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Review

Wind Energy Harvesting and Conversion Systems: A Technical Review

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Abstract: Wind energy harvesting for electricity generation has a significant role in overcoming the challenges involved with climate change and the energy resource implications involved with population growth and political unrest. Indeed, there has been significant growth in wind energy capacity worldwide with turbine capacity growing significantly over the last two decades. This confidence is echoed in the wind power market and global wind energy statistics. However, wind energy capture and utilisation has always been challenging. Appreciation of the wind as a resource makes for difficulties in modelling and the sensitivities of how the wind resource maps to energy production results in an energy harvesting opportunity. An opportunity that is dependent on different system parameters, namely the wind as a resource, technology and system synergies in realizing an optimal wind energy harvest. This paper presents a thorough review of the state of the art concerning the realization of optimal wind energy harvesting and utilisation. The wind energy resource and, more specifically, the influence of wind speed and wind energy resource forecasting are considered in conjunction with technological considerations and how system optimization can realise more effective operational efficiencies. Moreover, non-technological issues affecting wind energy harvesting are also considered. These include standards and regulatory implications with higher levels of grid integration and higher system non-synchronous penetration (SNSP). The review concludes that hybrid forecasting techniques enable a more accurate and predictable resource appreciation and that a hybrid power system that employs a multi-objective optimization approach is most suitable in achieving an optimal configuration for maximum energy harvesting.

Keywords: wind energy harvesting; forecasting techniques; turbine technology; maximum power point tracking; hybrid systems and optimization

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1. Introduction

Electricity generation from renewable energy (RE) technologies such as solar, wind, hydro, biomass and geothermal offers sustainable energy sources of energy, and mitigates against detrimental environmental issues such as global warming and climate change [1]. RE also has economic importance, as the economy benefits from reduced cost of electricity generation, with RE generation derived from natural, renewable resources [2]. Figure 1 shows the total renewable energy usage for electricity generation from 2010 to 2020 [3]. According to the International Energy Agency (IEA) and their global energy review in 2021 [4], the total renewable energy usage has shown a significant increase, from 4098 TWh in 2010 to 7627 TWh in 2020. Whereas hydropower contributes the largest portion of renewable energy capacity around the world for electricity generation, wind energy generation also shows a significant increasing trend. The 2021 International Renewable Energy Agency (IRENA) report [5] presents the economics for renewable energy in 2021. The report indicates that global weighted average levelized cost of energy (LCOE) of new onshore wind projects added in 2021 fell by 15%, year-on-year (to USD 0.033/kWh), whereas the cost of electricity for new onshore wind projects, excluding China, fell by a more modest 12% year-on-year to USD 0.037/kWh. The offshore wind market, saw unprecedented expansion in 2021 (21 GW added), as China increased its new capacity additions and the global weighted average cost of electricity fell by 13% year-on-year (to USD 0.075/kWh). If these figures are considered over a ten-year period, the LCOE has actually dropped by 68% and 60%, respectively, for onshore and offshore wind energy.

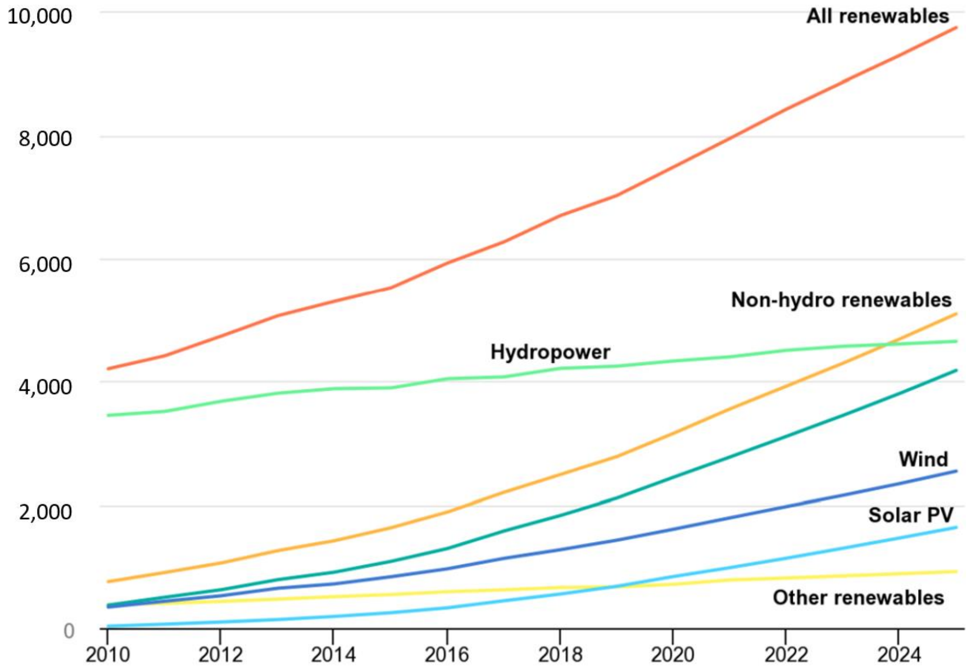


Figure 1. Total renewable energy usage for electricity generation (2010–2025) (Reprinted with permission from Ref. [3]. 2020, IEA).

Wind energy harvesting for electricity generation, which was first introduced in 1970, has gained large popularity as the world moves to a carbon neutral renewable energy focus. Wind energy has a significant role in overcoming the challenges associated with fossil fuel depletion and environmental concerns it creates, as well as the ever-rising energy demand owing to population growth, economic growth, urbanization, lifestyle changes, and technological development [6,7]. It is abundant, extensively distributed, and ecofriendly. As explained by Ang et al. [1], the majority of wind energy capture opportunities are situated onshore. However, there is significant growth in offshore wind energy capacity, especially in Europe with turbine capacity growing at a constant rate of 16% since 2016 [8]. The location selection for wind turbines depends on the localized wind resource, which should be sufficient to generate the estimated power. For example, widespread land with high elevation or seashore is ideal for onshore wind energy harvesting [1]. The wind power market, which is resilient and cost-competitive, has quadrupled in the last decade [9]. According to the wind energy report by the Global Wind Energy Council (GWEC) in 2021, newly added wind energy capacity exceeded 93 GW (onshore 86.9 GW and offshore 6.1 GW) which is a 53% year-over-year increase compared to 2019 and it sums the global cumulative wind power capacity to 743 GW [10,11]. Global wind power capacity statistics in 2021, reported by GWEC [11], are presented in Figure 2. Wind energy, perceived to be a socio-economically and environmentally viable source of energy, is forecasted to contribute 22% of the global electrical energy by 2030 [12].

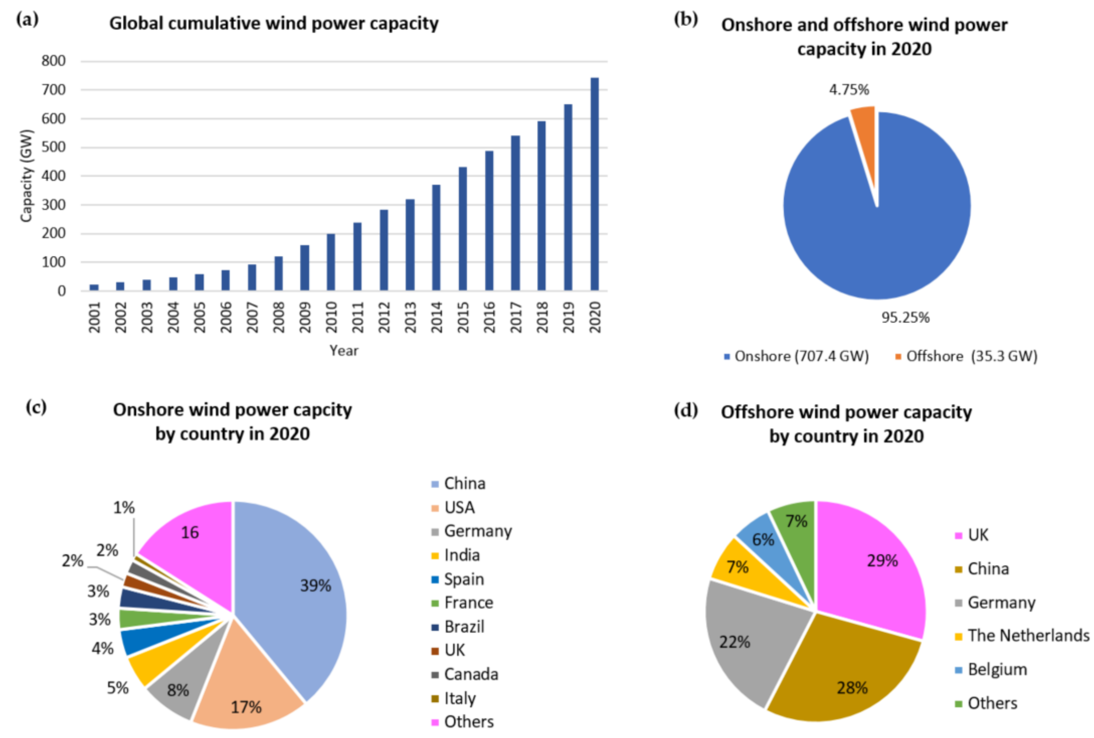


Figure 2. Global wind power capacity statistics in 2020.

Nevertheless, exploitation of wind energy has ever been problematic owing to the uncertainty and variability of wind power owing to the cubic relationship between wind power and wind speed. The following Equation (1) gives the power generated by a turbine.

$$Power\ (P) = \frac{1}{2} C_p \rho A V^3 \quad (1)$$

where C_p is the power coefficient or the power extracted by the turbine relative to that available in the wind stream, ρ is air density (kg/m^3), A is swept area of the blade (m^2) and V is wind speed (m/s).

Equation (1) applies for wind speeds below the rated wind speed (at which rated power output is achieved). Above rated wind speed, the output is controlled to be constant at rated power, up to the cut-out wind speed.

Wind speed is subject to complex seasonal and stochastic characteristics [13]. Accurate wind speed and wind power predictions are essential for stable and reliable power system operation. Further, they are essential to enhance the competitiveness of the power market. As a result, wind energy forecasting has been a hot topic in the field of renewable energy with numerous research around the world trying to develop accurate wind forecasting models, thus resulting in tremendous progress in the recent past. Variability in wind speed directly affects the wind power, resulting in unsteady power generation, which affects the power grid with voltage and frequency fluctuations [12,14]. This causes a significant challenge in the integration of wind power into the grid and may lead to system failures and performance degradation, which incur additional operation and maintenance costs [9].

Another issue, and particularly important in the context of grid integration, is that wind energy sources behave quite differently from conventional, synchronous generators [15]. Synchronous generators have mechanical inertia and are therefore capable of storing kinetic energy in their rotating mass and these machines are directly linked with the network. Therefore, during disturbances, energy is inherently exchanged with the system, which makes the network less prone to frequency fluctuations in case of an imbalance between generation and demand. In general, renewable or asynchronous generation units (e.g., photovoltaic solar and wind power), on the other hand, are equipped with power electronic converters, which decouple the generators from the grid and as such provide no inertia to the system, leading to the reduction, and even in some cases a shortage, of system strength and inertia. As discussed by Eggleston et al. [16], lower levels of available 'system strength', contribute to inverter instabilities affecting fault ride through (FRT) performance, inverter interactions and general issues with voltage control and power quality. Moreover, reduced levels of synchronous inertia, which affects the rate-of-change-of-frequency (ROCOF) that can be experienced, particularly after large contingency events.

High-precision wind speed forecasting is salient in wind resource assessment and wind power forecasting [17]. Wind power grid integration is challenging and requires an accurate forecasting method to minimize operational risk while improving the scheduling efficiency of the grid. More importantly, it helps to maintain the supply–demand balance, facilitating wind-power trading [18]. Further, it is useful for scheduling the spinning reserve capacity, scientifically formulating dispatch plans, performing peak and frequency modulation work, planning maintenance and reducing system operating costs, and maintaining the power balance of the system [9]. According to Zhang et al. [19], wind power generation increases by about 30% for a 10% increase in prediction accuracy. This shows the importance of accurate forecasting of wind speed and power.

The performance of wind turbines relies on many parameters, which need to be controlled for better performance. In the operation of wind turbines, system optimization is required to achieve objectives such as power maximization, energy cost minimization, and system safety. Maximum power point tracking control is used for high efficiency and pitch control facilitates power and load control for optimal operation of the wind turbines. Variable-speed wind turbines are commonly used and are generally more efficient with maximum power point tracking control. Further, the maximum power point tracker (MPPT) controls the restoring torque of the electrical generator for optimum system operation.

In consideration of wind turbine installations, and before a wind turbine is installed, the most appropriate location needs to be determined. The major objective of the siting process is to locate a wind turbine (or turbines) such that net revenue is maximized while minimizing noise pollution, environmental and visual impacts, and overall cost of energy. The scope of this process can have a very wide range, which could include everything from wind prospecting for suitable turbine sites over a wide geographical area to considering the placement of a single wind turbine on a site or of multiple wind turbines in a wind farm; this is generally called micro-siting. Software tools assist in the micro-siting process with optimization algorithms maximizing annual energy production while minimizing the cost of energy generation and considering environmental and social issues.

Most hybrid systems, or systems that involve more than one energy producer and which may include storage options, are stand-alone systems, which operate "off-grid" or not connected to an electricity distribution system. The battery bank or engine generator is used to fulfill the demand as wind and solar generations change continuously. In a hybrid system, component size needs to be optimized for minimizing the cost of energy generation to fulfill demand with resource availability.

The work presented in this paper reviews the literature concerning successful wind energy harvesting opportunities, aiming to answer the following questions:

- What is the status in respect to wind capacity and what is the trajectory for wind energy in the near future?
- What are the advantages and limitations of wind energy as a proponent of an enhanced renewable energy infrastructure?
- What are the primary issues and technological considerations associated with effective wind energy harvesting?
- What configuration(s) are available for effective wind energy harvesting?
- What is the state of the art in respect to wind energy harvesting system optimization?

The paper is presented as follows: Section 2 considers the wind energy resource, focusing on the influence of wind speed, wind energy production and the various forecasting models and their implications. Technological and systematic concerns with respect to turbine system operation and network interaction, including system protection implications, are considered in Section 3. Additionally discussed in Section 3 are the opportunities for wind energy as a constituent of hybrid systems that incorporate other energy systems such as solar PV. In Section 4, optimization for effective harvesting of the available wind resource and the various modeling possibilities employed to achieve that goal, are considered. Finally, conclusions are given in Section 5.

2. Wind Speed and Wind Power Forecasting

Feasibility analysis accompanied by an accurate wind resource assessment is critical for wind farm (or turbine) construction. In fact, it allows for finding the best potential location for the wind turbine that yields the highest profit. During the resource assessment phase, one or more anemometric towers are typically installed in the candidate location and wind data is generally gathered over the period of a year or more. Then the collected on-site data and wind data obtained from nearby meteorological stations for the last few decades are used for wind forecasting. The traditional method of linear correlations between the on-site data and meteorological data lacks accuracy and hence multivariate analyses, such as multivariate regression analysis and factor analysis are employed in wind forecasting, involving complex systems with many meteorological factors [20].

A vast number of forecasting techniques are reported in the literature. The published forecasts are mainly categorized as long-term and short-term. The former (long-term) forecasts wind over several days or months into the future and it is a relatively difficult and long process due to many variables influencing the weather. They are primarily essential for wind energy resource assessment. On the contrary, the latter (short-term) predicts wind in minutes or hours which is generally more stable and practical in applications [12,21]. Some references have classified wind forecasts into four based on the time scale, i.e., ultra short-term, short-term, medium-term, and long-term as illustrated in Figure 3. Here, the ultra short-term is usually referred to as a few seconds to 30 min range, whereas the medium-term means typically 6 to 24 h range [17]. Two types of data, i.e., historical power data (used for the historical data prediction model) and numerical weather forecast data (numerical weather forecast model) are used to construct wind forecasting models.

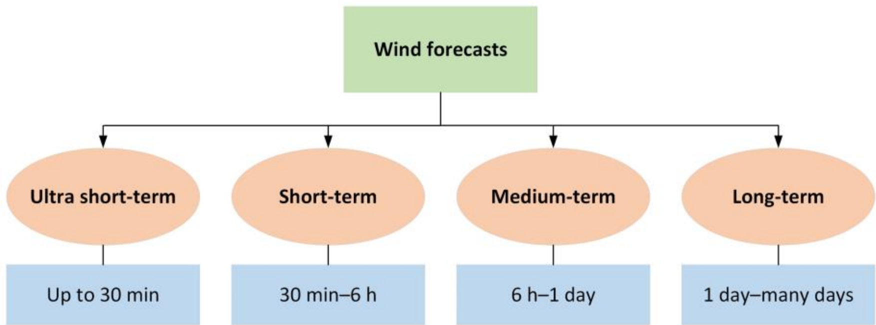


Figure 3. Classification of wind forecasts based on a temporal scale.

Wind forecasting methods published in the literature can typically also be classified into four groups (physical methods, statistical methods, intelligent learning methods, and hybrid methods) [21] as depicted in Figure 4. Statistical methods are relatively simple and less expensive. Physical methods are more suitable for long-term forecasting whereas statistical methods are more applicable to short-term forecasting. The intelligent learning methods, which characterize non-linear correlations between input data and wind turbine power (harvested), are suitable for short-term forecasting. Hybrid methods, which encompass superior features of more than one model, are versatile and have comparatively superior prediction accuracies and capabilities. Though both intelligent learning methods and hybrid methods have superior forecasting capabilities, they have computational limitations [21]. On some occasions, wind forecasting models are classified into two categories: data-driven models and physical-driven models. The former basically maps the input variables and target variables while the latter is based on the numerical weather prediction system (NWP) [14]. In the modern day, the trend is to use hybrid models which encompass superior features of more than one algorithm. The hybrid models typically are versatile and have superior prediction accuracies and capabilities compared to traditional single methods [12]. Some authors have classified wind forecasting methods into two, i.e., direct methods and indirect methods. The former determines correlations between the related inputs (historical wind power data) and the future power target whereas the latter forecast wind speed first and then find the power forecasts using a wind power curve. The indirect forecasting methods can be used to assess the power generation potential of a planned wind turbine installation [9].

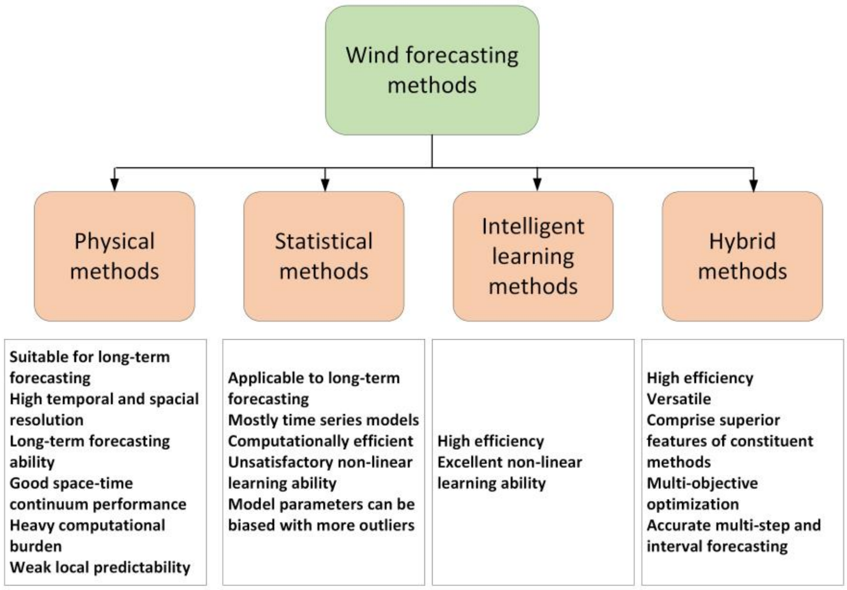


Figure 4. Wind forecasting methods.

Though several review studies have been conducted on wind speed and power forecasting techniques, their scope is limited [22–25] or they do not critically elaborate on the uniqueness of individual models, limitations, and forecasting performance [26–30]. Additionally, most of these reviews do not include the most recent advances published in the last couple of years [31–33]. This study critically evaluates the most recent studies conducted in the field of wind speed and power forecasting, elaborating on the above-mentioned.

2.1. Statistical Methods

Statistical methods are typically based on time series models which characterize and analyze the trend of wind power data on the basis of maximum likelihood estimation and the least squares method. They typically use historical wind speed data as inputs without considering the meteorological information. Some of the frequently reported forecasting models based on statistical methods are autoregressive (AR), persistence model (PM), autoregressive moving average (ARMA), Markov chain model, autoregressive integrated moving average (ARIMA), autoregressive simple moving, vector autoregression moving average, fractional ARIMA, and generalized autoregressive conditional heteroskedasticity (GARCH) [9,18]. Though statistical models deliver highly accurate predictions for the linear component in data, predictions lack accuracy when the data are strongly nonlinear [17]. In comparison to physical methods and intelligent learning methods, statistical methods are computationally efficient. Some major drawbacks of statistical methods include the data-station hypothesis, strict distribution assumption, possible statistically biased estimators due to outliers, and lack of non-linear learning ability [18].

2.2. Physical Methods

Physical methods are fundamental analyses developed from physical theorems and related assumptions. In physical methods, the atmospheric evolution of meteorological phenomena and associated physical processes are modeled by a set of mathematical formulae and are numerically solved with pertaining initial and boundary conditions to simulate wind behavior in special and temporal scales [18]. Meteorological information such as humidity, temperature, pressure, surface roughness, obstacles, etc., is required for physical methods [9]. One of the popular techniques in physical methods is numerical weather prediction (NWP), which is capable of producing accurate results for long-term wind forecasting [10]. Furthermore, it can directly make power predictions from real-time data. However, it demands a large amount of historical data [19]. Spatial correlation models predict wind speed at different locations, using spatial relationships of wind speed and they provide higher accuracies on certain occasions [34].

Most of the physical methods are based on computational fluid dynamics (CFD) models. Some of the existing mainstream models based on physical methods are the regional ocean model system, the weather research and forecasting model (WRF), the community earth system mode, the fifth-generation mesoscale model (MM5), the European Centre for Medium-Range Weather Forecasts (ECMWF) model, and the global/regional assimilation and prediction system [9]. These models are capable of accurate long-term forecasting and have higher spatial and temporal resolutions as well as better space–time continuum performance. Moreover, physical methods generally do not demand an abundance of historical data, and data is usually needed only for model validation. However, they have heavy computational burdens making them time-consuming and susceptible to weak local predictability [9,18].

2.3. Intelligent Learning Methods and Hybrid Methods

Artificial intelligence learning methods have recently gained wide attention in wind forecasting, primarily owing to their excellent nonlinear learning ability and high efficiency. Compared to the statistical methods, the intelligent methods typically have more parameters and hence they can effectively model nonlinearities within data via iterative optimization [17]. These methods can either be used as single models or hybrid models. One-dimensional convolutional neural networks and radial basis function neural networks are two frequently used single models in wind forecasting [18]. Combined methods and hybrid methods have become popular for wind forecasting due to their superior accuracies compared to single models [18]. Combined methods are based on ensemble learning in which bagging, boosting, or stacking strategies are employed to have individual predictors. Here, model building depends on the integration weights of individual predictors. The combined methods usually have a higher computational burden due to multi-predictors. In contrast, hybrid methods only use one type of predictor, and all other components are employed to enhance the performance of the predictor [17].

Intelligent learning models can be basically categorized as shallow learning models and deep learning models. Some of the popular shallow learning models are support vector machine (SVM), back-propagation (BP) neural network, general regression neural network (GRNN), extreme learning machine (ELM), radial basis function neural network (RBFNN), echo state network (ESN), Elman neural network (ENN), etc. [9,14]. These models are prone to cause issues such as overfitting, poor convergence, and falling into local optima. On the other hand, deep learning models have gained popularity in many fields including wind forecasting due to their superior attributes such as strong generalization ability, big data training, and unsupervised feature learning [14]. They are excellent at capturing features from the original data and modeling interdependencies between historical data and targets. As a result, they are widely used for temporal dependence modeling and feature extraction. Some popular feature extraction models are deep belief network (DBN), stacked autoencoder (SAE), and convolutional neural network (CNN) [14]. These models do not have connections between neurons in the same layer.

For most real wind forecasting applications, single methods may not satisfy the expected higher accuracy levels despite their superior prediction performances. This is mainly because wind speed and power generation are affected by various natural and operational factors such as wind speed and direction, air pressure, wind turbine friction, weather conditions, etc. Consequently, time series data which comprise both linear and nonlinear information cannot be accurately modeled by merely using either statistical models or intelligent models. Hence, hybrid models are the best candidates for real-world wind forecasting applications [19]. Hybrid models proposed in the literature for wind forecasting mostly contain intelligent learning algorithms owing to their superior performance [9]. Typical structures of hybrid models are illustrated in Figure 5, adapted from [9].

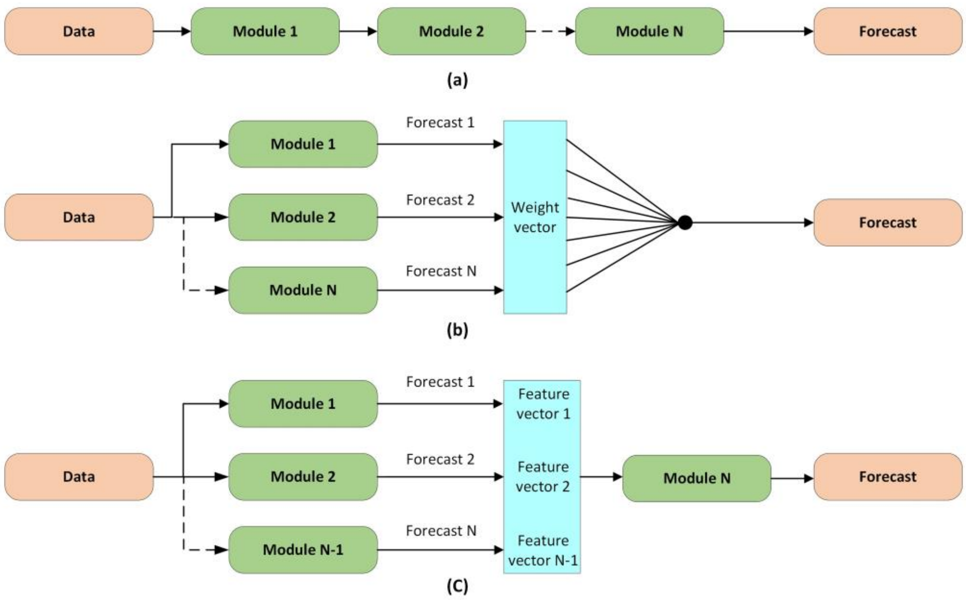


Figure 5. Typical structures of hybrid models. (**a**) Series hybrid model; (**b**) Parallel hybrid model; (**c**) Series-parallel hybrid model.

The framework of hybrid models is typically integrated with data preprocessing strategies such as feature extraction and selection, denoising, and decomposition [17]. One of the most popular decomposition strategies is wavelet transform (WT), which decomposes the signal into a low-frequency component and a high-frequency component, thus making further analysis more insightful [19]. In addition, the mode decomposition techniques such as empirical mode decomposition (EMD), ensemble empirical mode decomposition (EEMD), complementary ensemble empirical mode decomposition (CEEMD), complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN), and variational mode decomposition (VMD) are commonly used for data preprocessing [17]. Despite the shortcoming that the number of decomposed modes is selected by experience in VMD, it has been shown to have good performance in wind forecasting applications [17]. Nevertheless, experienced-based selection can be unreliable in some situations.

2.3.1. Wind Speed Forecasting

In hybrid models, more parameter optimization components are employed to enhance the forecast accuracy. There are two classifications of hybrid models based on the setting of the objective function; these are single-objective optimization and multi-objective optimization. In the former, the objective function is typically based on the prediction error (sum of squared error SSE or mean square error MSE) and it does not explain overfitting on some occasions. Particle swarm optimization (PSO), firefly optimization algorithm (FA), and genetic algorithm are three commonly used intelligent single-objective optimization algorithms [17]. On the other hand, the objective of the latter is based on both prediction accuracy (mean squared error (MSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) and prediction stability (variance of error). Further, the two objective functions need to be conflicting, thus a Pareto optimum exists between the two. However, such a conflict of metrics lacks theoretical rationality and needs to be verified [17].

The general framework of wind forecasting based on artificial learning methods is described by Navas and Prakash, and Wu et al. in [30,33] respectively as depicted in Figure 6.

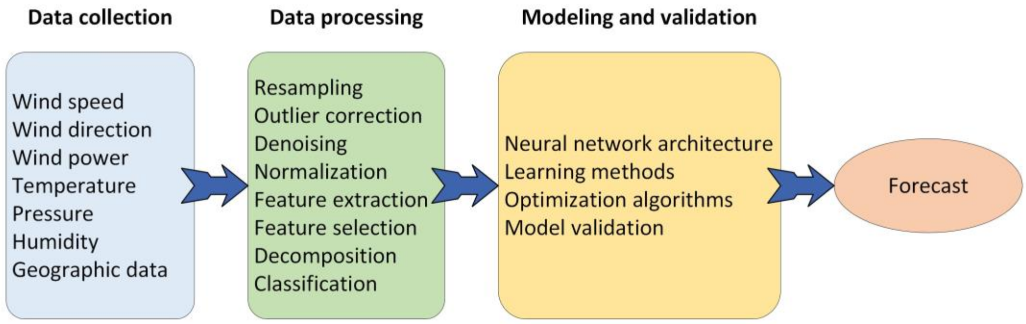


Figure 6. Framework of wind forecasting using artificial intelligent learning methods.

For this purpose, Gao et al. [17] proposed a multi-component ensemble hybrid model for ultra-short-term onshore wind speed forecasting. The framework of the model includes a decomposition and integration strategy (mode discrimination degree, adaptive variational mode decomposition), k-point modified multi-objective golden eagle optimizer (k-MoGE), and weight hybrid kernel extreme learning machine [17]. Here, k-MoGE based on bootstrap bias–variance tradeoff theory addresses the unproven conflict between the objective functions. The proposed model can produce both single-step and multi-step ahead forecasts with higher accuracy compared to most existing conventional statistic models, shallow neural network models, and deep neural network models. In addition, it has superior direction accuracy and out-of-sample prediction ability. Moreover, the proposed model has the ability to overcome the decline resulting from an increasing forecast horizon and it has an enhanced generalization ability.

Support vector machine (SVM) is a method in supervised learning and is used for regression, classification, and detection of outliers [12]. In SVM regression, the aim is to identify a plane that separates all data into two distinct regions so that the data distribution is accurately predicted. The Jaya optimization algorithm developed by Rao [35] is an algorithm for the optimization of both constrained and unconstrained optimization problems. It is a simple, yet powerful algorithm and the aim is to achieve the optimal solution avoiding inferior solutions. More importantly, this algorithm does not require any additional algorithm-specific control parameters except for common control parameters such as the population size and the number of iterations. Liu et al. [12] proposed a Jaya algorithm-based SVM (Jaya-SVM) model for multistep short-term wind speed forecasting and compared its performance against seven other forecasting models such as extreme gradient boosting model, stacked sparse autoencoder, multi-layer perceptron regression model, least absolute shrinkage and selection operator, deep belief network, granular computing method, and Gaussian process regression. The wind speed data from 1 October 2013 to 17 December 2013, in Jilin, China were recorded at every 10 min interval, and a total of 11,000 data with minimum and maximum, respectively, being 0 and 16.67245 ms^{-1} were used in this study. The performance assessment proved that the proposed Jaya-SVM model had the lowest MSE and the highest R square (R^2) in comparison to the other seven models mentioned above. Further, the proposed model was reported to have higher reliability. However, the higher the number of prediction steps, the lower the accuracy and reliability of the Jaya-SVM model. The impact of seasonal variations on the wind speed is not considered in this study and hence the reliability of this model under the influence of seasonal variation needs to be assured.

Point forecast (PF) is the most common in many wind forecasting studies, and it does not provide information on real data distribution [10]. Developing optimal strategies based only on PF is difficult and increases the decision-making risk. As a result, interval forecast (IF) is important to minimize the uncertainty associated with PF. Xing et al. [10] developed a wind speed forecasting system with a novel multi-objective optimizer for PF and IF (multi-objective Aquila optimizer (MOAO)). Data pre-processing (fuzzy information granulation (FIG)) and optimal benchmark model selection (OBMS) are also included in the proposed system. The study used six intervals of wind speed from two sites and employed 14 benchmark models and 3 combined forecasting models. Here the FIG uses fuzzy windows to extract effective wind speed data and it significantly enhances the forecasting effectiveness. On the other hand, OBMS chooses the optimal five models having the best performance in a specific situation, which significantly improves the combined model performance. The optimal solutions were effectively achieved by MOAO and the proposed model was reported to have better stability and superior forecasting effectiveness.

The long short-term memory (LSTM) network is appealing for time series prediction problems owing to its superior ability to handle long-term dependency problems [36]. It has gained wide attraction due to its ability to address the gradient explosion problem in conventional neural networks. Moreover, it learns and remembers both short-term and long-term information making it suitable for time-series predictions [19].

Chen et al. [36] constructed a novel hybrid model based on the LSTM network and the BP neural network for short-term wind speed forecasting. This study has used two sets of wind data from a wind power plant in China and each set contains 2000 data points sampled over a period of 15 min. Here, data de-noising is performed by using SSA, whereas CEEMDAN is used to decompose the de-noised data into IMF components, which significantly improves the signal-to-noise ratio. The error accumulation and computational redundancy are minimized by determining the time complexity and the correlation of each IMF component using fuzzy entropy value and the Spearman correlation, respectively. Training and prediction are carried out by the LSTM network and BP neural network optimized by the sparrow search algorithm and results were obtained by superimposing the results of two schemes. The proposed hybrid model by the authors has higher accuracy and stability compared to the seven other models considered in this study. Nevertheless, the impact of missing values in data on the model predictions is not assessed by this study. Furthermore, the influence of factors such as wind directions, wind conditions, geographical location, etc., is not studied.

Though quantile-based probabilistic forecasting models are capable of producing satisfied prediction intervals, the obtained prediction intervals can be crossed and may violate the monotonicity of different conditional quantiles. Moreover, the forecasting performance of the models is affected by the completeness and quality of features. Consequently, mining adequate information from limited data is crucial.

For this purpose, Zou et al. [9] developed a hybrid probabilistic wind forecasting model based on deep learning, multi-scale feature (MSF) extraction, kernel density estimation (KDE), and non-crossing quantile loss. Here, the multilayer CNN is employed to extract MSFs with simple patterns. Further extractions and encoding of temporal information for features are conducted by using attention-based LSTM, which reduces the computational cost. The positive difference of adjacent conditional quantiles was obtained from the final feature obtained by concatenating all the encoded feature vectors. The monotonicity of different conditional quantiles was ensured based on non-crossing quantile loss. The forecasting uncertainty was comprehensively evaluated by estimating probability density functions (PDFs) for prediction intervals using KDE. The study used wind data in four different places in South Dakota in 2012 as four datasets and each dataset has 8760 data and is divided into training (first 8 months' data) and test (last 4 months' data) sub-datasets. It has been reported that MSFs improve forecasting performance and the crossing problem associated with quantile-based models can be effectively solved by non-crossing quantile loss. The proposed model generates highly accurate one-step-ahead wind speed forecasts. This model can further be upgraded for multi-step ahead probabilistic forecasting.

The convolutional neural network (CNN) is a popular deep neural network. It is multilayered and feed-forwarding (continuous learning in one direction). CNN has gained attraction due to its superior ability to extract hidden spatial features. It requires a lesser number of parameters compared to other deep neural network models, thus making it converge faster. In addition, connectivity and weight sharing are comparatively lower in CNN [13]. During the training phase, the regular recurrent neural networks only consider the previous correlation of sequential data. Bi-directional long short-term memory (Bi-LSTM) is a modification of LSTM which considers both forward and backward layers of LSTM. The forward LSTM extracts the past information of the input sequence whereas the backward LSTM obtains the future features of the sequential data. It uses both connections before and after updating the sequential neurons' weights to simultaneously analyze the past and future information of time series data [13]. In the quaternion convolutional neural network (QCNN), interior relationships are encoded using the quaternion algebra while exterior relationships are trained by the convolutional method.

Accurate long-term wind forecasting is indispensable since wind turbine installation location is mainly determined based on the long-term wind energy potential. As a result, economic feasibility analysis for a potential wind turbine as well as the selection of wind power equipment attributes depends upon the long-term wind forecast. Neshat et al. [13] constructed a hybrid wind forecasting model based on QCNN and Bi-LSTM for long-term wind forecasting. The model can predict the wind speed highly accurately for up to 1 day into the future. An adaptive decomposition technique including VMD and arithmetic optimization algorithm (AOA) was used to obtain IMFs. Here, the VMD decomposes the wind data into optimal signal components while the AOA optimizes the parameters of the VMD. Wind data from 2011 to 2020, in Lesvos and the Samothraki Greek islands, were used to construct and validate the model. The performance of the proposed hybrid model was compared with five popular machine learning models including Bi-LSTM and standard LSTM and two other hybrid models; the proposed model has superior accuracy and stability. The applicability of the proposed model to other wind datasets from different regions needs to be evaluated.

An ensemble multi-feature complementary prediction model for wind speed forecasting was constructed by Wang et al. [37]. In this model, the SAE algorithm is employed to reconstruct wind speed subsequences decomposed by VMD. Multiple features of wind speed sequence can be fully explored by SEA. In addition, it minimizes the complexity of the algorithm and, avoids redundancy. The complementary prediction algorithm used in this model consists of support vector regression (SVR) and bidirectional LSTM which is integrated and weighted by the linear weighted sum method (LWSM). The proposed algorithm eliminates the local minimum problem. For optimizing the prediction results, the model uses the bidirectional gated recurrent unit (BiGRU) which applies cuckoo linear integration to integrate the results of LWSM. The proposed model is claimed to have a better generalization ability and higher accuracy compared to other models.

A one-day-ahead wind speed forecasting model based on a deep learning gated recurrent unit (GRU) network was developed by Wu et al. [38]. The performance of the GRU network was enhanced by selecting the necessary input variables according to the correlation coefficients with large values based on the Pearson correlation, the partial correlation, and the maximum information coefficient analyses. Further, hyperparameters of the network were determined by auto-correlation and partial auto-correlation analyses. The performance of the proposed model was evaluated by using the single error evaluation criteria (run-time, MAPE, and MSE error evaluation criteria) as well as the average accuracy evaluation technique based on the Friedman and Nemenyi hypothesis tests. The proposed model has better accuracy compared to three other popular models (the persistence model, SVR, and LSTM). This strategy of selecting input variables and setting hyperparameters can be used in other similar models to improve accuracy.

2.3.2. Wind Power Forecasting

Multi-step ahead time series forecasting models are usually two types, i.e., direct forecasting and recursive forecasting. However, in some instances, two approaches are combined as direct-recursive forecasting to minimize the forecasting error. The kernel-based machine learning is commonly used in wind forecasting, and the least-squares support vector machine (LSSVM) is one such method [21]. Here, the kernel function separates originally complex sample data with different dimensions and maps the corresponding data to a higher-dimensional space. The local kernel is sensitive to data distance characteristics whereas the global kernel is not affected by data distance. The hybrid kernel methods which combine features of multiple kernels are more efficient. Time series forecasting models are simple and effective. However, traditional time series forecasting models are prone to inaccuracies in multi-step time series forecasting [21].

A multi-step time series forecasting model based on a hybrid-kernel LSSVM was developed by Ding et al. [21] for short-term wind forecasting. This model is based on three processes, i.e., decomposition, classification, and reconstruction. Decomposing wind power time series and classification of decomposed components into three amplitude-frequency classes were conducted based on maximal wavelet decomposition and fuzzy C means (MWD-FCM) algorithm. Time series models were developed for each class separately based on the LSSVM with three different kernels and they were optimized by non-dominated sorting genetic algorithm II (NSGA-II). Two data sets which comprise real wind farm data sampled at an interval of 15 min in Shanxi Province, China in May 2016, and historical wind power generation data sampled at an interval of 10 min, in Sotavento in October 2017, were used to develop the model. The proposed model was compared with two benchmark models (empirical-mode-decomposition-LSSVM model and wavelet-decomposition-LSSVM model) and performance was analyzed by root mean square error (RMSE) and MAE. The proposed model was reported to have better accuracy in 5-step, 10-step, and 15-step ahead wind forecasting. Nonetheless, the model needs to be upgraded with further information for medium-term and long-term forecasting.

In wind forecasting systems, data pre-processing is crucial for the effective extraction of original data features and for minimizing the signal-to-noise ratio. Some of the commonly used signal decomposition algorithms in wind data pre-processing are empirical wavelet transform (EWT), wavelet decomposition (WD), EMD and derivative algorithms, VMD, and singular spectral analysis (SSA) [14]. The basis function and threshold can impact the effect of WD. EMD and associated derivative algorithms are prone to the "endpoint effect". In contrast, VMD is less sensitive to noise and is able to decompose components with similar frequencies [14].

Most wind forecasting models adopt linear weighted combinations. A hybrid wind forecasting model consisting of decomposing strategy, a nonlinear weighted combination, and two deep learning models was proposed by Jiandong et al. [14] for short-term forecasting. Here, the VMD technique was employed to decompose the original power series to enhance predictability. Sub-series (IMFs) prediction models were constructed by using the long short-term memory (LSTM) network and deep belief network combined with particle swarm optimization (PSO-DBN). The final prediction value was achieved by the non-linear combination mechanism based on the PSO-DBN model proposed. The nonlinear combination strategy is reported to be more effective than a linear combination strategy. Despite being time-consuming, the proposed hybrid model has enhanced performance overall to single models (the LSTM model, the PSO-DBN model, the BP model, and the Elman model). However, this model can be further improved by minimizing the delay characteristics in the algorithm and reducing the complexity. Moreover, the impact of non-Gaussian noise on the model performance needs to be investigated.

A two-step wind power forecasting method based on an improved residual-based CNN was developed by Yildiz et al. [39] for very short-term forecasting. In this model, VMD-based processes extract features and convert them into images. Then an improved residual-based deep CNN with the stochastic gradient descent (SGD) optimization algorithm is employed to predict wind power. The combined dataset of wind speed, wind direction, and wind power from a wind farm in Turkey between January and December 2018 was used to develop the model. The proposed model was compared with other novel deep learning architectures such as SqueezeNet, VGG-16, GoogLeNet, AlexNet, and ResNet-18 and its forecasting accuracy was superior.

Attention mechanisms that assign different weights to different input features to quantify their relevant importance in forecasting can greatly improve the accuracy and generalization of forecasting models [18]. Only a few studies have been conducted on attention mechanisms and most of them have focused on the attention design of input features without much focus on information extraction from hidden layers [18].

Tian et al. [18] developed a novel single-step-ahead wind power forecasting model which includes feature decomposition, self-attention, forecasting, optimization, and performance evaluation modules. The feature decomposition module employs improved complete ensemble empirical mode decomposition with adaptive noise (ICEEMDAN) to decompose wind power data into several intrinsic mode functions (IMFs) with different frequencies, and high-frequency IMFs are removed as redundant noise. The self-attention module is based on a dual-stage self-attention mechanism (DSSAM), and it assigns relevant attention weights to features in the input layers as well as hidden layers. In the forecasting module, a gated recurrent unit (GRU) combined with the DSSAM predicts wind power. The adaptive moment estimation (Adam) is used to optimize the parameters of the forecasting module by means of minimizing the MSE. The performance of the proposed model was compared with existing linear and nonlinear benchmark models with and without other feature decomposition methods. The authors claimed that ICEEMDAN enhances forecasting accuracy and DSSAM improves performance significantly. Moreover, the proposed hybrid structured deep learning forecasting model is greatly efficient compared to linear models. However, meteorological factors such as temperature, humidity, pressure, etc., have not been considered in this study.

The wind power produced by turbines is influenced by meteorological factors such as temperature, moisture, pressurization, wind direction, and wind speed. Al-qaness et al. [40] used a time series forecasting approach based on a modified adaptive neuro-fuzzy inference system (ANFIS) for wind power forecasting. Four wind power datasets from wind turbines in France, from 2017 to 2020, were used for the model development. A modified marine predator algorithm (MPA) which improves the searchability of the standard MPA was used to enhance the conventional ANFIS so that ANFIS parameters are optimized for improved prediction accuracy. The proposed model was compared with other modified ANFIS models and some benchmark models (LSTM, NN, and SVM) and demonstrated that it has significantly better performance and accuracy.

In developing or enhancing wind power forecasting models, the majority of the studies have focused on point forecasting and only a few have considered interval forecasting. Compared to interval forecasting, point forecasting generates limited information beyond the predicted value. Prediction errors are inevitable in wind power forecasting due to the impact of local topography, nonlinear dynamics of wind turbines, and unplanned downtime. Interval prediction is more useful in this regard as it yields a range of predicted values with probability, thus making decision-making and risk analysis easier. An ideal prediction interval should have valid coverage in finite samples and should be as narrow as possible in the input space. The broader the interval, the higher the uncertainty of the prediction. Some of the popular and simple interval forecasting methods are mean-variance estimation, Bayesian, bootstrap-based method, etc. [41]. However, Bayesian and bootstrap-based methods usually have a high computational burden, making them time-consuming. Furthermore, the mean-variance estimation method suffers from low empirical coverage probability. Further, these methods require predefined assumptions or other prior hypotheses on the probability distribution of wind data. On the other hand, methods such as quantile regression, kernel density estimation, and ensemble simulations require no such prior assumptions [41]. However, valid coverage in finite samples is not always guaranteed with these methods. In contrast, conformal prediction can construct prediction intervals with valid coverage without prior distributional assumptions. Full conformal prediction and split conformal prediction are the two most common conformal prediction methods [41].

A wind power interval forecasting model based on a temporal convolutional network (TCN) combined with the conformalized quantile regression (CQR) algorithm was developed by Hu et al. [41]. The proposed model can control the mis-coverage rate without depending on the choice or the accuracy of the underlying estimators while adapting heteroscedasticity within the wind data, resulting in narrow prediction intervals that lead to higher accuracy. The proposed model was compared with some benchmark models (BPNN, RNN, LSTM, and GRU) and it was shown to have better performance in both point prediction and interval prediction with valid coverage and shorter interval bandwidth. More importantly, drawbacks such as iterative propagation and gradient explosion associated with conventional RNN-based models do not present in the proposed model and it is capable of handling very long sequences concurrently. This model needs to be further improved to overcome the crossing problem associated with quantile prediction. In addition, the structure of the model can be further modified to achieve joint multi-interval prediction and mitigate limitations with the network depth and the dilation factor.

Zang et al. [19] constructed a hybrid model based on ARIMA with an additional seasonal component and LSTM network for short-term wind power forecasting of an offshore wind turbine. Neither linear nor nonlinear assumption was required as the proposed model was composed of linear and non-linear techniques. The decomposition technique discrete wavelet transform (DWT) was used to improve the prediction accuracy of the model. In addition, data preprocessing techniques such as re-sampling, isolation forest (IF), and interpolation were used to enhance the quality of the datasets used in the study. Data used in this study was collected from the Supervisory Control and Data Acquisition (SCADA) database with a sampling rate of 1 s. The authors claim the proposed model has good prediction accuracy. However, the impact of missing data points, datasets from different sources, and strong guts on the model performance need to be investigated. Moreover, the efficiency and the impact of other wavelets such as Harr wavelet, Coiflet wavelet, Daubechies wavelets, etc., can be analyzed to come up with the most optimized wavelets. The model architectures, applications, and prediction accuracies of the above-reviewed wind speed and wind power forecasting models are summarized in Table 1.

Table 1. Model architectures, applications, and prediction accuracies of wind speed and wind power forecasting models.

Authors	**Model Architecture**	**Application**	**Prediction Accuracy**
Gao et al. [17]	Weighted hybrid kernel extreme learning machine with k-MoGE optimizer	Ultra-short-term onshore wind speed forecasting Single-step or multi-step (1–3 steps)	$0.0699 < \text{RMSE} < 0.1306$ $1.9236 < \text{MAPE} < 6.5364$
Liu et al. [12]	Support vector machine with Jaya optimization algorithm	Short-term onshore wind speed forecasting Single-step or multi-step (1–3 steps)	$0.6451 < \text{MSE} < 1.0154$ $0.5909 < \text{MAE} < 0.7633$ $11.87 < \text{MAPE} < 15.34$
Xing et al. [10]	Optimal benchmark model selection with multi-objective Aquila optimizer and fuzzy information granulation	Short-term onshore wind speed forecasting Single-step or multi-step (1–3 steps)	$0.4897 < \text{RMSE} < 2.4219$ $0.3821 < \text{MAE} < 1.7404$ $4.122 < \text{MAPE} < 33.725$
Chen et al. [36]	A hybrid model of the LSTM and BP neural networks with the sparrow search algorithm	Short-term onshore wind speed forecasting Single-step or multi-step (1–3 steps)	$0.039 < \text{MAE} < 0.135$ $0.051 < \text{RMSE} < 0.273$ $0.929 < \text{MAPE} < 2.478$ $0.003 < \text{MSE} < 0.062$

Table 1. *Cont.*

Authors	Model Architecture	Application	Prediction Accuracy
Zou et al. [9]	A hybrid probabilistic model of multilayer CNN and attention-based LSTM based on non-crossing quantile loss	Onshore Wind speed forecasting Single step	0.6610 < MAE < 0.7075 1.0102 < RMSE < 1.0556 13.21 < MAPE < 14.15
Neshat et al. [13]	A hybrid model based on QCNN and Bi-LSTM integrated with an adaptive decomposition technique.)	Long-term onshore wind speed forecasting. One-day ahead forecasting (single-step)	0.0087 < MSE < 0.0138 0.0935 < RMSE < 0.1178 0.0510 < MAE < 0.0721
Wang et al. [37]	An ensemble multi-feature complementary prediction model based on SVR and bidirectional LSTM. LWSM with CS algorithm is used to optimize of weight assignment	Onshore wind speed forecasting Single step	0.063 < RMSE < 0.072 0.054 < MAE < 0.057 36.48 < MAPE < 57.35
Wu et al. [38]	A deep learning gated recurrent unit (GRU) network	Long-term onshore wind speed forecasting. One-day ahead forecasting (single-step)	22.29 < MAPE < 30.61 3.1754 < MSE < 8.1566
Ding et al. [21]	Hybrid-kernel least-squares support vector machine with maximal wavelet decomposition and fuzzy C-means algorithm	Short-term wind power forecasting Multi-step (5–15 steps)	8.78 < RMSE < 16.78 6.59 < MAE < 13.11
Yildiz et al. [39]	An improved residual-based CNN with stochastic gradient descent optimization algorithm	Very short-term wind power forecasting Multi-step (1–3 steps)	0.0248 < RMSE < 0.1362 0.0187 < MAE < 0.0827
Jiandong et al. [14]	A hybrid model of the LSTM network and DBN network with particle swarm optimization	Short-term wind power forecasting Single step	MAE = 35.3776 RMSE = 42.9055
Tian et al. [18]	A gated recurrent unit with a dual-stage self-attention mechanism	Single-step-ahead wind power forecasting	80.6 < RMSE < 148.1 52.8 < MAE < 102.8
Al-qaness et al. [40]	A hybrid technique of an augmented version of the marine predator algorithm using the mutation operators and adaptive neuro-fuzzy inference system	Short-term wind power forecasting Single step	0.0056 < RMSE < 0.1757 0.0001 < MAE < 0.0050
Hu et al. [41]	Temporal convolutional network combined with the conformalized quantile regression algorithm	Wind power forecasting Interval forecasting	44.60 < MAE < 934.16 82.20 < RMSE < 1371.22

This section highlighted the complexities associated with the variability of wind speed for optimal energy harvesting, with the inevitable system failures and performance degradation that consequently incur additional operational and maintenance costs for wind turbines. Current literature describes the different categories of forecasting techniques. However, the superior features of hybrid systems can facilitate improved prediction accuracies and capabilities for wind energy applications. The following section describes the state of the art as it applies to the technological applications in respect to wind energy harvesting and the implications inherent in extracting from the primary input.

3. Technical Considerations

3.1. System Considerations

A small-scale wind energy conversion system (WECS) has wide-ranging use and operating conditions and, consequently, has evolved rapidly along with the large scale WECS for generation of electricity for either on-grid or off-grid applications. Such a WECS is considered as a complex system of many subsystems ranging from mechanical (rotor, hub, gear box, etc.), to electrical (generator, converter/inverter, rectifier, control) systems and loads. However, the integration of wind generation and the intermittent power injected by wind turbines, causes significant challenges for the reliable operation of power grids [42].

In low power applications, two types of generators are employed, namely induction generators (IGs) and permanent magnet synchronous generators (PMSGs) [43,44]. The majority of commercially available small wind turbines (SWTs) are based on permanent magnet generators. At very low capacity, microgeneration (namely ca 2.5 kW), a permanent magnet generator (PMG) turbine is a DC generator, operating at variable speed that uses a magnet as an external field and a wound armature. The faster the turbine blades rotate, the higher DC voltage is derived. A PMSG, on the other hand, incorporates a three-phase AC stator winding and a permanent magnet rotor so it needs no brush gear. As with the PMG, the faster the blades rotate, the higher voltage is produced. However, the output is also characterized by a higher frequency voltage, hence it is deemed "wild". PMSG-based WECS are integrated to a three-phase grid via two conversion stages. An AC/DC conversion stage at the machine side applying a diode rectifier-boost topology followed by a DC/AC (inverter) conversion stage at the grid side featuring a three-phase voltage source inverter (VSI) [45]. PMSG turbines operate as variable speed wind turbines employing these power electronic converters to connect the generator to the grid [46]. The converter decouples the generator from the grid, maintaining synchronization whilst allowing the turbine speed to vary depending on wind conditions. Thus, there is no need for pitch control, or it can be very simple. Compared to fixed-speed system, variable-speed systems have improved system efficiency, energy capture and reduced mechanical stresses. In comparison to largescale wind turbine systems, the system is relatively simple. The most prominent variable speed wind energy system for large capacity wind turbines is the doubly-fed-induction-generator (DFIG), consisting of a wound rotor induction generator with the stator directly connected to the grid, and the rotor connected to the grid via a bi-directional back-to-back voltage source converter.

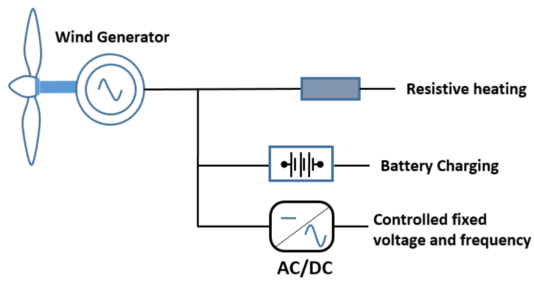
WECS installations can operate as both an autonomous and grid-connected system. In autonomous systems, the system's own loads consume the energy generated, usually with the support of a local energy storage system. In grid-connected systems, the loads can consume the energy produced and at the same time import, any extra needed from the grid or supply any excess energy to the grid. An example of an off-grid SWT installation is one that incorporates battery storage. When the battery is fully charged, any surplus energy produced from the wind turbines is diverted, e.g., into hot water storage through a diversion control system to ensure that all of the renewable energy produced is utilised across the premises.

Three classes of wind turbine electricity system are proposed are proposed by Twidel [47] as summarised in Table 2 and illustrated in Figure 7. These classes are described based on the relative capacity of the wind turbine generator (P_T) and the capacity of other electricity generators and/or batteries connected in the system (P_G).

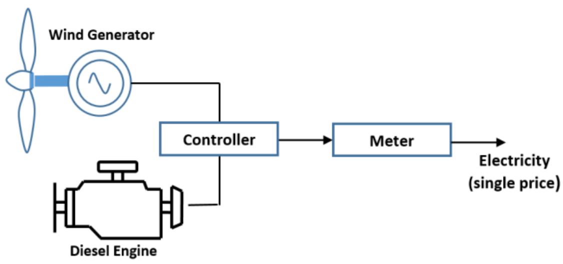
For class A, autonomous, stand-alone system; used in small capacity contexts (>2 kW) for household, small commercial contexts and where battery storage is likely to be incorporated to stabilize the voltage and store electricity. Class B is deployed in remote area applications (small grid contexts) where the other generator capacity is likely powered by a diesel engine. The principal purpose of the wind turbine, in this regard, is fuel saving. However, a 24 h maintained supply without load management control would depend on the diesel generator since wind is not always available. Moreover, the diesel generator is either kept running continuously (frequently on light load, even when the wind power is available) or switched off when the wind power is sufficient. For a class C system, the most common arrangement, P_G is usually from the utility where control of the frequency across the network is performed.

Table 2. A classification of wind turbine electricity systems.

Class/	**A**	**B**	**C**
Summary	**Figure 7a**	**Figure 7b**	**Figure 7c**
P_T: wind turbine capacity; P_G: linked generation capacity	$P_T \gg P_G$	$P_T \sim P_G$	$P_T \ll P_G$
Example of PG Example of system	Battery Autonomous	Diesel generator Wind/diesel	Central power station Grid embedded
Common wind turbine generator type	Permanent Magnet	Induction	(a) doubly-fed induction (b) multi-pole with AC/ DC/AC interface



(**a**)



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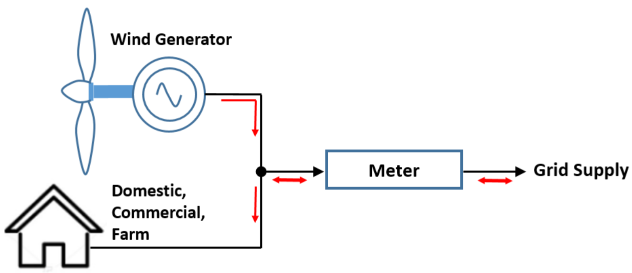

(**c**)

Figure 7. Wind turbine electricity system classification examples. (**a**) Class A: Stand-alone small-wind energy system with the wind turbine as the dominant supply (high-quality electricity via 'piggy-backing' on a dominant supply of less quality); (**b**) Class B: Wind/battery supply mode: single mode (using all wind-generated power in windy conditions and as the wind speed decreases, the cheaper serviced loads are automatically switched off to decrease the demand); (**c**) Class C: Small-wind energy system grid-linked wind turbine slaved in a large system.

3.1.1. Off-Grid Systems

The primary factors to consider in a wind energy harvesting system [48], particularly in an off-grid context, include flexibility (in the context of a hybrid solution) to meet energy needs: Existing and anticipated power requirements should be evaluated in advance and the following factors should be taken into consideration:

- Variety of loads: lighting, refrigeration, small appliances, etc.
- Peak consumption: when, how much power, and how often
- Average consumption: ongoing loads which are typically in use or on standby
- Minimum consumption: loads being run all the time and consistently
- AC or DC needs: (i.e., may require additional auxiliary components)
- Required availability: system as back-up or supplementary power supply.

Erturk [49] describes the considerations involved in sizing a stand-alone off-grid wind turbine-battery system for a remote house. Component sizing involves matching the turbine capacity to the minimum number of batteries to supply uninterrupted continuous power. Battery system configuration, as outlined by Belouda et al. [50] is a significant consideration involving the sizing of each system component based on the matching of the wind turbine and understanding of the power source.

In an off-grid wind turbine system, the wind turbine and the battery bank must be chosen carefully in order to provide continuous secure power supply to the end user. With appropriate planning, system's selection and sizing, stand-alone off-grid systems can supply secure reliable and economic power to remote locations and distributed micro-grids [49].

An estimated 759 million people lack access to electricity [51], so off-grid applications are particularly relevant in rural contexts for developing countries [52]. However, when one considers efficiency of scale, power quality, and energy continuity (in the context of redundancy opportunities), the majority of wind energy harvesting opportunities internationally will increasingly become grid-connected (or micro-grid) systems. Moreover, wind energy opportunities will likely focus on rural locations that are adjacent to larger load centres, such as cities. Urban harvesting opportunities are possible, for example through building-integrated wind turbines [53]. However, the inherent challenges arising from a depleted resource, such as the prevalence of turbulence and visual and noise impacts [54] make for an arduous resource harvesting opportunity.

3.1.2. Grid-Connected Systems

As Wu et al. conveyed [55], system frequency and voltage (inertial control) are mostly determined by conventional thermal power plants in traditional power systems. However, as the penetration of wind power increases, the voltage or frequency supports are expected to become increasingly provided by the wind generators. Moreover, with increasing renewable power generation and integration into the utility grid, the grid integration requirements have become the major concern as renewable energy sources (RESs), such as wind, are replacing conventional power plants [56]. In the following, focus is on the ramifications of faults should they arise in wind energy systems. In addition, installation requirements in the context of the regulatory considerations are discussed.

The unique characteristics of wind energy systems, including intermittent, turbine technology, and protection issues, bring significant challenges for successful and economic integration to the grid [57]. It is important to ensure that the system does not interfere with other users of the power network. As Ahmed et al. discuss [57], there are a number of challenges in integrating wind energy into an electrical network, ranging from power prediction and quality to grid reliability and resilience as a consequence of the variability of the primary resource.

Voltage fluctuations or 'flicker' are rapid changes in the supply voltage magnitude within the statutory limits of the usual slow variations of ($\pm$5% of nominal value). Flicker can cause the malfunction of connected sensitive equipment or may otherwise reduce their expected lifetime [58]. From a consumer perspective, voltage flicker is a serious power quality problem [59,60].

Due to their irregular characteristics, causing undesirable problems and power quality issues, harmonics, and the voltage and current distortions created, are the most common problem in renewable-based power generation technologies [61]. Variable-speed wind turbines in particular are generally grid-friendly machines in most power quality respects, but harmonics generated by the grid-side power converters may be of concern in networks, where harmonic resonance conditions may exist [62]. However, whereas the emission from individual turbines is relatively small, some authors point to a relatively high emission at higher harmonic orders and for other frequencies where the distortion levels are traditionally lower and particularly in the context of wind farms [63,64].

Other power quality concerns include fault feed-in and voltage (current) transients. The former creates a need for fault ride-through considerations to ensure a reliable and stable operation of power systems [65], whereas the latter, particularly during the presence of unsymmetrical faults [66], must be controlled so as to not create adverse operation conditions for the network.

Fault Ride Through

Ahmed et al. outline a significant number of international grid codes that give close attention to the fault ride-through capability of the wind turbine [57]. Increased penetration of wind power produces a potentially negative impact on the stability of existing power system [67] when a grid fault occurs. It causes a voltage dip, and the detection of such causes the disconnection of the connected wind generator in order to shield the plant from the detrimental effects of voltage drop [68]. However, this disconnection also creates an adverse influence on the remaining generation systems which can be detrimental to the overall system stability. So, the grid codes prescribe fault ride-through (FRT) requirements to avoid this problem [69].

Fault ride-through is a requirement for distributed generators to remain connected to the grid during a fault for a short period (needed by the grid protection system to clear the fault). So, if frequency/voltage disturbance is detected, the generator must not trip if the fault lies within specified criteria defined by the grid code. Buraimoh et al. consider a generic low-voltage ride-through (LVRT) capability curve [68]. This is demonstrated in Figure 8, where under normal operating conditions, a generating unit operates in normal mode (V_n) with its point of common coupling (PCC) voltage. When a fault occurs (at time t_0), the generating unit encounters a voltage sag (V_0) at the PCC. Generating units have to endure the voltage drop until a particular time and remain grid connected. If the generating unit experiences a substantial voltage decrease, the generating unit has the freedom to detach from the power grid. Upon removal of fault at the time past period (t_2), the voltage returns to V_{n0} and operation returns to normal.

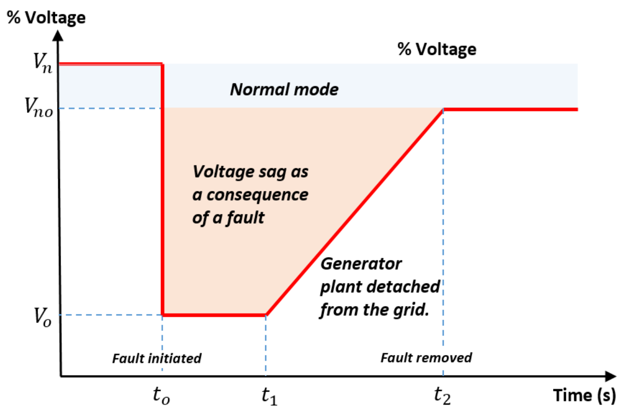

Figure 8. Generic fault ride-through capability curve.

The capability of generators to remain connected to the power system during and following system faults depends heavily on the generator technology, design and control characteristics and short circuit levels [70]. Other factors that are of importance are system characteristics, protection operation and protection fault clearance times. In order to be capable to remain in service in the event of a fault and return quickly to the pre-fault output after fault clearance, certain generating technologies may require additional dynamic voltage control (inbuilt or external).

Installation Requirements

It is essential that wind energy systems do not present dangers to effective network operation. For instance, if a feeder supplying a region with a DG is disconnected during a fault on the grid, islanding operation keeps that region of the utility (the island connected to the DG) energized [71]. This is potentially hazardous for line operators who want to deal with the cause of the fault and restore supply [72]. Moreover, a long duration islanding could produce conflict for the automatic reclosing of the utility protection devices. Wind energy systems may be capable of operating in islanding mode, but this is not allowed with current legislations due to safety and technical problems: mainly providing safe earthing and balancing supply and demand (to maintain constant voltage and frequency). Chen et al. [73] discuss islanding control architecture for smart grids to avoid power imbalances that may lead to system frequency instability with the loss of adequate power reserves from the external grid.

For on-grid DG, such as wind energy systems, it is essential to ensure that the system can only operate when connected to the grid. In this regard, the system is disconnected from the grid, properly shuts down and protects itself under grid fault conditions if any of the following exceeds a pre-set level: frequency, ROCOF or voltage level. Following power imbalances, particularly in the context of system faults, a higher ROCOF is manifest. This is because renewable energy technologies are typically decoupled from the grid by power electronic converters that limit their natural response to frequency variations [74]. In the first few seconds following a major frequency event, system inertia is critical and plays an essential role in reducing ROCOF and counterbalancing the frequency recovery to the pre-event value. Large system ROCOF may result in unintended wind farm tripping, costumer load shedding and could eventually lead to a total system blackout [75].

There are other factors to consider in respect to the installation of wind energy systems. These include

- Type and capacity of the generator and the voltage level for connection to the grid (point of common coupling, PCC)
- Availability of power generated
- Variation of power generated with time and predictability of variation
- Reliability of the plant
- Technology and regulations for connection.

In particular, there are specific requirements underpinning the design, control and management of wind energy plant. The IEC 61400 is a series of standards to ensure that wind turbines are appropriately engineered [74]. They include everything from assessing the structural integrity of onshore wind turbine support structures (IEC 61400-6:2020), power quality characteristics (IEC 61400-12-1:2017), to specifying a procedure for measuring the power performance characteristics of a single wind turbine (IEC 61400-12-1:2017). Authors such as Wang et al. [76] have explored the utilisation of modelling constraints as provided in the IEC 61400 series in the context of system design. Legislatively, however, there are also standards and legally binding requirements at national levels.

3.1.3. Grid Codes for Wind Turbine Connection

The technical specifications of the electricity grid for safe, secure, reliable, and economical operation is commonly known as the grid code [57]. These grid codes are designed to assure the integrity and operation of the power system. Wind power plants are increasingly facing system stability support requirements similar to conventional power stations, which is as a consequence of a growing share of wind power in the generation mix [77]. As discussed by Rona and Güller [78], it is possible to expand the penetration with reduced wind power curtailment levels under the introduction of new regulations for grid code compliance. Each country implements a specific regulatory framework driven by several factors: their own renewable energy targets, local availability of renewable resources, energy mix structure and existing infrastructures as well as other factors such as public perception, geographical distribution of electricity generation and consumption points. Connection requirements for large wind power plants can vary substantially from one system operator to another, leading to gross inefficiency and additional costs imposed on wind turbine manufacturers and wind farm developers [79]. Serrano González and Lacal-Arántegui [80], analysed the potential barriers for wind energy deployment and found that the stability of regulatory framework is one of the most important concerns for investors.

The general procedure for grid connection in most European countries is described by González and Lacal Arántegui [80]. Figure 9 in this regard highlights the role of the distribution service operator (DSO) and transmission service operator (TSO) in the capacity assessment [81]. After performing the basic technical project development study of the wind farm, the plant developer sends the application to the system operator to request connection approval. In a feasibility study, the system operator examines whether the network conditions existing at the planned point of connection are technically adequate. If the technical requirements of the electrical system at the intended connection point are not adequate, the grid operator furnishes evidence of this inadequacy and proposes the necessary modifications or network reinforcements. Following this feasibility study, the formal connection offer is proposed.

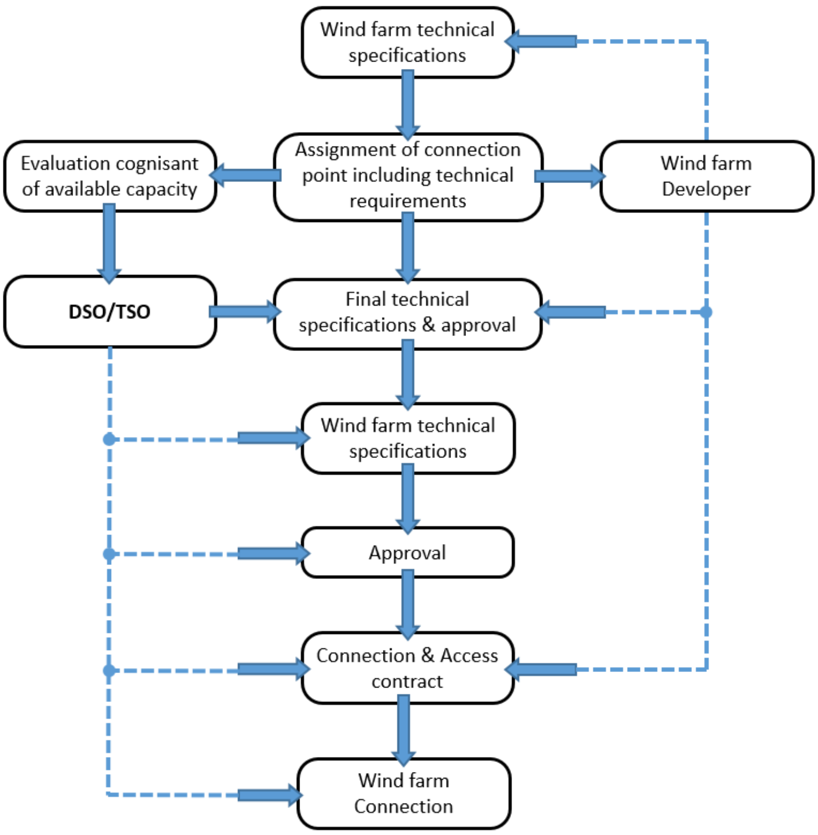

Figure 9. General connection procedure for wind power plants.

Looking at the UK, as a case study, there are two engineering recommendations (EREC). The first is EREC G98, which covers the connection requirements of microgenerators (up to and including 16 A per phase) in parallel with the public LV distribution network. The second is EREC G99, which covers generator connection requirements for larger generators in excess of 16 A per phase. Specific differences and some further information about the two connection types are illustrated in Table 3.

Table 3. EREC (UK) and the microgeneration connection requirements.

	G98	G99	
Generator power	P_{rated}: 3.68 kW (1-ph) P_{rated}: 11.04 kW (3-ph)	Type A	The registered capacity is >16 A/phase and above, but less than 1 MW
		Type B–D	The connection point is below 110 kV (in practice in GB this is at 66 kV or below).
Voltage at point of common coupling (PCC)	V_{rated} = 400 V 3-p HV_{rated} = 230 V 1-ph	Type A	Installations where the registered capacity is at or above 1 MW,
		Type B	Generation connected at or above 110 kV (in practice in GB this is at 132 kV or above)

3.2. Hybrid Systems

Increasingly, there is a role for hybrid, off-grid connected wind turbines to employ battery technology. For instance, battery storage systems can promote self-consumption and self-efficiency, as discussed by Nyhom et al. [82]. Or in the context of utilising a form of LV demand response and renewable energy, or dispatchable load, O'Shaughnessy et al. considered the combination of PV and battery energy storage to reshape customer load profiles and thereby optimise the renewable energy generation potential to increase self-consumption [82].

There are multiple examples of hybrid systems incorporating wind energy along with solar PV and/or (battery) storage. Such systems can be stand-alone [83,84], or grid-tied [85,86]. Jadhav et al. [87] summarise the main constituent parts of such a system, as represented in Figure 10. An important note is that if in a stand-alone mode of operation, some means of 'dumping' is required when wind power generation becomes excessive relative to demand.

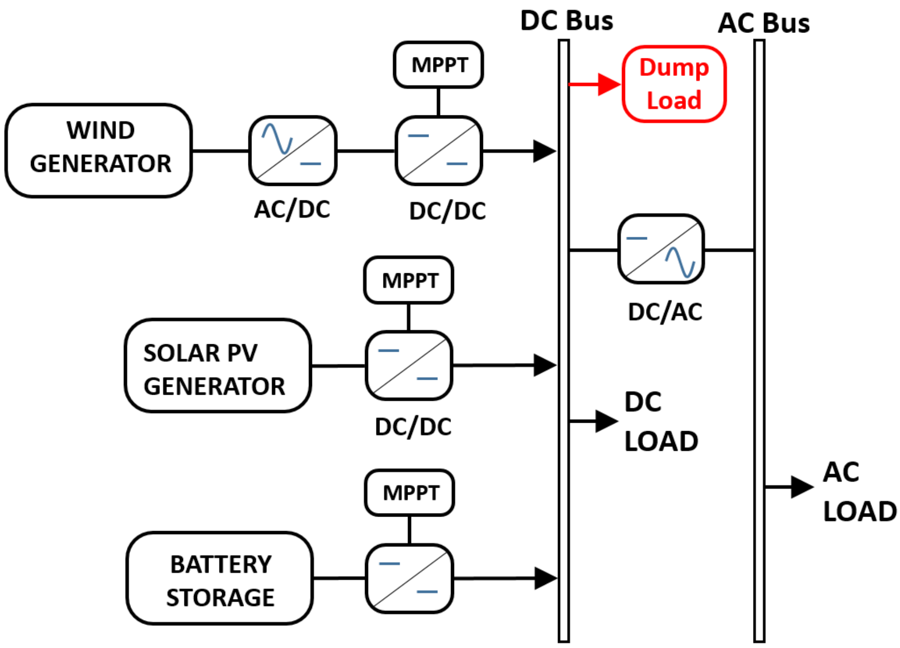

Figure 10. General block diagram depicting a hybrid RES system incorporating wind energy.

The range of opportunities for such hybrid approaches is wide. Sharma and Sandeep [88] look at optimal energy scheduling for commercial loads such as food courts and commercial kitchens through a combination of wind energy and battery energy storage system. Sakti et al.

consider something similar in the context of a remote area power supply [89]. These studies identify the primary challenges when it comes to small wind energy integration. Whereas the former prioritises the utilisation of generated electricity for an enhanced self-consumption and reduced cost for the prosumer, the latter points to the power quality challenges arising out of these hybrid energy harvesting/storage systems.

Self-consumption, utilising the benefits of renewable energy generation capacity, has a role by including extra load dimension. This involves the incorporation of storage opportunities, e.g., electric vehicles in a distribution network context. For instance, Stroe et al. [86] investigated modelling strategies to consider energy management in a residential setting incorporating a PV–wind system. In particular, they were interested in the charging stresses imposed on the battery energy system to facilitate the required energy management. Khezri [90] looked at the optimal sizing of wind turbine and battery storage with the provision of electric vehicle consideration. More specifically, they developed a practical capacity model in consideration of all the uncertainties associated with the primary renewable energy source, wind, load and EV charging demand.

Another issue influencing the incorporation of wind energy harvesting/storage systems involves the associated costs. Hemmati [91] undertook a technical and economic analysis in that regard. His work considered a range of operating conditions for a home energy management system incorporating wind and energy storage in the context of network energy purchasing and sell, prioritising a standalone mode and demonstrates that the battery energy storage system reduces the cost of purchasing energy from the gird by 14%. Haces-Fernandez et.al [92] observed that wind energy is influenced by a host of other factors, such as financial viability, environmental concerns, government incentives, and the impact of wind on the ecosystem.

This section considered the primary technological considerations involved in transducing the energy available in the wind for electricity demand requirements, in terms of design components and their applications. In harvesting wind energy, the primary concern is the optimization of energy capture regardless of the variability in the wind; and the literature is increasingly pointing to the benefits in addressing this in terms of hybrid energy capture/storage systems. The following section discusses the optimization challenges, available methodologies for optimization and how optimal solutions can be achieved through hybrid approaches.

4. Optimizing/Maximizing Potential

The performance of wind turbines is reliant on many parameters, which need to be controlled for better performance. Further, in the operation of wind turbines, system optimization is required to achieve certain objectives such as power maximization, energy cost minimization, and system safety. The maximum power point tracking control is used maximising energy capture and pitch control is used for power and load control for optimal operation of the wind turbine. Variable-speed wind turbines are commonly used and are generally more efficient with maximum power point tracking control. A maximum power point tracker (MPPT) is used to control the restoring torque of the electrical generator for optimum system operation and maximum energy capture.

As outlined in Section 1, the siting of wind turbines as a process includes everything from wind prospecting for suitable turbine sites over a wide geographical area to considering the placement of a single wind turbine on a site or of multiple wind turbines in a wind farm; this is generally called micro-siting. Software tools are used for micro-sitting and then optimization algorithms are used to maximize annual energy production while minimizing the cost of energy generation by considering environmental and social issues.

Hybrid systems, on the other hand, require a battery bank or engine generator to fulfill the demand, as wind and solar generations vary with resource variation. In a hybrid system, component size needs to be optimized for minimizing the cost of energy generation to fulfill demand with resource availability.

4.1. Wind Turbine Power Optimizing Technology

In a wind turbine, wind energy is converted to mechanical energy by a wind rotor and then converted to electrical energy by a generator. This system consists of different units, which have different characteristics and are required to match the performance for optimal operation. The wind speed varies always, and the wind rotor energy is maximum at a certain tip speed ratio. The tip speed ratio (TSR) is a dimensionless parameter, which refers to the ratio between the wind speed and the speed of the tips of the wind turbine blades. Therefore, the wind rotor rotational speed should be controlled according to the wind speed variation and also needs to control generator operations for maximum power extraction as described by Narayana et al. [93]. The wind rotor power versus rotational speeds for different wind speed, are illustrated in Figure 11.

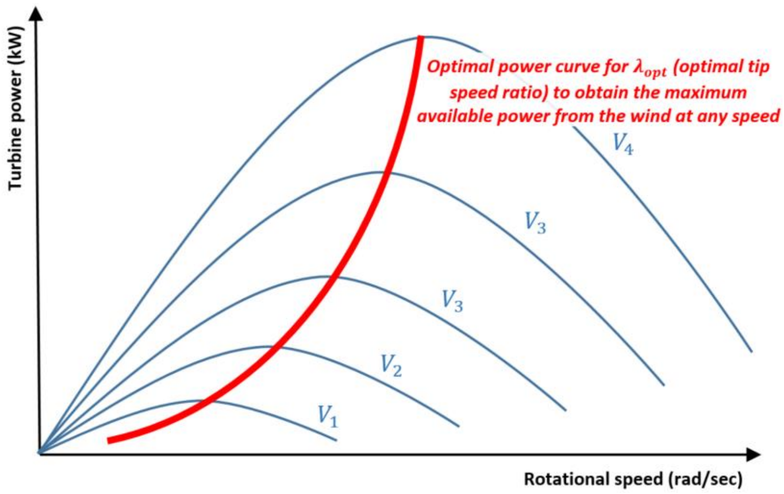

Figure 11. Wind rotor power vs. rotational speed for different wind speeds.

As can be noted, the generator power input needs to track the optimal (maximum) power curve to maximize the energy generation. Therefore, it is required to control the wind rotor rotational speed by manipulating the generator power generation. An example of a control strategy of a wind turbine system is described by Narayana et al. [94] as illustrated in Figure 12. Maximum power point control strategies are used to track the optimal power curve with the variation of wind speed, when a wind turbine is operated at wind speeds that do not yield nominal power generation [95].

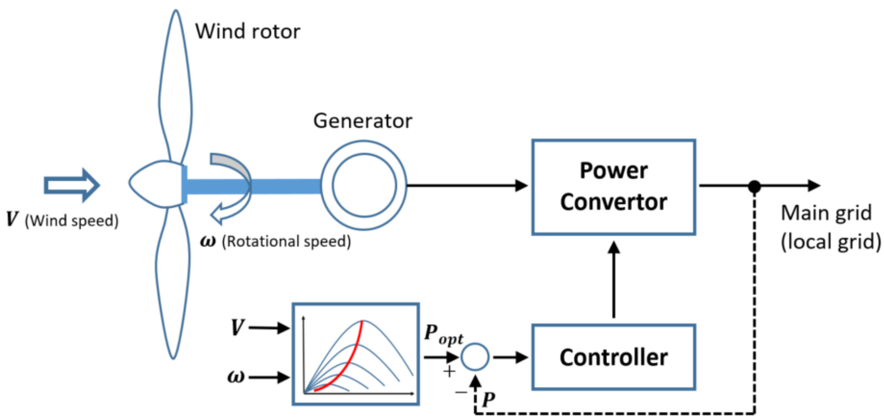

Figure 12. Control strategy of a wind turbine system.

The output power of a wind turbine is maximized if the wind rotor is driven at an optimal rotational speed for a particular wind speed. To achieve this, a maximum power point tracking (MPPT) controller is usually used. To implement the MPPT controller, the turbine dynamics and instantaneous measurements of the wind speed and rotor speed are required. The wind turbine's operation is affected by the wind speed variations, which cannot be followed by the wind rotor due to the large moment of inertia [96]. MPPT control of wind turbines is required due to fluctuation of wind speed and becomes difficult due to wind rotor inertia. An adaptive filter together with a fuzzy logic-based MPPT controller has been used to overcome the wind rotor inertia effect, by reference estimation without predetermined wind turbine characteristics [97]. Estimating the control reference, such as the tip speed ratio, is also difficult without accurate wind speed measurement, which is not always possible and is often estimated. The wind speed provided by the anemometer is measured at a single point of the rotor plane, which is not the accurate wind speed [98]. Then wind turbine outputs such as rotor rotational speed and generated torque are usually used to predict the wind speed [99]. Main MPPT control strategies are tip speed ratio control, optimal torque control, power signal feedback control and perturbation and observation control [100–108].

The aerodynamic efficiency of a wind rotor depends on the angle of attack to the rotor blades, which is dependent on pitch angle, rotational speed, and wind velocity. If rotational speed variations are restricted due to system inertia and generator side limitation, pitch control is useful for power optimization. Turning the blades around their own axes changes the relative wind flow and, consequently, the aerodynamic loads exerted on the rotor. The power coefficient $C_p(\lambda, \beta)$ varies according to the pitch angle and, consequently, the power capture varies as well [108]. Beyond the rated wind speed, pitch angle control is used for power control to match with machine-rated capacity. If the power exceeds the rated power or exceeds the load power requirement, the pitch controller is activated to turn the blade outward [109]. Further, pitch control needs to be quickly activated to protect the system from mechanical stress or failure. Control system delays caused by hydraulic pressure-driven units in wind turbines may degrade and even destabilize the pitch control system, leading to the performance degradation or collapse of the whole wind turbine energy conversion system. Then, the pitch controlling mechanism should be operated with minimum delay to overcome the adverse effects from the unknown delays caused by the hydraulic driven units. Signal compensation techniques can be implemented to remove the effect of the delay-perturbation on the turbine output [110]. Future wind speeds are predicted by deep learning techniques and then effective wind speed can be estimated and used with appropriate controller (e.g., fuzzy logic control) for pitch controlling to avoid delays and uncertainties of the system dynamics [111].

4.2. Optimization of Wind Turbine Design

The wind is freely available and wind turbines are used to convert it into useful energy. In a wind turbine, rotor performance is required to consider for maximum wind energy harnessing. There are many studies on optimal rotor design for maximum energy extraction. The computational fluid dynamics (CFD) model was developed to simulate wind turbines with the untwisted blade to determine the optimal angle of attack that produces the highest power output of wind turbines [112,113]. A genetic algorithm with an inverse design method as an optimization method was used for stall-regulated horizontal-axis wind turbines to maximize the annual energy production (AEP) [114]. For optimization, the energy yield needs to be maximized while minimizing the cost of energy generation. The optimization of the wind turbine involves many objectives such as AEP, the air loads of the tower, blades and rotors, and the mass of the blades. Therefore, multi-objective optimization techniques are suitable in the design stage of wind turbines to maximize energy production and minimize the cost of energy generation. The cost of energy generation depends on the reliability, capital, and maintenance cost of the system, and then it is required to consider reducing fatigue, extreme loads, and material and production costs. Fuglsang and Madsen presented a numerical multi-disciplinary optimization method that included multiple constraints; the object was the minimum cost of energy (COE), which estimates the fatigue and extreme loads in the design stage for capital cost and the annual energy production for a given site condition [115]. The sequential quadratic programming (SQP) method was used to optimize the (COE) cost of energy to maximize the AEP while keeping the cost fixed to the original baseline design [116]. Xudong et al. [117] presented a gradient-based method for the optimization of three different wind turbine rotors with the objective of minimum COE. For optimal operation, wind turbines need to be designed by considering wind characteristics in the site, which are turbulence, wind speeds, and directional distributions. Power generation is highly affected by wind speed and wind directional variations. In turbulent urban conditions, power generation is reduced due to the yaw behavior of small wind turbines, which needs to consider in the design stage for these types of site conditions [118].

4.3. Optimization and Enhanced Wind Energy Harvesting: A Hybrid Modality Consideration

Optimization of hybrid wind power system, as illustrated in Figure 10, is the process of selecting suitable components, sizing and a control strategy to provide an efficient, reliable, and cost-effective alternative energy supply. Resource availability, energy demand, and technology assessment are required to evaluate the potential of power generation. Wind and solar power development, the availability of the associated (primary) resources and land area are the constraints and hybrid systems are considered for maximum power generation.

Minimized total annual cost of the system is achieved by determining the appropriate numbers of components, such that the desired load can be economically and reliably satisfied under the given constraints. Then, the total annual cost of hybrids of wind and solar renewable energy systems is optimized to satisfy the predesigned load and employing gravitational search algorithm (GSA) for the optimization process [119]. Load uncertainties and fluctuations in renewable power production led to new challenges in power systems' operation and distribution, which required proper energy management. Hence, the stochastic nature of wind energy and photovoltaic units, along with the uncertainties associated with plug-in electric vehicles' (PEV) charge/discharge dynamics must be taken into consideration when integrating these intermittent energy sources into the grid. Here, the Monte Carlo simulation (MCS) was combined with the antithetic variates method (AVM) to determine the probability distribution function (PDF) of the power generated by the hybrid system [120]. Then the optimal power flow was evaluated using a master–slave parallel epsilon variable multi-objective genetic algorithm (Pev-MOGA) [120].

Hybrid systems are commonly used in off-grid applications with an energy storage facility. Economic viability should be the top priority over technical feasibility while designing the hybrid system for off-grid applications. A system consisting of a photovoltaic, wind with batteries and converter was simulated by iHOGA (improved hybrid optimization algorithm) and evaluated sensitivity analysis to find out suitable combinations [121]. In the off-grid applications, sizing of each component is crucial for economic viability. Energy demand pattern and resources with time domain need to be considered for generation and energy storage. A hybrid genetic algorithm with particle swarm optimization (GA-PSO) was applied for the optimal sizing of an off-grid house with photovoltaic panels, wind turbines, and battery and compared with the HOMER (hybrid optimization of multiple energy resources) results [122]. HOMER is a popular tool for micropower optimization [123].

Renewable energy sources realise intermittent generation output. So, system sizing should be optimized by considering the cost and reliability of the system. A multi-objective optimization approach, namely, PSO was used to design an optimal design of a hybrid wind turbine/PV/battery energy system for a household application by comprehensively investigating the effects of various factors on the cost-reliability relations [124]. Ekren et al. introduced a statistical and mathematical method called response surface methodology (RSM) to explore the relationships of the design parameters such as the PV size, wind turbine rotor swept to the hybrid system cost of an autonomous PV/wind integrated hybrid energy system with battery storage [125]. RSM includes optimization procedures for the settings of factorial variables such that the hybrid system cost reaches the desired minimum value for optimization. Another study by Traore proposed a method for optimal sizing of an off-grid hybrid micro-grid (MG) system to achieve a certain load demand [126]. This hybrid MG is consisting of a solar photovoltaic (PV) system, wind turbine (WT), and energy storage system (ESS). An enhanced genetic algorithm (GA) is used to optimize the system design parameters for minimizing the total cost of the system. The reliability of this MG system is modelled based on the loss of power supply probability (LPSP). Sawle et al. implemented both GA and PSO algorithms for optimal planning of a PV-wind-biomass system with energy storage and a backup diesel generator [127]. In this study, The cost of energy (COE) or electricity price is minimized as an objective function using GA and PSO. The optimal configuration of the hybrid system is obtained based on minimum COE. The optimal solution consists of high reliability, the maximum value of the renewable fraction, less emission, and low penalty cost according to minimum COE.

4.4. Comparison of Optimization Techniques

Optimization tools, such as those identified in Section 4.3 such as iHOGA and HOMER are suitable for sensitivity analysis and micropower optimization respectively. Table 4 provides a summary of different optimization methods, as they apply to wind energy considerations in terms of the tools (software) and the associated methodologies involved. In particular, HOMER software consists of optimization and sensitivity algorithms, which make options for evaluation easier. It considers combinations to satisfy all the constrain that the user defines, and sizes the hybrid renewable energy system for the least value of NET present cost (NPC). HOMER is user-friendly and has less computational time compared to iHOGA. HOMER is a single objective optimization software. iHOGA on the other hand, is a program that uses a genetic algorithm to determine the optimal sizing of the desired energy system. This software employs two algorithms: one to optimize the system configuration, and the second is used for deciding the control strategy in the operation. iHOGA has the flexibility to choose all combinations for both primary and secondary algorithms to produce 100% population. iHOGA has a multi-objective optimization facility.

Table 4. Summary of optimization techniques.

Method/Software	Model/Software Objectives/Capabilities	Ref.
Computational Fluid Dynamics (CFD) model and rotor free-wake modeling using a pseudo implicit relaxation algorithm	Flow simulation of wind turbines with the untwisted blade to determine the optimal angle of attack that produces the highest power output of wind turbines.	[112,113]
Genetic Algorithm with an inverse design method	To determine the optimum blade pitch and blade chord and twist distributions that maximize the annual energy production.	[114]
Numerical Multi-disciplinary Optimization Method	Minimum cost of energy (COE), cognizant of fatigue and extreme loads in the design stage for capital cost and the annual energy production for a given site condition.	[115]
Sequential Quadratic Programming (SQP) method	Optimizing for the COE to maximize the annual energy production (AEP) cognizant of the original baseline design.	[116]
Gradient-Based Optimization method	Optimization of three different wind turbine rotors with the objective of minimum COE.	[117]
Dynamic Analysis by MATLAB/SIMULINK	Effect of yaw behaviour for power generation in small wind turbines.	[118]
Gravitational Search Algorithm (GSA)	Optimisation in terms of total annual cost evaluation of wind and solar (hybrid) renewable energy systems to satisfy the predesigned demand.	[119]
Monte Carlo Simulation (MCS) combined with Antithetic Variates Method (AVM)	Determining the probability distribution function (PDF) of the power generated by the hybrid system.	[120]
iHOGA	Employing a genetic algorithm to determine the optimal sizing of the desired hybrid energy system.	[121]

Table 4. *Cont.*

Method/Software	Model/Software Objectives/Capabilities	Ref.
HOMER	Micro power optimization tool, which consists of optimization and sensitivity algorithms.	[122,123]
Particle Swarm Optimization (PSO)	A multi-objective optimization approach to design an optimal design of hybrid wind turbine/PV/battery energy system by comprehensively investigating the effects of various factors on the cost-reliability relations.	[124]
Response Surface Methodology (RSM)	Employing design parameter relationships such as the PV size, wind turbine rotor swept area, etc., to determine the system cost of an autonomous (hybrid) PV/wind integrated hybrid energy system with battery storage.	[125]
Enhanced Genetic Algorithm (GA)	System design parameter optimisation for minimizing the total cost of the system, while incorporating the micro-grid system reliability based on the loss of power supply probability.	[126]
GA combined with PSO	Optimal planning/configuration of a PV-wind-biomass system with energy storage and a backup diesel generator, with minimized COE as an objective function.	[127]

This section considered the state of the art in respect to optimisation techniques and how they can facilitate a more effective symbiosis between the highly variable wind resource, and enhanced harvesting opportunities. Once again, hybrid, or the conflation of multiple techniques, offers the best opportunity for most efficient extraction of the available energy in the wind.

5. Conclusions

The exploitation of wind energy has ever been challenging owing to the uncertainty and volatility of wind speed. Wind speed is subject to complex seasonal and stochastic characteristics. Instabilities in wind directly affect wind power, resulting in unsteady power generation and subsequent voltage and frequency fluctuations that affect the power grid. This brings challenges and additional operational and maintenance costs in the integration of wind power to the grid, which, if not adequately addressed may lead to system failures and performance degradations. High-precision wind speed forecasting is salient in wind resource assessment. Wind power grid integration requires accurate wind power forecasting to maximize energy capture and minimize operational risk while improving the scheduling efficiency of the grid. Wind power generation significantly increases for a small increase in forecasting accuracy. This shows the importance of accurate forecasting algorithms and models.

A vast number of forecasting techniques have been reported in literature published in the past few decades. Forecasting techniques are mainly categorized into four groups (physical, statistical, intelligent learning, and hybrid methods). Hybrid methods which encompass superior features of more than one model are versatile and have comparatively superior prediction accuracies and capabilities. Consequently, the current trend is to use hybrid models of multiple intelligent learning methods. The latest hybrid models with multi-objective optimization algorithms can produce multi-step ahead forecasts with very high accuracy. Moreover, they can efficiently generate interval forecasts with superior accuracies.

The wind turbine consists of a wind rotor and an electric generator, which have different operational characteristics. The literature points to several factors involved in optimal wind energy harvesting, which include type and capacity of the rotor and generator as well as the variation of the power generated, predictability of variation and network regulations governing connection (including the voltage level for connection to the grid PCC). The literature demonstrates the significance of bringing together forecasting accuracy and system operation optimization to ensure generation and demand can symbiotically align.

For maximum energy extraction, the wind rotor needs to be operated at an optimal tip-speed ratio. This means that with the variation of wind speeds, the rotational speed of the wind rotor should be changed when wind speed is below the rated value for the nominal power generation. A maximum power point tracking controller is used for optimal operation of the wind rotor. Further, the pitch controller is activated, when wind power exceeds the rated value or the load power requirement. Wind speed can be predicted by deep learning techniques and the effective wind speed can be estimated for MPPT-controlling and pitch controlling to avoid delays and uncertainties of the system dynamics. This may also be used for supply management to maintain grid flexibility.

In a wind turbine, rotor performance is an important consideration for maximum wind energy harnessing. Methods to consider maximum energy extraction include CFD modelling or genetic algorithms. For energy yield optimization to be maximized the optimization of the wind turbine involves many objectives and, in that regard, multi-objective optimization techniques, such as numerical multi-disciplinary optimization, and the sequential quadratic programming (SQP) method are suitable in the design stage of wind turbines to maximize energy production and minimize the cost of energy generation.

A hybrid wind power system may consist of a combination of power generation sources, such as wind, solar, and grid. Selecting suitable power sources and their sizing should be optimized to fulfil the demand for minimum cost and high reliability. The potential of power generation is evaluated by resource availability, energy demand, and technology assessment. The constraints are land area, and resource availability to maximize power generation by a hybrid power system with the minimum cost of energy generation. It follows that a multi-objective optimization approach is needed to design an optimal configuration of a hybrid power system.

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