IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received October 20, 2019, accepted October 29, 2019, date of publication November 4, 2019, date of current version November 13, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2951153

Current Perspective on the Accuracy of Deterministic Wind Speed and Power Forecasting

MUHAMMAD UZAIR YOUSUF [1,2], IBRAHIM AL-BAHADLY [1], (Senior Member, IEEE), AND EBUBEKIR AVCI [1], (Member, IEEE)

[1]Department of Mechanical and Electrical Engineering, Massey University, Palmerston North 4442, New Zealand
[2]Department of Mechanical Engineering, NED University of Engineering and Technology, Karachi 75270, Pakistan

Corresponding author: Muhammad Uzair Yousuf (m.u.yousuf@massey.ac.nz)

This work was supported in part by the Department of Mechanical and Electrical Engineering, Massey University, and in part by the Higher Education Commission (HEC) Pakistan Human Resource Development (HRD) program "HRD Initiative-MS Leading to Ph.D. Program of Faculty Development for UESTPs/UETs Phase-I" Grant 5-1/HRD/UESTPI(Batch VI)/6082/2019/HEC.

ABSTRACT The intermittent nature of wind energy raised multiple challenges to the power systems and is the biggest challenge to declare wind energy a reliable source. One solution to overcome this problem is wind energy forecasting. A precise forecast can help to develop appropriate incentives and well-functioning electric markets. The paper presents a comprehensive review of existing research and current developments in deterministic wind speed and power forecasting. Firstly, we categorize wind forecasting methods into four broader classifications: input data, time-scales, power output, and forecasting method. Secondly, the performance of wind speed and power forecasting models is evaluated based on 634 accuracy tests reported in twenty-eight published articles covering fifty locations of ten countries. From the analysis, the most significant errors were witnessed for the physical models, whereas the hybrid models showed the best performance. Although, the physical models have a large normalized root mean square error values but have small volatility. The hybrid models perform best for every time horizon. However, the errors almost doubled at the medium-term forecast from its initial value. The statistical models showed better performance than artificial intelligence models only in the very short term forecast. Overall, we observed the increase in the performance of forecasting models during the last ten years such that the normalized mean absolute error and normalized root mean square error values reduced to about half the initial values.

INDEX TERMS Deterministic, wind speed, wind power, forecasting accuracy, normalized statistical indicators.

I. INTRODUCTION

In recent years, wind power is the most competitively priced technology in many markets. According to Global Wind Energy Council (GWEC) Annual Report 2018 [1], the cumulative wind power installed during 2001 to 2018 is 591 GW that is expected to reach 908 GW by the end of 2023 as shown in Fig. 1. Despite providing more than half of renewables growth [2], the intermittent nature of wind raised multiple challenges to the power systems and is the biggest challenge to declare wind energy a reliable source.

The challenges that raised to the power system due to the intermittent nature of wind includes planning and operational difficulties, quality of power, and standard of inter-connections. For example, the system operator needs to allocate additional energy reserves in case any power

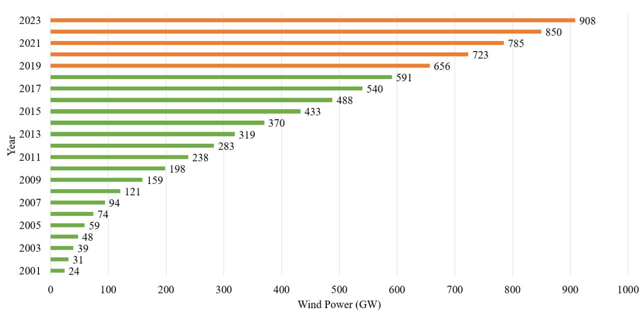


FIGURE 1. Cumulative installed wind power for 2001-2018 and forecast for 2019-2023 according to GWEC [1].

The associate editor coordinating the review of this manuscript and approving it for publication was Ching-Ter Chang.

fluctuation occurs between programmed and actual power produced. This additional reserves would increase the operational costs, which subsequently increases the final energy prices [3]. Albadi and Saadany discussed a detailed review of wind power intermittency impacts on power systems [4].

One solution to overcome this problem is wind energy forecasting. A precise forecast would help to develop appropriate incentives and well-functioning hour-a-head or day-ahead electric markets [5]. Reliable forecasts help system operators to integrate wind energy into the grid with lesser complications. Literature suggests that accurate wind speed and power forecasting is a significant factor for various wind applications varying from siting till integration [6]. Even Liu *et al.* [7] predicted wind for railway warning systems for train protection. Some of the standard applications discussed in the literature are siting and designing of wind farm, grid integration and operations (dispatch planning, unit commitment decisions, farm regulations, maintenance scheduling, energy storage, reserve planning), stability (power stability, reducing breakdown probability) and revenue generation (tariff in the electricity market, electricity bidding and trading).

Forecasting is a way of predicting future events and is seen as a method of extrapolation. Forecasting process includes defining a problem, collecting data, analyzing data, selecting and fitting model to a set of data, validating the model using new data, model deployment, and performance evaluation [8]. Wind energy forecasting depends on cross-disciplinary approaches, including mathematics, statistics, meteorology, and power systems engineering [9]. There are two subcategories of wind speed and power forecasting: deterministic and probabilistic. Deterministic forecasting helps in evaluating point forecast for a specific time horizon while the probabilistic forecasting provides confidence intervals for the uncertainty of wind energy. As mentioned by Liu *et al.* [10], deterministic forecasting is the principal research direction of many scholars. Therefore, deterministic wind speed and power forecasting is the study focus of this review paper. Comprehensive reviews on probabilistic wind power forecasting are available in the literature [11], [12].

A. OBJECTIVES AND MOTIVATIONS

The motivation of this study is twofold. In recent years, various review papers are available on wind energy forecasting. Foley *et al.* [13] presented a review of the physical and statistical models. Tascikaraoglu and Uzunoglu [14] and Xiao *et al.* [15] reviewed the hybrid wind forecasting models based on weighted, decomposition (pre-processing), feature & optimization, and error processing (post-processing) approach. Qian *et al.* [16] further discussed the three structures of decomposition (pre-processing) approach, whereas Bokde *et al.* [6] reviewed the Empirical Mode Decomposition (EMD) based hybrid models. All these reviews are of significant importance in the field. However, in recent years, many models are updated. For example, Wind Power Prediction Tool (WPPT) was analysed as a statistical model earlier [13]; however, WindFor has replaced WPPT, which is the combination of advanced learning methods with a physical model [17]. Similarly, a comprehensive review of probabilistic wind power forecasting is presented [11], but no comprehensive study covering recent developments in deterministic forecasting methods has carried out.

Secondly, the papers published are limited to a specific site(s). The datasets are non-identical, and forecasting model is different in step size and location, which limits the comparison and applicability of the suggested model for the other regions. For comparative analysis and general conclusions, it is necessary to test the model performance for numerous case studies with diversified climatic regions. Some other review papers also mentioned the same perspective, but no detailed study was carried out.

In contrast with recent review papers, the major contribution is to present a comprehensive review of deterministic wind speed and power forecasting models from all the major perspectives. We explore the detailed classifications of wind speed and power forecasting and discussed the performance and limitations of forecasting models adopted in recent years. Also, we relate the performance and trend of recently developed forecasting models to present the performance of deterministic wind forecasting models for power generation. The motivation of this study is the review article of Blaga *et al.* [18], in which authors presented a detailed review of the performance evaluation of solar irradiance forecasting models based on available statistical indicators. After analyzing a large number of papers published between 2010-2019, twenty-eight papers ([57]–[58], [61], [72], [77]–[79], [82]–[83], [91], [97]–[114]) were shortlisted based on following criteria: the model performance is reported in terms of normalized mean absolute error (nMAE), and normalized root mean square error (nRMSE). In case the results are not presented in normalized values, then the statistical indicators of wind data must be listed in the paper. The normalized values help for inter-comparison analyses. After the selection of papers, we analysed a total number of 634 entries consisting of pair of nMAE and nRMSE. We investigated the study from three perspectives: forecasting models, time scale and performance trend over time. A brief description of shortlisted papers is enlisted in Table 3. First, we shall introduce the major classifications of the existing wind speed and power forecasting models in the next section. Later on, we shall analyse the performances of wind energy forecasting models, reported in shortlisted research articles, in section III to present inter-comparison analyses.

II. DETERMINISTIC WIND SPEED AND POWER FORECASTING CLASSIFICATION

In this section, we classify wind speed and power forecasting according to input data, time-scale, power output and forecasting method. Fig. 2 presents the overall classification of deterministic wind speed and power forecasting.

TABLE 1. **Available global and regional NWP models.**

Model	Developer	Model Type	Horizontal Resolution	Vertical Level	Forecast Length	Reference
ICON (ICOsahedral Nonhydrostatic)	DWD (Deutscher Wetterdienst)	Global	13 km	90	7 days	[22]
COSMO-DE (Consortium for small-scale modelling)		Regional	2.8 km	50	27 hr	[23]
IFS-HRES (Integrated Forecasting System - High RESolution)	ECMWF (European Centre for Medium-Range Forecast)	Global	9 km	137	10 days	[24]
SEAS5 (Integrated Forecasting System - SEASonal set V)		Global	36 km	91	13 months	[25]
Deterministic Global	UK Met Office	Global	10 km	70	6 days	[26]
Deterministic UK		Regional	1.5 km (inner) 4 km (outer)	70	120 hr (inner) 54 hr (outer)	[26]
GSM (Global Spectral Model)	JMA (Japan Meteorological Agency)	Global	20 km	100	84 hr	[27]
LFM (Local Forecast Model)		Regional	2 km	58	9 hr	[28]

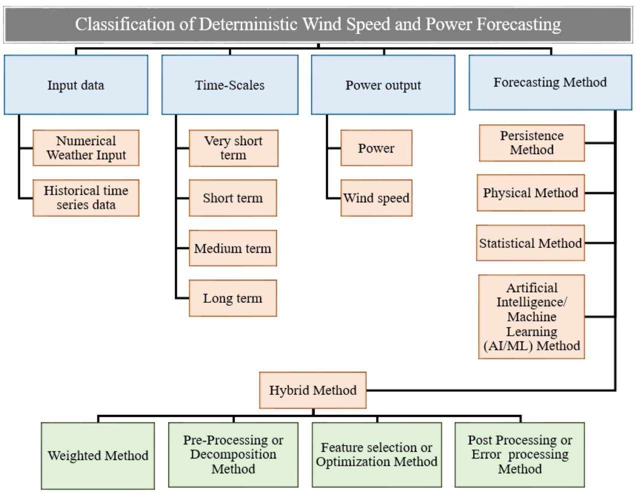


FIGURE 2. **Detailed classification of deterministic wind speed and power forecasting.**

A. INPUT DATA

There are two subclasses according to input data: Numerical Weather Prediction (NWP) input and historical time series data.

Meteorologists have developed NWP models to simulate the Earth's atmosphere to predict the weather. NWP model is a numerically approximate solution, based on equations associated with atmospheric processes and it changes. The primary equations are conservation of mass, conservation of energy, conservation of momentum, conservation of water and equation of state [19]. In NWP models, the atmosphere is divided into 3D cubes having a horizontal and vertical model resolution. The horizontal resolution presents orography, whereas vertical resolution presents weather phenomenon. The size of the resolution profoundly influenced the model. For example, a coarse resolution provides only limited details of valleys and height of mountains. The higher resolution provides better prediction but on a cost of more computational time. NWP models are available for both global and regional level. Table 1 presents a description of some of the available NWP models.

Most statistical methods use historical time speed data to correlate the wind speeds of the site. A mast is installed at the wind farm with at least one anemometer mount at the hub height to measure a minimum of six months data. Also, meteorological departments of countries and some global sources managed to record the data.

The primary benefit of NWP input is their applicability to predict long term horizon. The models using NWP data can provide forecasts for several days as well as several wind farms. Commercial procedures and software are available for NWP models. However, these models loss their applicability as the prediction horizon decreases, especially to predict very short term winds. One possible reason for this is the high wind variation that affects the model performance. Also, these models are complex to construct and need higher time to operate. In case of insufficient grid resolution, NWP models might contain systematic errors due to lack of handling sub-grid phenomena or physical parameterization.

In contrast to NWP data, time-series data requires lesser computational resource and time to model and operate. The traditional approach for long term forecasting is to use Measure–Correlate–Predict (MCP) approach. MCP approach takes into account the wind speed measurements at the wind farm and correlates with long term meteorological station data using a linear regression technique. However, several problems are associated with time-series data; the planning of meteorological mast, availability of suitable and calibrated weather station, and precise measurements from the meteorological station. Most importantly, the high cost associated with the weather stations resulting in a limited number of meteorological stations run in many countries.

B. TIME-SCALES

The time scale for a forecast depends on end-user requirements, technical conditions and regularity situations. The forecasting limits, according to time scales, are not well defined in the literature. However, keeping in view the literature, we divide the time horizon into four categories: Very short term forecasts (0-30 min), short term forecasts (30 min - 6 hours), medium-term forecasts (6 hours - 1 day ahead) and long term forecasts (>1 day ahead) [20], [21].

Very short term forecasts vary from few seconds to 30 minutes ahead. The major applications include wind turbine regulation and control strategies, electricity market clearing and real-time grid operation. These forecasts are possible based on time series data and do not require NWP data. Short term forecasts comprise of 30 minutes to 6 hours ahead. This category factored into economic load dispatch planning, operational security in the electric market and load decisions for increments. Online measurement data from the meteorological station, numerical weather prediction (NWP) or combination of both is used as input data, expecting that the weather condition will remain the same in short time horizon. However, the impact of NWP data is the least. Medium-term forecasts cover 6 hours to one day ahead and applied for decision making of unit commitment, reserved requirement and generator operation. NWP data is necessary for the medium-term forecast. Long term forecasts comprise of one day or more ahead. These forecasts use in maintenance scheduling, optimizing operational cost and feasibility study for designing a wind farm. Long term forecast necessarily requires NWP data for accurate estimation. In most of the literature, the performance of forecasting models is evaluated based on mean absolute percentage error (MAPE), mean absolute error (MAE), and root mean square error (RMSE). MAPE is a relative error and evaluates the ratio between residuals and actual values. A smaller error in the lower winds may have a smaller effect on MAPE may have a larger effect or a larger error in the higher winds MAE determines the difference between the actual and the estimated values. This performance evaluator is more robust to large errors. RMSE also evaluates the model dispersion but is very sensitive to the large errors due to the squared values.

The performance accuracy decreases as the time horizon increases. MAE for 40 min, 50 min and 1 hr ahead predictions was reported as 6.419 m/s, 7.085 m/s and 7.712 m/s [29]. Even in some cases, a lesser increase in forecast length results in a greater reduction in forecast accuracy. The MAPE for 10 s forecast length was 5.92 %, which increased to 7.81% for 20 s [30].

C. OUTPUT

There are two ways to get the forecast output. The first way is to forecast wind power generation directly from supervisory control and data acquisition (also termed as direct method). The second method is to forecast wind speed first, and then power curves are used to convert these forecasts into wind power as a next step (also termed as indirect method).

Kusiak *et al.* [31] applied the kNN model for both of the cases and concluded that the direct model offers better prediction performance than the indirect model. For the same dataset, MAE varied from 8.41% to 11.49% for direct method, whereas MAE varied from 9.67% to 12.72% for indirect method. Similarly, Renani *et al.* [32] also compared both direct and indirect approaches for a case study of a wind farm in Northern Iran. The analysis showed that errors increased by more than 100%. More specifically, the MAPE for 5 min, 15 min, 30 min and 60 min was 1.47%, 1.37%, 1.30% and 1.48% respectively in case of direct prediction which increased to 3.41%, 3.17%, 3.22% and 3.62% respectively in case of indirect prediction. The larger errors were due to the integration of two errors: one at wind speed prediction and second at wind power prediction. However, according to the argument of Zhu and Genton [33], the indirect method is a better approach than the direct method as the nearby wind farms with different wind turbines will experience the same wind speed. Therefore, it is better to convert the standard wind speed forecasts to their respective power curves, instead of performing individual wind farm power forecasts. Hong *et al.* [34] also supported the argument and discussed that wind power is dependent on multiple factors, including orography, wind speed, direction, and wake effects. Also, the rapid fluctuations and randomness in wind power data of a single wind farm will not guarantee to mine the wind regularity. Therefore, it is better to apply an indirect method which does not require correlation analysis of wind with other factors.

D. FORECASTING MODEL

1) PERSISTENCE METHOD

Persistence method (also termed as 'Naïve Predictor') is based on a high correlation between the present and immediate future wind speed. In this method, the wind speed at a time $(t + \Delta t)$ is assumed to be the same as was at the time (t), i.e.

$$v\,(t + \Delta t) = v(t). \tag{1}$$

The persistence method shows good accuracy when dealing with very short term forecasts. Wegley *et al.* [35] analysed three forecasting models: persistence, autoregressive (AR) and generalized equivalent Markov (GEM) on spring season data of Oklahoma City for 10, 30 and 60 minutes time interval and concluded that persistence method is superior in the 10-minute time interval. Authors suggested that AR and GEM can upgrade for further improvement, but persistence cannot. Also, the accuracy of the persistence method degrades rapidly as time increases. The method is served as a benchmark to compare improvement for newly developed forecast models [5], [36].

2) PHYSICAL METHOD

The physical method requires meteorological and other factors such as pressure, temperature, local surface roughness, obstacles, and wind turbines power curves for prediction.

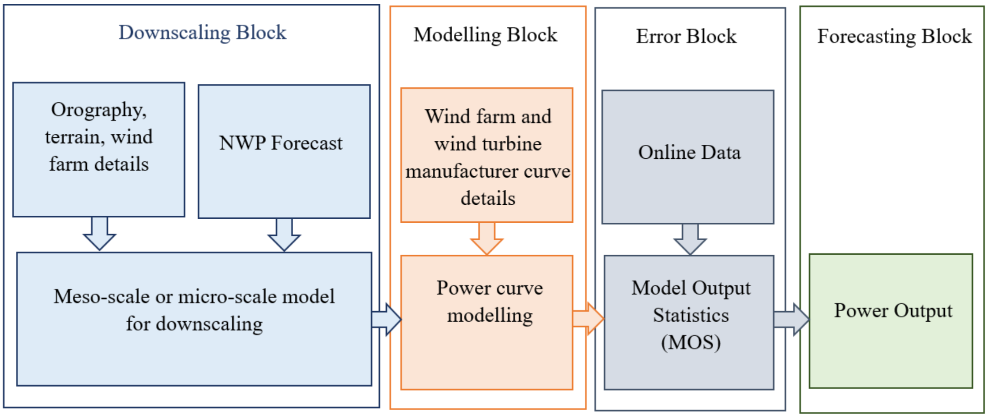


FIGURE 3. Flowchart for the physical method.

The physical methods are of two types: Diagnostic Model and Computational Fluid Dynamics (CFD) model. Diagnostic models [13] use parameterizations of boundary layer whereas CFD models simulate the wind flow fields dynamically. Diagnostic models are suitable for flow over flat terrain, whereas CFD models are appropriate for flow over complex terrain [37], [38].

The commercial methods for wind power forecasting use NWP wind forecasts as the input data and then carry out the necessary refinement of these output data (wind speed forecast) to the on-site conditions. The physical methods use a mesoscale or microscale model for the downscaling [39] for interpolating wind speed forecasts to the hub height of the wind farm. The attainable resolution and range of domain size differentiate the meso and micro model. The forecasted wind speed is used to estimate power. The easiest way is to utilize the manufacturer's power curve. Also, the Model Output Statistics (MOS) approach corrects the scaling errors. Fig. 3 illustrates the overall process.

Physical models incorporate orography, thus enables physical behavior understanding. These models generate regional and global forecasts using initial conditions to solve complex numerical systems. The historical data is of lesser importance in such models. However, to accurately predict the winds, it is necessary to have extensive information on surface roughness and characteristics of wind farms. Thus, these models need extensive efforts to set up. Table 2 provides details of some commercially available physical wind power forecasting models.

3) STATISTICAL METHOD

Statistical methods use time-series data to find out the relations generally by recursive techniques [14]. These models are easy and cheaper to build and provide precise predictions when dealing with short term forecasting. NWP input is optional for these models, as shown in Fig. 4. The accuracy of the statistical model degrades as time increases. These models are based on patterns and do not use any predefined mathematical model [5]. Statistical methods include autoregressive moving average (ARMA) [40], autoregressive integrated moving average (ARIMA) [41], fractional-ARIMA [42], seasonal-ARIMA [43], ARMA with exogenous input (ARMAX) [44], grey predictors [45], and exponential smoothing [46].

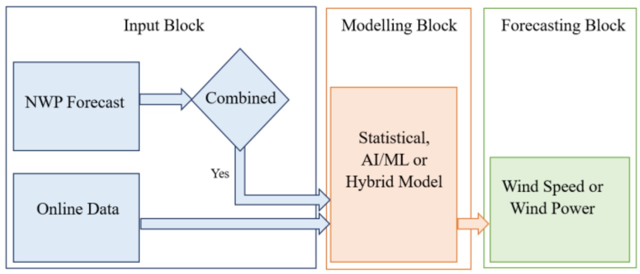


FIGURE 4. Flowchart for the statistical method.

ARIMA models are the most commonly used statistical models. The general non-seasonal model structure form is ARIMA (p, d, q) where p is the order of autoregressive (AR) part, d is the degree of differencing taken to make time-series stationary, and q is the order of moving average (MA). The linear expression of ARIMA (p, d, q) is expressed in the form:

$$y_t = c + \left(\sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j}\right), \tag{2}$$

where c is the constant term, ϕ_i is the coefficient of the i^{th} autoregressive parameter, θ_j is the coefficient of the j^{th} moving average parameter, y_{t-i} is the value at a time $(t - i)$, and ε_{t-j} is the error between the predicted value and actual value at $(t - j)$. ARIMA is a three-step iterative process. First, a tentative model is identified by analysing the time series data. Second, the unknown parameters are estimated. Third, the adequacy of the model is inspected through residual analysis. The residual analysis assists in performing the diagnostic checks or in specifying the potential improvements.

In comparison with physical models, statistical models do not require any real insight. Therefore, these models are easy to build and fast to calculate. However, for these models,

TABLE 2. Description of commercially available physical, statistical and combined models.

Prediction Model	Developer	Model Type	Description	Prediction Horizon	Ref
SOWIE (Simulation Model for the Operational Forecast of the Wind Energy Production in Europe)	EuroWind	Physical	SOWIE is a multi-model forecast that utilizes NWP data includes GFS, ECMWF, HIRLAM, and UKMET. It provides forecasts from single wind farm to regional level.	180 hrs	[47]
Previento	University of Oldenburg	Combined	It is the optimal combination of different NWP models input. This model uses weather services data from multiple services. Optimization is carried out using Kombibox procedure, i.e. lesser error predictions will be provided more weight.	15 days	[48]
WPMS (Wind Power Management System)	Fraunhofer Institute for Energy Economics and Energy System Technology	Statistical	WPMS is operational in three European countries. WPMS is based on Artificial Neural Network (KNN) and uses extrapolation algorithm to upscale the prediction of the wind farm to the regional level.	96 hrs	[49]
DNV GL	DNV GL	Statistical	Provide four services: Forecaster Now, Live, Plus and Solutions. The model works on auto-adaptive algorithms and uses SCADA data for MOS correction. Forecasts are available for a single plant as well as the market aggregate level.	15 days	[50]
EPREV	Prewind	Statistical	The model incorporates SCADA data and employs three statistical models: PCM, AR and NNAM. The model can forecast the wind power of a single wind turbine, wind farm or a region.	168 hrs	[51]
AleaWind	Alea Soft	Statistical	The model works on Neural Networks and Genetic Algorithms.	10 days	[52]
Scirocco	Aeolis Forecasting Services	Combined	The model is powered by NWP data and involves three adjustment schemes: Model Output Statistics, physical terrain and Model Chain Output Statistics. Calibration is done through error backpropagation. With ECMWF, the model can forecast long term winds.	15 days	[53]
WindFor (Former WPPT)	ENFOR	Combined	WindFor is a combination of advanced learning methods with a physical model. It can be initiated through time-series data or manufacturer's wind power curve. It can accurately predict short term data when integrated with the SCADA system.	15 days	[17]

the performance is highly dependent on the accuracy of the available data. Also, the lesser number of observations can limit the model performance. Furthermore, statistical models cannot deal with nonlinear conditions. Table 2 describes some commercially available statistical models.

Both the physical and statistical methods have performance limitations in different time horizon. Physical models predict a long-term wind precisely whereas the statistical models have high precision in short-term prediction. Therefore a combination of both will improve the performance of wind power forecasting. Physical models predict the long term trend, whereas statistical models improve the precision of local prediction. Table 2 provides details of some commercially available combine models.

4) ARTIFICIAL INTELLIGENCE/ MACHINE LEARNING METHODS

Artificial Intelligence/ Machine Learning (AI/ML) techniques are the most popular method for wind speed and power forecasting. These techniques train past data to find out the relationship between input and output wind-speeds. Common AI techniques include Artificial Neural Network (ANN) [54], Support Vector Machine (SVM) [55], and Adaptive Neuro-Fuzzy Inference System (ANFIS) [56]. The most commonly used AI model is ANN.

ANN is motivated by the way the human brain would solve the problem. The general form of ANN is a black-box approach and is used to handle non-linear data. A typical ANN has three layers: input layer (the original predictors), one or more hidden layer (set of constructed variables) and output layer (the responses).

Each variable in the layer is termed as a node. In the first step, a weight is used to measure the strength of each connection. The input nodes are multiplied by associative weights, and the net is summed up as in (3):

$$net = w_1x_1 + w_2x_2 + w_3x_3 + \ldots + w_nx_n = \sum_{i=1}^{n} w_ix_i. \quad (3)$$

Next, an activation (or transfer) function f is chosen to transform the net signal of each node i. Mathematically, the output form is:

$$output = f(net + b), \tag{4}$$

where b is the bias term, also called the activation threshold for the corresponding node. It is an offset value that regulates the signal and is same as the intercept term in the regression model. The activation function is typically a non-linear and the selection depends on the nature of the response variable. The commonly used activation function is logistic or hyperbolic tangent function.

SVM is based on the Statistical Learning Theory (SLT) and Structural Risk Minimization (SRM). SVM for data regression (SVR) maps the input data into a high-dimensional feature space through nonlinear kernel function and then generates a linear regression function in this hyperspace. The linear regression function is expressed as in (5):

$$f(x) = \sum\nolimits_{i=1}^{n} w_i \varphi_i(x) + b, \tag{5}$$

where w is the associative weight, b is the bias term and $\varphi(x)$ is the mapping function that maps x into high dimensional feature space. The regression is then expressed by the optimization problem and is solved by the quadratic programming technique. Finally, the estimation function is obtained as in (6):

$$f\left(x, \alpha, \alpha^*\right) = \sum\nolimits_{i=1}^{n} \left(\alpha - \alpha^*\right) k(x_i, x) + b, \tag{6}$$

where α and α^* are the Lagrange multipliers and $k(x_i, x)$ is the kernel function. Different kernel functions are used in SVM models. The commonly used kernel function is a Radial Basis Function (RBF). There are other variants of SVR employed in wind speed and power forecasting including Least Square SVM (LSSVM) [57], Twin SVR (TSVR) [58] and Reduced SVM (RSVM) [59].

ANFIS is a class of adaptive multilayer feedforward network that integrates fuzzy logic principles and neural networks. It develops fuzzy rules with suitable membership functions to produce required inputs and outputs. The ANFIS model has five layers: fuzzification, rule evaluation, normalization, defuzzification and summation. Initially, the system designer sets the learning rules and membership functions based on expertise, and later ANFIS adjusts the rules and functions to minimize the output error index. Most commonly utilized membership function is bell-shaped.

Other than traditional machine learning models, extreme learning and deep learning is gaining much more attention in wind speed and power forecasting. These advanced learning model showed higher accuracy and can learn more complex nonlinear relations. Some notable architectures of deep learning utilized in wind speed and power forecasting includes Deep Belief Network (DBN) [60] and Long Short Term Memory (LSTM) [61].

Extreme Learning Machine (ELM) is a type of feedforward neural network with a single hidden layer. It has better generalization performance and higher convergence speed than the traditional neural network. In ELM, the input weights and hidden biases are generated randomly without iterative tuning. Therefore, the output weights between hidden and output layers are determined as finding the least square solution to the given linear system. Other variants of ELM utilized in wind speed and power forecasting include Hysteresis ELM (HELM) [61], Online Sequential ELM (OSELM) [62], Stacked ELM (SELM) [63], Regularized ELM (RELM) [64], and Weighted RELM (WRELM) [65]. Reference [66] discussed in detail the trends in ELM.

DBN is a multi-layered stochastic generative model, constructed by stacking multiple Restricted Boltzmann Machines (RBMs) [67]. RBM is an undirected bipartite graphical model in which visible observations (v) are connected to stochastic binary hidden units (h) using undirected weighted connections (w_{ij}) [68]. It is characterized by the energy function $E(v, h)$, defined as in (7):

$$E(v, h) = -\sum\nolimits_{i=1}^{n}\sum\nolimits_{j=1}^{m} w_{ij} v_i h_j - \sum\nolimits_{i=1}^{n} a_i v_i - \sum\nolimits_{j=1}^{m} b_j h_j \tag{7}$$

where a_i and b_j are the biases, and n and m are the numbers of neurons in the visible and hidden layers, respectively. The joint probability distribution of visible and hidden layers is expressed as in (8):

$$p(v, h) = \frac{e^{-E(v,h)}}{\sum_v \sum_h e^{-E(v,h)}} \tag{8}$$

For RBM, the individual activation probability of h_j or the conditional probability of v_i is expressed as:

$$P\left(h_j = 1 | v\right) = \frac{1}{1 + exp\left(-\sum_{i=1}^{n} w_{ij} v_i - b_j\right)} \tag{9}$$

$$P\left(v_i = 1 | h\right) = \frac{1}{1 + exp\left(-\sum_{j=1}^{m} w_{ij} h_j - a_i\right)} \tag{10}$$

The unknown parameters can be determined by training the model.

Deep Boltzmann Machine (DBM) is also based on stacked RBM and is applied in wind speed and power forecasting [69]. In contrast with DBN, all connections are undirected in DBM. In DBN, the top two layers have undirected connections, whereas the lower layers have directed connections [70].

LSTM is a variant of Recurrent Neural Network (RNN) and has a stable and excellent ability to solve long-term dependencies. In LSTM, the traditional node of the hidden layer is replaced by a memory cell (a core component of LSTM). The memory cell acts as an accumulator of state information. LSTM has three gates: input (write), output (read) and forget (reset), through which the state information is updated as: The information of incoming input will be accumulated to the cell if input gate is activated. The prior cell status will be forgotten if forget cell is activated. The latest cell output will be propagated to the final state if the output gate is activated.

In comparison with statistical models, AI/ML models have stronger nonlinear estimation ability. However, the problems associated with AI/ML models are slower convergence speed, overfitting, computational complexity, slow speed and generalization problems. Most commonly used AI/ML model is ANN that exhibits overtraining. When the training capacity is too large, it allowed too many iterations that caused over-training.

Both the statistical and AI/ML methods have limited applicability and thus limited prediction accuracy. Therefore, combining both statistical and AI/ML models have better prediction accuracy.

5) HYBRID METHOD

Hybrid forecasting methods take advantage of combining different forecasting methods to improve the performance of the final forecast. An individual model has limited performance in multiple situations. The hybrid model provides superiority as it utilizes capabilities of the individual model and therefore saves time with the better performance [14]. We used the same definition of hybrid models as discussed by Tascikaraoglu and Uzunoglu [14] and Xiao *et al.* [15]. The subclasses of hybrid methods include weighted method, preprocessing or decomposition method, feature selection or optimization method, and postprocessing or error processing method.

In the weighted method, a weight coefficient is assigned to each individual model forecast based on model effectiveness. There are two different arrangements of the weighted method hybrid model: Fixed weight and Variable Weight. The coefficient can be calculated in different ways. This may be weighted average [71], weighted median [71], or varied weights based on optimization algorithm [72]. According to a study conducted by Li *et al.* [72], the variable weight forecasts show better performance than fixed weight forecasts. The variable weight combination forecasting model can better adapt to changes in the sample, and match the weight of the sample points in the corresponding model. Multiple optimization algorithms are utilized to determine the optimal weights. Zhang *et al.* [73] applied CLSFPA (Flower Pollination Algorithm with Chaotic Local Search) to calculate optimum weights with NNCT (No Negative Constraint Theory) and compared the results of the combined model with other single prediction models (BPNN, RBFNN, ENN, GRNN, WNN and ARIMA) at four sites. Similarly, Li *et al.* [72] used BA (Bat Algorithm) with NCFM (Novel Combined Forecasting Model), Xiao *et al.* [15] applied CPSO (Chaos Particle Swarm Optimization) and GA (Genetic Algorithm) with NNCT whereas Okumus and Dilner [74] used LSM (Least Square Method) with FNN and ANFIS. All these models showed better performance than the individual prediction models. Instead of focusing on a single objective optimization algorithm, some researchers have focused on the multi-objective optimization algorithm. Niu and Wang [75] have applied MOGOA (Multi-Objective Grasshopper Optimization Algorithm) to calculate weight coefficient and compared the results with models based on CS (Cuckoo Search) algorithm and FA (Firefly Algorithm). Results showed that MOGOA based model performed very well for the considered five sites at 10 min, 20 min and 30 min prediction ahead followed by FA and CS.

Most of the hybrid models reported in the literature are decomposition-based approaches. In the decomposition method, pre-processing techniques are applied to decompose the non-stationary time series data into stationary subseries. Decomposition approaches widely reported in the literature including Wavelet Transform (WT) [58], Wavelet Packet Decomposition (WPD) [76], Empirical Mode Decomposition (EMD) [72], variants of EMD including Ensemble EMD (EEMD) [77], Fast EEMD (FEEMD) [64], Complementary EEMD (CEEMD) [78], Complete EEMD with Adaptive Noise (CEEMDAN) [73], Improved CEEMDAN (ICEEMDAN) [79], Intrinsic Time Scale Decomposition [80], Seasonal Adjustment Methods [81], Variational Mode Decomposition (VMD) [82], Optimized VMD (OVMD) [83], Empirical Wavelet Transform (EWT) [84], and Improved EWT (IEWT) [85]. There are two subtypes of decomposition: primary and secondary. In the primary arrangement, a decomposition model is used to decompose the non-stationary time series data into several stationary subseries at the time series and then a separate prediction model is on each subseries. In the latter arrangement, a secondary decomposition model is used to decompose further the most non-stationary subseries. The further method would be the same as the first arrangement. It is not necessary to use the same prediction model for the decomposed series. Han *et al.* [86] used Wavelet decomposition with ARMA and LSSVM to predict high and low-frequency subseries. Similarly, Zhang *et al.* [87] applied EEMD decomposition with SARIMA and ANFIS for periodic and nonlinear components modelling.

Feature selection and optimization technique are applied to remove the redundant data, thus improves the model performance. Several optimization algorithms are reported in the literature. Wang et al. used GA to optimize BP [88], Meng *et al.* used CSO (Crisscross Optimization) to optimize BP [89], Liu *et al.* used GA and MEA (Mind Evolutionary Algorithm) to optimize MLP (Multi-Layer Perceptron) [90], Kong *et al.* used PSO to optimize RSVM [59] and Osório *et al.* [91] used EPSO (Evolutionary PSO) to optimize ANFIS. Feature selection for unsupervised learning can further classify into two methods: wrapper and filter. The wrapper approach uses a search algorithm to rank the feature subset. This method requires a prediction model performance. The subset that shows the best prediction performance is selected as the final feature subset. The filter method uses arithmetic analysis and does not require prediction model performance. Therefore, filter methods are faster than wrapper methods, but the performance is worse than the wrapper method. This argument is supported by the study conducted by Carta et al. [92]. In this study, the authors analysed both Wrapper and Filter method for a case study of Spain. *CfsSubsetEval* is used as filter whereas *WrapperSubsetEval* is used as a wrapper method. Analysis of two years of data for five stations showed that the wrapper approach provided lower mean errors than the filter method in all of the cases. It was also concluded that the wrapper method is more significant when non-linear relation between features increases such as wind direction significance in complex terrain. This improved performance is achieved on a cost of higher computational time. On the other hand, if this relation is not of the higher-order, then the Filter method has the advantage of lower computational time without losing prediction accuracy. Some studies discussed combine method of wrapper and filter, thus take advantages of both methods. It uses filter algorithm information to accelerate wrapper algorithm convergence [82].

Studies based on post-processing techniques considered the influence of error factors on the performance of the model. The purpose is to analyse the errors after primary prediction model and then incorporate a post-processing model. The results of the post-processing model help to improve the initial forecast results in producing the final forecasts. Hao and Tian [93] discussed a two-stage forecasting model in which error factor is considered. In the first stage, VMD is used as the decomposition model and ELM optimized by MOGWO (Multi-Objective Grey Wolf Optimization) is used as a prediction model for the forecasting error. In a second stage, the nonlinear ensemble method is developed to integrate variational modes and forecast error predictors to get the final forecast. Comparisons are made between individual statistical and ANN models, a single decomposition model and the proposed model. The proposed model significantly increased the model accuracy.

References [14], [15], [20] provide details of sub-classes of hybrid models.

III. METHODOLOGY

A. PERFORMANCE INDICATORS

The forecast results are comprehensively evaluated based on several performance indicators. Jiang *et al.* [77] discussed three aspects of evaluation metrics: accuracy, stability and direction. MAE and RMSE are used to evaluate the accuracy, variance to measure the stability and direction-accuracy to estimate correctness. However, most of the studies inferred the results based on accuracy indicators only. The commonly used mean absolute error and root mean square error are defined as in (11) and (12), respectively.

$$MAE = \frac{1}{N}\sum\nolimits_{i=1}^{N}\left|y_i - \hat{y}_i\right|, \tag{11}$$

$$RMSE = \sqrt{\frac{1}{N}\sum\nolimits_{i=1}^{N}\left(y_i - \hat{y}_i\right)^2}, \tag{12}$$

where N is the number of entries, y_i is the i^{th} measurement, and $\hat{y}_i$ is the i^{th} forecasted value. The average of measured values is denoted by $\bar{y}$. These performance indicators evaluate quantitative measures and have similar physical units as the dependent parameter.

Inner-comparison of results, published in terms of absolute values, is not possible due to non-identical datasets. For comparing the accuracy results, it is necessary to convert the absolute values in normalized values. There are different normalization techniques available. The most common reference quantity is the mean value (μ) as:

$$\mu = \frac{1}{N}\sum\nolimits_{i=1}^{N} y_i. \tag{13}$$

Other reference quantities include present value (y_i), deviation from average ($|y_i - \bar{y}|$) and dynamic characteristics ($|y_i - y_{i-1}|$) as reported by Gensler *et al.* [94]. In this study, we select all the choices of normalization. The accuracy sets, where normalized values are not available, we use mean value as the reference quantity: nMAE $=$ MAE/μ and nRMSE $=$ RMSE/μ.

Vargas *et al.* [95] presented a systematic review for wind power generation based on citation network analysis (CNA). According to the study, physical models had aroused during the 90's whereas AI/ ML and hybrid models have been emerging since the last decade. Also, most studies used hourly data frequency and more than half studies implement wind speed as input and output variable. Almost two-thirds of the studies are related to China. After analysing 143 articles spread over 33 years (1985-2018), the authors concluded that wind energy studies started growing considerably after 2010. Keeping in view this analysis and the procedure adopted by Blaga *et al.* [18], the following criteria are set for the selection of paper:

1) The publishing year of the paper must be in between 2010-2019.
2) The model performance is reported in terms of normalized Mean Absolute Error (nMAE) and normalized Root Mean Square Error (nRMSE).
3) In case the results are not presented in normalized values, then the statistical indicators of wind data must be listed in the paper.

We shortlisted twenty-eight papers for the analysis. The final database comprises of 634 entries spread over 50 locations covering ten countries. The description of selected papers is given in Table 3, and the overall summary is presented in Fig. 5 [96]. The papers are listed according to the publication year.

B. PERFORMANCE ANALYSIS OF THE DATASET

Fig. 6a summarizes the performance of prediction models in terms of averaged values. The statistical indicators are averaged over all entries of that specific paper. The 28 circles refer to 28 papers (as indexed in Table 3), the diameter of the circle reflects the number of data entries, and the color of the circle indicates the year of publication. For example, index 7 shows that the paper published in 2014 with 15 entries having averaged nMAE $=$ 13.31% and averaged nRMSE $=$ 19.04%. Fig. 6a also shows the variability in data as some averaged values contain smaller nRMSE but larger nMAE and vice-versa. For example, index 19 and 20 both published in 2017 having almost the same number of data entries but contradictory averaged results. The averaged nMAE, and nRMSE values for index 19 is 3.19% and 5.33% respectively whereas averaged nMAE and nRMSE values for index 20 is

TABLE 3. Description of the papers included in the study.

Index	Year	Author	Ref	Input Data	Time scale	Forecasted variable	Forecasting Method	Country	Data Summary
1	2010	Cadenas and Rivera	[97]	TS	ST	wind speed	S, AI	Mexico	3 locations with 744, 672 and 720 observations respectively
2	2011	Blonbou	[98]	TS	VST	power	AI	France	2 locations with data ranging from July 2002 to March 2005
3	2011	An *et al.*	[99]	TS	VST	power	H	China	1 location with 470 points
4	2014	Wang *et al.*	[100]	TS	ST	wind speed	Per, AI, H	China	1 location with data ranging from January 1, 2010 to March 31, 2011
5	2014	Haque *et al.*	[101]	TS	MT, LT	power	Per, AI, H	USA	1 location with data from 2011
6	2014	Mandal *et al.*	[102]	TS	ST, MT	power	Per, AI, H	Canada	1 location with data ranging from January to December 2009
7	2014	Chen *et al.*	[103]	TS, NWP	MT	power	Per, S, AI, P	China	2 locations with data ranging from April 2010 to April 2013
8	2015	Liu *et al.*	[104]	TS	ST	wind speed	S, AI, H	China	1 location with data from July and August 2011
9	2015	Chitsaz *et al.*	[105]	TS	ST	power	Per, AI, H	Canada	1 location with data from 2012
10	2015	Osorio *et al.*	[91]	TS	ST	power	H	Portugal	1 location with data ranging from 2007-2008
11	2015	Wang *et al.*	[106]	TS	VST	wind speed	H, S, AI	China	8 locations with 1096 observations for four locations, 486 observations for one location, 551 observations for two locations, and 557 observations for the last one
12	2015	Ozkan and Karagoz	[107]	TS, NWP	LT	power	P, AI	Turkey	1 location with data ranging from June 2012 and the end of December 2012
13	2016	Zhang *et al.*	[108]	TS	ST	wind speed	AI, H	China	3 locations with data ranging from March 1, 2012 to March 31, 2012
14	2016	Abdoos	[82]	TS	VST, ST	power	AI, H	Spain, USA	1 location from each country with observations from 2014 (Spain) and 2006 (USA)
15	2016	Cadenas *et al.*	[109]	TS	ST	wind speed	Per, AI	Mexico	1 location with data ranging from May 1, 2006 to June 30, 2007
16	2016	Liang *et al.*	[110]	TS	ST	power	Per, S, AI, H	China	1 location with data ranging from April 19 to September 30, 2013
17	2017	Wang *et al.*	[78]	TS	VST	wind speed	Per, AI, H	China	1 location with 2880 observations
8	2017	Zhang *et al.*	[83]	TS	VST	wind speed	S, AI, H	China, Spain	2 locations from China with 600 observations and 1 location from Spain with data ranging from March 3 to March 12, 2017
19	2017	Liu *et al.*	[111]	TS	LT	power	AI	China	1 location with data from 2012
20	2017	Ranganayaki and Deepa	[112]	TS	ST	power	AI, H	India	1 location with data ranging from January 2010 to December 2014
21	2017	Feng *et al.*	[113]	TS	Short term	wind speed	Per, AI	USA	7 locations with data ranging from January 2015 to December 2015
22	2018	Lu *et al.*	[57]	TS	VST	wind speed	AI, H	China	1 location with data from 2016
23	2018	Li *et al.*	[72]	TS	VST	wind speed	H	China	1 location with 2304 observations
24	2018	Hu and Chen	[61]	TS	VST, ST	wind speed	S, AI	China	1 location with 720 observations
25	2018	Song *et al.*	[79]	TS	VST	wind speed	S, AI, H	China	1 location with data ranging from May 1, 2011 to May 18, 2011
26	2019	Aasim *et al.*	[114]	TS	VST	wind speed	Per, S, H	Ireland	1 location with data from December 2017
27	2019	Jiang *et al.*	[77]	TS	VST	wind speed	Per, S, AI, H	China	1 location with data ranging from 1 January to 20 January 2011
28	2019	Dhiman *et al.*	[58]	TS	VST, ST	wind speed	Hybrid	Spain, USA, India	1 location from Spain with data of October 2017, 4 locations of the USA with data ranging from January 1 to January 7, 2011and 1 location from India with data from January 2019

TS=Time Series, NWP= Numerical Weather Prediction, VST=Very Short Term, ST=Short Term, MT= Medium Term, LT= Long Term, Per=Persistence, P=Physical, S=Statistical, AI=Artificial Intelligence, H=Hybrid

9% and 7.18% respectively. Also, the number of entries is significant in some articles, whereas few of them shows only a handful of data. From descriptive statistics, the 95% confidence interval (CI) for the mean, for averaged nMAE and nRMSE varies between 6.73% to 10.07% and 8.276% to 12.550% respectively. Similarly, the 95% confidence

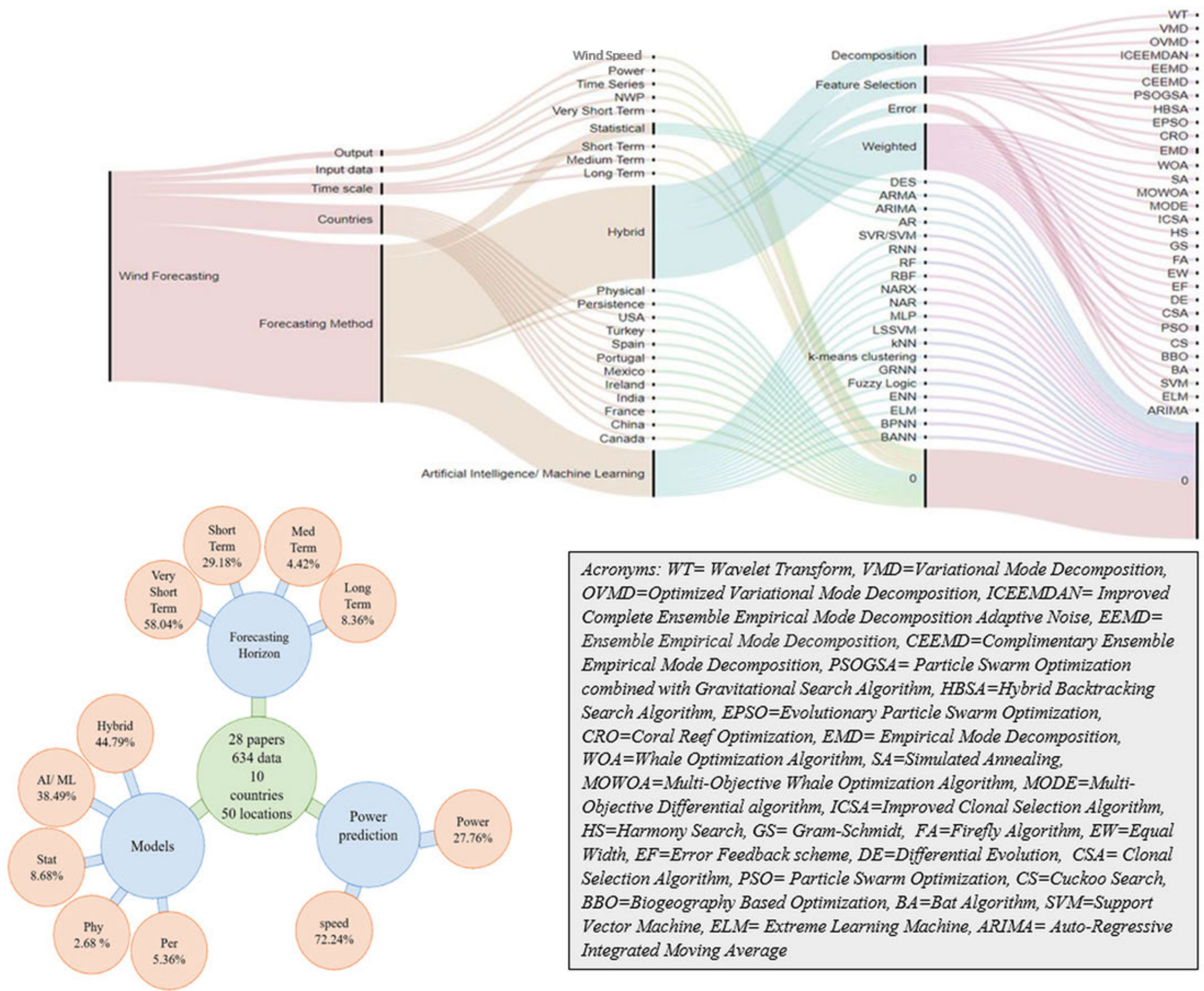


FIGURE 5. Overall Summary of the selected 28 papers based on forecasting classification. The percentages (%) indicate the frequency of data implemented for each sub category out of 634 data entries.

interval (CI) for the median, for nMAE and nRMSE varies between 6.14% to 9.41% and 7.548% to 12.085% respectively. Fig. 6b shows a two-dimensional histogram. The width and height of the bar show the relative size of datasets for forecasting horizon and predicting models respectively. For example, the Artificial Intelligence and Machine Learning (AI/ML) models comprised 38% of all data entries for which 48% is very short term, 36% is short term, 3% is the medium term, and 13% is long term.

Visual inspection displays that the physical models were used only for medium and long term forecasts, whereas statistical models hardly used for long term forecasts. In general, most of the work was done for very short term and short term forecasts using AI/ML and hybrid models. The number of data entries for AI/ML and hybrid models are considerably more significant than the others. This number is due to the eligibility criteria for the selection of papers. The authors of these papers either provided the mean values of input data or the normalized values of the output data in their studies.

Fig. 7a displays model performance per forecasting method and Fig. 7b per time scale. Visual inspection of Fig. 7a indicates that the physical models have the largest errors, whereas hybrid models have the smallest one. Also, the performance of AI/ML models is better than statistical models. From Fig. 7b, it is as per expectations that the performance decreases as the time horizon increases.

If we compare the interdependence of both graphs, we analyse that the most substantial errors are witnessed for the physical models because these models are applied primarily for medium-term and long term forecasts. On the other hand, the hybrid models are applied mostly for the very short term, and short term forecasts and therefore, these models showed the best performance. Persistence model and AI/ML

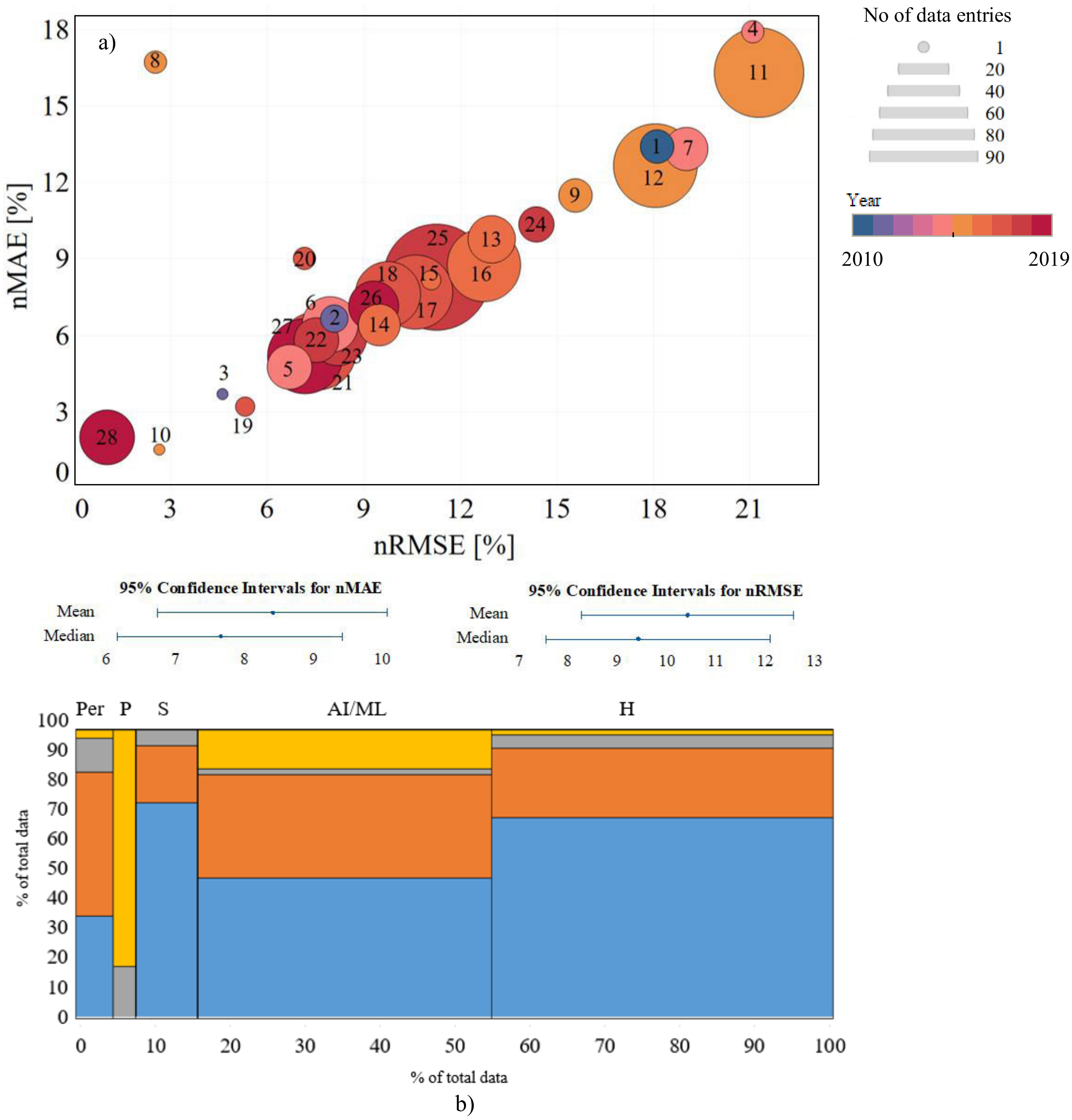


FIGURE 6. a) Illustrative plot presenting the performance of the model reported in the selected papers, b) 2-dimensional histogram presenting the qualitative picture of datasets.

models show close results. This unexpected output is due to the significant number of entries for AI/ML models. AI/ML models contain seven times more data than persistence models. Especially for long term forecast, AI/ML models contain four times more data entries than persistence models. Fig. 7a and 7b are generated based on averaged values which do not provide in-depth knowledge for the spread of error. Box and whiskers plot (Fig. 8) and standard deviation present the spread of errors more clearly.

In box and whisker plots, the lower and upper values of the box indicate the interquartile range (IQR) corresponds to 25th and 75th percentile, whereas the whiskers extend to 1.5 times the IQR. The standard deviation is a measure used to quantify the amount of variation or dispersion of a dataset and is defined as:

$$\sigma = \sqrt{\frac{1}{N}\sum\nolimits_{i=1}^{N}(y_i-\mu)^2}. \tag{14}$$

From Fig. 8a and 8b, the length of the whiskers are the largest for the persistence model ($IQR_{nMAE} = 6.6434\%$, $IQR_{nRMSE} = 8.1072\%$). It shows that the variation range of error is largest for the persistence model. In terms of median values, persistence is the same as AI/ML models. However, the spread of errors is 12% more in the case of nMAE and 13% more in the case of nRMSE for the persistence model. It proves our previous argument that despite having close results in Fig. 7a, AI/ML models perform better than persistence. The length of the whiskers for the physical model,

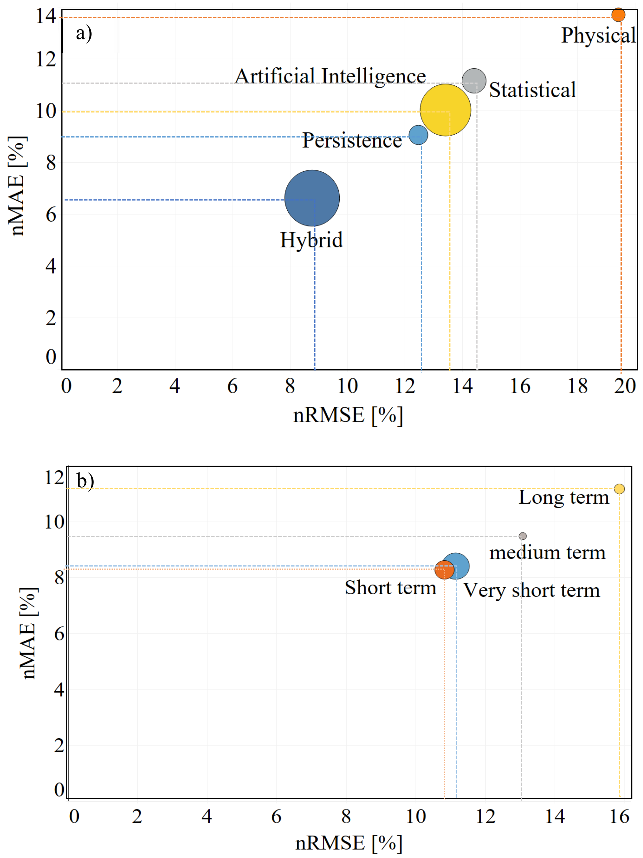


FIGURE 7. The performance of a) prediction models, b) time scale, in terms of averaged values.

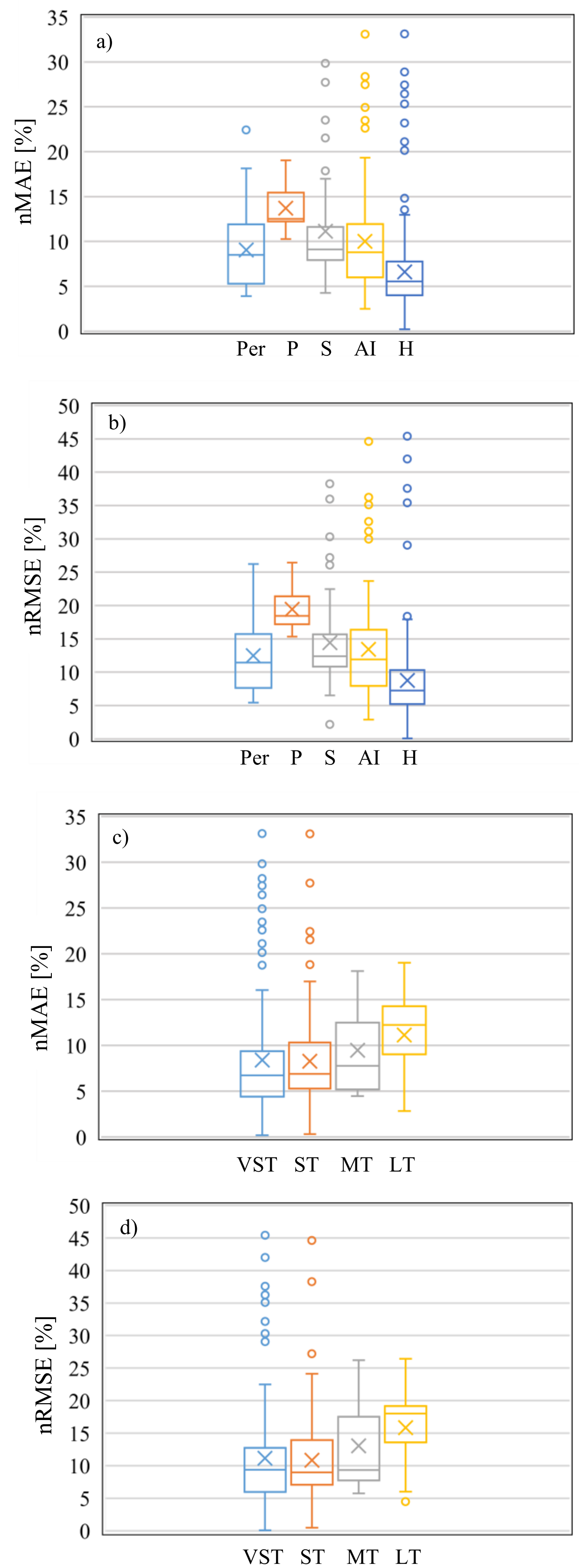


FIGURE 8. Performance indicators (a) nMAE (b) nRMSE, for forecasting model, (c) nMAE (d) nRMSE, for time scale.

statistical model the physical models are nearly 2.5 times, and statistical models are 1.8 times higher than the hybrid models, respectively. It shows that the best performance is of hybrid models. Although and hybrid model is almost the same, the median values of the physical models have a larger mean value of nRMSE ($\mu_{nRMSE} = 19.43\%$) but have small volatility ($\sigma_{nRMSE} = 3.29$). It shows that the model errors are systematic and not stochastic. Hence, post-processing the errors will further improve model accuracy. Out of all models, 10% outliers found for statistical models, 2.5% for AI/ML models and 4% for hybrid models. Mainly, the outliers are due to medium term and long term forecast. Similarly, from Fig. 8c and 8d, the whisker length shows that the accuracy decreases as the forecast horizon increases. In terms of nMAE median values, very short term forecast has a value of 6.73% that increases to 6.9% and 7.77% for short term and medium term forecast. Finally, the long term has the largest value of 12.24%. Based on previous analysis, here we again observe that the long term models have a larger mean value of nRMSE ($\mu_{nRMSE} = 15.86\%$) but small volatility ($\sigma_{nRMSE} = 5.74$). It again shows that the model errors are systematic and not stochastic. Thus, post-processing the errors will increase the model performance. In general, hybrid models outperform all the models.

TABLE 4. Performance of forecasting models according to time horizon and impact of input data on forecasting accuracy.

		Persistence	Physical	Statistical	Artificial Intelligence/ Machine Learning	Hybrid
Horizon	very short term	good	poor	good	good	good
	short term	average	average	good	good	good
	medium term	poor	good	average	average	good
	long term	poor	good	poor	poor	good
Input	NWP	not required	higher impact	lower impact	lower impact	higher impact in case of medium and long term forecast
	historical time series data	higher impact	lower impact	higher impact	higher impact	higher impact

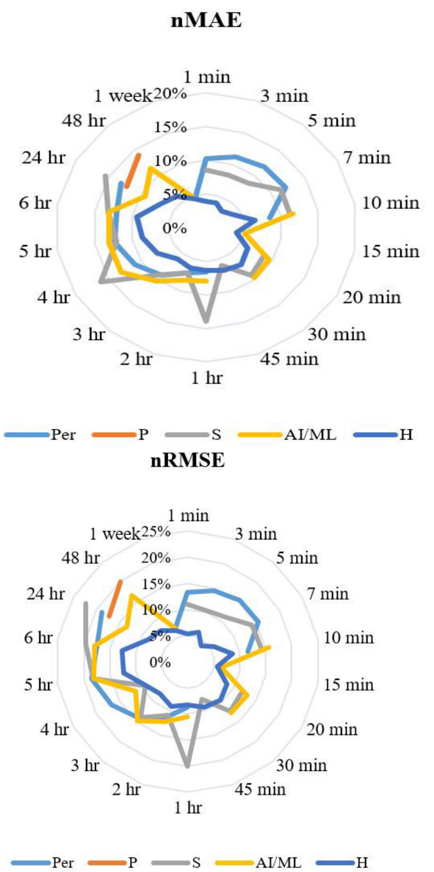


FIGURE 9. Statistical indicators with respect to the time horizon.

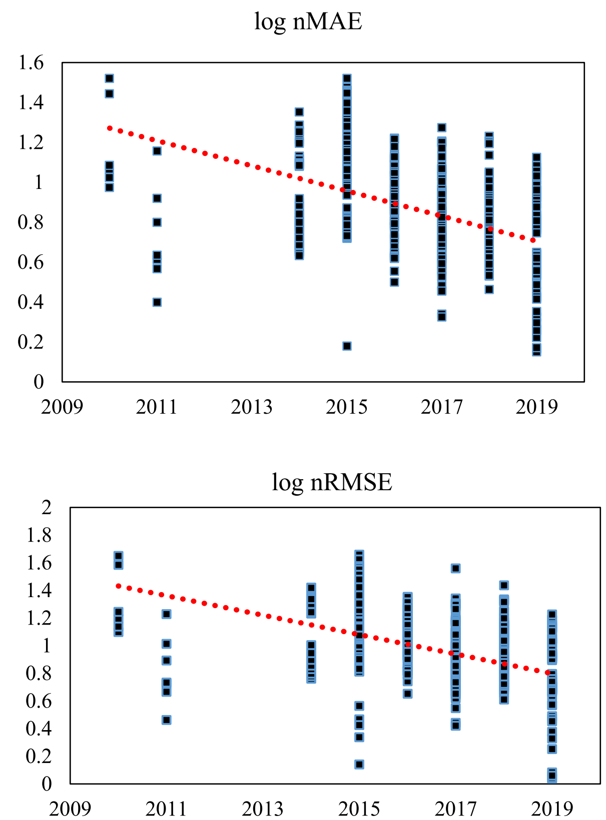


FIGURE 10. Linear trend of statistical errors with respect to publication year.

Fig. 9 indicates the dependence of statistical errors on the time horizon. Before interpreting the results, the reader may note that the number of entries is non-uniform in time horizon. The most significant subset is available for very short term forecasts. Also, the time steps are not equidistant. The available time horizons include 1 min, 3 min, 5 min, 7 min, 10 min, 15 min, 20 min, 30 min, 45 min, 1 hr, 2 hr, 3 hr, 4 hr, 5 hr, 6 hr, one day, two days and one week.

Persistence model performs the worst even in the very short term forecast. The performance of statistical models is excellent in the very short term such that it outperforms the AI/ML model (see 10 min). At 30 min, both of the models show almost the same results. From 1 hr onwards, the errors of statistical models start to increase, on average, by a factor 1.19. The data for physical models is only available for medium-term and long term forecast. The performance of the physical model outstrips persistence and statistical model, show the close result with AI/ML model and underperform the hybrid models. Overall, the hybrid models perform best for every time horizon. However, the errors almost doubled at the medium-term forecast from its initial value.

Among all discussions, it should be noted that model accuracy comparison between different techniques cannot be entirely justified until the same data set and the same level of effort is utilized. However, based on available studies, the performance of forecasting models according to time horizon and the impact of input data on forecasting accuracy is shown in Table 4. It is concluded that the best-suited models, among all, which work well for any time horizon and with any input data, are hybrid models. More specifically, the decomposition model with an optimization algorithm or error factor outperforms all the model when dealing with the short term forecast.

According to the analysis of Vargas *et al.* [59], wind power generation started growing substantially from the last decade. Therefore, it is a topic of interest to quantify the overall improvement of forecasting performance. Fig. 10 presents the linear trend of statistical errors with respect to publication year on a semi-logarithmic scale. The negative trend shows that the errors reduced every year. The slope (m) of regression line fitted to the $\log(nMAE)$ is $m = -0.069$ and for $\log(nRMSE)$ is $m = -0.0704$. It shows that the nMAE decreases with a factor of $\exp(-0.069) = 0.94$ every year. So, during the whole decade, nMAE drops to a factor of 0.533.

Similarly, the nRMSE drops with a factor of $\exp(-0.0704) = 0.93$ every year. So, during the whole decade, nRMSE drops to a factor of 0.49. It denotes that during the last ten years, the errors are reduced to about half the initial values.

IV. CONCLUSION

This paper reviewed the recent developments reported in the literature for deterministic wind speed and power forecasting. We classified and discussed the forecasting models as input data, time scale, power output, and forecasting methods. There is always a shortcoming of comparing different forecasting models. The studies available in the literature are not of identical datasets and authors have used data based on availability. Therefore, in each case study, the data is different in the forecasting horizon, model formation and location. The present study overcame this limitation and associated the performance and trend of recently developed forecasting models. Following conclusions are drawn from the detailed analysis:

- From descriptive statistics, the 95% CI for the mean, for averaged nMAE and nRMSE varies between 6.73% to 10.07% and 8.276% to 12.550% respectively. Similarly, the 95% CI for the median for nMAE and nRMSE varies between 6.14% to 9.41% and 7.548% to 12.085% respectively.
- In terms of median values, persistence is the same as AI/ML models. However, the spread of errors is more for the persistence model. Therefore, AI/ML models perform better than persistence, which is not expected from the illustrative plot.
- The most significant errors are witnessed for the physical models because these models are applied primarily for medium-term and long-term forecasts.
- The physical models have large nRMSE values but small volatility. Therefore, we conclude that the model errors are systematic and not stochastic. Hence, post-processing the errors will further improve model accuracy.
- Overall, the hybrid models perform best for every time horizon. However, the errors almost doubled at the medium-term forecast from its initial value.
- Based on the available dataset, the performance increased during the last ten years. On average, the errors are reduced to about half the initial values.

Improving the performance of wind forecasts is still a challenge for the researchers. A detailed study is required in this context to cover datasets from different climatic zones to analyse the performance of different forecasting models. The comprehensive review presented in this paper would help professionals and researchers to improve forecasting accuracy and to come up with more precise wind energy forecasts.

REFERENCES

[1] (2018). *Annual Global Wind Report*. Accessed: Sep. 3, 2019. [Online]. Available: https://gwec.net/wp-content/uploads/2019/04/GWEC-Global-Wind-Report-2018.pdf
[2] 67th ed. (2018). *BP Statistical Review of World Energy*. Accessed: Sep. 3, 2019. [Online]. Available: https://www.bp.com/content/dam/bp/business-sites/en/global/corporate/pdfs/energy-economics/statistical-review/bp-stats-review-2018-full-report.pdf
[3] A. Fabbri, T. G. S. Roman, J. R. Abbad, and V. H. M. Quezada, "Assessment of the cost associated with wind generation prediction errors in a liberalized electricity market," *IEEE Trans. Power Syst.*, vol. 20, no. 3, pp. 1440–1446, Aug. 2005.
[4] M. H. Albadi and E. F. El-Saadany, "Overview of wind power intermittency impacts on power systems," *Electr. Power Syst. Res.*, vol. 80, no. 6, pp. 627–632, 2010.
[5] S. S. Soman, H. Zareipour, O. Malik, and P. Mandal, "A review of wind power and wind speed forecasting methods with different time horizons," in *Proc. North Amer. Power Symp.*, Sep. 2010, pp. 1–8.
[6] N. Bokde, A. Feijóo, D. Villanueva, and K. Kulat, "A review on hybrid empirical mode decomposition models for wind speed and wind power prediction," *Energies*, vol. 12, no. 2, p. 254, 2019.
[7] H. Liu, H.-Q. Tian, and Y.-F. Liu, "An EMD-recursive ARIMA method to predict wind speed for railway strong wind warning system," *J. Wind Eng. Ind. Aerodyn.*, vol. 141, pp. 27–38, Jun. 2015.
[8] D. C. Montgomery, C. L. Jennings, and M. Kulahci, *Introduction to Time Series Analysis and Forecasting*. Hoboken, NJ, USA: Wiley, 2008.
[9] J. M. Morales, A. J. Conejo, H. Madsen, P. Pinson, and M. Zugno, *Integrating Renewables in Electricity Markets: Operational Problems*. New York, NY, USA: Springer, 2013. Accessed: Sep. 3, 2019. [Online]. Available: https://link.springer.com/content/pdf/10.1007%2F978-1-4614-9411-9.pdf, doi: 10.1007/978-1-4614-9411-9.
[10] H. Liu, C. Chen, X. Lv, X. Wu, and M. Liu, "Deterministic wind energy forecasting: A review of intelligent predictors and auxiliary methods," *Energy Convers. Manage.*, vol. 195, pp. 328–345, Sep. 2019.
[11] Y. Zhang, J. Wang, and X. Wang, "Review on probabilistic forecasting of wind power generation," *Renew. Sustain. Energy Rev.*, vol. 32, pp. 255–270, Apr. 2014.
[12] J. Yan, Y. Liu, S. Han, Y. Wang, and S. Feng, "Reviews on uncertainty analysis of wind power forecasting," *Renew. Sustain. Energy Rev.*, vol. 52, pp. 1322–1330, Dec. 2015.
[13] A. M. Foley, P. G. Leahy, A. Marvuglia, and E. J. McKeogh, "Current methods and advances in forecasting of wind power generation," *Renew. Energy*, vol. 37, no. 1, pp. 1–8, 2012.
[14] A. Tascikaraoglu and M. Uzunoglu, "A review of combined approaches for prediction of short-term wind speed and power," *Renew. Sustain. Energy Rev.*, vol. 34, pp. 243–254, Jun. 2014.

[15] L. Xiao, J. Wang, Y. Dong, and J. Wu, ''Combined forecasting models for wind energy forecasting: A case study in China,'' *Renew. Sustain. Energ. Rev.*, vol. 44, pp. 271–288, Apr. 2015.
[16] Z. Qian, Y. Pei, H. Zareipour, and N. Chen, ''A review and discussion of decomposition-based hybrid models for wind energy forecasting applications,'' *Appl. Energy*, vol. 235, pp. 939–953, Feb. 2019.
[17] *Windfor*. Accessed: Sep. 3, 2019. [Online]. Available: https://enfor.dk/services/windfor/
[18] R. Blaga, A. Sabadus, N. Stefu, C. Dughir, M. Paulescu, and V. Badescu, ''A current perspective on the accuracy of incoming solar energy forecasting,'' *Progr. Energy Combustion Sci.*, vol. 70, pp. 119–144, Jan. 2019.
[19] G. J. Haltiner, *Numerical Weather Prediction*. New York, NY, USA: Wiley, 1971.
[20] H. Liu and C. Chen, ''Data processing strategies in wind energy forecasting models and applications: A comprehensive review,'' *Appl. Energy*, vol. 249, pp. 392–408, Sep. 2019.
[21] J. Jung and R. P. Broadwater, ''Current status and future advances for wind speed and power forecasting,'' *Renew. Sustain. Energy Rev.*, vol. 31, pp. 762–777, Mar. 2014.
[22] *ICOsahedral Nonhydrostatic*. Accessed: Sep. 3, 2019. [Online]. Available: https://www.dwd.de/DE/forschung/wettervorhersage/num_modellierung/01_num_vorhersagemodelle/icon_beschreibung.html?nn=512942
[23] *Consortium for Small-Scale Modelling*. Accessed: Sep. 3, 2019. [Online]. Available: https://www.dwd.de/DE/forschung/wettervorhersage/num_modellierung/01_num_vorhersagemodelle/regionalmodell_cosmo_de.html?nn=512942
[24] *Integrated Forecasting System—High RESolution (IFS-HRES)*. Accessed: Sep. 3, 2019. [Online]. Available: https://www.ecmwf.int/en/forecasts/datasets/set-i
[25] *SEASonal Set V*. Accessed: Sep. 3, 2019. [Online]. Available: https://www.ecmwf.int/en/forecasts/datasets/set-v
[26] *Deterministic Global & Deterministic UK*. Accessed: Sep. 3, 2019. [Online]. Available: https://www.metoffice.gov.uk/research/modelling-?systems/unified-model/weather-forecasting
[27] *Global Spectral Model*. Accessed: Sep. 3, 2019. [Online]. Available: http://www.jma.go.jp/jma/en/NMHS/table/spec_GSM.pdf
[28] *Local Forecast Model*. Accessed: Sep. 3, 2019. [Online]. Available: https://www.jma.go.jp/jma/jma-eng/jma-center/nwp/specifications/specifications_LFM.pdf
[29] A. Kusiak, H. Zheng, and Z. Song, ''Short-term prediction of wind farm power: A data mining approach,'' *IEEE Trans. Energy Convers.*, vol. 24, no. 1, pp. 125–136, Mar. 2009.
[30] A. Kusiak and Z. Zheng, ''Short-horizon prediction of wind power: A data-driven approach,'' *IEEE Trans. Energy Convers.*, vol. 25, no. 4, pp. 1112–1122, Dec. 2010.
[31] A. Kusiak, H. Zheng, and Z. Song, ''Wind farm power prediction: A data-mining approach,'' *Wind Energy, Int. J. Progr. Appl. Wind Power Convers. Technol.*, vol. 12, no. 3, pp. 275–293, 2009.
[32] E. T. Renani, M. F. M. Elias, and N. A. Rahim, ''Using data-driven approach for wind power prediction: A comparative study,'' *Energy Convers. Manage.*, vol. 118, pp. 193–203, Jun. 2016.
[33] X. Zhu and M. G. Genton, ''Short-term wind speed forecasting for power system operations,'' *Int. Stat. Rev.*, vol. 80, no. 1, pp. 2–23, 2012.
[34] D. Y. Hong, T. Y. Ji, L. L. Zhang, M. S. Li, and Q. H. Wu, ''An indirect short-term wind power forecast approach with multi-variable inputs,'' in *Proc. IEEE Innov. Smart Grid Technol.-Asia (ISGT-Asia)*, Nov./Dec. 2016, pp. 793–798.
[35] H. L. Wegley, M. R. Kosorok, and W. J. Formica, ''Subhourly wind forecasting techniques for wind turbine operations,'' Pacific Northwest Lab., Richland, WA, USA, Tech. Rep. PNL-4894, 1984.
[36] Y.-K. Wu and J.-S. Hong, ''A literature review of wind forecasting technology in the world,'' in *Proc. IEEE Lausanne Power Tech*, Jul. 2007, pp. 504–509.
[37] Y. Wang, Y. Liu, L. Li, D. Infield, and S. Han, ''Short-term wind power forecasting based on clustering pre-calculated CFD method,'' *Energies*, vol. 11, no. 4, pp. 1–9, 2018.
[38] F. Castellani, D. Astolfi, M. Mana, M. Burlando, C. Meißner, and E. Piccioni, ''Wind power forecasting techniques in complex terrain: ANN vs. ANN-CFD hybrid approach,'' *J. Phys., Conf. Ser.*, vol. 753, no. 8, 2016, Art. no. 082002.
[39] G. Kariniotakis, P. Pinson, N. Siebert, G. Giebel, and R. Barthelmie, ''The state of the art in short-term prediction of wind power—From an offshore perspective,'' in *Proc. SeaTechWeek*, Brest, France, Oct. 2004.
[40] J. Wang, Q. Zhou, and X. Zhang, ''Wind power forecasting based on time series ARMA model,'' *IOP Conf. Ser., Earth Environ. Sci.*, vol. 199, no. 2, 2018, Art. no. 022015.
[41] S.-K. Sim, P. Maass, and P. G. Lind, ''Wind speed modeling by nested ARIMA processes,'' *Energies*, vol. 12, no. 1, p. 69, 2019.
[42] R. G. Kavasseri and K. Seetharaman, ''Day-ahead wind speed forecasting using f-ARIMA models,'' *Renew. Energy*, vol. 34, no. 5, pp. 1388–1393, 2009.
[43] J. L. T. García, E. C. Calderón, G. G. Ávalos, E. R. Heras, and A. M. Tshikala, ''Forecast of daily output energy of wind turbine using sARIMA and nonlinear autoregressive models,'' *Adv. Mech. Eng.*, vol. 11, no. 2, 2019, Art. no. 1687814018813464.
[44] M. Lydia, S. S. Kumar, A. I. Selvakumar, and G. E. P. Kumar, ''Linear and non-linear autoregressive models for short-term wind speed forecasting,'' *Energy Convers. Manage.*, vol. 112, pp. 115–124, Mar. 2016.
[45] N. Shi, S.-Q. Zhou, X.-H. Zhu, X.-W. Su, and X.-Y. Zhao, ''Wind speed forecasting based on grey predictor and genetic neural network models,'' in *Proc. 2nd Int. Conf. Meas., Inf. Control*, vol. 2, Aug. 2013, pp. 1479–1482.
[46] T. Jónsson, P. Pinson, H. A. Nielsen, and H. Madsen, ''Exponential smoothing approaches for prediction in real-time electricity markets,'' *Energies*, vol. 7, no. 6, pp. 3710–3732, Jun. 2014.
[47] *Simulation Model for the Operational Forecast of the Wind Energy Production in Europe*. Accessed: Sep. 3, 2019. [Online]. Available: http://www.eurowind.info/en/services/forecasts-and-actual-data/#c84
[48] Previento. Accessed: Sep. 3, 2019. [Online]. Available: https://www.energymeteo.com/products/power_forecasts/wind-solar-power-forecasts.php#Windsolar
[49] *Wind Power Management System*. Accessed: Sep. 3, 2019. [Online]. Available: https://www.iee.fraunhofer.de/de/projekte/suche/laufende/wind_power_managementsystem.html
[50] *Det Norske Veritas—Germanischer Lloyd*. Accessed: Sep. 3, 2019. [Online]. Available: https://www.dnvgl.com/services/forecaster-introduction-3848
[51] EPREV. Accessed: Sep. 3, 2019. [Online]. Available: https://www.prewind.eu/services
[52] AleaWind. Accessed: Sep. 3, 2019. [Online]. Available: https://aleasoft.com/wind-energy-forecasting/
[53] Scirocco. Accessed: Sep. 3, 2019. [Online]. Available: http://www.windknowhow.com/upload/scirocco_brochure_english.pdf
[54] A. K. Yadav and H. Malik, ''Short-term wind speed forecasting for power generation in Hamirpur, Himachal Pradesh, India, using artificial neural networks,'' in *Applications of Artificial Intelligence Techniques in Engineering*. Singapore: Springer, 2019, pp. 263–271.
[55] A. Khosravi, L. Machado, and R. O. Nunes, ''Time-series prediction of wind speed using machine learning algorithms: A case study Osorio wind farm, Brazil,'' *Appl. Energy*, vol. 224, pp. 550–566, Aug. 2018.
[56] A. Khosravi, R. N. N. Koury, L. Machado, and J. J. G. Pabon, ''Prediction of wind speed and wind direction using artificial neural network, support vector regression and adaptive neuro-fuzzy inference system,'' *Sustain. Energy Technol. Assessments*, vol. 25, pp. 146–160, Feb. 2018.
[57] P. Lu, L. Ye, B. Sun, C. Zhang, Y. Zhao, and J. Teng, ''A new hybrid prediction method of ultra-short-term wind power forecasting based on EEMD-PE and LSSVM optimized by the GSA,'' *Energies*, vol. 11, no. 4, p. 697, 2018.
[58] H. S. Dhiman, D. Deb, and J. M. Guerrero, ''Hybrid machine intelligent SVR variants for wind forecasting and ramp events,'' *Renew. Sustain. Energy Rev.*, vol. 108, pp. 369–379, Jul. 2019.
[59] X. Kong, X. Liu, R. Shi, and K. Y. Lee, ''Wind speed prediction using reduced support vector machines with feature selection,'' *Neurocomputing*, vol. 169, pp. 449–456, Dec. 2015.
[60] K. Wang, X. Qi, H. Liu, and J. Song, ''Deep belief network based k-means cluster approach for short-term wind power forecasting,'' *Energy*, vol. 165, pp. 840–852, Dec. 2018.
[61] Y.-L. Hu and L. Chen, ''A nonlinear hybrid wind speed forecasting model using LSTM network, hysteretic ELM and differential evolution algorithm,'' *Energy Convers. Manage.*, vol. 173, pp. 123–142, Oct. 2018.
[62] D. Zhang, X. Peng, K. Pan, and Y. Liu, ''A novel wind speed forecasting based on hybrid decomposition and online sequential outlier robust extreme learning machine,'' *Energy Convers. Manage.*, vol. 180, pp. 338–357, Jan. 2019.
[63] X. Luo, J. Sun, L. Wang, W. Wang, W. Zhao, J. Wu, J.-H. Wang, and Z. Zhang, ''Short-term wind speed forecasting via stacked extreme learning machine with generalized correntropy,'' *IEEE Trans. Ind. Informat.*, vol. 14, no. 11, pp. 4963–4971, Nov. 2018.

[64] W. Sun and M. Liu, "Wind speed forecasting using FEEMD echo state networks with RELM in Hebei, China," *Energy Convers. Manage.*, vol. 114, pp. 197–208, Apr. 2016.
[65] J. Wang, Y. Wang, and Y. Li, "A novel hybrid strategy using three-phase feature extraction and a weighted regularized extreme learning machine for multi-step ahead wind speed prediction," *Energies*, vol. 11, no. 2, p. 321, 2018.
[66] G. Huang, G.-B. Huang, S. Song, and K. You, "Trends in extreme learning machines: A review," *Neural Netw.*, vol. 61, pp. 32–48, Jan. 2015.
[67] G. E. Hinton, S. Osindero, and Y.-W. Teh, "A fast learning algorithm for deep belief nets," *Neural Comput.*, vol. 18, no. 7, pp. 1527–1554, 2006.
[68] A.-R. Mohamed, G. Dahl, and G. Hinton, "Deep belief networks for phone recognition," in *Proc. Nips Workshop Deep Learn. Speech Recognit. Rel. Appl.*, Vancouver, BC, Canada, 2009, vol. 1, no. 9, p. 39.
[69] M. Santhosh, C. Venkaiah, and D. M. V. Kumar, "Short-term wind speed forecasting approach using ensemble empirical mode decomposition and deep Boltzmann machine," *Sustain. Energy, Grids Netw.*, vol. 19, Sep. 2019, Art. no. 100242.
[70] Y. Guo, Y. Liu, A. Oerlemans, S. Lao, S. Wu, and M. S. Lew, "Deep learning for visual understanding: A review," *Neurocomputing*, vol. 187, pp. 27–48, Apr. 2016.
[71] D. K. Barrow and S. F. Crone, "A comparison of AdaBoost algorithms for time series forecast combination," *Int. J. Forecasting*, vol. 32, no. 4, pp. 1103–1119, 2016.
[72] H. Li, J. Wang, H. Lu, and Z. Guo, "Research and application of a combined model based on variable weight for short term wind speed forecasting," *Renew. Energy*, vol. 116, pp. 669–684, Feb. 2018.
[73] W. Zhang, Z. Qu, K. Zhang, W. Mao, Y. Ma, and X. Fan, "A combined model based on CEEMDAN and modified flower pollination algorithm for wind speed forecasting," *Energy Convers. Manage.*, vol. 136, pp. 439–451, Mar. 2017.
[74] I. Okumus and A. Dinler, "Current status of wind energy forecasting and a hybrid method for hourly predictions," *Energy Convers. Manage.*, vol. 123, pp. 362–371, Sep. 2016.
[75] X. Niu and J. Wang, "A combined model based on data preprocessing strategy and multi-objective optimization algorithm for short-term wind speed forecasting," *Appl. Energy*, vol. 241, pp. 519–539, May 2019.
[76] H. Liu, X. Mi, and Y. Li, "Comparison of two new intelligent wind speed forecasting approaches based on wavelet packet decomposition, complete ensemble empirical mode decomposition with adaptive noise and artificial neural networks," *Energy Convers. Manage.*, vol. 155, pp. 188–200, Jan. 2018.
[77] P. Jiang, H. Yang, and J. Heng, "A hybrid forecasting system based on fuzzy time series and multi-objective optimization for wind speed forecasting," *Appl. Energy*, vol. 235, pp. 786–801, Feb. 2019.
[78] J. Wang, P. Du, T. Niu, and W. Yang, "A novel hybrid system based on a new proposed algorithm—Multi-objective whale optimization algorithm for wind speed forecasting," *Appl. Energy*, vol. 208, pp. 344–360, Dec. 2017.
[79] J. Song, J. Wang, and H. Lu, "A novel combined model based on advanced optimization algorithm for short-term wind speed forecasting," *Appl. Energy*, vol. 215, pp. 643–658, Apr. 2018.
[80] L. L. Zhang, M. S. Li, T. Y. Ji, and Q. H. Wu, "Short-term wind power prediction based on intrinsic time-scale decomposition and LS-SVM," in *Proc. IEEE Innov. Smart Grid Technol.-Asia (ISGT-Asia)*, Nov./Dec. 2016, pp. 41–45.
[81] W. Zhang, J. Wang, J. Wang, Z. Zhao, and M. Tian, "Short-term wind speed forecasting based on a hybrid model," *Appl. Soft Comput.*, vol. 13, no. 7, pp. 3225–3233, 2013.
[82] A. A. Abdoos, "A new intelligent method based on combination of VMD and ELM for short term wind power forecasting," *Neurocomputing*, vol. 203, pp. 111–120, Aug. 2016.
[83] C. Zhang, J. Zhou, C. Li, W. Fu, and T. Peng, "A compound structure of ELM based on feature selection and parameter optimization using hybrid backtracking search algorithm for wind speed forecasting," *Energy Convers. Manage.*, vol. 143, pp. 360–376, Jul. 2017.
[84] H. Liu, X.-W. Mi, and Y.-F. Li, "Wind speed forecasting method based on deep learning strategy using empirical wavelet transform, long short term memory neural network and elman neural network," *Energy Convers. Manage.*, vol. 156, pp. 498–514, Jan. 2018.
[85] L. Xiang, Z. Deng, and A. Hu, "Forecasting short-term wind speed based on IEWT-LSSVM model optimized by bird swarm algorithm," *IEEE Access*, vol. 7, pp. 59333–59345, 2019.
[86] X. Han, X. Zhang, F. Chen, Z. Song, and C. Wang, "Short-term wind speed prediction method based on time series combined with LS-SVM," in *Proc. 31st Chin. Control Conf.*, Jul. 2012, pp. 7593–7597.
[87] J. Zhang, Y. Wei, Z.-F. Tan, W. Ke, and W. Tian, "A hybrid method for short-term wind speed forecasting," *Sustainability*, vol. 9, no. 4, p. 596, 2017.
[88] S. Wang, N. Zhang, L. Wu, and Y. Wang, "Wind speed forecasting based on the hybrid ensemble empirical mode decomposition and GA-BP neural network method," *Renew. Energy*, vol. 94, pp. 629–636, Aug. 2016.
[89] A. Meng, J. Ge, H. Yin, and S. Chen, "Wind speed forecasting based on wavelet packet decomposition and artificial neural networks trained by crisscross optimization algorithm," *Energy Convers. Manage.*, vol. 114, pp. 75–88, Apr. 2016.
[90] H. Liu, H. Tian, X. Liang, and Y. Li, "New wind speed forecasting approaches using fast ensemble empirical model decomposition, genetic algorithm, mind evolutionary algorithm and artificial neural networks," *Renew. Energy*, vol. 83, pp. 1066–1075, Nov. 2015.
[91] G. Osório, J. C. O. Matias, and J. Catalão, "Short-term wind power forecasting using adaptive neuro-fuzzy inference system combined with evolutionary particle swarm optimization, wavelet transform and mutual information," *Renew. Energy*, vol. 75, pp. 301–307, Mar. 2015.
[92] J. A. Carta, P. Cabrera, J. M. Matías, and F. Castellano, "Comparison of feature selection methods using ANNs in MCP-wind speed methods. A case study," *Appl. Energy*, vol. 158, pp. 490–507, Nov. 2015.
[93] Y. Hao and C. Tian, "A novel two-stage forecasting model based on error factor and ensemble method for multi-step wind power forecasting," *Appl. Energy*, vol. 238, pp. 368–383, Mar. 2019.
[94] A. Gensler, B. Sick, and S. Vogt, "A review of deterministic error scores and normalization techniques for power forecasting algorithms," in *Proc. IEEE Symp. Ser. Comput. Intell. (SSCI)*, Dec. 2016, pp. 1–9.
[95] S. A. Vargas, G. R. T. Esteves, P. M. Maçaira, B. Q. Bastos, F. L. C. Oliveira, and R. C. Souza, "Wind power generation: A review and a research agenda," *J. Cleaner Prod.*, vol. 218, pp. 850–870, May 2019.
[96] M. Mauri, T. Elli, G. Caviglia, G. Uboldi, and M. Azzi, "RAWGraphs: A visualisation platform to create open outputs," in *Proc. 12th Biannual Conf. Italian SIGCHI Chapter*, 2017, p. 28.
[97] E. Cadenas and W. Rivera, "Wind speed forecasting in three different regions of Mexico, using a hybrid ARIMA–ANN model," *Renew. Energy*, vol. 35, no. 12, pp. 2732–2738, 2010.
[98] R. Blonbou, "Very short-term wind power forecasting with neural networks and adaptive Bayesian learning," *Renew. Energy*, vol. 36, no. 3, pp. 1118–1124, 2011.
[99] X. An, D. Jiang, C. Liu, and M. Zhao, "Wind farm power prediction based on wavelet decomposition and chaotic time series," *Expert Syst. Appl.*, vol. 38, no. 9, pp. 11280–11285, 2011.
[100] J. Wang, W. Zhang, Y. Li, J. Wang, and Z. Dang, "Forecasting wind speed using empirical mode decomposition and Elman neural network," *Appl. Soft Comput.*, vol. 23, pp. 452–459, Oct. 2014.
[101] A. U. Haque, M. H. Nehrir, and P. Mandal, "A hybrid intelligent model for deterministic and quantile regression approach for probabilistic wind power forecasting," *IEEE Trans. Power Syst.*, vol. 29, no. 4, pp. 1663–1672, Jul. 2014.
[102] P. Mandal, H. Zareipour, and W. D. Rosehart, "Forecasting aggregated wind power production of multiple wind farms using hybrid wavelet-PSO-NNs," *Int. J. Energy Res.*, vol. 38, no. 13, pp. 1654–1666, 2014.
[103] N. Chen, Z. Qian, I. T. Nabney, and X. Meng, "Wind power forecasts using Gaussian processes and numerical weather prediction," *IEEE Trans. Power Syst.*, vol. 29, no. 2, pp. 656–665, Mar. 2014.
[104] D. Liu, J. Wang, and H. Wang, "Short-term wind speed forecasting based on spectral clustering and optimised echo state networks," *Renew. Energy*, vol. 78, pp. 599–608, Jun. 2015.
[105] H. Chitsaz, N. Amjady, and H. Zareipour, "Wind power forecast using wavelet neural network trained by improved clonal selection algorithm," *Energy Convers. Manage.*, vol. 89, pp. 588–598, Jan. 2015.
[106] Y. Wang, J. Wang, and X. Wei, "A hybrid wind speed forecasting model based on phase space reconstruction theory and Markov model: A case study of wind farms in northwest China," *Energy*, vol. 91, pp. 556–572, Nov. 2015.
[107] M. Ozkan and P. Karagoz, "A novel wind power forecast model: Statistical hybrid wind power forecast technique (SHWIP)," *IEEE Trans. Ind. Informat.*, vol. 11, no. 2, pp. 375–387, Apr. 2015.
[108] C. Zhang, H. Wei, J. Zhao, T. Liu, T. Zhu, and K. Zhang, "Short-term wind speed forecasting using empirical mode decomposition and feature selection," *Renew. Energy*, vol. 96, pp. 727–737, Oct. 2016.

[109] E. Cadenas, W. Rivera, R. Campos-Amezcua, and C. Heard, "Wind speed prediction using a univariate ARIMA model and a multivariate NARX model," *Energies*, vol. 9, no. 2, p. 109, 2016.

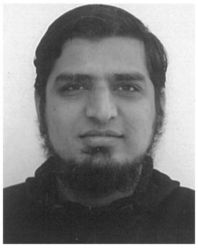
[110] Z. Liang, J. Liang, C. Wang, X. Dong, and X. Miao, "Short-term wind power combined forecasting based on error forecast correction," *Energy Convers. Manage.*, vol. 119, pp. 215–226, Jul. 2016.

[111] J. Liu, X. Wang, and Y. Lu, "A novel hybrid methodology for short-term wind power forecasting based on adaptive neuro-fuzzy inference system," *Renew. Energy*, vol. 103, pp. 620–629, Apr. 2017.

[112] V. Ranganayaki and S. N. Deepa, "SVM based neuro fuzzy model for short term wind power forecasting," *Nat. Acad. Sci. Lett.*, vol. 40, no. 2, pp. 131–134, 2017.

[113] C. Feng, M. Cui, B.-M. Hodge, and J. Zhang, "A data-driven multi-model methodology with deep feature selection for short-term wind forecasting," *Appl. Energy*, vol. 190, no. 15, pp. 1245–1257, Mar. 2017.

[114] Aasim, S. N. Singh, and A. Mohapatra, "Repeated wavelet transform based ARIMA model for very short-term wind speed forecasting," *Renew. Energy*, vol. 136, pp. 758–768, Jun. 2019. [Online]. Available: https://www.scopus.com/authid/detail.uri?authorId=57202388377&eid=2-s2.0-85048151311



MUHAMMAD UZAIR YOUSUF received the B.E. and M.E. degrees in mechanical engineering from the NED University of Engineering and Technology, Karachi, Pakistan, in 2013 and 2016, respectively. He is currently pursuing the Ph.D. degree in mechanical and electrical engineering with Massey University. His current research interests include wind energy forecasting and solar energy modeling.

IBRAHIM AL-BAHADLY received the B.Sc. (Eng.) degree from the Baghdad University of Technology, in 1987, and the M.Sc. and Ph.D. degrees from Nottingham University, in 1990 and 1994, respectively, all in electrical and electronic engineering. From 1994 to 1996, he was a Research Associate with the Electric Drives and Machines Group, University of Newcastle upon Tyne, U.K. Since 1996, he has been with Massey University, where he is currently an Associate Professor in electrical and electronic engineering. His research interests include power electronic applications, variable speed machines and drives, renewable energy systems, instrumentation, robotics, and automation.

EBUBEKIR AVCI received the Ph.D. degree in robotics from Osaka University, Japan, in 2013. He was a Postdoctoral Researcher with the Toyota Technological Institute, Japan, in the field of parallel mechanism robots, from 2013 to 2014. Then, he was a Research Associate with the Hamlyn-Centre-for-Robotic-Surgery, Imperial-College-London, U.K., from 2014 to 2015. He is currently a Lecturer in mechatronics with Massey University.