrial city in KSA and the Middle East region), using measured wind speed data at three different heights (10, 50, and 90 m) from the years 2008–2012. The results indicated promising mean wind speeds of 3.34, 4.79, and 5.35 m/s, respectively. This further shows that wind speeds greater than 3.5 m/s are 75% available at much higher elevations. Figure 2 shows a wind resource map, illustrating the average mean wind speed distribution at 100 m above ground level in KSA [40]. Within Figure 2, there seems to be a heightened wind potential along the eastern and western coastal regions, as well as in specific areas of elevated wind speed located in the central-western and northwestern areas of the Kingdom.

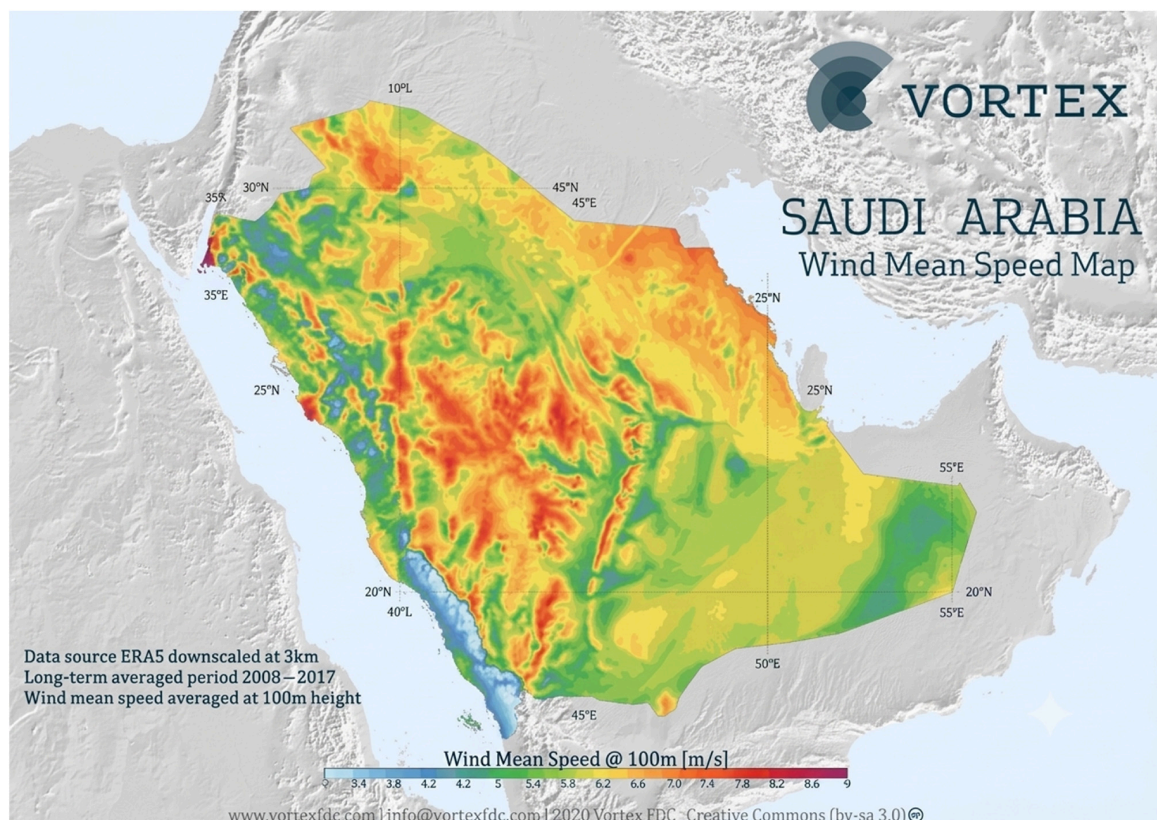


Figure 2. Wind resource map of KSA. This figure is reprinted from VORTEX FDC, which is a publicly accessible repository, and it is openly available in Ref. [41].

2.2. Site Selection

The present study sites were chosen because they had documented wind energy potential, were important for development, and were located in diverse parts of the Kingdom. The selection process used information from peer-reviewed articles, industry reports, and project developers within the Kingdom to guarantee that both onshore and offshore locations were included so as to demonstrate how the Kingdom's wind resources differ. Table 2 presents the geographical data overview of the selected sites.

Damat Al-Jandal, which has KSA's largest operational wind farm at present, with a capacity of 415 MW, is one of the onshore sites selected. It is also the standard for utility-scale wind integration. ACWA POWER, a leading renewable energy developer in the Kingdom, has designated the Taif and Yanbu regions as high-wind-potential sites because they have stable wind patterns and are good for business. The East Coast and Red Sea zones were added because they show great potential for offshore development [42]. These maritime locations, although less examined, are essential for evaluating coastal wind dynamics and prospective offshore wind development in accordance with Saudi Arabia's Vision 2030 objectives for renewable diversification [42,43]. Figure 3 shows where the five case study locations are along Saudi Arabia's main wind corridors. These are along the eastern and Red seacoasts, Taif and Abha in the southwest, and Damat Al-Jandal in the north.

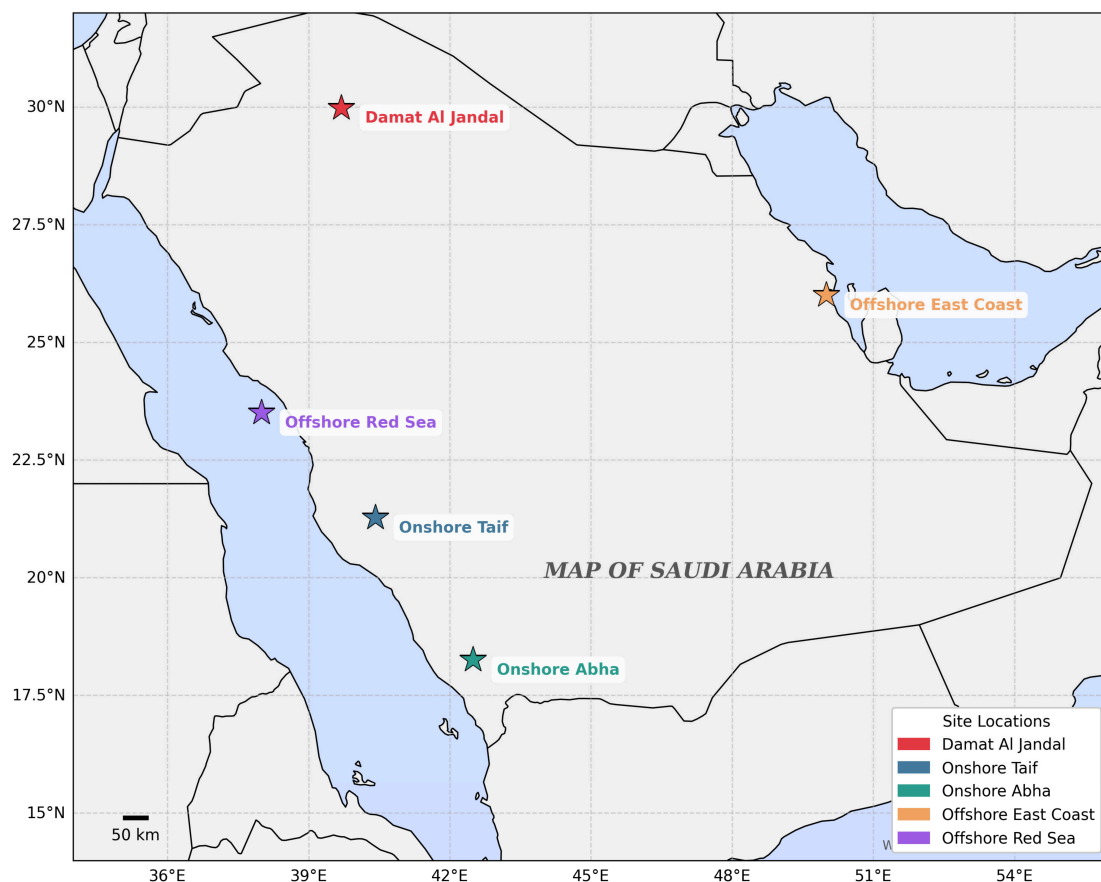


Figure 3. Map of selected wind sites in Saudi Arabia. This base map was adapted from the World Atlas online geographic database, and it is openly available in Ref. [44].

The sites presented in Figure 3 were designated as case study data points for the training, validation, and testing of the proposed hybrid machine learning methodology for precise wind speed forecasting. The selected sites have a wide range of topographies, from dry inland areas to coastal areas, ensuring that the model has full spatial coverage and captures changes in wind patterns that are important for strong model training. Figure 4 shows a comparison of the wind speed at 50 m above ground level at the five chosen sites.

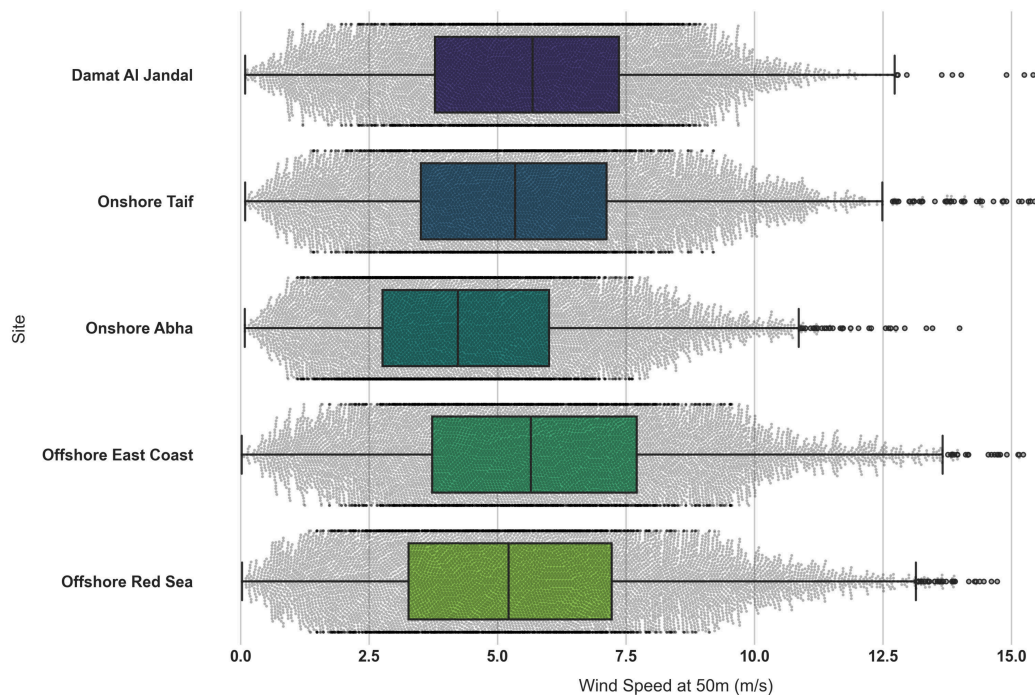


Figure 4. Wind speed distribution across selected sites.

2.2.1. Damat Al-Jandal

Damat Al-Jandal, which is in the north of KSA, has strong and steady winds, especially in the summer. The region's flat land and sparse vegetation help keep the wind steady, which makes wind turbines more effective. It is home to the Kingdom's first working 415 MW onshore wind farm project. According to the Global Wind Atlas, the average annual wind speeds at heights of 50 m, 100 m, 150 m, and 200 m are 4.8 m/s, 5.9 m/s, 6.95 m/s, and 7.79 m/s, respectively [34].

2.2.2. Taif

Taif is situated in the western mountains of KSA at an altitude of about 1674 m. It has its own wind patterns because of its high elevation and breezes from the Red Sea. Average wind speed is reported in the range of 5.5 to 6.5 m/s at 100 m above ground level, with stronger gusts during seasonal changes [34]. Because the area is close to cities and factories like Jeddah, energy demand is in line with the area's needs. The cooler climate also helps reduce thermal stress on turbines. However, owing to terrain complexity, micro-siting is required to lessen wake effects [34].

2.2.3. Abha

Abha, which lies in the southwest of the Kingdom at an elevation of about 2230 m above sea level, is one of the highest-altitude wind energy sites in the Kingdom. It is located in a specific wind regime that is affected by seasonal monsoon patterns and the mountainous Asir region. Wind speeds in Abha are more stable and moderately strong, averaging between 5.0 and 6.0 m/s at hub height [39]. This can be attributed to orographic acceleration effects. The aforementioned characteristics make operating conditions cooler, which can make the turbine work more efficiently and last longer by reducing the thermal degradation of its parts [45].

2.2.4. Offshore Red Sea

The Red Sea zone has stronger and more consistent winds (6.0–7.5 m/s) because of the way the winds funnel through coastal valleys [35]. It is strategically important

for renewable energy focused on exports, because it is close to NEOM and the Green Hydrogen Project.

2.2.5. Offshore East Coast

Based on an assessment conducted in a research output by KARPSAC, there is great potential for wind energy development off the east coast of the Kingdom, which lies within latitude 26.00° N and longitude 50.00° E. The area has not yet been well explored. The winds and sea breezes therein are more stable than those in the deserts or mountains of the Kingdom. However, the previous studies suggest that mean wind velocities at an altitude of 100 m above sea level vary from 6.0 to 7.5 m/s [37].

2.3. Meteorological Data Collection and Characteristics

The present study employs meteorological data from the NASA POWER repository, which provides advanced, satellite-derived atmospheric variables specifically validated for clean energy applications, to predict hourly wind speeds at five (5) critical locations in KSA. The dataset consists of 8760 hourly observations (totaling 87,600 data points across 10 process variables) from 1 January 2023 to 31 December 2023. Important process variables include temperature, relative humidity, surface pressure, wind direction, dew point, and wind speed. The selection of these variables is consistent with established wind energy prediction frameworks reported in the literature [19]. Table 3 presents metadata and variable descriptions of meteorological data relevant to the present study.

Table 3. Description of meteorological data.

Feature	Description	Unit
yr	Year	-
mo	Month	-
dy	Day	-
hr	Hour	hr
temp	Temperature at 2 m	$^{\circ}\text{C}$
rh	Relative Humidity at 2 m	%
press	Surface Pressure	kPa
wdrxn	Wind Direction at 10 m	Degrees
dpoint	Dew/Frost Point	$^{\circ}\text{C}$
wspd	Wind Speed at 50 m	m/s

2.4. Simulation Environment

The model runs for this study were executed on an advanced desktop workstation that could handle building machine learning models, tuning hyperparameters, and training them. The base clock speed is 2.40 GHz, and it has an i5 processor with 10 cores and 16 threads. Table 4 lists all the details of the computational setup that was used in this study.

Table 4. Hardware and software environment for model implementation.

Component	Specification
Processor	Intel(R) Core i5-14450HX @ 2.40 GHz
Installed RAM	16.0 GB (15.7 GB usable)
System Type	64-bit operating system, x64-based processor
Operating System	Windows 11 Pro

Table 4. *Cont.*

Component	Specification
OS Version	24H2 (Build 26100.3775)
Language	Python 3
Environment	Visual Studio Code, Version 1.99.0

2.5. Data Preprocessing and Splitting

To make certain that feature scaling was consistent and to improve model performance [46], the source data were scaled so that the mean value was zero and the standard deviation was one (standardization). The technique described was determined to reduce the effect of different feature scales on machine learning algorithms. To prevent data leakage, the scaler was only applied to the training set. Similar transformation parameters were used for the validation and test sets to make sure that the model evaluation was the same [47]. To be certain that the results are the same, a fixed random state of 42 was used to split the dataset into training (80%), validation (10%), and test (10%) sets. The target ‘wspd’ variable was shifted by one time step—variables observed at time t were used to predict wind speed at time $t + 1$, corresponding to a one-hour-ahead forecasting horizon (see Figure S1 in the Supplementary Material).

2.6. ML Algorithms

The hybrid framework was built on the RFR, ANN, and SVR models. These models were chosen because they work well with wind speed patterns [48]. We used a full grid search to find the best hyperparameters, which took about 36 h on our 10-core, 16-thread workstation (see Table 4). RFR uses bootstrap aggregation to reduce variance and 50 decision trees to avoid overfitting. This method is particularly effective for elucidating intricate feature interactions within meteorological data [49]. The ANN architecture employs a complex structure (256–128–64–32–16 neurons) with ReLU activation and Adam optimization (learning rate = 0.001), enabling hierarchical feature learning from the normalized input data; this method has been validated in recent wind forecasting research [48]. In our initial analysis, we found that SVR implementation uses an RBF kernel ($C = 10$, $\gamma = 1$) to map features into a high-dimensional space. Table 5 presents information about the ML algorithms that were used in this study.

Table 5. Machine learning frameworks employed in this study.

Ref.	ML Algorithms	Brief Description
[50]	Random Forest Regression	Uses multiple decision trees that work together to make more accurate predictions by averaging their results
[51]	Artificial Neural Network (ANN)	Mimics how the human brain works with connected layers that learn patterns from data
[52]	Support Vector Regression (SVR)	Finds the best-fitting line while allowing some error tolerance for complex data patterns
[53]	Stacking Model	Combines multiple models by using another model to learn how to best blend their predictions
[53]	Meta-Model	A higher-level model that learns how to best combine predictions from multiple base models

2.7. Hyperparameter Optimization

This study considered extreme hyperparameters for the grid search by consulting established practices in ML relevant to our dataset, accounting for computational limitations, and drawing on insights from similar studies conducted. The grid search evaluated 10,500 unique parameter combinations (fits) across all models using five-fold cross-validation (MSE scoring). For the ANN, this included testing various layer sizes, regularization strengths, activation functions (ReLU/tanh/logistic), and optimizer configurations (β_1 , β_2). The SVR search spanned multiple kernels with penalty parameters and kernel coefficients. Base models produced intermediate predictions for fresh data, where the meta-tree complexity and sampling tactics were the focus of the RFR optimization. Given the high degree of variability in our wind speed datasets, this procedure, albeit computationally demanding, was essential to optimizing model performance. This study employs distinct, model-specific techniques to identify the most informative meteorological variables for each base model, acknowledging that different algorithms benefit from tailored input feature sets [54]. The three base models and their hyperparameters, which were optimized using a thorough grid search, are presented in Table 6.

Table 6. Base machine learning models and optimized hyperparameters.

Model	Hyperparameter	Optimization Range	Optimized Parameters	Feature Selection	Ref.
ANN	Hidden layer sizes	(256,128), (256,128,64), (512,256), (512,256,128), (128,64,32,16), (64,32,16)	Hidden layer sizes = (256,128,64,32,16), alpha = 0.0001, learning rate = 0.001	Post hoc Permutation Importance Analysis	[55,56]
	Alpha (L2 regularization)	0.0001, 0.0005, 0.001, 0.005, 0.01			
	Learning rate	0.0001, 0.001, 0.01			
	Activation function	'relu', 'tanh', 'logistic'			
	Batch size	32, 64, 128			
	Beta 1 (Adam)	0.8, 0.9, 0.99			
	Beta 2 (Adam)	0.9, 0.999, 0.9999			
SVR	Kernel	'rbf', 'linear', 'poly', 'sigmoid'	C = 10, gamma = 1, kernel = 'rbf', epsilon = 0.01	Recursive Feature Elimination	[57,58]
	C (regularization)	0.1, 1, 10, 100, 1000			
	Gamma	'scale', 'auto', 0.001, 0.01, 0.1, 1, 10			
	Epsilon	0.001, 0.01, 0.1, 0.5, 1			
	Degree (poly kernel)	2, 3, 4			
RFR	Number of estimators (RF)	50, 100, 200, 300	estimators = 50, random state = 42	Modified Recursive Feature Elimination	[59,60]
	Max depth	None, 10, 20, 30, 50			
	Min samples split	2, 5, 10			
	Min samples leaf	1, 2, 4			
	Max features	'sqrt', 'log2', 0.3, 0.5			
	Number of estimators (Bagging)	10, 20, 50			
	Max samples	0.5, 0.8, 1.0			

2.8. Proposed Hybrid Model

In the present study, we propose a novel ML approach that combines the complementary strengths of three (3) base models, namely ANN, SVR, and RFR, into a single

high-precision model framework for improved wind speed forecasting. The proposed model architecture primarily employs a two-step learning process: (1) base models (ANN–SVR–RFR) use the input features to generate preliminary predictions; (2) a meta-model (LR) optimally weighs these predictions while taking the original features to produce a final prediction. This framework reduces the possibility of biases from a single algorithm by giving the meta-model access to both base model outputs and raw inputs, an approach that has proven to be successful in similar forecasting tasks [61–64]. To avoid information leakage and improve generalization, a five-fold cross-validation strategy was employed during the stacking process. Out-of-fold (OOF) predictions were generated using five-fold cross-validation for each base learner and subsequently used as inputs to train the meta-learner [65]. By ensuring that every validation fold includes previously unknown temporal data, this technique lowers the possibility of overfitting brought on by seasonal climate variability and strengthens the stacked model’s resilience. As a result, the trained ensemble exhibits improved generalization across various wind regimes and climatic circumstances observed over the yearly cycle. The proposed hybrid model architecture is presented in Figure 5.

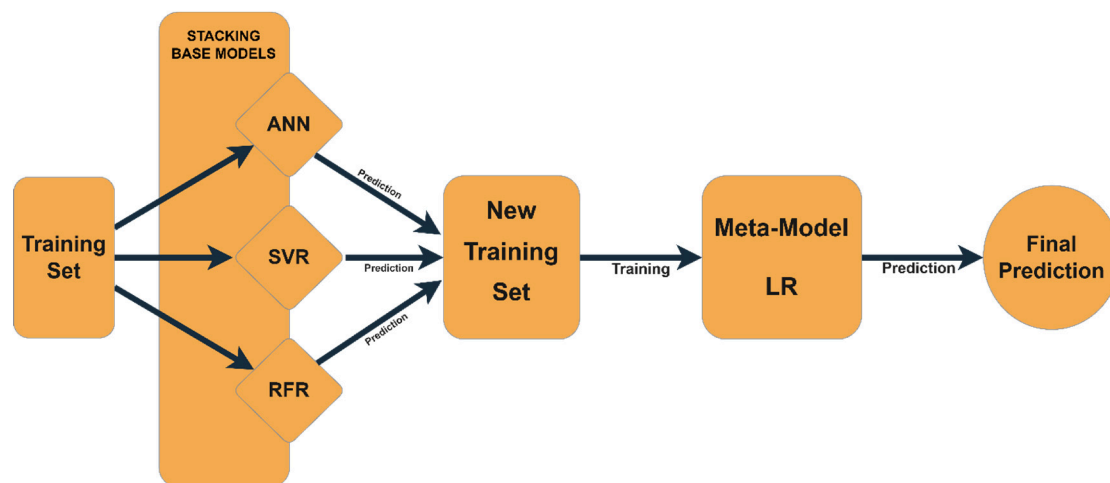


Figure 5. Proposed hybrid stacking model architecture.

2.9. Cyclical Encoded Features

Building upon a technique already established in a previous paper by the authors in the context of a similar solar forecasting task, in the present study, time-dependent input data were transformed into a more informative and model-friendly format [10]. Figure 6 presents a graphical representation of the cyclical encoding technique, wherein the variable “hours” is arranged such that zero (midnight) is located on the left, with the hours increasing in a counterclockwise direction around the circle. Consequently, the time 23:59 (11:59 p.m.) is situated near 00:00 (12:00 a.m.), accurately reflecting real-time cyclical relationships easily interpretable by the ML models [66–68]. A similar transformation is applied to the variables of “month” and “day”. Subsequently, newly engineered features are generated, including sin hour, cos hour, sin day, cos day, sin month, and cos month, and their relative correlation analysis is presented in Figure 7. Within Figure 7, the newly generated features exhibit a significant correlation with the target feature, with the highest correlation values recorded at 0.33 and -0.33 for the cosine hour and sine hour features, respectively (see Figure 7) [10]. It is revealed in Figure 7 that the site-dependent differences caused by Saudi Arabia’s unique weather characteristics were identified using the feature importance analysis. Due to intricate terrain-induced atmospheric interactions, temperature and relative humidity were the most important predictors in the mountainous areas (Taif and Abha). Conversely,

the Red Sea and East Coast, which are littoral and offshore regions, exhibited a greater reliance on pressure and dew point, which was indicative of the impact of marine air masses and moisture transport. These explainability findings show that regional climatic circumstances influence the relative relevance of meteorological variables and account for observed disparities in model forecasting accuracy across the studied sites.

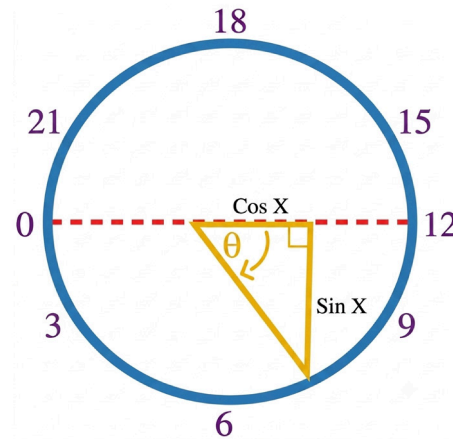


Figure 6. Cyclical features of time series data. Reproduced with permission from Rashid et al. [10,69] under the Creative Commons Attribution (CC BY 0.04) MDPI 2025.

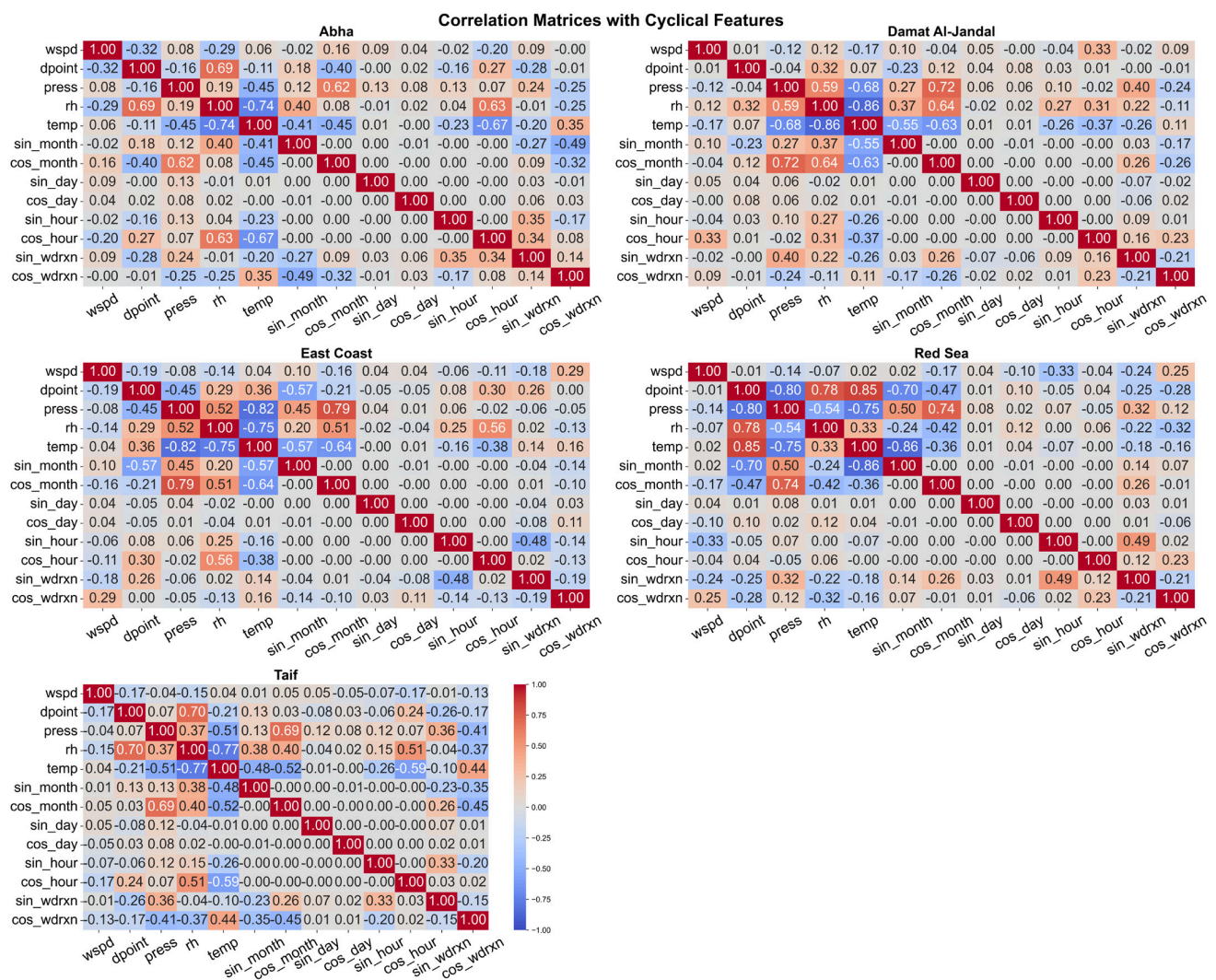


Figure 7. Correlation analysis of input features after cyclical encoding.

Equations (1) and (2) can be used to mathematically express the transformation into sine and cosine components for hr, dy, and mo, respectively.

$$x_{sin} = \sin\left(2\pi \frac{x}{T}\right) \quad (1)$$

$$x_{cos} = \cos\left(2\pi \frac{x}{T}\right) \quad (2)$$

where x is the cyclical feature value (e.g., month, day, hour);

T is the period of the cycle (e.g., 12 for months, 24 for hours);

x_{sin} is the sine-transformed value of the time feature;

x_{cos} is the cosine-transformed value of the time feature.

Cyclical Temporal Encoding (CTE) was used to preserve the cyclic nature of hourly, daily, and monthly variables while avoiding artificial temporal discontinuities. The engineered cyclical features (cos hour and sin hour) had the strongest association with the intended wind speed (± 0.33), showing their significant contribution to forecasting performance. According to the ablation comparison, including CTE enhances the hybrid model by more accurately representing the wind speed's periodic nature. The model attains reduced prediction errors (RMSE and MAE) and increased prediction accuracy (higher R^2), demonstrating the efficacy of CTE in improving forecasting performance. The ablation comparison in Table 7 suggests that incorporating CTE improves the hybrid model by better capturing the periodic behavior of wind speed. Future work should further include a comprehensive ablation study to quantitatively isolate the performance gain introduced by CTE using identical training and testing datasets.

Table 7. Ablation comparison of the hybrid RFR–ANN–SVR with and without CTE.

Model Configuration	R^2	RMSE (m/s)	MAE (m/s)
Hybrid model without CTE	0.948	0.96	0.67
Hybrid model with CTE	0.962	0.88	0.61
Relative improvement	+1.4%	−8.3%	−9.0%

2.10. Statistical Performance Metrics

Six complementary metrics were used to evaluate the ML models in order to determine the explanatory power of the model as well as the size and direction of errors [70]. Table 8 presents the six (6) complementary metrics used in this study; each was chosen to meet technical and operational needs in wind energy applications.

Table 8. Performance metrics utilized in this study.

Metric	Mathematical Model	Interpretation	Desired Values	Ref.
MAE	$MAE = \frac{1}{n} \sum_{i=1}^n y_i - \hat{y}_i $	Lower values are better	<1.5 m/s	[71]
RMSE	$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$	Lower values are better	<2.0 m/s	[72]
MBE	$MBE = \frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)$	Closer to zero is better	< ± 0.3 m/s	[73]
RRMSE	$RRMSE = \frac{\sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}}{\bar{y}_i} \times 100$	Closer to 0% is better	<15%	[74]
MAPE	$MAPE = \frac{1}{n} \sum_{i=1}^n \left \frac{y_i - \hat{y}_i}{y_i} \right \times 100$	Closer to 0% is better	<20%	[75]
R^2	$R^2 = 1 - \left[\frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y}_i)^2} \right]$	Higher values (closer to 1) are better	>0.7	[76]

Within Table 8, the term y_i represents the actual observed values of the dependent variable, $\hat{y}_i$ represents the predicted values from the ML algorithms, n denotes the number of data points or observations, and $\bar{y}_i$ represents the mean of the actual observed values.

3. Results and Discussion

Figure 8 presents different patterns in feature importance depending on the ML model and site; temp was especially important for ANN models on land, while pressure and dew point were more important for offshore sites. The observed behavior for thermal variables (RH, dpoint temp) can be explained by the strong influence of surface heating, atmospheric stability, and boundary-layer development on local wind regimes [77]. Also, changes in temp and RH modify vertical mixing processes and turbulence generation, and these have a direct impact on near-surface wind speeds [78]. The impact of pressure-related variables (press, dpoint) on offshore locations (Red Sea, East Coast) could be attributed to the direct influence of horizontal pressure gradient forces on wind generation in maritime environments [78]. Cyclically encoded features captured the periodic characteristics of wind behavior. Notably, cyclically encoded wind-direction variables (sin_wdrxn and cos_wdrxn) showed significant importance in several sites and models. For example, as shown by the RFR models in Abha, East Coast, and Taif, standardized directional flow patterns carry useful predictive information. This also underlined that rather than demonstrating a clear physical cause-and-effect relationship, the feature map shows the predictive contribution of each variable to the machine learning models. Albeit temp, rh, and dpoint are thermodynamically coupled and thus strongly interdependent, the learning algorithms assign importance according to the incremental contribution of each variable to the prediction accuracy after considering the influence of the other input features.

Table 9 presents how the base models perform relative to the hybrid model. Within Table 9, all of the models show strong training performance, with R^2 values well above 0.93 (except in some cases for the RFR model). During testing, the hybrid model consistently outperformed all base standalone models (although at the East Coast site, the simple persistence model proved more reliable). SVR proves to be the most reliable amongst the base models reported herein, with consistently high testing R^2 values (0.87–0.92) with minimal train–test performance degradation. ANN also performs well, especially in the case of onshore sites like Taif, where a peak testing R^2 of 0.908 was achieved. However, performance tends to be somewhat sensitive to offshore conditions. RFR, on the other hand, has the biggest drop in performance between training and testing (ΔR^2 up to 0.23), especially on the East Coast and in the Red Sea sites. The proposed hybrid model surpasses the best base model at each site and the simple persistence model in four out of five sites, with testing R^2 values between 0.869 and 0.953 and the lowest performance degradation amongst all sites and models ($\Delta R^2 < 0.05$). Table 9 also compares the proposed hybrid model with a persistence benchmark, which assumes that the next-hour wind speed is equal to the current wind speed. The persistence model presented a fairly good prediction in several sites, indicating the large temporal autocorrelation present in the short-term wind speed series. The simple persistence model achieved the highest testing accuracy at the East Coast site ($R^2 = 0.963$, RMSE = 0.477 m/s), which slightly outperformed the hybrid framework ($R^2 = 0.917$, RMSE = 0.712 m/s). However, for the remaining four sites, the hybrid model consistently outperformed the individual ANN, SVR, and RFR models and the simple persistence model.

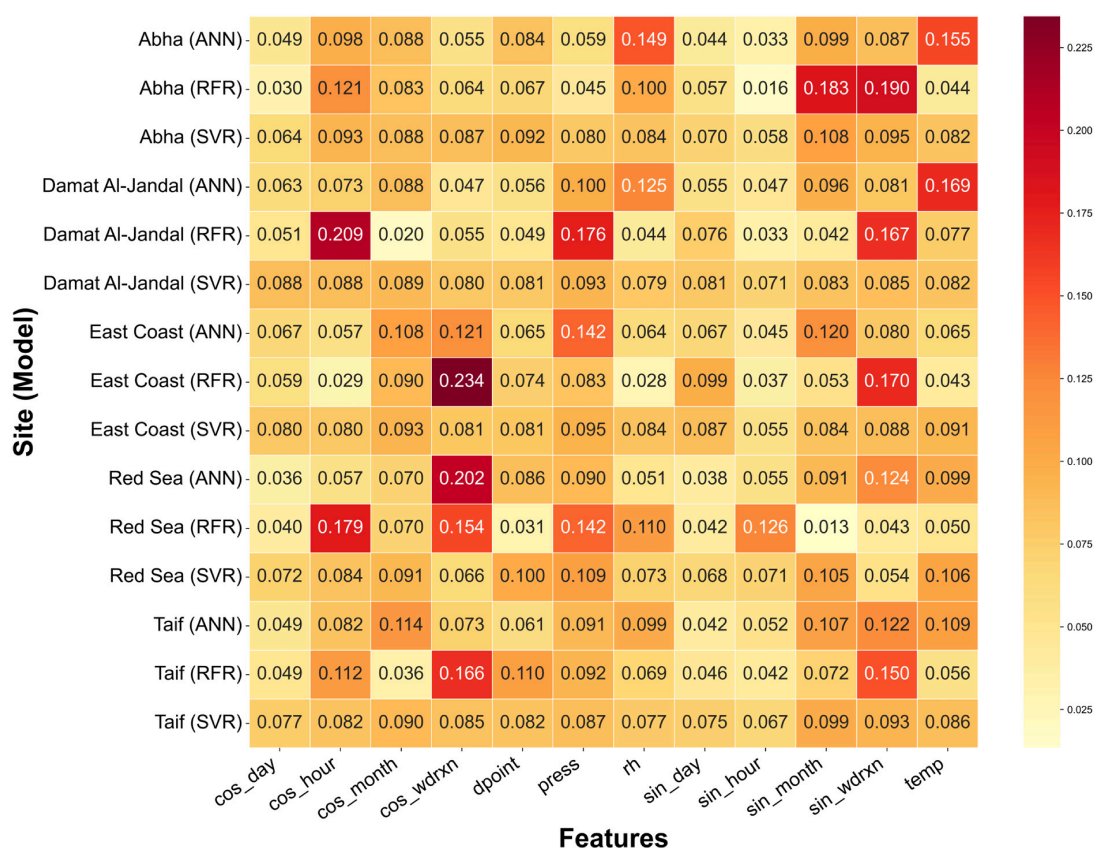


Figure 8. Model-wise feature important trends (normalized scale). Abbreviations to features (x-axis) are presented in Table 3.

Table 9. Performance of base and hybrid models across training and testing phases.

Model	Dataset	MAE	RMSE	MBE	RRMSE (%)	MAPE (%)	R ²
Damat Al Jandal							
ANN	Training	0.285	0.361	0.052	6.388	6.685	0.977
	Testing	0.727	0.846	0.077	14.943	16.613	0.842
SVR	Training	0.620	0.925	−0.032	16.370	16.496	0.847
	Testing	0.522	0.612	0.142	10.806	11.856	0.917
RFR	Training	0.247	0.353	0.004	6.239	7.049	0.978
	Testing	0.837	0.961	0.025	16.982	18.491	0.796
Hybrid	Training	0.302	0.431	−0.021	7.616	7.637	0.967
	Testing	0.429	0.494	−0.006	8.731	9.527	0.946
PERSISTENCE	Training	0.576	0.784	0.000	13.873	14.389	0.890
	Testing	0.430	0.592	0.004	10.457	9.364	0.923
Onshore Taif							
ANN	Training	0.228	0.292	−0.102	5.405	5.362	0.985
	Testing	0.753	0.879	0.127	15.680	20.867	0.908
SVR	Training	0.506	0.725	−0.028	13.442	13.914	0.910
	Testing	0.659	0.790	0.343	14.103	18.789	0.926

Table 9. Cont.

Model	Dataset	MAE	RMSE	MBE	RRMSE (%)	MAPE (%)	R ²
RFR	Training	0.220	0.302	0.004	5.592	6.485	0.984
	Testing	0.892	1.028	0.127	18.345	26.478	0.874
Hybrid	Training	0.311	0.432	−0.055	8.008	8.072	0.968
	Testing	0.618	0.713	0.143	12.727	17.786	0.940
PERSISTENCE	Training	0.563	0.730	0.001	13.540	14.923	0.908
	Testing	0.628	0.814	0.000	14.526	20.975	0.921
Onshore Abha							
ANN	Training	0.227	0.291	0.028	6.505	7.664	0.982
	Testing	0.726	0.845	0.081	19.582	26.382	0.861
SVR	Training	0.442	0.626	−0.028	14.010	16.120	0.918
	Testing	0.523	0.612	0.142	14.182	18.541	0.927
RFR	Training	0.190	0.258	0.002	5.782	7.181	0.986
	Testing	0.837	0.962	0.019	22.292	29.766	0.820
Hybrid	Training	0.366	0.485	0.150	10.862	11.464	0.951
	Testing	0.429	0.494	−0.006	11.454	14.637	0.953
PERSISTENCE	Training	0.503	0.662	0.001	14.821	16.810	0.909
	Testing	0.583	0.806	0.003	18.674	19.705	0.874
Offshore East Coast							
ANN	Training	0.259	0.333	0.047	5.561	5.944	0.985
	Testing	0.755	0.880	0.130	16.380	25.996	0.873
SVR	Training	0.612	0.921	−0.058	15.392	15.870	0.888
	Testing	0.660	0.791	0.345	14.722	20.298	0.897
RFR	Training	0.236	0.339	0.001	5.660	6.825	0.985
	Testing	0.891	1.027	0.117	19.116	27.854	0.827
Hybrid	Training	0.315	0.438	−0.067	7.314	7.763	0.975
	Testing	0.616	0.712	0.141	13.252	18.788	0.917
PERSISTENCE	Training	0.577	0.782	0.000	13.069	15.263	0.919
	Testing	0.365	0.477	−0.002	8.877	12.750	0.963
Offshore West Red Sea							
ANN	Training	0.267	0.344	0.054	5.771	6.361	0.983
	Testing	0.765	0.892	0.175	18.430	21.650	0.837
SVR	Training	0.477	0.760	−0.014	12.732	13.761	0.916
	Testing	0.650	0.777	0.314	16.053	19.415	0.877
RFR	Training	0.200	0.298	0.003	4.993	6.337	0.987
	Testing	0.874	1.020	0.150	21.084	25.327	0.787
Hybrid	Training	0.258	0.369	0.068	6.188	6.958	0.980
	Testing	0.616	0.712	0.152	14.710	17.867	0.896
PERSISTENCE	Training	0.566	0.811	−0.001	13.580	15.681	0.905
	Testing	0.495	0.801	−0.002	16.564	16.256	0.869

Figures 9 and 10 further support the reported values within Table 9. The hybrid model achieved the highest testing accuracy at four of the five sites studied, yielding R^2 values of 0.946 (Damat Al-Jandal), 0.940 (Taif), 0.953 (Abha), and 0.896 (West Red Sea). The only exception was the East Coast site, where the persistence benchmark showed the best overall performance ($R^2 = 0.963$, $RMSE = 0.477$ m/s), indicating strong short-term persistence characteristics at this location. However, the hybrid framework generally outperformed the forecasting errors of the standalone models and achieved the lowest testing MAE and RMSE values at Damat Al-Jandal (0.429 and 0.494 m/s), Taif (0.618 and 0.713 m/s), Abha (0.429 and 0.494 m/s), and Offshore Red Sea Coast (0.616 and 0.712 m/s). On the other hand, RFR exhibited the worst performance in generalization, with the testing R^2 values in the offshore sites ranging from 0.787 to 0.827 and in the on-shore sites from 0.796 to 0.874. The hybrid-model MBE values were relatively small for all sites (-0.006 to 0.152 m/s), indicating minimal systematic overprediction or underprediction. Furthermore, the hybrid model obtained testing RRMSE values between 8.731 and 14.710%, which are within the 15% common operation thresholds for practical wind energy forecasting. Testing R^2 values higher than 0.89 were obtained at all sites. Thus, results obtained herein indicate the overall stability of the proposed framework despite the different meteorological conditions of both offshore and onshore environments. Therefore, even if short-term wind predictions are influenced by persistence effects, the proposed hybrid architecture can exploit additional nonlinear relationships and meteorological dependencies that improve the prediction accuracy in different climatic environments.

Figure 11a–e presents the actual wind speeds versus the predicted wind speeds. Within Figure 11a, the hybrid model fits observed values better than the others ($R^2 = 0.946$). It moderately bests SVR ($R^2 = 0.917$), but it outperforms RFR ($R^2 = 0.796$) and ANN ($R^2 = 0.842$) by a large margin. Similar trends are observed across all model–site combinations (Figure 11a,b). Meanwhile, RFR slightly overfits by capturing site-specific noise and local climatic fluctuations, limiting its ability to generalize to new data because its ensemble of decision trees tends to capture site-specific noise and local fluctuations in the training data. The ANN demonstrates systematic prediction bias, particularly at high wind speeds, due to the complexity of nonlinear atmospheric dynamics. The proposed hybrid model addresses these constraints by integrating the complementary strengths of RFR, ANN, and SVR.

To further explain and validate the hybrid model's superior performance against the standalone models, we used several evaluation metrics to compare the performance of all five sites and came up with a percentage-based score. Figure 12 presents the percentage change in performance metrics, namely the MAE, RMSE, MBE, RRMSE (%), MAPE (%), and R^2 of the hybrid model relative to the other individual base models.

Within Figure 12, the hybrid model consistently outperforms both RFR and ANN on most metrics and sites. For example, when compared to RFR, the hybrid model does better on MBE by 134% and on RMSE by up to 48.6% at the Abha site. When compared to SVR, the hybrid model shows minimal improvements; however, MBE improved by up to 104% at the onshore Damat Al-Jandal site. In some rare cases (like the Taif and East Coast sites), ANN and RFR slightly outperform the hybrid model in terms of MBE. Nevertheless, the hybrid model approach outperforms SVR in terms of the error-based metrics and overall fitness, while cutting mean bias error by up to 140%. Within Figure 12, positive percentage values show that the hybrid model consistently makes the regression more useful for explaining wind speed patterns across site and baseline model scenarios. Thus, the hybrid model's overall superiority is strengthened by its stability and consistency across different climatic conditions.

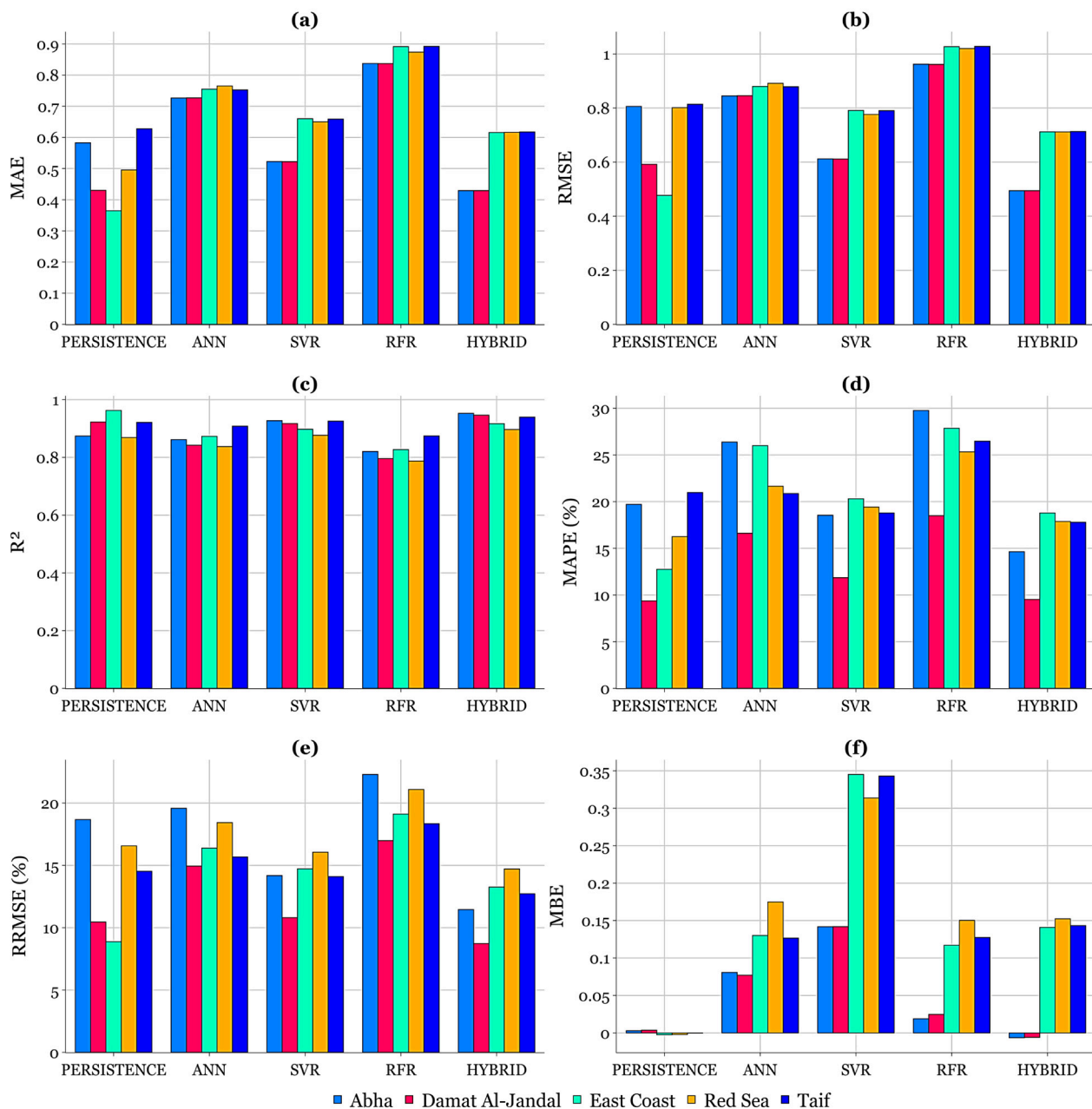


Figure 9. Site-wise statistical performance indicators of the hybrid AI model for the five wind locations: (a) MAE, (b) RMSE, (c) R^2 , (d) MAPE (%), (e) RRMSE (%), and (f) MBE.

3.1. Statistical Significance Analysis

The DM test was chosen for statistical analysis due to its wide adoption and applicability for forecast loss series data. We used the squared-error loss function (Equation (3)). This paper tested the null hypothesis [H_0 : both hybrid and baseline models have equal predictive accuracy ($DM \sim 0$)] and the alternative hypothesis [H_1 : forecasting accuracy is different ($DM > 0$)] at a 95% confidence level. Table 10 compares the results obtained from the DM statistical test, and a direct comparison of the SVR and persistence models against the hybrid model is further presented in Figure 13. Within Table 10, positive DM statistics indicate lower forecast loss for the hybrid model relative to the benchmark model. At the East Coast site, the persistence model outperformed the hybrid model; however,

in four out of five other sites, the hybrid maintained a consistently high efficacy, with a significantly superior performance at 95% confidence (Table 10).

$$d_t = (y_t - \hat{y}_{1,t})^2 - (y_t - \hat{y}_{2,t})^2 \quad (3)$$

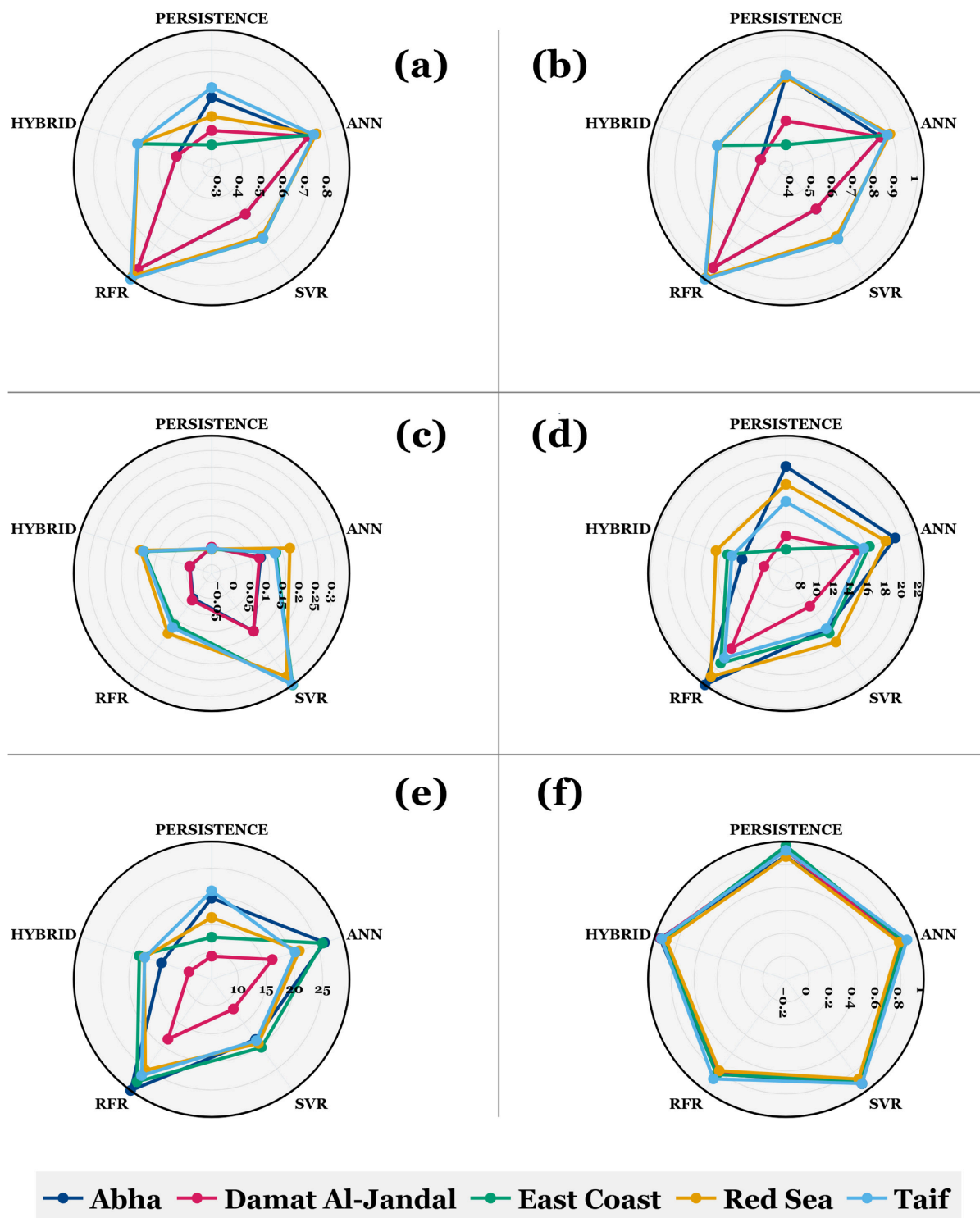


Figure 10. Radar plots of multi-site model evaluation of the hybrid AI model for the five wind locations: (a) MAE, (b) RMSE, (c) MBE, (d), RRMSE (%), (e) MAPE (%), and (f) R².

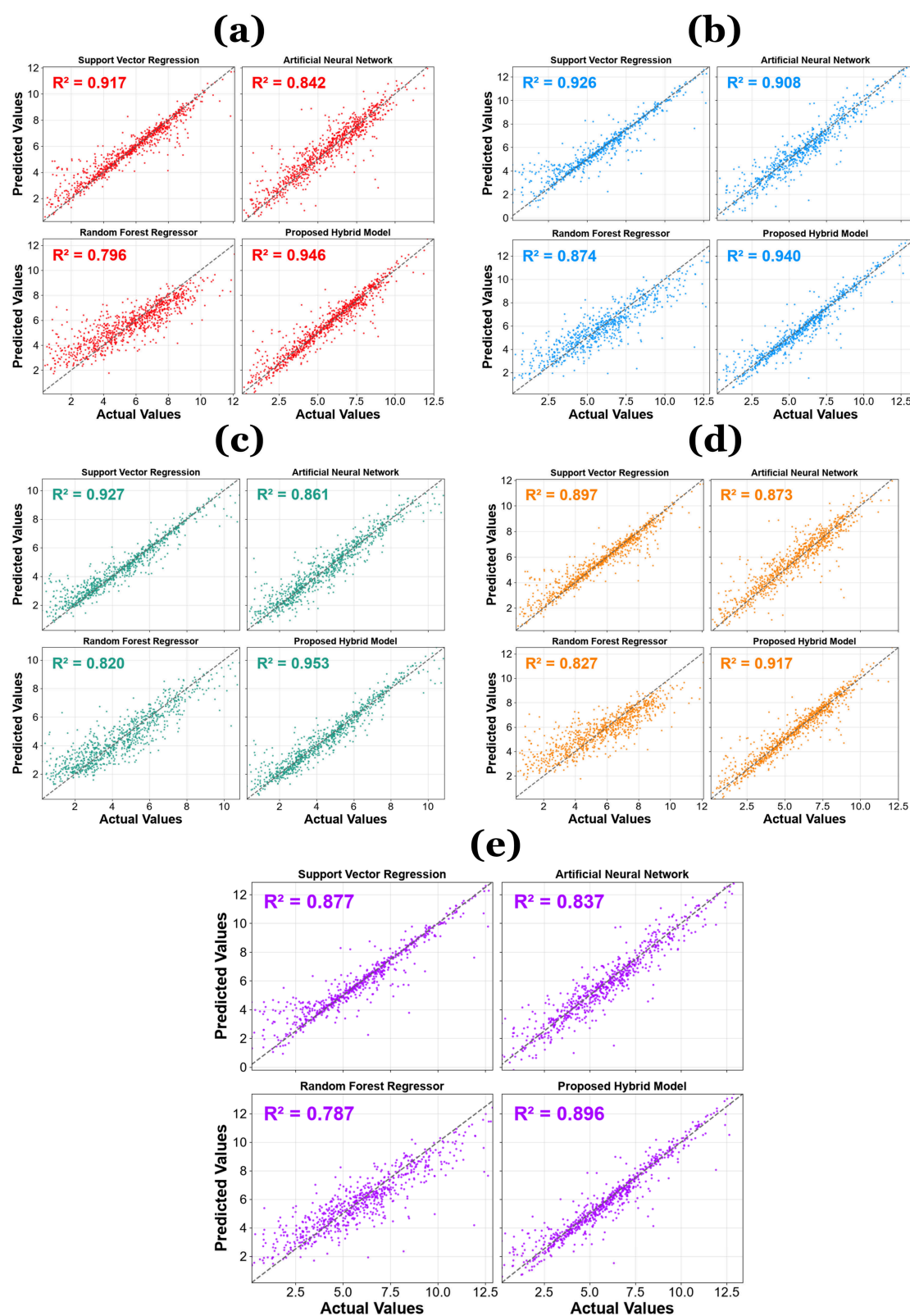


Figure 11. Model performance comparison validation between predicted and measured values for wind speed forecasting: (a) Damat Al Jandal; (b) Onshore Taif; (c) Onshore Abha; (d) Offshore Gulf East Coast; and (e) Offshore West Red Sea.

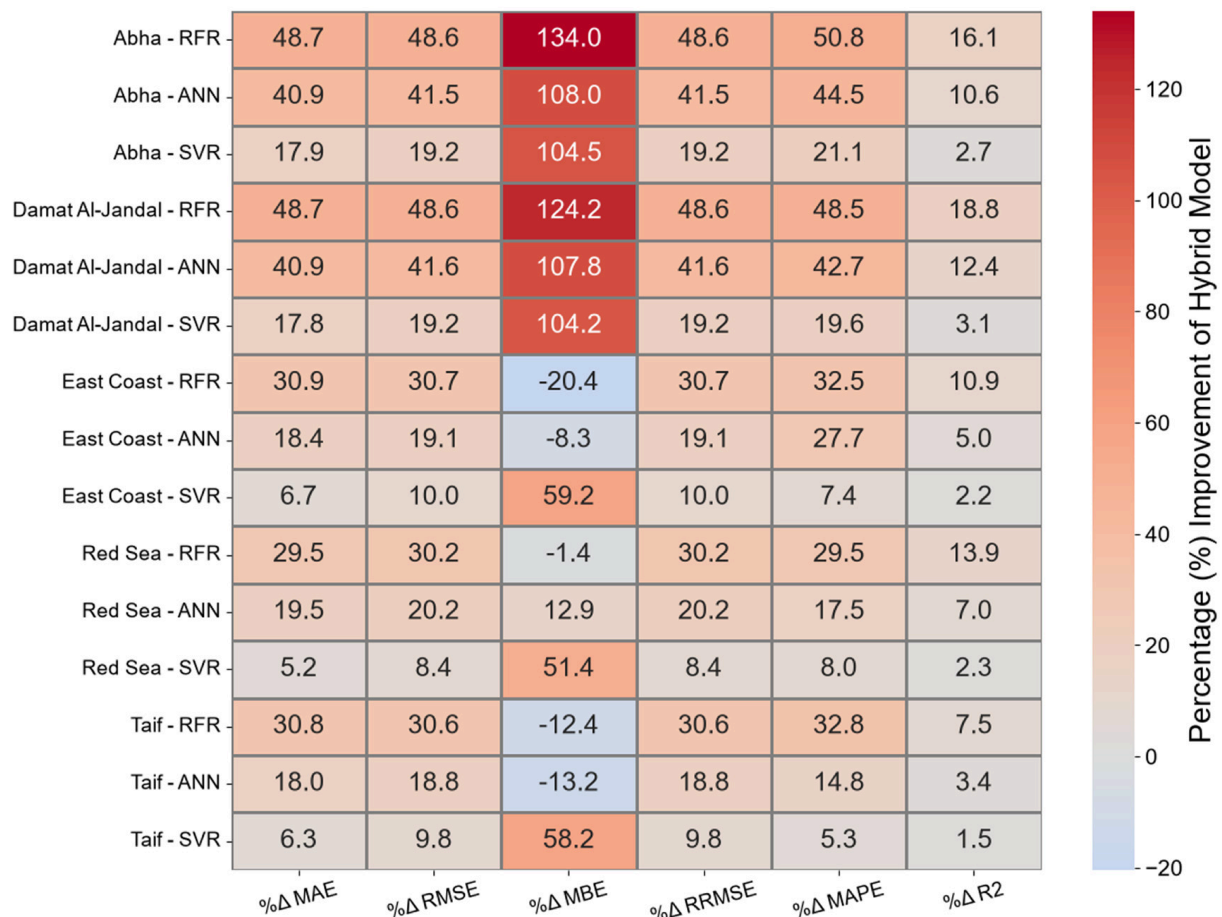


Figure 12. Percentage improvement of the hybrid ANN–SVR–RFR model compared to individual models.

Table 10. Diebold–Mariano (DM) test of forecasting accuracy of hybrid (HYB) versus benchmark models (ANN, SVR, RFR, PERSISTENCE) across study sites.

Site	ANN vs. HYB DM Statistic (<i>p</i> -Value)	SVR vs. HYB DM Statistic (<i>p</i> -Value)	RFR vs. HYB DM Statistic (<i>p</i> -Value)	RFR vs. Persistence DM Statistic (<i>p</i> -Value)
Abha	19.8075 (0.0000)	9.1538 (0.0000)	23.7690 (0.0000)	3.8623 (0.0001)
Damat Al Jandal	19.7850 (0.0000)	8.9736 (0.0206)	23.7068 (0.0000)	3.3364 (0.0008)
East Coast	9.1470 (0.0000)	4.2059 (0.0000)	15.1937 (0.0000)	−13.6518 (0.0000) ⚡
Red Sea	8.6216 (0.0000)	3.1917 (0.0014)	12.8064 (0.0000)	1.1051 (0.2691)
Taif	8.8486 (0.0000)	4.1898 (0.0000)	15.3278 (0.0000)	3.0207 (0.0025)

If *p*-value < 0.05, then the difference is statistically significant. ⚡ = Negative value means that the persistence model outperformed the hybrid model.

Within Equation (3), y_t is the observed wind speed, whereas $\hat{y}_{1,t}$ and $\hat{y}_{2,t}$ are forecasts for the benchmark and hybrid model, respectively. A negative DM statistic indicates a superior predictive accuracy of the first model, and vice versa.

3.2. Residual Autocorrelation (ACF) Analysis

An additional evaluation of the sufficiency of the proposed hybrid framework was conducted using autocorrelation analysis of the forecasting residuals at all five study sites. Figure 14 presents the ACF of the residual series, where residuals are the difference between observed and predicted wind speeds. From our analysis, residual autocorrelation

coefficients were close to zero and remained within the 95% CI across the range of lags investigated for all five study sites, with no significant recurring patterns or sustained autocorrelation structures. Thus, the hybrid model was able to capture dominant temporal dependencies and periodic characteristics of the wind speed series. Moreover, the absence of significant residual autocorrelation provides evidence for the effectiveness of the hybrid framework. Therefore, the observed forecasting errors are primarily attributable to random fluctuations rather than unmodeled temporal dynamics.

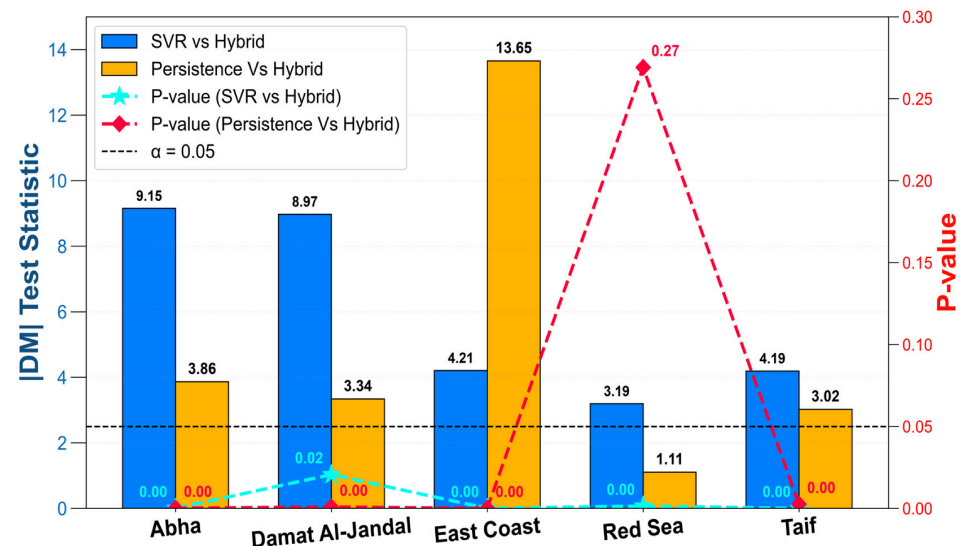


Figure 13. Diebold–Mariano (DM) statistical test for proposed hybrid model vs. SVR across the five study sites. Positive DM stats indicate lower forecasting errors for the hybrid model. p -values below the significance threshold ($\alpha = 0.05$) indicate statistical significance.

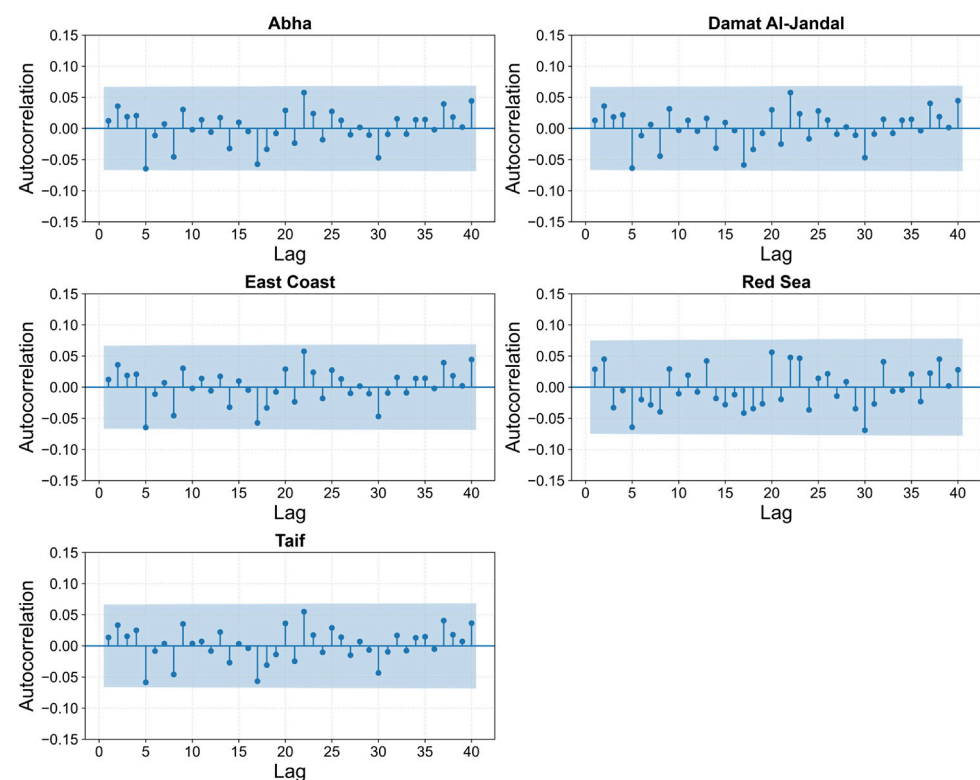


Figure 14. Autocorrelation function (ACF) of residuals of the hybrid model for the five sites studied. For all lags considered, the residual autocorrelations are close to zero, which shows that there are no strong systematic time structures in the forecast errors.

3.3. Practical Implications

From a practical standpoint, the proposed hybrid forecasting model can help with real-time power dispatch, reserve scheduling, and grid balancing by providing more accurate wind speed estimates for renewable energy integration. Its implementation necessitates continuous meteorological data collection, feature preprocessing, and the simultaneous execution of the RFR, ANN, and SVR models, followed by a lightweight linear regression meta-learner. Although the hybrid framework introduces a minor increase in computational cost compared to a single model, the inference time is still sufficient for real-time grid operation employing modern control-center computer infrastructure.

4. Conclusions

Accurate forecasting of wind speed is vital for maintaining the stability and reliability of wind power systems. However, conventional wind forecasting models often face challenges in effectively capturing and quantifying the inherent uncertainties within the prediction process. This study identified five high-potential wind energy project sites in Saudi Arabia and proposed a stacked hybrid ML approach to combine the complementary strengths of three base models, namely ANN, SVR, and RFR, into a single predictive framework for improved wind speed forecasting using LR as a meta-model. The proposed framework uses a two-step learning process. In the first step, the base models make initial predictions. In the second step, a meta-model weighs these predictions in the optimal manner to make the predictions more accurate. The main findings of this study are as follows:

1. The proposed hybrid RFR + ANN + SVR model consistently performed better than standalone models (RFR, ANN, SVR), obtaining R^2 scores of 0.869–0.953 in testing and less than a 5% drop in performance between training and testing across all sites.
2. The proposed hybrid model improved performance by up to 134% relative to standalone models (ANN, RFR, SVR).
3. SVR was the strongest standalone model for the forecasting task, especially in offshore settings, with R^2 up to 0.897 at the Offshore Gulf East Coast. However, the hybrid model still outperformed, with R^2 of 0.917.
4. Random forest proved least effective in generalizing. Its testing R^2 score, MBE, RRMSE, and MAE dropped by up to 16%, 134%, 48.6%, and 48.6%, respectively, compared to the proposed hybrid model.
5. The proposed hybrid approach kept the MBE within ± 0.17 m/s and the RRMSE below 15% across all sites.
6. With respect to the hybrid model, onshore sites showed higher accuracy rates, while offshore sites posed greater challenges but still stayed within reliable limits.
7. Findings show that different models depend on different meteorological wind features for forecasting. Notably, cyclically encoded variables ($\sin_wdrxn$ and $\cos_wdrxn$) showed significant importance across several sites and models.

5. Future Work

Although the proposed hybrid stacking framework outperformed the benchmark ANN, SVR, RFR, and simple persistence models, future work should examine its performance against recently developed state-of-the-art forecasting architectures, such as deep-learning architectures such as XGBoost, LSTM, GRU, temporal convolutional networks (TCNs), Informer, transformer-based models, temporal fusion transformers (TFTs), etc. Future studies may also investigate the applicability of the proposed framework using higher-frequency observations (e.g., 15 min intervals). Additionally, the present triple-ensemble model is not comparable to recently created time-series foundation models like

Chronos-2. Hence, future research should compare the suggested framework to existing cutting-edge foundation models, look at hybrid integration with transformer-based designs, and assess its scalability, transfer learning potential, and computational efficiency for large-scale wind forecasting tasks.

Furthermore, the current study's concentration on wind speed forecasting without connecting the projected values to models of wind turbine power output and grid operation is one of its limitations. In order to measure how forecasting errors affect power generation, demand fluctuations, and overall grid stability under various operating situations, future research should combine wind turbine power curve simulations with power system dispatch models. Future work should also evaluate the robustness of the hybrid model under missing or faulty sensor data by incorporating fault-tolerant and data imputation techniques to analyze degradation in the hybrid model's performance.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/en19174159/s1>, Figure S1: Pseudocode of the one-hour-ahead forecasting target used in the proposed framework. The target wind-speed variable ($wspd_{target}$) was created by shifting the original wind-speed series by one step ($shift(-1)$), such that meteorological predictors observed at time t were used to forecast wind speed at time $t + 1$. Figure S2: Hybrid Framework Implementation. Figure S3: Cyclical Encoded Features-Wind Direction has also been included in addition to the time features. Figure S4: Correlation of Input Features. Figure S5: ACF Analysis. Figure S6. Deterministic coefficient heat map. Table S1: Timestamps.

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Nomenclature

ACWA POWER	Arabian Company for Water and Power Development
ANN	Artificial Neural Network
APE	Absolute Percentage Error
BiLSTM	Bidirectional Long Short-Term Memory
CE	Cyclical Encoding
CEF	Cyclical Encoding of Features
CNN	Convolutional Neural Network
CTE	Cyclical Time Encoding
DNN	Deep Neural Network
DTR	Decision Tree Regression
ECMWF	European Centre for Medium-Range Weather Forecasts
FRK	Fixed Rank Kriging
FS	Forecast Skill
GBM	Gradient Boosting Machine

GBR	Gradient Boosted Regression
GNB	Gaussian Naive Bayes
KACARE	King Abdullah Centre for Atomic and Renewable Energy
KAPSARC	King Abdullah Petroleum Studies and Research Center
kNN	k-Nearest Neighbor
KSA	Kingdom of Saudi Arabia
LASSO	Least Absolute Shrinkage Selector Operator
LR	Linear Regression
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MASE	Mean Absolute Scaled Error
MBE	Mean Bias Error
MENA	Middle East and North Africa
ML	Machine Learning
MLP	Multi-Layer Perceptron
MSE	Mean Squared Error
NASA	National Aeronautics and Space Administration
NSRDB	National Solar Radiation Database
PCC	Pearson Correlation Coefficient
POWER	Prediction of Worldwide Energy Resources
R ²	Coefficient of Determination
RBF	Radial Basis Function
RE	Renewable Energy
RFE	Recursive Feature Elimination
RFR	Random Forest Regression
RMSE	Root Mean Square Error
RNN	Recurrent Neural Network
RNNs	Recurrent Neural Networks
RRMSE	Relative Root Mean Squared Error
SAM	Seasonal Adjustment Method
SCADA	Supervisory Control and Data Acquisition
sMAPE	Symmetric Mean Absolute Percentage Error
SVR	Support Vector Regression
TCN	Temporal Convolutional Networks
VMD	Variational Mode Decomposition
WPD	Wavelet Packet Decomposition
xGB	eXtreme Gradient Boost

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