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Review

Wind Generation Forecasting Methods and Proliferation of Artificial Neural Network: A Review of Five Years Research Trend

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Abstract: To sustain a clean environment by reducing fossil fuels-based energies and increasing the integration of renewable-based energy sources, i.e., wind and solar power, have become the national policy for many countries. The increasing demand for renewable energy sources, such as wind, has created interest in the economic and technical issues related to the integration into the power grids. Having an intermittent nature and wind generation forecasting is a crucial aspect of ensuring the optimum grid control and design in power plants. Accurate forecasting provides essential information to empower grid operators and system designers in generating an optimal wind power plant, and to balance the power supply and demand. In this paper, we present an extensive review of wind forecasting methods and the artificial neural network (ANN) prolific in this regard. The instrument used to measure wind assimilation is analyzed and discussed, accurately, in studies that were published from May 1st, 2014 to May 1st, 2018. The results of the review demonstrate the increased application of ANN into wind power generation forecasting. Considering the component limitation of other systems, the trend of deploying the ANN and its hybrid systems are more attractive than other individual methods. The review further revealed that high forecasting accuracy could be achieved through proper handling and calibration of the wind-forecasting instrument and method.

Keywords: environment; sustainability; quality of life; forecasting; instrument; ANN; wind energy

1. Introduction

The advancement of civilizations, and their capability to withstand bulk populations, are similar challenges to changes in the volume and nature of energy available to meet the demand for nourishment, quality of life and to complete tasks [1–3]. Lower access to energy is an undesirable impact of poverty

and the most probable cause of inferior efficiency and a human's quality of life. Indeed, energy is fundamental to providing sufficient services such as food, primary healthcare, water, education, communication, and reasonable employment. The majority of electricity used by our societies has been generated from fossil and nuclear fuels, which are today facing severe issues, such as diminished supply and security, financial affordability, ecological sustainability and disaster hazards [4,5]. For fix these undesirable issues, many countries are enacting sustainable energy policies to focus on increasing, integrating and developing renewable energy technologies. Resources are increasing significantly in the energy mix around the globe [4,6]. Among renewable energy resources, the wind is one of the oldest renewable sources used for power generation worldwide. Global wind power generation has reached about 20% annually within the past decade. Figure 1 depicts the annual addition and previous year's capacity atlas of wind power (2014–2018), while the world top 10 countries wind energy capacity is presented in Figure 2 [7].

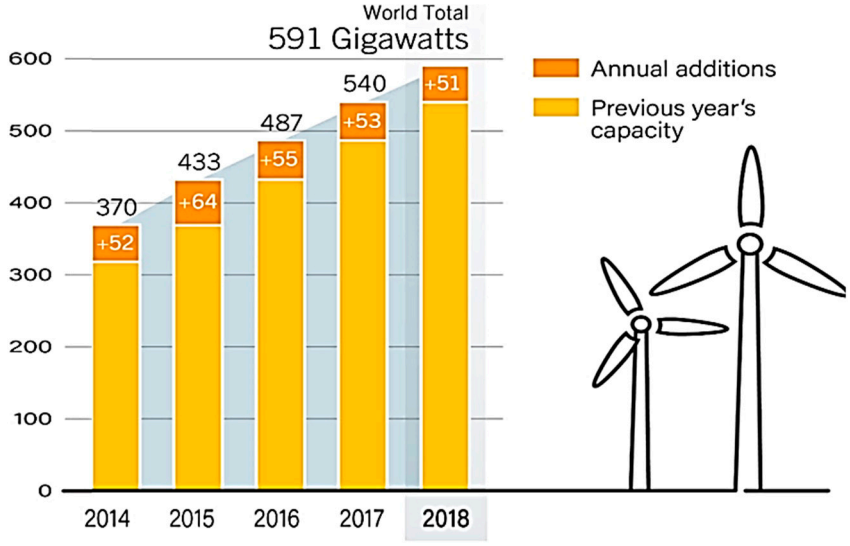

Figure 1. The world annual addition and previous year's capacity atlas of wind power (2014–2018).

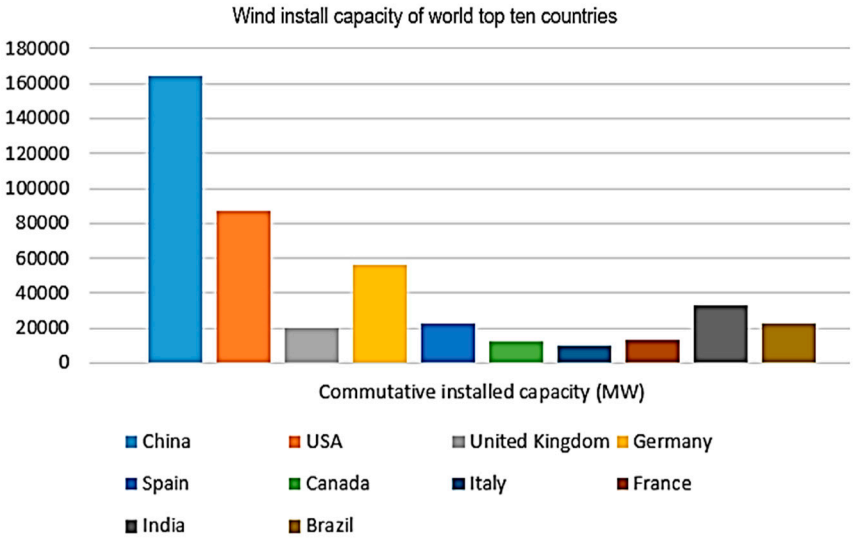

Figure 2. The world top 10 countries atlas of installed wind power capacity in 2018 [7].

Wind energy has become an essential source of energy worldwide, and in 2018, the global capacity reached 600 GW, so the construction of a new generation of wind energy varies from year to year and by region. For example, in Europe, wind power capacity has decreased by 32% in 2018, compared to

2017. The countries with the largest wind capacity are China, the United States, the United Kingdom, Germany, Canada, Italy, France, India, and Brazil [7].

China's installed capacity is 221 GW, and is the world leader in wind energy, producing more than a third of the world's capacity. The province of Gansu has the largest onshore wind farm in the world, and currently has an output of 7965 MW: five times more than its closest rival. The farm currently operates at only 40% of its capacity, and a total of 120,000 MW can be installed by 2020 to achieve a total capacity of 20,000 MW (20 GW), which is expected to cost USD 17.5 billion. Despite their size, Gansu turbines appear to be "scarecrow inactive", due to lower demand [8,9]. The USA occupies second place, with 96.4 GW installed capacity, and is particularly resistant to onshore wind energy. Six of the ten largest onshore wind farms are located in the United States. These include the Alta Wind Energy Center in California, the second-largest onshore wind farm in the world with an output of 1548 MW, Shepherd's Flat wind farm in Oregon (845 MW), and the Roscoe wind farm in Texas (781 MW). Texas alone produces 24.9 GW of American wind power, delivering more wind power than the other 25 countries. Germany has the highest installed wind power in Europe with 59.3 GW. The largest offshore wind farm is Gode Windfarms (phases 1 and 2), with a total output of 582 MW. The Nordsee One offshore wind farm, with an output of 382 MW and 400,000 households, is also located in Germany. According to Wind Europe, Europe installed 11.7 GW of wind energy in 2018, with Germany increasing 29% of this capacity to less than 3.4 GW—2.4 GW—on land and less than 3.4 GW—1 GW—on the ocean. India is the second-largest wind power in Asia and is the only Asian country with 35 GW outside China [10,11]. Indonesia has a wind turbine in Muppandal in Tamil Nadu (1500 MW) in southern India and a wind farm in Jaisalmer in Rajasthan (1064 MW) in northern India. The Indian government has set itself the goal of installing 60 GW of wind power by 2022 and plans to install 25 GW over the next three years.

Spain has 23 GW of electricity, accounting for 18% of Spain's electricity supply, and is a major player in wind energy. In terms of onshore and offshore wind farms, it does not rank in the top 20 in terms of capacity but ranks fifth in the world. In recent years, the Spanish wind power industry has shrunk dramatically. After adding no energy in 2015, the energy mix from 2016 to 2017 only expanded to 104 MW. Employment opportunities in this industry have also dropped to 22,500 from 41,500 in 2008 [7,12]. The UK is the third-largest country in Europe, with a total installed capacity of over 20.7 GW. The UK is particularly worth mentioning in the offshore wind power industry. Among the 10 most powerful offshore wind power projects in the world, there are six in the UK. One of them is the Walney project on the coast of Cumbria in northwest England. This is the largest offshore wind power project in the world. Walney 1 and 2 (367 MW) and Walney Extension (659 MW) total 1026 MW. The Walney plant will be completed in 2020, and the Hornsea One project in Beihai will be transformed with 1218 MW. France ranks seventh among the top ten wind power countries. The company is currently moving away from nuclear energy, which accounts for 75% of its national energy needs, and will close the gap by increasing the renewable energy budget for 2019–2028 to 71 billion euros. As a result, by 2030, its onshore wind power capacity will triple. However, France's hostility to "wind energy is deeply ingrained". Brazil's largest installed capacity of wind power in South America is 14.5 GW, which is a significant increase. According to the latest data, wind power has increased by 8.9% [7–9,12]. Wind energy ranks fourth in the entire energy structure of Brazil and accounts for about 8% of the total Brazilian energy capacity—162.5 GW. Under the leadership of the populist President Jair Bolsonaro, there is concern about the future of wind energy. On the one hand, they expressed their support for the development of wind energy, but a neo-liberal economic policy could reduce the subsidies. Canadian renewable energy capacity is 12.8 GW, and the newly installed capacity in 2018 is 566 MW. A total of 299 wind farms and 6596 wind turbines generate this energy. Ontario has the largest wind energy, with an installed capacity of more than 5 GW. These include the 230 MW Niagara area north of Toronto and the 199.5 MW Cai wind farm. The largest wind farm in Canada is the Rivière-du-Moulin project in Quebec, with a total installed capacity of 300 MW. Wind power accounts for 5% of Canadian renewable energy sources, including 67.5% hydropower. The top ten

wind energy generated by Italy in 2018 was just over 10 GW. Until recently, wind energy in Italy was solely dependent on onshore wind energy. This month, German wind turbine manufacturers Senvion and Renexia signed a contract to build the first offshore wind farm near the Apulian coast in southern Italy. The Italian wind industry focuses on the south and the island. For example, the entire onshore wind energy of the Italian energy company ERG is located in the south of Rome, and the strongest markets are Apulia (248.5 MW) and Campania (246.9 MW) [10,11].

Since the 50% of the world's wind energy has been mixed in the past five years and it is currently the prominent source of new energy capacity in Europe and many other countries [8,9], so, it is essential to study the performance dependent parameters and measurement tools to gain better efficiency. It should also be emphasized that wind-based energy plays a vital role in mitigating climate change, which has become a priority for the international community [7,12]. Climate variation solely is a potential hazard for the generation of electricity from wind, because changes to the climate can change the dynamics of the atmosphere and affect wind patterns [10,11,13]. Therefore, it is more essential to assess the influence of imminent climate variations with wind speed, and other factors that may affect wind energy production, as these factors contribute to a high risk for investors [14,15]. Wind turbines increase not only capacity but also size, which marks them even more sensitive.

During the last decade, much research has been done to predict long-term wind models in the context of climate variation. Most of this research focused on developed countries, especially in China, the United States, etc. [16–18]. In recent years, several developing countries have also considered adopting wind energy [18–20]. Most of these studies predict a future decrease in wind speed [20,21]. Some studies suggest that average wind speed and energy density probably do not change more than the inter-annual variability [21,22]. However, the nature of wind is intermittent, and wind energy led to difficult integration and reliability features, including complex technology and costly solutions [23–25]. In addition, the availability of resources for wind depends on the specific weather characteristics and its location [26,27].

Effective energy production planning is an essential function of energy companies, especially in the area of forecasting. As the grid evolves, planning and procedures must adapt to these changes [28,29]. Therefore, in the context of economic operation, accurate forecasting techniques should be used to predict wind power generation. For many reasons, an accurate forecast of wind energy is essential because it is a crucial element of the planning process. Considering the forecast of wind as a primary essential factor in ensuring sustainable electricity output, the manufacturers and end-users of wind energy need an improved method to predict wind energy. Different factors affect wind energy forecasts, such as environmental conditions, time of day, and weather. The weather is interrupted, and sudden significant and unexpected changes can ruin the weather forecast. The earliest reference for wind volume data prediction is from 1977 [16,27]. This document describes the use of random time series modelling in the technical description. Many wind resource prediction methods have been proposed since 1977, and many scholars agree that different prediction ranges require different methods [17,30].

The non-linear function of energy production based on weather conditions and artificial intelligence as an alternative method to predict wind energy has attracted extensive attention [31]. A hybrid system—based on an artificial neural network (ANN) and analogue set (AnEn) to forecast the amount of electricity generation of the wind power plant—the numerical weather forecast is used as a forecast system, which improves the efficiency of the proposed method compared to traditional methods [32]. The improved results are observed by the proposed method and are shown in large-scale wind farm systems that require much computational analysis. This outcome is reliable, according to the results of subsequent research by Ni et al., which optimizes ANN and multi optimization–avant-garde objectives [33]. The algorithm is used together with a new method system for the short-term energy forecast in wind farm energy management [34].

Many exciting results have revealed the potential of ANN in the forecasting of wind power generation [35]. The implementation of a hybrid ANN system with other algorithms can further improve the accuracy of ANN prediction [36]. This article provides a more detailed description of

wind measurement instruments and ANN implementation in wind power forecasting. The first part of this article introduces the background of weather forecasting and the instruments used to measure wind speed, and then introduces forecasting methods. The second part of this article reviews the implementation of ANN in the field of wind prediction. The last part of this article is based on a five-year retrospective analysis that evaluates the research trends in predicting wind power generation in the implementation of artificial neural networks.

Search Strategy

Published and unpublished studies from six significant databases, namely, (1) Direct Science, (2) IEEE Xplore, (3) Google Scholar, (4) MDPI, (5) SAGE Publication, and (6) Scopus, between May 1st, 2014 to May 1st, 2019 were examined in this review paper, and overall workflow is presented in Figure 3.

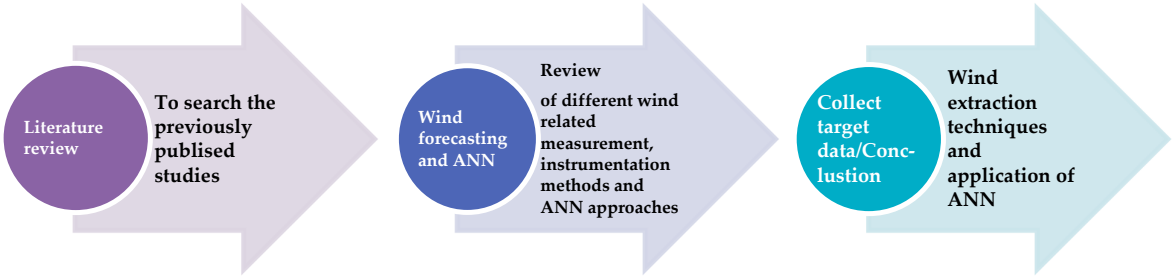

Figure 3. The overall workflow of the adopted methodology.

2. Wind Forecasting Background

Wind speed measurement is usually carried out using wind cup anemometers [37,38]. The wind cup anemometer has a vertical axis and three wind cups that capture the wind [39]. The device generates a voltage related to wind speed or electronically records the number of revolutions per unit time. Generally, anemometers are associated with wind vanes to detect the wind direction [40,41]. Other types of anemometers include ultrasonic anemometers that detect changes in the phase of a sound, and laser anemometers that use coherently scattered light from air. The hot-wire anemometers detect wind speed based on the small temperature difference between the wires placed between the wind and the downwind side (shadow) of the wind [42–44]. One advantage of non-mechanical anemometers is that they are less sensitive to icing. However, cup anemometers are usually used anywhere, and unique models with electrically heated windows and cups can be used in the Arctic. Spiral anemometers are also commonly used in practice [45,46]. The method to measure wind speed at the potential location of the wind turbine is to mount the anemometer on top of the mast, which is the same height as the expected height of the wind turbine to be used. For adopting this method, the un-specificity caused by converting the wind speed to another altitude is avoided [47]. Various techniques/methods have been implemented to predict wind speed [45]. Besides, compared to the standard fan-shaped power curve, it is also possible to obtain the power curve of the wind direction determined by LIDAR, in which the shaft is behind the turbine to be tested [46]. The simulation study shows that the measurement of the wind speed at different heights in the swept rotor area determines the electrical power based on the "equivalent wind speed" taking into account wind intensity and turbulence. It can be seen that electricity has a better correlation with the single point wind speed at hub height, compared to the equivalent wind speed. Even in locations with simple configurations, where high-quality measurements are made at hub height and at a reasonable distance from the potential wind turbine, significant errors in the assessment of the wind speed can occur. Mounting the anemometer on top of the mast minimizes interference with the airflow of the mast itself. If the anemometer is located on the side of the mast, it must be placed in the prevailing direction of the wind to minimize the wind shadow of the tower.

3. Wind Extraction Method

Although wind speed can easily be predicted by the approaches deliberated in the section above, the practical improvement of forthcoming wind speed has not yet established. In this study, we discuss the wind speed forecasting method based on memory. We start with a mathematical model of wind speed and then build a predictor of a stage of wind speed. An average estimate of wind energy is required at a potential site of the wind [47,48]. It needs long-term wind variation information to obtain improved wind energy forecasting. However, collecting measurement data at potential locations is expensive, especially in national investigations. Usually, wind farms are projected in open fields, but not at weather stations. Several characteristics of the altitude and terrain lead to accurate wind speed prediction. Therefore, wind speed to the proposed wind farm is adjusted according to the neighbouring weather station at the height of the turbine. By relying on this practice, wind production can be estimated by matching the perceived wind speed information with the power curve of the turbine. Also, we used the actual output power to refine the theoretical estimate of wind energy performance during threshold relapse. The obtained model can be used to estimate the average wind energy outcomes of further weather stations. The hourly information of the weather station is implemented to estimate the generation of electricity by the wind turbine and at the ground, where wind speed varies significantly with altitude. Contrary to the use of predefined wind direction and wind coefficients to estimate wind speed, the best practice in the field of wind energy is to make different measurements of wind speeds at different heights and to obtain the height of the wind shear coefficient at a specific interval from the power law, as shown below. The following formula is adopted to assess the inconsistency of wind-based on its up-height [49–51].

$$\alpha = \frac{\ln(v_2) - \ln(v_1)}{\ln(z_2) - \ln(z_1)} \tag{1}$$

where, v_1 represents the wind speed at reference position z_1 and v_2 represents the wind speed at the elevated position z_2.

3.1. Weibull Distribution—Wind Speed Modelling

The Weibull distribution has gained recognition by analyzing wind speed information [52,53]. The Weibull distribution of two parameters contains shape parameters and scale, and the Weibull distribution can be projected by using wind speed distribution. Following is the Weibull distribution function of probability density (PDF):

$$f(v) = \frac{k}{c}\left(\frac{v}{c}\right).^{k-1} e^{-\left(\frac{v}{c}\right).^{k}} \tag{2}$$

where:

c > 0 represents the scale parameter of the distribution
k > 0 represents the shape parameter

Among the techniques applying the estimation of distribution, the Weibull parameters and the maximum value of likelihood evolution (MLE) exceed other approaches [54,55]. Therefore, the MLE technique is used to iteratively estimation for distribution Weibull parameters c and k by deploying the mentioned values [56,57].

$$k = \left(\frac{\sum_{i=1}^{n} v_i^k \ln(v_i) P(v_i)}{\sum_{i=1}^{n} v_i^k P(v_i)} - \frac{\sum_{i=1}^{n} \ln(v_i) P(v_i)}{P(v \geq 0)} \right)^{-1} \tag{3}$$

$$c = \left(\frac{1}{P(v \geq 0)} \sum\nolimits_{i=1}^{n} v_i^k P(v_i) \right)^{1/k} \tag{4}$$

where v_i is the wind speed central to bin i, n is the number of bins, $P(v_i)$ is the frequency with which the wind speed falls within bin i, $P(v \geq 0)$ is the probability that the wind speed equals or exceeds zero. While Equation (3) must be solved iteratively, after which Equation (4) can be solved explicitly.

3.2. Electricity Generation

For facilitate the calculation with the expected electricity generation, the performance curve of the wind turbine is estimated in several equations [58,59]. The deterministic part corresponds to the actual behaviour of the wind turbine, and the stochastic part corresponds to other external factors, such as wind turbulence. The output power of the wind turbine is described as a stochastic process that fulfils the Markov property and can, therefore, be divided into a drift and a diffusion part [58,59]:

$$P(\mathrm{t}) = P_{stat}(\mathrm{u}) + \mathrm{p}(\mathrm{t}) \tag{5}$$

where $P(\mathrm{t})$ is the time series power data, P_{stat} is the stationary power value dependent on the wind speed u, and p(t) corresponds to short-time fluctuations around this value caused by wind turbulence. However, the expected amount of electricity generation generally deviates from the actual production. This can be due to mechanical restrictions, fluctuations in the speed of the wind, and further undetected dynamics. Authors [60], used the threshold regression to establish the difference between actual and expected electricity generation:

$$P_p = C_l + \beta_{1l} E_p + \beta_{2l}\, E_p^2 + \beta_{3l}\, E_p^3 + \beta_{4l}\, E_p^4 + \varepsilon; E_p \in I_l, l = 1, \ldots\ldots M \tag{6}$$

where P_P is definite electricity production, E_P is estimated electric generation, I_l is the l-th threshold interval, and M is the number of threshold intervals.

4. Overview of Wind Instrumentation and Measurement

Currently, the wind energy industry is facing an inaccuracy prediction risk, which is a threat to the entire industry. Global estimates indicate that wind farms are 10% worse than the pre-building energy efficiency estimates in all regions [61,62]. Wind farm best location choice is the first significant step in physical advancement [63]. Wind energy assessment report commonly referred to as a "bank report which attracts and influences the decision of investors to invest in this project." Usually, these bank reports need a rigorous valuation of wind conditions within 12 months before the investment. Industry experts suggest that the presence of wind measurement technology in-ground facilities is not a task to provide sufficient data or to accurately assess the potential of wind resources at a given location. It is partly due to the lower air pressure of the extracted wind direction and speed data, and the incapability of fully considering existing turbulence technologies.

4.1. Anemometer

The origin of word anemometer arises from the Greek word "anemos", so it means measuring the wind [16]. In 1450, documented evidence revealed the first time wind speed was measured by the Italian architect Leon Ballista Alberti, who produced a movable plate and designed the first known anemometer [64]. In 1664, Robert Hooke introduced a new version of the modified deflection anemometer, and it was re-designed by Roger Pickering in 1744. A British meteorologist, E.D. Archibald, flew a kite to elevate the anemometer for 500 m to quantify wind speed in 1833 [64,65]. In 1846, the Irish scientist, Dr John Thomas Robinson, made a breakthrough in the development of the anemometer by the introduction of the single-cup design. Then, the four-cup anemometer design was introduced by Robinson's [66,67]. After modifications, the EN 61400-12-1 model adopted as a measuring instrument for the wind energy industry. In 1889, during the Royal Meteorological Society meeting, British meteorologist William Henry Dines offered the prototype of a pressure tube anemometer [68,69]. The first instrument named anemometer was adopted to measure wind speed

and direction and relied on measurements of pressure tubes and rotating blades to keep the tubes in line with the wind [70].

The wind energy application forecasting models with various time horizons. Are presented in Table 1 [71], while the numerous types of anemometers that can forecast wind speed, cup anemometers, sound anemometers, and laser Doppler anemometers are listed in Table 2. The cup anemometer consists of rotating blades with cups at both ends of the blade, which rotate to measure the wind speed [72]. Laser Doppler anemometers use a beam of light to measure the speed of moving particles, which effectively characterizes air velocity [73]. The sound anemometer uses sensors to send and receive sound pulses through the route. The speed of the pulse determines the wind speed. Wind speed measurements are essential for determining climate hazards, especially for tornado warnings and exposure to high-speed winds [73,74].

Table 1. Wind energy-forecasting methods with various time horizons and application [71].

Property	Description
Time horizon	• Very short-term • Short-term • Medium-term • Long-term
Application	• Turbine installation rules • Power market robustness • Pre-load sharing • Power allocation • Power system management • Equipment maintenance

4.2. Cup Anemometer

With the penetration of wind power share in the electric industry, cup anemometer utilization is growing and is shown in Figure 4 [37]. It is a fact that these instruments have a huge need for adjustment because accuracy is essential for estimating the installed wind speed by an anemometer on a wind-based generator, so any flexibility/error will have the effect of a profound economic revenue impact because the generated power is directly proportional of wind speed [75]. So far, many articles have been published and analyzed experimentally and analytically for the use of wind speed tests [75]. An exhaustive review of the literature on published research related to this instrument was carried out. This review includes research carried out for more than a century, and the first research was published by T.R. Robinson [39,75]. The development of the research associated with this instrument is summarized in several kinds of literature: Robinson was the first scientist who characterized the development and expansion of this field [2–6], and, further, only a few analytical readings and the experimental work of Brazier. Within a short time after this preliminary period, two investment contracts were signed. Three cups, instead of four, methods were introduced by Patterson, who well-defined the pre-eminent rotor geometry for a cup anemometer, which achieved the significant work on a cup anemometer, a significant analytical approach based on aerodynamics performance of the cup test [39]. The third period starts at the beginning of 1030, which signifies the efforts to understand the mature behaviour and flexibilities of the cup anemometer, the new analytical approach, and the impact of wind unpredictability [75]. In [76], the authors defined the last period, which began with the work of Busch and Kristensen [77], which has well-defined the cup anemometer. Such systems affected by the vertical and horizontal acceleration of disturbances of wind speed and present the statistical analysis in modelling.

4.3. Hot-Wire Anemometer

The hot wire form of anemometer used in environmental research, in which the hot wire electrically heated element is lowered down in temperature by the wind, and the heat loss rate is measured as wind speed, which is depicted in Figure 4 [37]. Unlike mechanical wind meters, these devices have a rapid response time and a lack of mechanically moveable parts, which are installed near the ground or inside the system, where it can measure small vortices and the impact of the local climate. However, relative unit spending is prohibitive for many environmental applications [78–81].

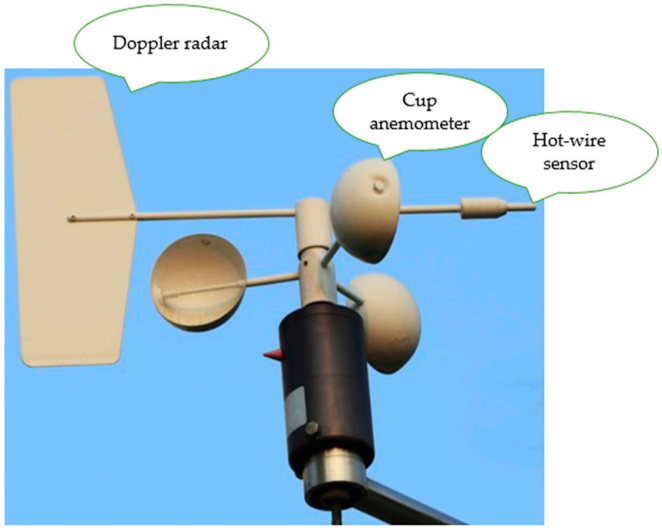

Figure 4. Cup and hot-wire, hybrid anemometer, Reprinted from Francisca et al. [40] with permission under the terms of the Creative Commons Attribution License. http://creativecommons.org/licenses/by/4.0.

4.4. Wind Vane

The weathervane has two metal plates, one for the cup type weathervane and other for the Y-shaped vane shown in Figure 5 [39]. The cup and moving angles are about 20 degrees, and weight; M is attached to the upper part of the shoulders to maintain balance. Steel pipes pass through the top and are connected to the roof, and the shafts are connected by steel. For indicate the rotational angle of the blade, the compass mounted directly on the rotation axis. To remotely indicator the rotation angle of the blade, a Selwyn potentiometer or motor is mounted on the rotation shaft. Previous studies have improved the measurement of wind forecasting by using an anemometer and are tabulated in Table 1, while selected methods of anemometer-based wind-forecasting measurement are presented in Table 2.

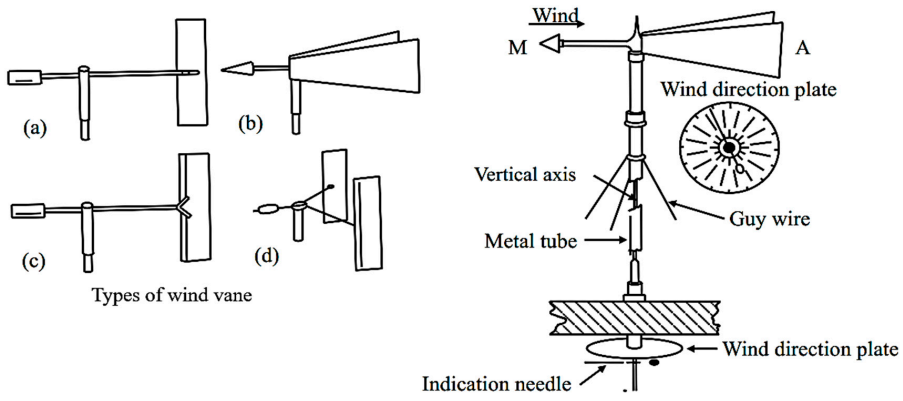

Figure 5. Wind vane and its types.

Table 2. Summary of anemometer technology characteristics of measuring wind.

Anemometer	Wind Speed	Wind Dir.	Range (m/s)	Sampling & Record Rate	Precision	Turbulence Measurement	Vert. Wind Shear	Horiz. Wind Shear	Weather	Recognized in Standards
Perfect Anem.	Yes	Yes	0–200	1000 Hz	100%	Yes	Yes	Yes	All weather	Yes
Cup Anem.	Yes	No	4–75	1 Hz	±2%	Yes but limited	No	Yes	All weather	Yes
Wind Vane	No	Yes	0–360°	1 Hz	<±1%	No	No	No	All weather	Yes
Sonic Anem.	Yes	Yes	0–65	20 Hz	±5%	Yes	No	Yes	Not heavy rain, snow	Yes some peripheral standards
Pressure Sphere	Yes	Yes	50–200	10 Hz	Low in 0–50 m wind	Yes	No	Yes	All weather	Not on market
Dines Anem.	Yes	Yes	4–75	Hourly	Low	No	No	No	All except extreme cold	Yes (but the standards are dated)
Hot-wire Anem.	Yes	No	0–200	>1000 Hz	±1%	Yes	No	No	No	No
LIDAR	Yes	Yes	0–75	1 Hz	±5%	Yes	No	Yes	Not heavy rain, snow, etc.	No
SODAR	Yes	Yes	0–75	1 Hz	±5%	No (except in clear conditions)	No	Yes	Not heavy rain, snow, etc.	No

The most extensively recognized wind measurement instruments in international standards are anemometers and wind vanes. However, recent research has highlighted concerns about their operating parameters, as investors demand increased wind energy security in one location. The new sound anemometer has higher wind speed sampling and recording rates, but, because of its sensitivity to faults in harsh environmental conditions and the inherent errors and interference associated with the use of anemometers, the technology does not meet international standards. Recognized researchers have developed a device called a metometer, which exceeds the specifications of other instruments currently on the market based on initial test results. The means of measuring the wind by anemometer methods are summarized in Table 3, while a complete flow chart of the anemometer-based ANN system is drawn in Figure 6.

Table 3. Anemometer-based wind forecasting measurement selected methods.

Method	Findings/Results	Author
Perceptron of two-layer multilayer (MLP)	Functions for linear activation	Pelletier Francis et al.
Machine- techniques learning	Power curve modeling	Marvuglia and Messineo.
Compared curve fitting approach	Genetic algorithm	Goudarzi, et al.
Compared approaches	Complex terrain	Bulavskaya et al.
Evolutionary programming (EP), genetic algorithm (GA), particle swarm optimization (PSO)	Application of the DE algorithm	Lyda et al.
Feed-forward neural network-based single layer function	WRF wind simulation	Z. Guo and X. Xiao.
Two power curve techniques	Outlier detection method	Guo and Xiao.
Neural network model	Power curve estimation	Li et al.
Inconsistent data forecasting for wind power	Novel power curve model	Wang et al.
High-Order neural network structures	Identification of Dynamic Systems	Kosmatopoulos, Elias B, et al.

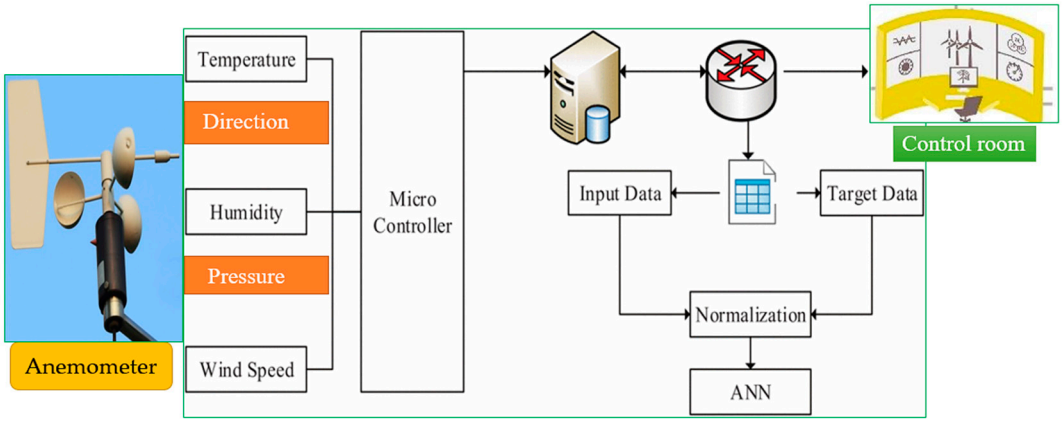

Figure 6. Wind power forecasting system.

5. Wind Power Forecasting Methods

Many wind forecasting techniques have been identified [82], and these techniques can be classified into numerical weather forecasting (NWP), statistical methods, and hybrid methods [83]. The positioning, navigation and timing (PNT) method is probably the forecasting performance for short-term speed. Generally, the statistical approach and numerous cutting-edge hybrid techniques based on observations will be more productive and accurate over a small period of forecasting [84].

5.1. Persistence Method

The persistence is one of the most straightforward possibilities to estimate the speed of wind and direction. This technique simply supposed that t + x is similar to wind speed at the wind variations at the time t rate. Simply, the hypothesis of a high correlation is based on robustness tools amongst

the current and future wind direction [85,86]. This approach has been industrialized as an evaluation tool to adjunct the PNT models by meteorologists. However, in short-term forecasts (minutes to hours), the simplified scheme is more effective than the Numeric Weather Prediction (NWP) model [87]. Model accuracy is likely to decrease dramatically as forecast latency increases.

5.2. Numeric Weather Prediction (NWP)

Based on the procedure of meteorological information with cutting-edge meteorology to forecast wind speed and energy, numerous physical models have been industrialized [88,89]. These models were industrialized based on several dynamics, including obstacle avoidance, local roughness and surface changes, terrain effects, acceleration or descent, the scale of local wind speeds within a wind farm, the fan power curves, and wind farm design. This NWP system frequently delivers a wind speed forecast for a grid. Depending on the NWP system type, the forecasts have a spatial resolution. This physical method uses a mesoscale or microscopic model to reduce and interpolate wind variation forecasts at the level of wind turbines [90]. For run the reduced model, the area surrounding the wind turbine is described in detail. However, gathering information about the state of the site is one of the significant difficulties in realizing the physical model. Several other advanced flow modelling tools, i.e., as mesoscale weather models (MM5), the computational fluid dynamics (CFD) method was used to forecast wind variation [91,92]. These cutting-edge models can improve wind flow modelling, especially in terrain complexity. Nevertheless, more controllers and computer functions are needed before merging these models into an operation system, because the mathematical complex NWP models are generally run on supercomputers, which bounds the practicality of NWP approaches to an online mode or to the operation of energy systems in the very short-term [93]. Meanwhile, high-resolution weather models are usually to be more accurate, but they need much time in terms of calculations to generate forecasting information, so they usually cannot update their results. Besides, according to some operational experience, accurate high-resolution predictions may slightly increase accuracy but might become expensive. Therefore, the outcomes of practical models are generally satisfied for an extended period of more than six hours. On the other hand, due to the complexity and difficulty of obtaining information, it is not suitable for a separate forecast for short-term calculations (minutes–hours) [93,94].

Unstable weather conditions can lead to useless weather forecasts numerically, which leads to incorrect wind energy forecasts. In contrast, because the weather conditions are stable, more accurate power forecasts can be expected, because the most mature input the speed wind is in wind power forecasting approaches. For forecast short-term wind energy, a common approach is to increase the results of the NWP model that the meteorological service runs to improve local wind disorders. The latest PNT model operates twice a day, with a horizontal resolution of five kilometres, and can predict conditions up to 72 h in advance [95].

5.3. Hybrid Methods

Numerous sets of hybrid models are installed to estimate wind energy [96]. The nature of the combined model can be (i) statistical, and physical approaches of the mix, (ii) short-medium range approaches, (iii) alternative statistical approaches in combination. The goal of the hybrid approach is to benefit from each method and gain the best predictive performance, globally. For example, in the autoregressive models with exogenous inputs (ARX), more than a few statistical approaches are managed to determine the best results between online measurements and weather forecasts. Generally, system participants can be compared by the history of predictions through actual available output data to track the wind performance of prediction measurement tools. It is essential to evaluate the performance of models related to several criteria, especially the use of RMSE and IEA predictions [97,98]. Figure 7 depicts the variation of wind speed over time (hours), while Figure 8 illustrates the atmospheric effects on the wind-based doubly fed induction generator (DFIG), producing energy and related control schemes for a sustainable system.

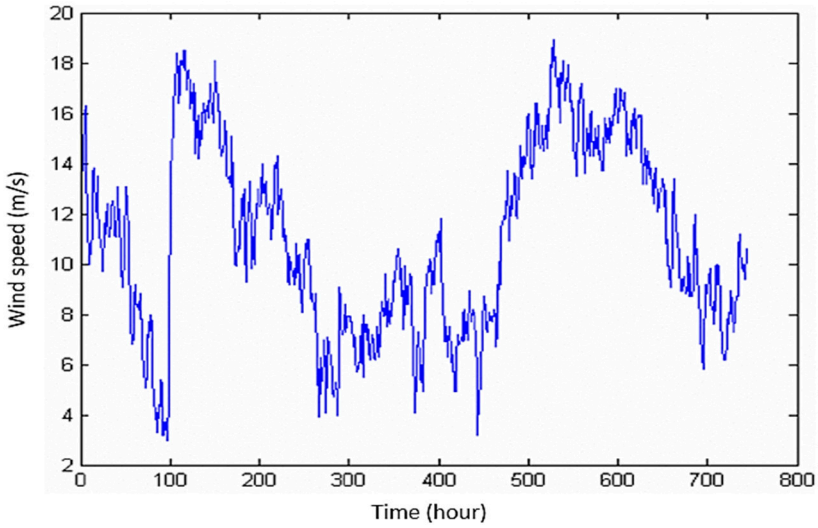

Figure 7. Variation of wind speed over a time.

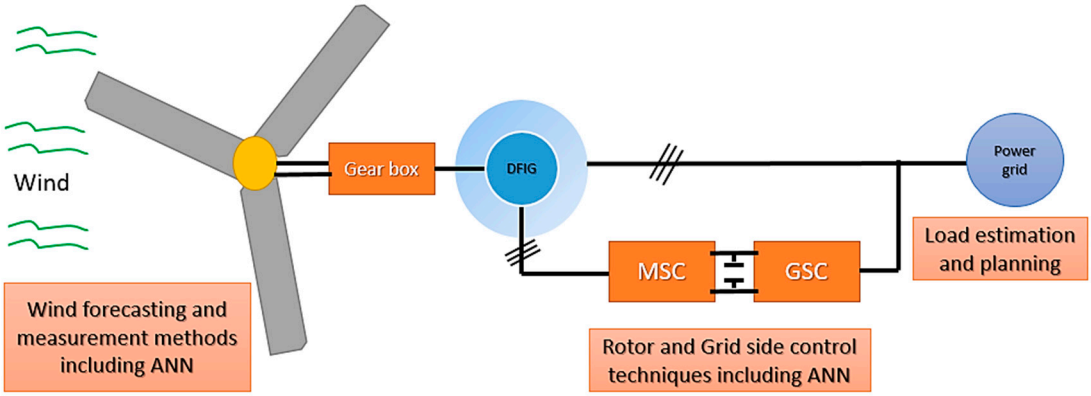

Figure 8. Illustration of the atmospheric effects on the wind-based doubly fed induction generator, producing energy and related control schemes for a sustainable system.

6. Evaluation of Wind Speed and Power Forecasts

The output energy of wind turbines is directly proportional to the various wind speeds over a long period, and the change in wind speed can be subject to weather circumstances regionally, seasonal period and terrain categories alteration [99]. The relationship between the hypothetical per unit energy of time duration, with wind fleeting through the capture area A (m^2) at a speed v (m/s), is presented in Equation (7) [100]:

$$P = \frac{1}{2}\rho A v^3 \tag{7}$$

where ρ is the density of the air (kg/m^3) and depends on the air pressure and temperature [101]. The favourable option to convert wind speed into an energy forecast to utilizes the power curve of the manufacturer [102]. However, here, the actual association between the power produced by the complete wind farm and capacity speed is more complicated than in Equation (1). It is due to ageing and control factors of the wind turbine. Besides, the power curve is separated into a sweeping curve, a turbine curve, and a group curve. The relationship between wind speed and output power should quantify a random wind speed and non-linear function that varies over time, which cannot be defined by a precise power curve of the machine, although we can deploy the ANN structure or fuzzy logic as a power curve for a specific region/area. Also, it is hard to convert wind speed into power where multiple directions and wind speeds were used to obtain a proper wind farm matrix.

The literature has shown that almost 20% efficiency can be extracted by employing a power curve calculated with the proper prediction of wind speed and power that is expected from the RMSE value compared to using only the manufacturer's power simulation result [103]. Hereafter, owing to the non-linearity of the curve power, at the wind-rated speed, where the slope between the speed wind of the activated turbine and the plateau is large, the wind speed prediction error will increase, and errors will be suppressed [91]. The emphasis is that the non-linearity of the power curve of the wind turbine will result in greater error amplification, and a smaller deviation from the wind speed will affect a larger power deviation. As a result, since a large amount of wind energy can soften the output power curve, a proper wind farm aggregation approach is desired to perform further prediction tests [104]. Authors [105], describe several models of statistical forecasting, named the autoregressive mechanically variant moving average (ARMA) approach, to calculate speed wind and energy addition in the first-hour markets. Here, it is necessary to mention that the aim of this review study is not to develop any kind of model that competes with commercial models with precise wind forecasting. On the other hand, the feasibility of testing a relatively economic statistical forecasting model requires no data, other than wind energy history. The empirical table shows that those model parameters can be a time function, and the capabilities of the ARMA predictive model will be different when applied to diverse time domains [106]. Authors [107] used the ARMA approach to calculate that the average speed wind per hour increased by 1~10 h. Taking into account the features of seasonal winds, the authors adopted different approaches for each calendar month [108,109]. Moreover, they emphasized that the utilization of power in one hour (MWh) from generation power (MW) for a power predictive parameter. Authors, in [108], proposed a technique for defining the correlation of speeds wind between adjacent sites. The purpose of this method utilized for wind speeds from nearby locations to forecast wind speeds at specific locations. The recommended technique includes the development of wind speed correlation (SCCF) between samples between two adjacent locations, but with several delays. This calculation will detect that the SCCF has the maximum delay [109]. It is the ANN training phase time, which will receive in two series. In [47], the authors propose a statistical forecasting system that combines statistical forecasting equations for wind energy from 1 to 48 h. The combination coefficients of each model change over time, comparable to non-parametric approaches. The purpose of the connection is to provide comparatively improved outcomes in a single model. Its benefit is that a location-independent forecast system is established, which is not only for a particular wind park but is applicable to other wind farms. In [47], the authors dealt with the next 72-h prediction of wind speed for meteorological data to indicate possible wind power. The three leading categories of local recurring ANN were used as estimation models. The essential six network entries contain wind speed and direction information for the other three closed wind farm locations. The purpose of this review was to recommend a technique that combines time series and atmospheric methods. In [105], the authors focused on getting information about wind changes 1 to 10 days in advance, and used the estimates of NWP computer models performed by the forecasting European Center for Mid-Range (ECMWP) [110,111]. The model has a spatial resolution of 60 km, and the published forecasts are each twelve hours' time duration. Also, these speed wind predictions have become the output power of the corresponding wind farm. However, the relationship between the speed of wind and output power is believed to be ideal. In adding, there is no necessary correction among the results of the NWP project prototype and the final energy of wind forecast. A method has been developed to model the autoregressive process of the speed of wind time series using Bayesian skeletons, where the Monte Carlo Markova Chain (MCMC) simulation is deployed to the parameters of the estimation approach [112]. The output of the Bayesian approach is specified as a probability distribution. This means that the parameters of the AR approach include the estimated confidence and mean interval, which will guarantee the correct range of the prediction. The study used annual and seasonal trends to provide wind speed forecasts one day in advance [113]. The authors point out that there may be some common trends in wind speed changes somewhere during a specific time. The preceding year's result, the speed of the wind, and the current year can be anticipated, based on

the wind data. However, few improved prognostic results can be achieved without understanding. Numerical forecasting systems are used for weather forecasting (NWP), but they use spatial coverage, model performance statistics (MOS), and wind turbine performance curves to develop the power output of the NWP approach and obtain local energy of wind [87]. The principle of the mentioned approach is to reduce the PNT forecasting-based error on spatial smoothing the combined power of many wind farms over a huge area. The basic process for combining the distribution spatial of a location is the figure of correlations differences between the predicted values and the values in each location. It also shows that the diversity spatial has a positive outcome on smoothing more or fewer changes in electricity, and thus develops the accuracy of forecasts of weather [87]. According to this study, due to the smoothing effect of the geographic spread compared to the error of a single wind farm, the error in predicting the entire system of many distributed wind farms can be reduced by around 30–50%.

A study describes a risk assessment technique for the short-term estimation energy of wind expending meteorological risk indicators (MRT) and production risk indicators (PRI) [114]. The definitions of MRT and RPI measure the outbreak of the forecast of weather and the energy of wind estimation over a period, indicating the relationship between the energy of wind and high prediction of weather. The weather-based forecasting system that employs online supervisory control and data acquisition (SCADA) geometric weather forecasts as energy prediction by wind inputs data [115]. These estimates are informed hourly, based on the updated energy from wind speed measurements. Forecast accuracy can be based on specific indicators, such as mean absolute error (MAE), absolute scale error (MASE), mean absolute percentage error (MAPE), evaluation of symmetric absolute percentage (SMAPE), and the sum of quadratic errors (SSE), the sum of absolute errors (SAE), mean square error (MSE), or mean square error (RMSE) [114]. In the author's study [115], minimizing MSS is used to evaluate the prognostic performance of training RNA, and calculate and evaluate RMSE.

Numerous practical and commercial modules, as well as the energy of wind forecasts, fall into this category. It also developed a climate stability indicator called the "Meteorological Risk Indicator", and established a more or less linear bond between the size indicator of the estimated error for each farm of wind. The best and worst cases corresponding to the most accurate total error of wind energy were determined according to the frequency of various climatic conditions, which are indicated by the meteorological threat index, and with an influence on the deviation standard of the estimate errors of the energy of wind.

7. The ANN Prolific in Wind Power Generation Forecasting

Artificial neural networks are extensively used in many areas of application. One of the most popular is prediction, which is described as a process of predicting future trends or events. Besides, forecasts in a variety of areas, such as the prediction of weather, asset prices, and economic downturn forecasts, are fairly common [31,116]. It is essential to emphasize that the predictions do not start with artificial neural networks since traditionally, many analysis tools have been used to predict future trends. Examples of algorithms are the Box–Jenkins model and the regression model. However, the use of artificial neural networks as an essential prediction tool is increasing. A neural network is an information method with which the relationships between different data can track and determined internally. Also, academic and industrial researchers have used ANN for a variety of predictive purposes, as it can compare self-study mechanisms between expected and actual results. The artificial neural network can teach itself, and its weighting factors can be adjusted to reduce future errors between the prediction results and the actual results, which facilitates its extensive application in prediction.

The capacity of ANNs for learning simulations in this manner has enabled them to adapt well to any application, especially where the dominion has not been well defined, such as in power generation by wind forecasting data. A three-layer power architecture was implemented as the system forecasting with the perceptron of the neural network. Based on the previous wind speed observations,

the selection of input data was established on the correlation of the coefficients. The proposed technique is implemented to calculate the speed of wind without the required weather data, but in this case, the achieved accuracy can be poor. In Germany, the ANN approach is extensively used to forecast daily wind energy. ANN training is used to learn about the physical consistency of wind speed and wind energy production for forensic meteorological factors and calculated power data. Additionally, the ANN application can smoothly deploy the weather data, such as to identify air temperature or pressure to improve the accuracy of forecasting. This technique is better than other adopted approaches due to the power curves of individual plant observations. Figure 9 [92], shows ANN-based wind forecasting, model design, system fault diagnosis, and control methods, where it can be observed that forecasting is more-essential, which is 38%. In contrast, Table 4 shows the previous five years' (2014–2018) studies on ANN-hybrid systems. Figure 10 illustrates the individual and mixed/hybrid neural network methods for wind forecasting.

Table 4. Five years of previous research on the artificial neural network (ANN)-hybrid system for wind forecasting.

Year	Research Area	Input Parameters	Hybrid System	Observation and Findings	Author
2014	Intelligent framework for wind power forecasting	Wind speed	ANN-signal processing and data mining	Improving the wind power forecasting performance	Haque, Ashraf U., et al.
2015	Improve the original SOM limitation by adding more types of neural functions for input patterns	Temperature, wind direction, wind speed, and Wind irradiance	ANN- Hebbian Learning (CHL)	Improve the accuracy of Wind power generation Prediction.	Ghayekhloo et al.
2015	Statistical hybrid wind power forecasting technique (SHWIP)	Statistical hybrid wind power	ANFIS	Statistical hybrid wind power	Ozkan M B, Karagoz P.
2015	Medium-term wind speeds forecasting	Wind speed	ANN- KF	Forecasting efficiency improved	Wang Jianzhou, et al.
2016	Wind Power Forecasting techniques in complex terrain	Computational fluid dynamics	ANN vs. ANN-CFD	Wind power forecasting	Castellani, Francesco, et al.
2017	Estimation of fractal representation of wind speed fluctuation	Wind speed	ANN- different training algorithms	wind speed fractal representation established	Petković, Dalibor, et al.
2017	Automatic load frequency control	Wind speed	Neuro-fuzzy intelligent controller (ANFIC)	hybrid multi-generation power systems	Prakash, S., & Sinha, S. K.
2018	Prediction of wind speed and direction	Wind speed	ANN- support vector regression	an adaptive neuro-fuzzy inference system	Khosravi, A., et al.
2018	Survey of artificial neural network	Wind speed	ANNs classified	Identified the most employed techniques	Marugán, Alberto Pliego, et al.
2018	ANN-based comparative analysis of wind speed	Wind speed-temperature -pressure	ANN-Mackey–Glass equation	Wind speed prediction	Haque, Ashraf U., et al.

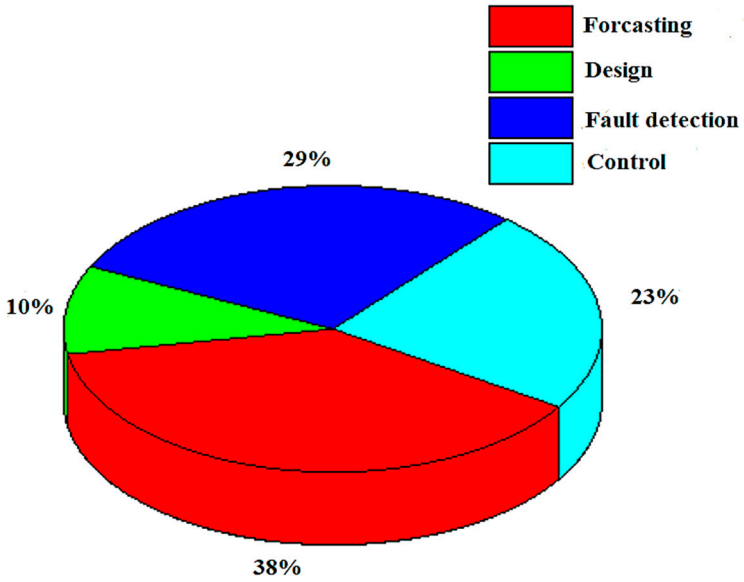

Figure 9. ANN-based approaches.

The performance of predicting wind speed and power for two hours in advance is based on cross-correlation in neighbouring locations [117]. It is considered, in the latest literature, that the speed of the wind is relationally delayed to the speed of wind estimating [31]. Therefore, the wind speed is measured in remote locations and used to predict wind in a local location, and the ANN method is used to build relationships between time sequences in the remote and local locations. Authors in [92], introduce an approach that synthesizes ANN expertise and linear regression, in which ANN is deployed to achieving short-term information patterns on long-term trends, which are provided for the development identification element that performs the first linear order. The neural network (4-8-1) is used to estimate the wind energy regression approach [110]. The measured data, including three other input data on wind speed and the directions of two meteorological towers, are used. Also, four value compression input functions were deployed to support ANN learning and function improvement. Authors in [111] introduce an ANN-based approach to estimate the energy of wind power production directly, based on the speed, direction, and amount of wind without the generation curve, and this is the best ANN performance related to the capacity to learn the dynamic presence of turbines in inconstant wind environs.

Previous studies have compared several multivariate ANN models for a week, before predicting wind energy in Gorakhpur, India [112]. In the case of research, RMSE assessments are used to compare the performance of various developments of wind forecasting methods [110]. The mathematical analysis showed that the model has a better average neural network performance. One study used the ANN algorithm to check the accuracy of wind speed predictions because it is highly dependent on the integrity data formed by the ANN neural network. The analysis shows that, based on annual wind intensity data, the accuracy of the forecast is 98%. The authors examined the implementation of the ANN algorithm in the short term between 1 and 6 h to predict the amount of electricity generated [113]. In their research, meteorological inputs (resolutions up to 900) for temperature, pressure, wind, humidity, and global wind radiation intensity were used as inputs to the model. The artificial neural network predicts power production. The results of the power production forecast show that the time between 4 and 6 h provided the best results for the ANN model. The above conclusions are consistent with the results of [118], in which an excellent artificial neural network model and the quality of data input were studied, so the prediction accuracy of wind power generation can be increased. The test results also show RMSE of 10% to 15% error. Table 5 lists previous weather forecast studies using the ANN algorithm as the primary model from 2014 to 2018.

Table 5. Five years of previous research on the ANN algorithm for wind power.

Research Area	Input Parameters	Accuracy/Error	Observations and Findings	Author
Hybrid intelligent model	Wind power	11.91% MAPE	probabilistic wind power	A.U. Haque, H.M. Nehrir, P. Mandal., (2014)
V-support vector regression	Noise model	3.79% MAPE	increase of monetary consumer benefit	Q. Hu, S. Zhang, Z. Xie, J. Mi, J. Wan., (2014)
Ramp forecasting	Wind power	2.70~7.82 MAE	short-term wind power forecasting	J. Zhang, A. Florita, B.M. Hodge, J. Freedman., (2014)
Wind speed & power forecasts	Wind power	0.096 s MAPE	recurrent neural network (LRNN)	Z.O. Olaofe., (2014)
Hybrid intelligent framework	Wind speed	~13.02% MAPE	hybrid intelligent framework	A.U. Haque, P. Mandal, H.M. Nehrir, A. Bhuiya, Baker., (2014)
Multi neural hybrid approaches	Wind speed	7.75% MAPE	short-term wind speed	Wang, J., & Hu, J., (2015)
Comparison of new hybrid Feemd-mlp, feemd-anfis	Wind speed	1.61% MAPE	wavelet-ANFIS for wind speed predictions	H. Liu, H.G. Tian, Y.F. Li., (2015)
Ensemble methods	Wind speed	0.051 RMSE	wind and solar power forecasting	Y. Ren, P.N. Suganthan, N. Srikanth., (2015)
Multi-scale chaotic characteristics	Wind power	4.3678 NMAE	Hurst analysis and Hilbert–Huang transform	Liang, Zhengtang, et al. (2015)
The adaptive neuro-fuzzy inference system	Wind power	3.75% MAPE	evolutionary particle swarm optimization,	G.J. Osorio, J.C.O. Matias, J.P.S. Catalao., (2015)
Spectral clustering and optimized echo state networks	Wind power	5.71% MAPE	short-term wind speed forecasting	D. Liu, J. Wang, H. Wang., (2015)
Wavelet decomposition and artificial bee colony Algorithm a hybrid approach	Wind speed	21.61% MAPE	relevance vector machine	S. Fei, Y. He., (2015)
Daily wind speed forecasting	Wind speed	23.73% MAPE	KF-ANN model based on ARIMA	O.B. Shukur, M.H. Lee., (2015)
Wind power forecast-novel approach	Wind power	8.90 NMAE	statistical hybrid wind power forecast technique (SHWIP)	M.B. Ozkan, P. Karagoz., (2015)
Wind power forecasting	Wind power	3.0 MAE	phase space reconstruction	L. Han, C.E. Romero, Z. Yao., (2015)
Medium-term wind speeds	Wind speed	15.32% MAPE	wind speeds forecasting	J. Wang, S. Qin, Q. Zhou, H. Jiang., (2015)

Table 5. *Cont.*

Research Area	Input Parameters	Accuracy/Error	Observations and Findings	Author
Deep neural networks	Transfer learning	8.01% MAPE	improvement of the persistence model	Q. Hu, R. Zhang, Y. Zhou., (2016)
Density neural networks	Wind speed	1.66 MAE (WS)	wind speed and power forecasting	Z. Men, E. Yee, F.S. Lien, D. Wen., (2016)
Support vector regression	Wind speed	MAE (WS) 2.65 m/s	wind speed forecasting	G. Santamaría-Bonfil, A. Reyes-Ballesteros, C. Gershenson., (2016)
Genetic programming-based ensemble of neural networks	Wind power	3.5 MAE	Intelligent and robust prediction	Zameer, Aneela, et al. (2017)
Singular spectrum analysis optimized by brain storm optimization for short-term	Wind speed	4.5 MAE	wind speed forecasting	Ma X, Jin Y, Dong Q. (2017)
The adaptive neuro-fuzzy inference system	Wind power	3.0 MAE	short-term wind power forecasting	Liu J, Wang X, Lu Y (2017)
Singular spectrum analysis	Brainstorm optimization	2.14% MAPE	singular spectrum	X. Maa, Y. Jin, Q. Dong (2017)
Wind-Water Pumping System	Wind speed	-	Intelligent MPPT control	Priyadarshi, Neeraj, et al. (2018)
Transient stability in DFIG-WTs-FRT solutions	Modification in RSC and GSC control of DFIG-WT	-	FRT solutions	Jerin, Amalorpavaraj Rini Ann, et al. (2018)

Although the ANN method is highly accurate in predicting wind energy generation, many researchers are still working for further improvements in the accuracy of ANN wind energy prediction. It is believed that optimizing the input of quality data into the ANN algorithm can provide a highly accurate output of ANN predictions. Recent trends indicate that extensive research has combined artificial neural network methods with other intelligent artificial techniques to produce hybrid systems with high prediction accuracy. The basic principle of integrating the algorithm into the ANN system is to make full use of other technologies to overcome the weaknesses of the ANN algorithm. In the NWP–ANN hybrid system, the NWP algorithm provides highly accurate input data to the ANN system, which significantly improves the prediction accuracy. Some published studies combine a wavelet time series and artificial neural network algorithms with improving weather forecast for artificial neural networks.

For predict wind energy in wind farms, a model named the high-order recurrent neural network (RHONN) was developed in [114]. This model can be adopted to calculate wind speed and power over a short-term time range, i.e., in seconds to three hours. The nonlinear simplex box approach used to solve the optimal architecture of this model and specific on the cross-validation process. In [115], the authors introduce a diffuse adaptive neuron inference system (ANFIS) for the calculation of the wind track vector of 2.5 min forward and consider the direction of wind and speed. A hybrid learning algorithm was adopted, with a least-squares estimator and a gradient method to deploy the ANFIS model [115]. This kind of design is very flexible and supportive of rapidly changing data patterns. This scheme covers short-term wind forecasting criteria.

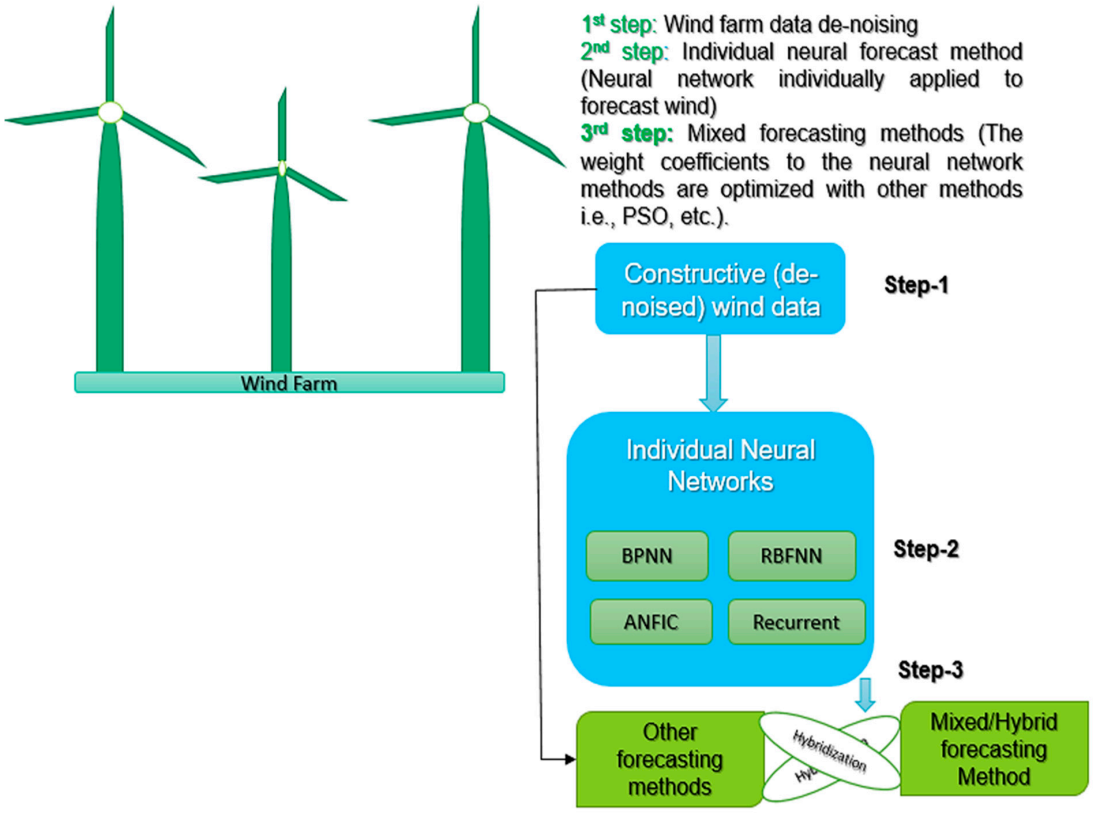

Figure 10. The individual and mixed/hybrid neural network methods for wind forecasting.

The feedback network and neural network technology or recursive network and time-series statistical methodologies are settled to forecast daily and monthly based wind speed in the sub-continent (India) [119,120]. These references disclosed that neural network-based schemes are more operative and effective than ARIMA based models [121]. However, average daily and monthly wind speeds can be easier than gathering hourly, which means it is not difficult to get accurate forecasts of daily and

monthly wind speeds. An ANN-based scheme deployed to forecast the average per hour speed of the wind [115]. In particular, the artificial neural wave network system uses the improved satellite image processed by the small wave algorithm as input into the artificial neural network.

Likewise, [122] proposes a self-configurable neural network evolution algorithm to improve the neural network algorithm in forecasting energy production. Compared to the stand-alone neural network system, the analysis of the system shows a significant improvement. Significant improvements in wind energy forecasting have also been observed for the Hebbian Learning neural network hybrid forecasting system. The system provides a cluster selection method to select the best wind energy data to use as input for the neural network system [122]. The comparative analysis shows that the proposed system has improved the calculation of electricity production. More fundamentally, this discovery was explained in [123], which demonstrated that the integration of neural network into wavelet and genetic algorithms could improve the accuracy of wind forecasts. The system applies global horizontal irradiation (GHI) data to the time series wavelets and uses it as an input to the neural network system to predict wind energy production [122]. Consequently, the proposed method attempts to develop an estimate of wind energy compared to existing methods. Overall, these studies show that integrating the artificial neural network method with other methods can increase the accuracy of the artificial neural network for power generation based on wind forecasts. Different methods and their annual number of ANN application in wind turbines are presented in Figure 11, while Table 5 presents the ANN-hybrid wind forecasting systems.

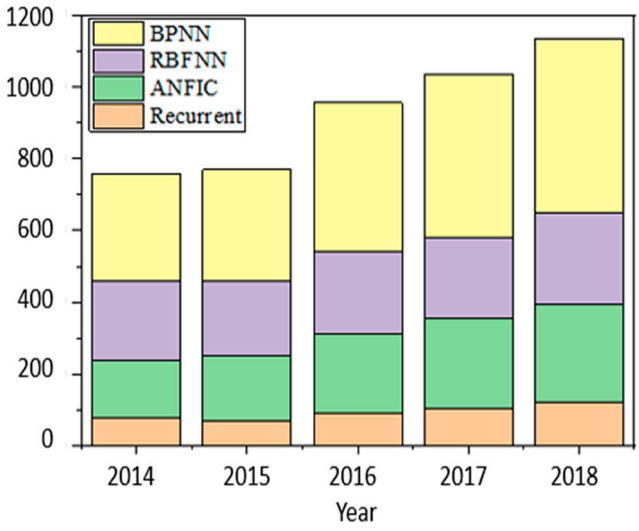

Figure 11. Different methods and their annual number of ANN application in wind forecasting.

8. Conclusions

Current research provides an in-depth review of the application, instrument measurement, and the prolific of ANN algorithms in wind intensity to forecast wind power generation. ANN-based methods are also used in wind model design, system fault diagnosis and control methods, etc., where forecasting is more-essential and shares 38% usage. This review extends the previous work and focuses on different perspectives in wind energy prediction. The accessible databases have been used as the primary source of previously published documents to make a significant contribution to knowledge. A rigorous set of paper selection criteria have been applied to ensure that current review articles have a solid understanding of the use of ANN models to predict wind energy trends. In this review reached some essential conclusions which are highlighted as follows:

(a) It is considered that accurate wind prediction is a necessary condition. To improve the level of integration of the wind power sustainable operation while maintaining the lowest cost to achieve economic viability and competitiveness;

(b) Instrument calibration and the measurement of surface weather components can provide reliable forecast data, and estimate the amount of wind energy in a given area;
(c) Predictions generated by a single method generally have several limitations.

The results of the current review highlight the ability of hybrid systems to combine methods, which significantly develop the accuracy of wind-based energy estimation. Considering the prolific of ANN methods, this study further allows manufactures to choose the best model for each condition, based on the range of diverse types of ANN for specific requirements. It turns out that the ANN hybrid is also useful in a variety of applications, and can be used in combination with different tools to take full advantage of the contribution over a hybrid system. Finally, we believe that this contribution provides a guideline for understanding the deployment of cutting-edge technology in the emerging wind energy industry.

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Nomenclature

ANN	artificial neural network
MLE	maximum value of likelihood evolution
GHI	global horizontal irradiance
GSC	Grid side converter
MSC	Machine side converter
NWP	numeric weather prediction
MM5	mesoscale weather models
ARMA	autoregressive mechanically variant moving average
ECMWP	European Centre for mid-range
MCMC	Monte Carlo Markova Chain
MOS	model performance statistics
MRT	meteorological risk indicators
PRI	production risk indicators
SCADA	supervisory control and data acquisition
PRI	production risk indicators
PDF	probability density function
MOS	model performance statistics
ANFIC	algorithm neuro-fuzzy intelligent controller

References

1. Weeks, J.R. *Population: An Introduction to Concepts and Issues*; Cengage Learning: Boston, MA, USA, 2020.
2. Feng, J. Evaluation of the onshore wind energy potential in mainland China—Based on GIS modeling and EROI analysis. *Resour. Conserv. Recycl.* **2020**, *152*, 104484. [CrossRef]
3. Sultan, H.M.; Diab, A.A.Z.; Kuznetsov, O.N.; Ali, Z.M.; Abdalla, O. Evaluation of the impact of high penetration levels of PV power plants on the capacity, frequency and voltage stability of Egypt's unified grid. *Energies* **2019**, *12*, 552. [CrossRef]
4. Feyen, E.H. *Macro-Financial Aspects of Climate Change*; World Bank Policy Research Working Paper (9109); International Monetary Fund: Washington, DC, USA, 2020.
5. Nazir, M.S.; Wang, Y.; Muhammad, B.; Hafiz, M.S.; Kadhem, A.A.; Nazir, H.M.R.; Abdalla, A.N.; Ma, Y. Comparison of Small-Scale Wind Energy Conversion Systems: Economic Indexes. *Clean. Technol.* **2020**, *2*, 144–155. [CrossRef]

6. Katsigiannis, Y.A.; Karapidakis, E.S. Operation of wind-battery hybrid power stations in autonomous Greek islands. In Proceedings of the IEEE 2017 52nd International Universities Power Engineering Conference (UPEC), Heraklion, Greece, 28–31 August 2017.
7. Nazir, M.S. Environmental impact and pollution-related challenges of renewable wind energy paradigm—A review. *Sci. Total Environ.* **2019**, *683*, 436–444. [CrossRef]
8. Söder, L. Review of wind generation within adequacy calculations and capacity markets for different power systems. *Renew. Sustain. Energy Rev.* **2019**, *119*, 109540. [CrossRef]
9. Xia, J. Application of a new information priority accumulated grey model with time power to predict short-term wind turbine capacity. *J. Clean. Prod.* **2020**, *244*, 118573. [CrossRef]
10. Nazir, M.S. Symmetrical Short Circuit Parameter Differences of Double Fed Induction Generator and Synchronous Generator based Wind Turbine. *Indones. J. Electr. Eng. Comput. Sci.* **2017**, *6*, 268–277. [CrossRef]
11. Nazir, S.M.; Wu, Q.; Li, M. Symmetrical Short-Circuit Parameters Comparison of DFIG–WT. *Int. J. Electr. Comput. Eng. Syst.* **2017**, *8*, 77–83. [CrossRef]
12. Nazir, M.S.; Abdalla, A.N. The robustness assessment of doubly fed induction generator-wind turbine during short circuit. *Energy Environ.* **2019**, *0*, 1–13. [CrossRef]
13. Fragaki, A.; Markvart, T.; Laskos, G. All UK electricity supplied by wind and photovoltaics–The 30–30 rule. *Energy* **2019**, *169*, 228–237. [CrossRef]
14. Santos, M.; González, M. Factors that influence the performance of wind farms. *Renew. Energy* **2019**, *135*, 643–651. [CrossRef]
15. Junior, P.R. Wind Power Economic Feasibility under Unspecificty and the Application of ANN in Sensitivity Analysis. *Energies* **2019**, *12*, 2281.
16. Heronemus, W.E. The Wind King. In *The Wind Power Story: A Century of Innovation that Reshaped the Global Energy Landscape*; John Willy & Sons: Hoboken, NJ, USA, 2019; p. 175.
17. Wei, C. An Adaptive Network-Based Reinforcement Learning Method for MPPT Control of PMSG Wind Energy Conversion Systems. *IEEE Trans. Power Electron.* **2016**, *31*, 7837–7848. [CrossRef]
18. Mahmoud, K.; Abdel-Nasser, M.; Mustafa, E.; Ali, M.Z. Improved Salp–Swarm Optimizer and Accurate Forecasting Model for Dynamic Economic Dispatch in Sustainable Power Systems. *Sustainability* **2020**, *12*, 576. [CrossRef]
19. Nazir, M.S.; Qi, W. Impact of symmetrical short-circuit fault on doubly-fed induction generator controller. *Int. J. Electron.* **2020**. [CrossRef]
20. Maeda, M.; Watts, D. The unnoticed impact of long-term cost information on wind farms' economic value in the USA–A real option analysis. *Appl. Energy* **2019**, *241*, 540–547. [CrossRef]
21. DeCastro, M. Europe, China and the United States: Three different approaches to the development of offshore wind energy. *Renew. Sustain. Energy Rev.* **2019**, *109*, 55–70. [CrossRef]
22. Bulut, U. Testing environmental Kuznets curve for the USA under a regime shift: The role of renewable energy. *Environ. Sci. Pollut. Res.* **2019**, *26*, 14562–14569. [CrossRef]
23. Peña Asensio, A. A voltage and frequency control strategy for stand-alone full converter wind energy conversion systems. *Energies* **2018**, *11*, 474. [CrossRef]
24. Bosch, J.; Staffell, I.; Hawkes, A.D. Temporally explicit and spatially resolved global offshore wind energy potentials. *Energy* **2018**, *163*, 766–781. [CrossRef]
25. Hernández-Escobedo, Q.; Perea-Moreno, A.-J.; Manzano-Agugliaro, F. Wind energy research in Mexico. *Renew. Energy* **2018**, *123*, 719–729. [CrossRef]
26. Eisenberg, D.; Laustsen, S.; Stege, J. Wind turbine blade coating leading edge rain erosion model: Development and validation. *Wind Energy* **2018**, *21*, 942–951. [CrossRef]
27. Hu, R.; Skea, J.; Hannon, M.J. Measuring the energy innovation process: An indicator framework and a case study of wind energy in China. *Technol. Forecast. Soc. Chang.* **2018**, *127*, 227–244. [CrossRef]
28. Nazir, M.S.; Wang, Y.; Mahdi, A.J.; Sun, X.; Zhang, C.; Abdalla, A.N. Improving the Performance of Doubly Fed Induction Generator Using Fault Tolerant Control—A Hierarchical Approach. *Appl. Sci.* **2020**, *10*, 924. [CrossRef]
29. Ali, Z.M.; Abusief, F.; Kamel, S. Voltage profile enhancement for remote areas through renewable energy resources integration. In Proceedings of the 2018 Twentieth International Middle East Power Systems Conference (MEPCON), Cario, Egypt, 18–20 December 2018.

30. Ferrari, L. Influence of actual component characteristics on the optimal energy mix of a photovoltaic-wind-diesel hybrid system for a remote off-grid application. *J. Clean. Prod.* **2018**, *178*, 206–219. [CrossRef]
31. Marugán, A.P. A survey of artificial neural network in wind energy systems. *Appl. Energy* **2018**, *228*, 1822–1836. [CrossRef]
32. Khosravi, A. Prediction of wind speed and wind direction using artificial neural network, support vector regression and adaptive neuro-fuzzy inference system. *Sustain. Energy Technol. Assess.* **2018**, *25*, 146–160. [CrossRef]
33. Momeni, F. Plant leaf-mimetic smart wind turbine blades by 4D printing. *Renew. Energy* **2019**, *130*, 329–351. [CrossRef]
34. Ramasamy, P.; Chandel, S.; Yadav, A.K. Wind speed prediction in the mountainous region of India using an artificial neural network model. *Renew. Energy* **2015**, *80*, 338–347. [CrossRef]
35. Okumus, I.; Dinler, A. Current status of wind energy forecasting and a hybrid method for hourly predictions. *Energy Convers. Manag.* **2016**, *123*, 362–371. [CrossRef]
36. Mert, İ.; Karakuş, C.; Üneş, F. Estimating the energy production of the wind turbine using artificial neural network. *Neural Comput. Appl.* **2016**, *27*, 1231–1244. [CrossRef]
37. Baseer, M.A. Performance evaluation of cup-anemometers and wind speed characteristics analysis. *Renew. Energy* **2016**, *86*, 733–744. [CrossRef]
38. Nazir, M.S.; Wu, Q.H.; Li, M.; Luliang, Z. Lagrangian-Based Approach for Non-linear Dynamic Control of an Islanded Power System. *Int. J. Comput. Sci. Inf. Secur.* **2017**, *15*, 24–29.
39. Roibas-Millan, E.; Cubas, J.; Pindado, S. Studies on cup anemometer performances carried out at idr/upm institute. Past and present research. *Energies* **2017**, *10*, 1860. [CrossRef]
40. Guerrero-Villar, F. Alternative Calibration of Cup Anemometers: A Way to Reduce the Unspecificty of Wind Power Density Estimation. *Sensors* **2019**, *19*, 2029. [CrossRef] [PubMed]
41. Khan, K.S.; Tariq, M. Wind resource assessment using SODAR and meteorological mast—A case study of Pakistan. *Renew. Sustain. Energy Rev.* **2018**, *81*, 2443–2449. [CrossRef]
42. Wu, Y.-T. Investigation of Multiblade Wind-Turbine Wakes in Turbulent Boundary Layer. *J. Energy Eng.* **2019**, *145*, 04019023. [CrossRef]
43. Garcia-Ruiz, A. Long-range distributed optical fiber hot-wire anemometer based on chirped-pulse ΦOTDR. *Opt. Express* **2018**, *26*, 463–476. [CrossRef]
44. Leoni, A. A Spherical Directional Anemometer Sensor System. In Proceedings of the Multidisciplinary Digital Publishing Institute Proceedings, Paris, France, 3–6 September 2017.
45. Alfredsson, P.; Segalini, A. *Introduction Wind Farms in Complex Terrains: An Introduction*; The Royal Society Publishing: London, UK, 2017. [CrossRef]
46. Demurtas, G.; Pedersen, T.F.; Zahle, F. Calibration of a spinner anemometer for wind speed measurements. *Wind Energy* **2016**, *19*, 2003–2021. [CrossRef]
47. Cheng, W.Y. Short-term wind forecast of a data assimilation/weather forecasting system with wind turbine anemometer measurement assimilation. *Renew. Energy* **2017**, *107*, 340–351. [CrossRef]
48. Nazir, M.S.; Ali, N.; Bilal, M.; Iqbal, M.H. Potential environmental impacts of wind energy development–A global perspective. *Curr. Opin. Environ. Sci. Health* **2020**, *13*, 85–90. [CrossRef]
49. Delgado, A. Evaluation of the variability of wind speed at different heights and its impact on the receiver efficiency of central receiver systems. *AIP Conf. Proc.* **2016**, *1734*, 030011.
50. Zhang, J. Comparison of numerical weather prediction based deterministic and probabilistic wind resource assessment methods. *Appl. Energy* **2015**, *156*, 528–541. [CrossRef]
51. Choukulkar, A.; Pichugina, Y.; Clack, C.T.; Calhoun, R.; Banta, R.; Brewer, A.; Hardesty, M. A new formulation for rotor equivalent wind speed for wind resource assessment and wind power forecasting. *Wind Energy* **2016**, *19*, 1439–1452. [CrossRef]
52. Kim, C.-K. Blade Optimization of a Small Vertical-Axis Wind Turbine Using the Response Surface Method. In *Renewable Energy and Sustainable Buildings*; Springer: Cham, Switzerland, 2020; pp. 801–812.
53. Saeed, M.A. An optimal approach of wind power assessment using Chebyshev metric for determining the Weibull distribution parameters. *Sustain. Energy Technol. Assess.* **2020**, *37*, 100612. [CrossRef]
54. Mazucheli, J.; Menezes, A.F.B.; Dey, S. Bias-corrected maximum likelihood estimators of the parameters of the inverse Weibull distribution. *Commun. Stat. Simul. Comput.* **2019**, *48*, 2046–2055. [CrossRef]

55. Sadani, S. A new estimator for Weibull distribution parameters: Comprehensive comparative study for Weibull Distribution. *arXiv* **2019**, arXiv:1902.05658.
56. Cruz, J.N.D.; Ortega, E.M.; Cordeiro, G.M. The log-odd log-logistic Weibull regression model: Modelling, estimation, influence diagnostics and residual analysis. *J. Stat. Comput. Simul.* **2016**, *86*, 1516–1538. [CrossRef]
57. Merovci, F.; Elbatal, I. Weibull Rayleigh distribution: Theory and applications. *Appl. Math. Inf. Sci.* **2015**, *9*, 2127.
58. Zhao, Y. Data-driven correction approach to refine power curve of wind farm under wind curtailment. *IEEE Trans. Sustain. Energy* **2017**, *9*, 95–105. [CrossRef]
59. Marčiukaitis, M. Non-linear regression model for wind turbine power curve. *Renew. Energy* **2017**, *113*, 732–741. [CrossRef]
60. Weideman, J.; Inglesi-Lotz, R.; van Heerden, J. Structural breaks in renewable energy in South Africa: A Bai & Perron break test application. *Renew. Sustain. Energy Rev.* **2017**, *78*, 945–954.
61. Kumar, Y. Wind energy: Trends and enabling technologies. *Renew. Sustain. Energy Rev.* **2016**, *53*, 209–224. [CrossRef]
62. Petković, D.; Pavlović, N.T.; Ćojbašić, Ž. Wind farm efficiency by adaptive neuro-fuzzy strategy. *Int. J. Electr. Power Energy Syst.* **2016**, *81*, 215–221.
63. Stram, B.N. Key challenges to expanding renewable energy. *Energy Policy* **2016**, *96*, 728–734. [CrossRef]
64. Blackledge, J.; Wind Measurement Technologies; Lipian, M.; Dobrev, I.; Karczewski, M.; Massouh, F.; Jozwik, K. *Small Wind Turbine Augmentation: Experimental Investigations of Shrouded-and Twin-Rotor Wind Turbine Systems*; Elsevier: Amsterdam, The Netherlands, 2019; p. 115855.
65. Rotch, A.L. The Use of Kites to Obtain Meteorological Records in the Upper Air at Blue Hill Observatory, USA. *Q. J. R. Meteorol. Soc.* **1897**, *23*, 251–253. [CrossRef]
66. Robinson, M. A history of the electric wind. *Am. J. Phys.* **1962**, *30*, 366–372. [CrossRef]
67. Gallicchio, N. Inventions of Weather Instruments (1400–1800). *Evol. Meteorol. Look Past Present Future Weather Forecast.* **2017**, 11–17.
68. Pike, W. William Henry Dines (1855–1927). *Weather* **2005**, *60*, 308–315. [CrossRef]
69. Solari, G. Wind Meteorology, Micrometeorology and Climatology. In *Wind Science and Engineering*; Springer: Berlin, Germany, 2019; pp. 325–440.
70. Nebeker, F. *Calculating the Weather: Meteorology in the 20th Century*; Elsevier: Amsterdam, The Netherlands, 1995; Volume 60.
71. Choon, T.W. Development of low wind speed anemometer. *Int. J. Adv. Sci. Eng. Inf. Technol.* **2012**, *2*, 237–240. [CrossRef]
72. Pedersen, T.F. On wind turbine power performance measurements at inclined airflow. *Wind Energy Int. J. Prog. Appl. Wind Power Convers. Technol.* **2004**, *7*, 163–176. [CrossRef]
73. Fritschen, L.J. A sensitive cup-type anemometer. *J. Appl. Meteorol.* **1967**, *6*, 695–698. [CrossRef]
74. Réthoré, P.-E. Systematic wind farm measurement data reinforcement tool for wake model calibration. In Proceedings of the European Offshore Wind Conference, (EOW 2009), Stockholm, Sweden, 14–16 September 2009.
75. Ramos-Cenzano, Á.; Ogueta-Gutiérrez, M.; Pindado, S. Performance analysis of present cup anemometers. *J. Energy Syst.* **2019**, *3*, 129–138. [CrossRef]
76. Floors, R.R. From lidar scans to roughness maps for wind resource modelling in forested areas. *Wind Energy Sci.* **2018**, *3*, 353–370. [CrossRef]
77. Ramos-Cenzano, A.; Ogueta-Gutierrez, M.; Pindado, S. Cup Anemometers Performance Analysis Today: Still Room for Improvement. *J. Electr. Syst.* **2019**, *3*, 129–138. [CrossRef]
78. Yatskikh, A.A. Investigation of laminar-turbulent transition of supersonic boundary layer by scanning constant temperature hot-wire anemometer. In Proceedings of the 19th International Conference on the Methods of Aerophysical Research, ICMAR 2018 (Том 2027), Novosibirsk, Russia, 13–19 August 2018.
79. Gao, R. Real-time fiber-optic anemometer based on a laser-heated few-layer graphene in an aligned graded-index fiber. *Opt. Lett.* **2017**, *42*, 2703–2706. [CrossRef] [PubMed]
80. Britcher, C.P. Studies of a Hot Wire Anemometer with Digital Feedback. In Proceedings of the 32nd AIAA Aerodynamic Measurement Technology and Ground Testing Conference, Washington, DC, USA, 13–17 June 2016.
81. Idjeri, B.; Laghrouche, M.; Boussey, J. Wind measurement based on MEMS micro-anemometer with high accuracy using ANN technique. *IEEE Sens. J.* **2017**, *17*, 4181–4188. [CrossRef]

82. Zhao, Y. A novel bidirectional mechanism based on time series model for wind power forecasting. *Appl. Energy* **2016**, *177*, 793–803. [CrossRef]
83. Han, L.; Romero, C.E.; Yao, Z. Wind power forecasting based on principle component phase space reconstruction. *Renew. Energy* **2015**, *81*, 737–744. [CrossRef]
84. Buhan, S.; Özkazanç, Y.; Çadırcı, I. Wind pattern recognition and reference wind mast data correlations with NWP for improved wind-electric power forecasts. *IEEE Trans. Ind. Inf.* **2016**, *12*, 991–1004. [CrossRef]
85. Yan, J. Reviews on unspecificty analysis of wind power forecasting. *Renew. Sustain. Energy Rev.* **2015**, *52*, 1322–1330. [CrossRef]
86. Jiang, P.; Wang, Y.; Wang, J. Short-term wind speed forecasting using a hybrid model. *Energy* **2017**, *119*, 561–577. [CrossRef]
87. Xu, Q. A short-term wind power forecasting approach with adjustment of numerical weather prediction input by data mining. *IEEE Trans. Sustain. Energy* **2015**, *6*, 1283–1291. [CrossRef]
88. Agarwal, P.; Shukla, P.; Sahay, K.B. A Review on Different Methods of Wind Power Forecasting. In Proceedings of the IEEE 2018 International Electrical Engineering Congress (iEECON), Krabi, Thailand, 7–9 March 2018.
89. Lawan, S. An Artificial Intelligence Strategy for the Prediction of Wind Speed and Direction in Sarawak for Wind Energy Mapping. In *Recent Advances in Mathematical Sciences*; Springer: Berlin, Germany, 2016; pp. 71–82.
90. Errouissi, R. Bootstrap prediction interval estimation for wind speed forecasting. In Proceedings of the IEEE 2015 IEEE Energy Conversion Congress and Exposition (ECCE), Montreal, QC, Canada, 29 October 2015.
91. Lydia, M. Wind resource estimation using wind speed and power curve models. *Renew. Energy* **2015**, *83*, 425–434. [CrossRef]
92. Liu, R.; Peng, M.; Xiao, X. Ultra-short-term wind power prediction based on multivariate phase space reconstruction and multivariate linear regression. *Energies* **2018**, *11*, 2763. [CrossRef]
93. Luo, X. Short-term wind speed forecasting via stacked extreme learning machine with generalized correntropy. *IEEE Trans. Ind. Inf.* **2018**, *14*, 4963–4971. [CrossRef]
94. Abdel-Rahim, O.; Ali, Z.M. Control of seven-to-three phase Direct Matrix Converter using Model Predictive control for multiphase wind generation. In Proceedings of the IEEE 2014 16th International Conference on Harmonics and Quality of Power (ICHQP), Bucharest, Romania, 25–28 May 2014; pp. 199–203.
95. Zhao, E. Hybrid wind speed prediction based on a self-adaptive ARIMAX model with an exogenous WRF simulation. *Energies* **2016**, *9*, 7. [CrossRef]
96. Kaur, D. Wind speed forecasting using hybrid wavelet transform-ARMA techniques. *Aims Energy* **2015**, *3*, 13. [CrossRef]
97. Zhang, Y. Wind Speed Prediction Research Considering Wind Speed Ramp and Residual Distribution. *IEEE Access* **2019**, *7*, 131873–131887. [CrossRef]
98. Kayri, I.; Gencoglu, M.T. Prediction of power production from a single axis photovoltaic system by Artificial Neural Networks. In Proceedings of the IEEE 2017 14th International Conference on Engineering of Modern Electric Systems (EMES), Oradia, Romania, 1–2 June 2017.
99. Kozmar, H. Complex terrain effects on wake characteristics of a parked wind turbine. *Eng. Struct.* **2016**, *110*, 363–374. [CrossRef]
100. Li, J.; Yu, X. Model and procedures for reliable near term wind energy production forecast. *Wind Eng.* **2015**, *39*, 595–607. [CrossRef]
101. Bulaevskaya, V. Wind power curve modeling in complex terrain using statistical models. *J. Renew. Sustain. Energy* **2015**, *7*, 013103. [CrossRef]
102. Castellani, F. Wind power forecasting techniques in complex terrain: ANN vs. ANN-CFD hybrid approach. *J. Phys. Conf. Ser.* **2016**, *753*, 082002. [CrossRef]
103. Yuan, R. Coupled wind farm parameterization with a mesoscale model for simulations of an onshore wind farm. *Appl. Energy* **2017**, *206*, 113–125. [CrossRef]
104. Sahoo, S.; Subudhi, B.; Panda, G. Pitch angle control for variable speed wind turbine using fuzzy logic. In Proceedings of the IEEE 2016 International Conference on Information Technology (ICIT), Bhubaneswar, India, 22–24 December 2016.
105. Ozkan, M.B.; Karagoz, P. A novel wind power forecast model: Statistical hybrid wind power forecast technique (SHWIP). *IEEE Trans. Ind. Inf.* **2015**, *11*, 375–387. [CrossRef]

106. Wang, S. Wind speed forecasting based on the hybrid ensemble empirical mode decomposition and GA-BP neural network method. *Renew. Energy* **2016**, *94*, 629–636. [CrossRef]
107. Raveh, D.E.; Iovnovich, M.; Nahom, T. Wind-tunnel study of the ARMA flutter prediction method. In Proceedings of the 2018 AIAA/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference, Kissimmee, FL, USA, 8–12 Janurary 2018.
108. Daili, Y.; Gaubert, J.-P.; Rahmani, L. Implementation of a new maximum power point tracking control strategy for small wind energy conversion systems without mechanical sensors. *Energy Convers. Manag.* **2015**, *97*, 298–306. [CrossRef]
109. Yin, H.; Zivanovic, R. An application of probabilistic collocation method in wind farms modelling and power system simulation. In Proceedings of the 2016 IEEE Innovative Smart Grid Technologies-Asia (ISGT-Asia), Melbourne, VIC, Australia, 28 November–1 December 2016. [CrossRef]
110. Khodayar, M.; Teshnehlab, M. Robust deep neural network for wind speed prediction. In Proceedings of the IEEE 2015 4th Iranian Joint Congress on Fuzzy and Intelligent Systems (CFIS), Zahedan, Iran, 9–11 September 2015.
111. Pelletier, F.; Masson, C.; Tahan, A. Wind turbine power curve modelling using artificial neural network. *Renew. Energy* **2016**, *89*, 207–214. [CrossRef]
112. Narain, A.; Srivastava, S. Forecasting Methodology Used in Restructured Electricity Market: A Review. In Proceedings of the 2018 5th IEEE Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering (UPCON), Gorakhpur, India, 2–4 November 2018.
113. Ren, Y.; Suganthan, P.; Srikanth, N. Ensemble methods for wind and solar power forecasting—A state-of-the-art review. *Renew. Sustain. Energy Rev.* **2015**, *50*, 82–91. [CrossRef]
114. Ruiz-Cruz, R. Real-time neural inverse optimal control for a wind generator. *IEEE Trans. Sustain. Energy* **2018**, *10*, 1172–1183. [CrossRef]
115. Syahputra, R.; Soesanti, I. DFIG control scheme of wind power using ANFIS method in electrical power grid system. *Int. J. Appl. Eng. Res.* **2016**, *11*, 5256–5262.
116. Ata, R. Artificial neural networks applications in wind energy systems: A review. *Renew. Sustain. Energy Rev.* **2015**, *49*, 534–562. [CrossRef]
117. Fazelpour, F.; Tarashkar, N.; Rosen, M.A. Short-term wind speed forecasting using artificial neural networks for Tehran, Iran. *Int. J. Energy Environ. Eng.* **2016**, *7*, 377–390. [CrossRef]
118. Kassa, Y. A GA-BP hybrid algorithm based ANN model for wind power prediction. In Proceedings of the 2016 IEEE Smart Energy Grid Engineering (SEGE), Oshawa, ON, Canada, 21–24 August 2016.
119. Kuamr, K.R.; Kalavathi, M.S. ANN-ANFIS Based Forecast Model for Predicting PV and Wind Energy Generation. In Proceedings of the World Congress on Engineering, London, UK, 29 June–1 July 2016.
120. Jamil, M.; Zeeshan, M. A comparative analysis of ANN and chaotic approach-based wind speed prediction in India. *Neural Comput. Appl.* **2019**, *31*, 6807–6819. [CrossRef]
121. Kassa, Y. Short term wind power prediction using ANFIS. In Proceedings of the 2016 IEEE International Conference on Power and Renewable Energy (ICPRE), Shanghai, China, 21–23 October 2016.
122. Mehr, H.D.; Polat, H.; Cetin, A. Resident activity recognition in smart homes by using artificial neural networks. In Proceedings of the IEEE 2016 4th International Istanbul Smart Grid Congress and Fair (ICSG), Istanbul, Turkey, 20–21 April 2016.
123. Sun, H.; Luo, X.; Wang, J. Feasibility study of a hybrid wind turbine system–Integration with compressed air energy storage. *Appl. Energy* **2015**, *137*, 617–628. [CrossRef]