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Review

Review of Estimating and Predicting Models of the Wind Energy Amount

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Abstract: Obtaining wind energy for the production of electric energy plays a key role in overcoming the problems associated with climate change and the dwindling reserves of traditional types of energy resources. The purpose of this work is to analyze current methods of energy estimation and forecasting, to consider the main classifications of forecasts and methods used in their construction and to review the main types of mathematical distributions used to calculate the speed and power of wind flow, depending on specific geographical conditions. In recent years, there has been an increase in the capacity of modern wind generators, which has significantly improved the efficiency of wind energy parks. The initial stage in determining the feasibility of involving a particular energy source in the overall energy system of the region is a preliminary assessment of the energy potential, allowing one to determine the possible percentage of substitution of traditional energy. To solve such a problem, it is necessary to use models of energy supply. Evaluation of wind as a resource creates certain difficulties in modeling because this resource is stochastic and variable. In this regard, this paper proposes to consider various models for estimating wind energy potential, which can be classified into empirical models and models based on the application of modern intelligent data analysis technologies. The paper presents an analysis of the existing models for estimating the amount of energy, which can be used in a system designed to determine the most optimal configuration of the energy system based on the use of different conversion technologies most relevant to the case under study, and it also serves as the basis for creating digital twins designed to model and optimize the operation of the projected energy complex.

Keywords: energy potential assessment models; intelligent models; renewable energy sources; wind energy

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1. Introduction

The increase in total costs and the adverse environmental impacts of traditional carbon energy have led to an increase in research in the field of alternative energy. Wind energy has been the fastest growing source of electricity generation in the world since the 1990s. One of the main hindering restrictions on the use of wind energy is its changeable nature, as well as the complex mechanism for storing wind energy generated by a wind turbine, which means that such energy must be quickly integrated into the electric grid. As more and more wind energy is included in the electricity markets, the ability to correctly and accurately predict wind speed and power is becoming an increasingly important and urgent task. Since many countries around the world are expanding their sources of renewable energy [1], it is important to ensure stable generation when they are involved in energy systems. The scope of renewable energy sources varies from large-scale and autonomous power generation (for rural and remote areas) [2,3] to heating/cooling systems and transport.

Power generation with renewable energy technologies (RES), such as solar, wind, hydro, biomass and geothermal energy, involves sustainable energy sources and mitigates detrimental environmental problems such as global warming and climate change [4]. To prevent global climate change, many countries in the world have begun to adhere to the goals of the decarbonization policy [5], according to which there is a transformation of the energy sector aimed at significantly increasing the share of environmentally friendly energy capacities in the world, such as photovoltaic and wind energy [6,7] and reducing the use of hydrocarbon resources.

According to the International Energy Agency (IEA) and their Global Energy Outlook 2021 [8], the total use of renewable energy sources increased significantly from 4098 TWh in 2010 to 7627 TWh in 2020.

According to projections [9], the total renewable energy generation will continue to grow further, as shown in Figure 1. It can be seen that the leading position is taken by hydropower generation; however, according to various sources, it is not attributed to renewable energy sources, but a separate category [10], as a result of which the first place in the amount of energy generated from the use of green energy is taken by wind energy generation.

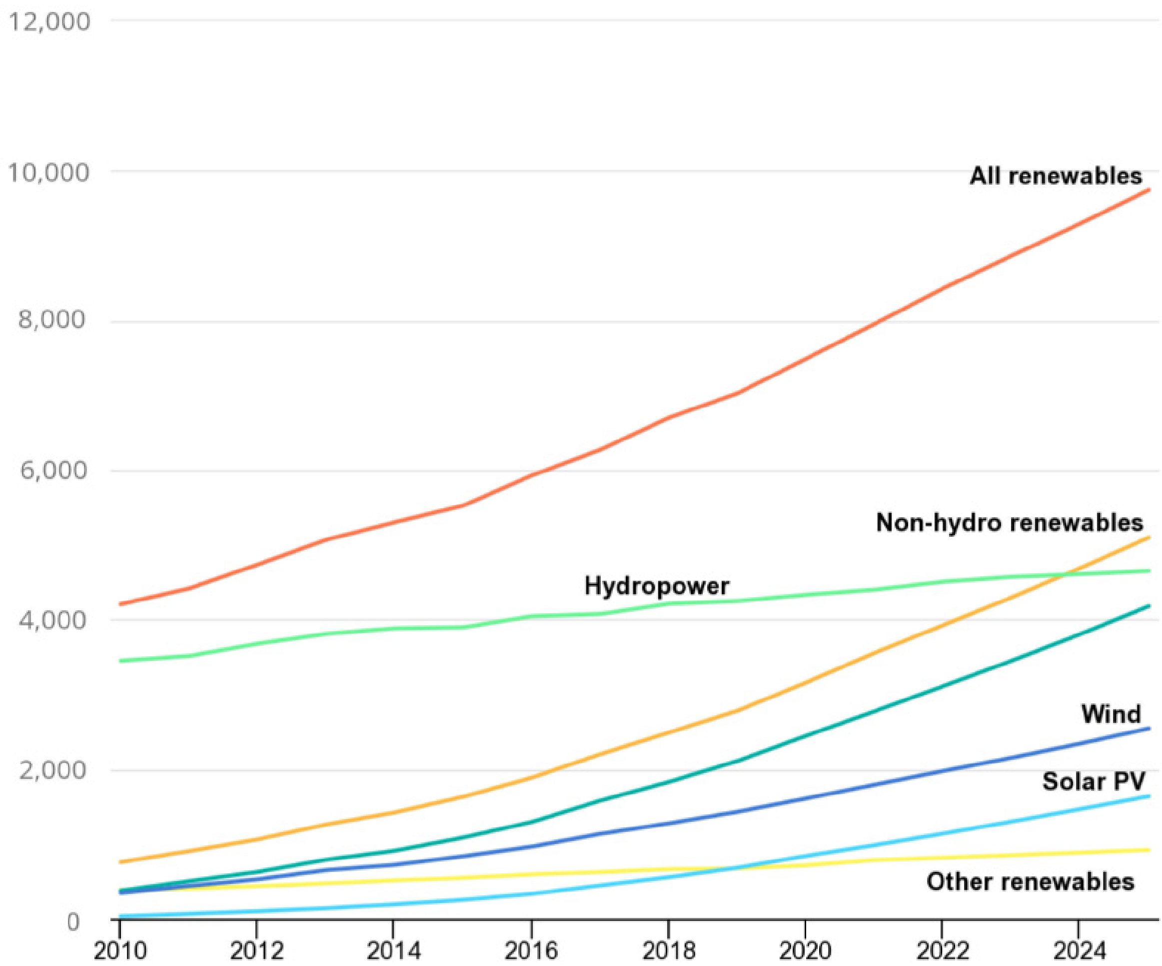

Figure 1. Total use of renewable energy sources for electricity generation (2010–2025).

The choice of location for wind turbines depends on the specifically localized wind resource, which must be sufficient to generate the estimated power needed to replace conventional energy. For example, flat terrain with high elevation or a seashore is ideal for collecting wind energy on land, as opposed to terrain with a complex landscape (e.g., mountainous terrain). Recently, there has been a significant increase in power generation capacity from offshore wind farms located in the world's oceans, which is especially noticeable in Europe, where there has been an annual increase in power generation since 2016 [11]. However, wind speed is subject to various seasonal and stochastic characteristics [12]. Accurate forecasts of wind speed and wind power are necessary for the stable and reliable operation of the power system, and for increasing the competitiveness of the electricity market. As a result, wind power prediction has become a hot topic in renewable energy, and numerous researchers around the world have been directed to develop the most accurate wind prediction models, leading to tremendous progress in the recent past. Variability in wind speed directly affects wind power, resulting in unsteady power generation, which is detrimental to the power system [13]. This creates serious problems when integrating wind power into the power grid and can lead to system failures and performance degradation, resulting in additional operation and maintenance costs.

Now the concept of organizing distributed electric networks [14] is becoming increasingly widespread, which can combine several different sources of generation (not only by location, but also by nature). When organizing such systems involving renewable energy sources, many difficulties arise, the most significant of which is a wide range of power fluctuations associated with the introduction of renewable energy generators, as a result of which the task arises of combating the emerging fluctuations in the generated capacities within the operated network, for which it is necessary to apply various technological solutions and models that allow for taking into account the influence of the nature of existing wind power fluctuations and resources on the modes of operation of the entire network [15,16]. Optimization of planning and operation of distribution networks, including transmission, substation, distribution and power equipment, is an intensively studied topic in the energy sector [17,18]. With the integration of a large number of distributed pieces of energy equipment, such as wind power, photovoltaic systems, and energy storage equipment, it is necessary to use new planning approaches for a modern distribution network in order to increase economic efficiency and determine the schedule of new connected equipment for renewable energy production.

The second important aspect of the use of such distributed networks is the organization of storage systems, the functioning of which also differs depending on the type of alternative energy source used (different models and algorithms are used for the operation of batteries) [19], which are an integral part of modern energy systems with renewable energy sources (both autonomous and distributed).

All these aspects require the use of specialized methods that differ from each other depending on the type of energy involved: solar, wind, biogas, hydro, etc. However, these stages follow after evaluating the efficiency of wind energy use in specific conditions of the region, for which various approaches to forecasting and evaluating wind energy are used, which will be considered in this work.

Currently, there are a large number of reviews on models and approaches in forecasting wind resources, which are devoted to various aspects: forecasting the power of wind flows, forecasting the amount of energy generated, estimates of the theoretical potential of energy, some of which are presented in Table 1. A distinctive feature of this work is the combination of approaches to estimating and forecasting energy, which, although similar to each other conceptually, have some differences. Various types of methods are also considered: from mathematical to models based on intelligent data processing and artificial intelligence technologies. Another task of this review is to update the information by considering the latest achievements and approaches in the field of forecasting and evaluation of wind energy resources.

Table 1. Some of the existing reviews of wind energy assessment and forecasting methods.

Literature	Year	Advantages	Limitations
Wen-Yeau Chang [20]	2014	The classification of forecasting models is considered, various approaches, including hybrid ones, are considered.	Classical mathematical models and models of wind energy distributions are not presented, there are outdated approaches.
Yuying Xie et al. [21]	2022	Various intelligent forecasting algorithms are presented, metrics for evaluating their accuracy are considered, and the performance of models is evaluated.	No attention is paid to the existing distribution of wind resources for the theoretical assessment of the potential.
S Rajendra Prasad et al. [22]	2022	Current intelligent forecasting models are presented.	There is no classification of methods, only classification according to the prediction horizon is presented.
Sanjeev Kumar Agarwal [23]	2013	Various statistical approaches for making forecasts are presented.	There is no clear classification, other approaches have not been considered, some of the methods have lost relevance.
Bo Yang et al. [24]	2020	Extensive classifications of methods for forecasting not only the power of the wind flow, but also the prediction of uncertain and unforeseen situations are presented. Forecasting criteria are presented.	Distribution models for estimating the theoretical potential are not considered.

This work is organized as follows: Section 2 presents the main approaches used for the theoretical assessment of wind potential and contains mathematical expressions necessary to calculate the amount of incoming energy. Section 3 examines an extensive class of forecasting methods based on various approaches: statistical intelligent and hybrid methods. Section 4 is a conclusion containing a summary of the results of this work and possible applications of the methods considered.

2. Methods for Assessing the Potential of Wind Energy

The rapid growth of energy capacities in the world is associated with various factors, such as the rapid development of society and the growth of the economic potential of various countries. Against this background, there is a need to involve new types of energy, one of which is wind energy, which has a number of advantages: abundance, prevalence, low cost and negligible impact on the environment. However, this type of energy has its own characteristic features (for example, changeable nature), as a result of which one of the necessary stages of involving this resource is the need to assess the theoretical potential of the amount of energy. A preliminary assessment of the energy potential is the first and most important stage of the involvement of this resource in the energy system [25], since these data are necessary for further forecasting the amount of energy received and generated, and as a consequence the effectiveness of the introduction of an energy complex based on wind turbines. In order to determine the most suitable location for installing a wind power plant, it is necessary to obtain wind data [26] for which one or more anemometers, capable of collecting data for a sufficiently long period of time (usually at least a year), are placed at the proposed locations, for which such a system must be autonomous and record the collected values [27,28], after which the obtained data are supplemented with the available data from meteorological stations, on the basis of which it is possible to start assessing the efficiency of the use of wind farms in the region under consideration. Another possible way to obtain data is to refer to statistical long-term observations that are available to various meteorological stations or can be obtained as a result of the operation of an existing wind complex [29,30], which has a large number of measuring instruments, collecting data for the implementation of internal monitoring procedures and optimization of the operation process. As a result, the data obtained can be used for further refined assessment of the potential of wind resources in a given area and the construction of more accurate and long-term forecasts for electricity generation.

Estimation of Wind Energy Potential Using Different Types of Distributions (Stochastic Wind Energy Estimation)

One of the common ways to estimate the wind energy resource is the use of models based on the probability Weibull distribution [31]. There are various approaches [32,33] aimed at estimating the energy potential of wind energy, but methods based on the Weibull and Rayleigh distributions have been found to be most applicable in practice [34].

The Weibull distribution function (probability density function) can be defined as [35]:

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

where $f(v)$ is the probability of wind speed, v is the wind velocity, and k and c are the shape and scale parameters. k has no dimensional units, whereas the c parameter has the dimensional unit as (m/s), similar to wind speed.

After integrating this expression, a cumulative Weibull distribution function can be obtained [33,36], which is defined as follows:

$$F(v) = \int_0^{\alpha} f(v)dv = 1 - e^{-\left(\frac{v}{c}\right)^k}, \tag{2}$$

where α represents the highest wind speed under consideration and it changes according to the site.

The predicted value of the wind speed, which is also known as the mean value, is obtained from the Weibull distribution parameters k and c and can be defined as:

$$v_m = c\Gamma\left(1 + \frac{1}{k}\right), \tag{3}$$

where "Γ" is known as the gamma function.

The standard deviation for the Weibull distribution is defined as:

$$\sigma = c\sqrt{\Gamma\left(1 + \frac{2}{k}\right) - \Gamma^2\left(1 + \frac{1}{k}\right)} \tag{4}$$

After calculating the values of σ and v_m, the shape and scale parameters can be defined as:

$$\left(\frac{\sigma}{v_m}\right)^2 = \frac{\Gamma\left(1 + \frac{2}{k}\right)}{\Gamma^2\left(1 + \frac{1}{k}\right)} \tag{5}$$

From Expression (6), k can be found, and once k is calculated c is determined from the following:

$$c = \frac{v_m}{\Gamma\left(1 + \frac{1}{k}\right)} \tag{6}$$

If the coefficient k = 2, the Weibull distribution is converted to a Rayleigh distribution calculated from the following expression:

$$f(v) = \left(\frac{v}{\alpha^2}\right)e^{-\frac{v^2}{2s^2}}, \tag{7}$$

where α is the scale parameter and its units are m/s.

The following expressions are used to determine the most likely velocity of belief and the energy produced:

$$V_{MP} = c\frac{(k-1)^{k^{-1}}}{k}, \tag{8}$$

$$V_{MaxE} = c\frac{k + 2^{\frac{1}{k}}}{k} \quad (9)$$

To determine the shape and scale parameters that are used in the Weibull distribution, there is a number of different methods, the main of which include: the maximum likelihood method, the method of moments, the least squares method, the graphical method, and so on.

A particular case of the method of moments is the empirical method [37], according to which:

$$k = \left(\frac{\sigma}{v_m}\right)^{-1.086} \quad (10)$$

A number of papers [38–50] are devoted to consideration of models based on Weibull and Rayleigh distributions. These papers describe various possible modifications applied to models based on Weibull and Rayleigh distributions.

For example, [38] considers the Grinevich distribution and a modification of the Weibull distribution, the Weibull–Hudrich distribution:

$$F(v, \overline{v},\ \Delta v) = \frac{\Delta v}{v} a \left(\frac{\Delta v}{v}\right) e^{-k\left(\frac{v_a}{v}\right)}, \quad (11)$$

where $F(v)$ is the wind speed repeatability, $\overline{v}$ is the average speed over the calculation period, v is the speed whose relative repeatability is defined in the interval from $(v - \Delta v/(2))$ to $(v + \Delta v/(2))$, Δv is the value of selected wind speed gradation. The values of the coefficient a and the indices of degrees p and n characterize local features of the wind regime and may vary within quite wide limits.

$$F(v) = k\frac{v^{k-1}}{A^k} e^{-\left(\frac{v}{A}\right)^k}, \quad (12)$$

where k is the shape parameter (depends on the area of the terrain), A is the scale parameter (depends on the average wind speed, A ~ 1.13 v).

According to the conclusion of the author of the paper, the Weibull–Hudrich distribution in various sources of literature is recognized as the most universal.

In [40], the authors additionally use expressions for determining the average energy power and energy density:

$$P_D = \frac{P(V)}{A} = \frac{1}{2}\rho V_m^3, \quad (13)$$

where $P(V)$ is defined as the wind power (in watt), P_D is defined as the power density of the wind (watt per square meter), ρ is defined as the site density of air that is assumed to be 1.225 kg/m^3 in this study, and A is the rotor blades' swept area (in square meter).

The energy density is calculated as:

$$E_D = \frac{1}{2}\rho c^3 \Gamma\left(1 + \frac{3}{k}\right) T, \quad (14)$$

where Γ is defined as a gamma function and T is the specific period of time.

The authors also considered expressions to take into account changes in the Weibull distribution parameters with height, because wind values that correspond to the height at which the blades of the wind turbine are located are not always available:

$$\frac{V}{V_0} = \left(\frac{h}{h_0}\right)^{\alpha}, \quad (15)$$

where v is defined as the wind speed hub height (h), v_0 is defined as wind speed original height (h_0), and α is defined as the surface roughness coefficient and is commonly assumed to be 0.143.

The parameters for the Weibull distribution, at the height difference, can be obtained from the following expressions:

$$k(h) = \frac{k_0\left[1 - 0.088ln\left(\frac{h_0}{10}\right)\right]}{\left[1 - 0.088ln\left(\frac{h}{10}\right)\right]} \tag{16}$$

$$c(h) = c_0\left(\frac{h}{h_0}\right)^n \tag{17}$$

$$n = [0.37 - 0.088\ln(c_0)] / \left[1 - 0.088ln\left(\frac{h}{10}\right)\right] \tag{18}$$

In [45], versions for two-parameter and three-parameter Weibull distributions are presented. The two-parameter Weibull distribution density function (PDF) and the cumulative distribution function for wind, respectively, are given as:

$$f(v) = \frac{k}{A}\left(\frac{v}{A}\right)^{k-1} e^{-\left(\frac{v}{A}\right)^k}; v > 0; k > 0; A > 0 \tag{19}$$

$$F(v) = 1 - e^{-\left(\frac{v}{A}\right)^k} \tag{20}$$

For the case with three parameters, these functions take the following form:

$$f(v) = \frac{k}{A}\left(\frac{v-\theta}{A}\right)^{k-1} e^{-\left(\frac{v-\theta}{A}\right)^k}; v > 0; k > 0; A > 0; -\infty < \theta < \infty \tag{21}$$

$$F(v) = 1 - e^{-\left(\frac{v-\theta}{A}\right)^k} \tag{22}$$

where $f(v)$ is the probability of observing wind, k is the shape parameter, A is the scale parameter (m/s) and θ is the shift or location parameter (m/s) of the distribution.

Using such distributions improves prediction accuracy but requires more input parameters and increases computational complexity.

It was determined that the three-parameter distribution is the most versatile, however, when it comes to low wind speeds. The two-parameter distribution is better suited.

In [47], the authors investigated fourteen different models based on the Weibull distribution to determine which ones provide the best results. In particular, such methods were investigated to estimate the parameters of the Weibull distribution: Graphical Method (GM) [51], Moment Method (MM) or standard deviation method [52], Empirical Method of Justus (EMJ) [53], Empirical Method of Lysen (EML) [54], Energy Pattern Factor Method (EPFM) [55], Maximum Likelihood Method (ML) [56], Modified Maximum Likelihood Method (MMLM) [54], Alternative Maximum Likelihood Method (AMLM) [57], Least Square Method (LSM) [58], Weighted Least Square Method (WLSM) [58], Curve Fitting Method (CFM) [53], Wind Variability Method (WVM) [55], Moroccan Method (MoroM) [55], and Median and Quartile Method (MQM).

As a result, the authors determined that the wind variability methods and the Moroccan method are the worst at different wind speeds, in contrast to the coefficient method of the energy model, which shows the best performance when evaluated by statistical criteria. Similar results were obtained when estimating the density of wind energy distribution.

In [59], a study of five methods for estimating parameters of the Weibull distribution was presented, and it was found that two methods, namely, the empirical method and the method of moments, give the best approximation for all months considered during the year.

It is worth noting that, in addition to the Weibull and Rayleigh distributions, other types of distributions can be used to estimate wind energy, as presented in Table 2.

Table 2. Different models characterizing the distribution of wind energy and wind speed.

Name	Wind Power Density Function
Rayleigh [60]	$f(x,\ \alpha) = \frac{x}{\alpha^2} exp\left[-\frac{1}{2}\left(\frac{x}{\alpha}\right)^2\right]$
Normal [52]	$f(x,\ \alpha,\ \mu) = \frac{1}{\alpha\sqrt{2\pi}} exp\left[-\frac{1}{2}\left(\frac{x-\mu}{\alpha}\right)^2\right]$
Log normal [61]	$f(x,\ \alpha,\ \mu) = \frac{1}{x\alpha\sqrt{2\pi}} exp\left[-\frac{1}{2}\left(\frac{\ln(x)-\mu}{\alpha}\right)^2\right]$
Truncated normal [62]	$f(x,\ \alpha,\ \mu) = \frac{1}{I(\alpha,\mu)\alpha\sqrt{2\pi}} exp\left[-\frac{1}{2}\left(\frac{x-\mu}{\alpha}\right)^2\right]$ where $I(\alpha,\mu) = \frac{1}{\alpha\sqrt{2\pi}}\int_0^\infty exp\left[-\frac{1}{2}\left(\frac{x-\mu}{\alpha}\right)^2\right]dx$
Logistic [62]	$f(x,\ \alpha,\ \mu) = \frac{1}{\alpha\left[1+exp\left(\frac{x-\mu}{\alpha}\right)\right]^2} exp\left(\frac{x-\mu}{\alpha}\right)$
Log logistic [63]	$f(x,\ \alpha,\ \mu) = \frac{1}{x\alpha\left[1+exp\left(\frac{\ln(x)-\mu}{\alpha}\right)\right]^2} exp\left(\frac{\ln(x)-\mu}{\alpha}\right)$
Generalised extreme value [52]	$f(x,\alpha,k,\mu) = \frac{1}{\alpha}\left[1-\frac{k}{\alpha}(x-\mu)\right]^{1/k-1} exp\left\{-\left[1-\frac{k}{\alpha}(x-\mu)\right]^{1/k}\right\}$
Nakagami [62]	$f(x,\alpha,k) = \frac{2k^k}{\Gamma(k)\alpha^k}x^{2k-1}exp\left(-\frac{k}{\alpha}x^2\right)$
Inverse Gaussian [60]	$f(x,\alpha,\mu) = \sqrt{\frac{\alpha}{2\pi x^3}} exp\left[-\frac{1}{2}\frac{\alpha}{x}\left(\frac{x-\mu}{\mu}\right)^2\right]$
Inverse Weibull [62]	$f(x,\alpha,k) = \frac{k}{\alpha}\left(\frac{\alpha}{x}\right)^{k+1} exp\left[-\left(\frac{\alpha}{x}\right)^k\right]$
Weibull [63]	$f(x,\alpha,k) = \frac{k}{\alpha}\left(\frac{\alpha}{x}\right)^{k-1} exp\left[-\left(\frac{x}{\alpha}\right)^k\right]$

In [64,65], approaches to wind energy estimation using non-Gaussian models are presented, the distinctive feature of which is the possibility of taking into account the asymmetry inherent in wind indicators, which has a detrimental effect on the prediction accuracy when using traditional models to work with time series for which asymmetric gamma distribution is used.

In the study [66], the authors propose the concept of using mixed distribution models, such as mixed Gaussian distribution, the mixed logistic distribution model and the mixed Weibull distribution model, to estimate wind flow power fluctuations. The mixed Gaussian distribution has the following form:

$$f_{MG}(x) = u_1\frac{1}{\sqrt{2\pi}\sigma_1}e^{-\frac{(x-\mu_1)^2}{2\sigma_1^2}} + u_2\frac{1}{\sqrt{2\pi}\sigma_2}e^{-\frac{(x-\mu_2)^2}{2\sigma_2^2}}, \tag{23}$$

where μ is the position parameter and expectation of the Gaussian distribution, σ is the scale parameter and variance of the Gaussian distribution, and u_1 u_2—weighted coefficients such that $u_1 + u_2 = 1$.

The mixed logistic distribution model can be defined as:

$$f_{ML}(x) = v_1\frac{e^{-\frac{x-a_1}{b_1}}}{b_1\left(1+e^{-\frac{x-a_1}{b_1}}\right)^2} + v_2\frac{e^{-\frac{x-a_1}{b_1}}}{b_2\left(1+e^{-\frac{x-a_2}{b_2}}\right)^2}, \tag{24}$$

where a_1, a_2 are position parameters of each logistic distribution, b_1, b_2 are scale parameters, and v_1, v_2 are weighted coefficients, with $v_1 + v_2 = 1$.

The mixed Weibull distribution model is presented below:

$$f_{MW}(x) = \begin{cases} \omega_1\frac{k_1}{\lambda_1}\left(\frac{x}{\lambda_1}\right)^{k_1-1}e^{\left(\frac{x}{\lambda_1}\right)^{k_1}} + \omega_2\frac{k_2}{\lambda_2}\left(\frac{x}{\lambda_2}\right)^{k_2-1}e^{\left(\frac{x}{\lambda_2}\right)^{k_2}}, x \geq 0 \\ 0,\ x < 0 \end{cases}, \tag{25}$$

Mixing models allows for increasing the overall accuracy when using a certain kind of distribution, but such an increase in the number of mixed models increases the nonlinearity of the model and can translate into excessive approximations, as a result of which incorrect results may be obtained.

Another model presented by the authors is the maximum entropy distribution model, which allows for the most complete consideration of all fluctuations. Emerging during wind power generation. The maximum entropy distribution model is presented below:

$$S = -\int_{P_{min}}^{P_{max}} f(P) \ln f(P) dP \,, \tag{26}$$

where P_{max} and P_{min}—maximum and minimum output power, respectively, and ln $f(P)$—self-information $f(P)$.

The authors of the study [67] investigate various types of Lindley distribution, such as Lindley's power distribution, Marshall–Olkin Lindley distribution, Lindley's Quasi distribution, Lindley's Gamma distribution, and Lindley's Extended distribution. Based on the analysis, the authors proposed the following new kind of distribution: "New Alpha Power Transformed Power Lindley Distribution (NAPTPL)", as presented below.

$$f(x) = \frac{\beta\theta^2(1+x^\theta)}{(1+\theta)} x^{\beta-1} e^{-\theta x^\beta} \alpha^{-(1+\frac{\theta}{1+\theta}x^\beta)e^{-\theta x^\beta}} \left[1 + \log(\alpha)\left\{1 - \left(1+1+\frac{\theta}{1+\theta}x^\beta\right)e^{-\theta x^\beta}\right\}\right], \tag{27}$$

where β and θ are scale parameters.

This distribution is much more flexible and versatile compared to the most common Weibull and Rayleigh distributions.

3. Methods of Forecasting the Amount of Wind Energy

After assessing the theoretical potential of wind energy in a particular region, it is possible to proceed to forecasting the amount of incoming and generated energy, taking into account the use of specific conversion technologies. The use of various algorithms and forecasting methods makes it possible to achieve a timely prediction of wind flow fluctuations, which makes it possible to optimize the operation of power plants, and the use of long-term forecasting methods makes it possible to estimate the amount of energy generated and the economic efficiency of the operation of a wind power plant. Currently, there are a huge number of forecasting methods, which are most often divided into long -term and short-term. Long-term forecasts allow for making an assessment for several days or months ahead, which requires a sufficiently large amount of data and consideration of a variety of input variables, allowing for different weather factors [68]. In contrast to short-term forecasts, long-term forecasts are most applicable for estimating the gross energy potential, while short-term forecasts allow for real-time optimization of the energy system.

Some sources divide forecasts into four categories [69]: ultra-short-term, short-term, medium-term, long-term, which are shown in Figure 2.

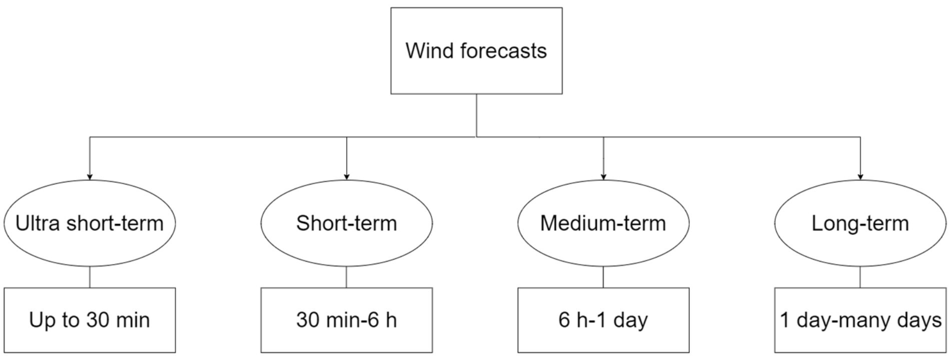

Figure 2. Types of forecasts by duration.

The work [21,70] presents the time limits for the allocated forecast scales presented in Table 3.

Table 3. Characteristics of forecast horizons.

Forecast Horizon	Characteristic
Ultra-short-term	Wind energy prediction from a few seconds to 30 min
Short-term	Wind energy forecast from 30 min to 6 h
Medium-term	Wind power forecast from 6 h to 1 day
Long-term	Wind energy forecast for more than 1 day

In this case, all methods can be divided into three groups—physical, statistical, and intelligent methods—based on the use of modern approaches in data processing and hybrid approaches [71], as illustrated in Figure 3.

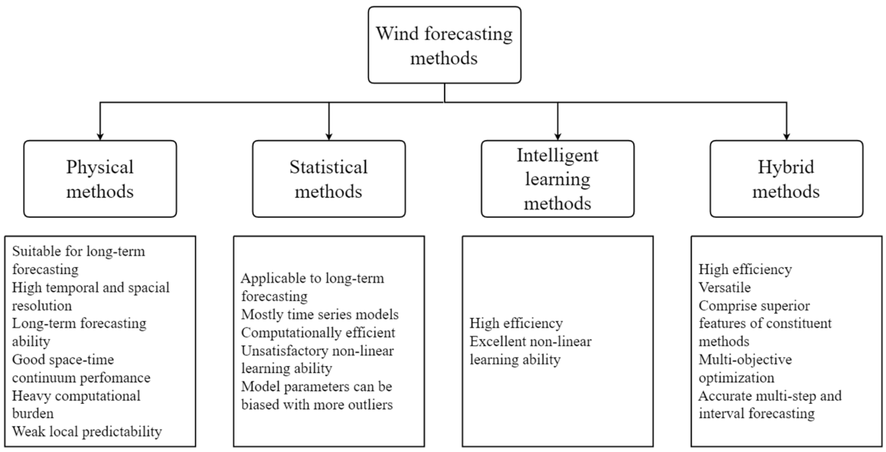

Figure 3. Classification of methods for predicting wind flow energy.

Each of these groups of methods has its own specific advantages and disadvantages. Thus, the simplest and least expensive are the statistical methods, which are most applicable for short-term forecasts, in contrast to the physical methods that can provide a sufficiently long period of the forecast [69].

3.1. Physical Methods of Wind Energy Forecasting

These methods are the most fundamental approach to wind energy forecasting, based on the use of various geographic parameters and meteorological data: humidity, air temperature, pressure, etc. [72]. Sometimes, such models are called numerical weather prediction.

Most of the physical methods are based on computational fluid dynamics (CFD) models. The most common models based on physical methods are:

- Regional ocean model system;
- Weather Research and Forecasting Model (WRF);
- Fifth generation mesoscale model (MM5);
- Numerical Weather Prediction Models (NWPMs).

These models are capable of accurate long-term prediction and have a higher spatial and temporal resolution. Moreover, physical methods generally do not require large amounts of historical data, and data are usually only needed to validate the model, but they have large computational burdens, which makes them time-consuming [73].

Current physical models are complex computational methods, organized using modern technology. For example, in [74], a physical model for wind distribution mapping was proposed, based on the use of Weibull distribution, geostatistical methods and machine learning. A distinctive feature of this model is its relative simplicity, since there is no need to solve complex systems of equations describing thermal phenomena affecting the state of the wind flow.

There are models [75] to simulate wind flow on rough terrain, resulting in the construction of a map of wind energy distribution, which is necessary for the effective implementation of wind power plants.

In [76], the authors presented an approach, based on neural networks, which allows for the simulation of turbulent flow and takes into account various physical effects (such as the velocity trail), but this method is subject to errors in conditions of complex topography and the presence of various obstacles, which are a priori facet of wind farm operation, which does not allow one to make an accurate assessment of turbulent flows throughout the wind power plant.

The study [77] presents an approach based on several numerical weather prediction models. As a result, it is possible to improve the accuracy by 8–20%. The following known NWPM models were applied in the study:

- ECMWF-ifs (IFS): a high-resolution global integrated forecasting system;
- Ukmo-euro 4 (EURO): a European model operated by the UK Meteobureau;
- MEPS: Norway's operational weather forecast model, which is an ensemble model with 10 members [78].

This combined use of several physical modeling methods has resulted in a new model that performs better than each of the PPP models alone. At the same time, this model makes it possible to successfully implement forecasts both at the point level and on a larger scale, for example, at the level of a power plant.

In [79], a study aimed at assessing the capabilities of numerical weather forecasts to estimate the energy potential of wind is presented. A specialized experimental setup was used for verification, and the model used distributions such as normal distribution, oblique normal distribution, stable distribution, and t-distribution. The authors hope in the future to combine their developments in statistical modeling with some model of NPP with a higher resolution, as a result of which the difference between the theoretically obtained values and real data sets can be reduced.

The study [80] considers a physical model capable of providing the results of modeling the movement of air flows in the atmosphere based on a large set of meteorological data. Thus, the work [81] presents a model, which is based on the Kalman filter, using a Gaussian distribution to describe and determine the meteorological parameters. Such approaches are capable of providing high forecast accuracy, but this requires a high degree of reliability of the input meteorological data, represented by a very extensive data set consisting of observations over a long period of time.

There are a number of models proposed by different authors [82–84], which are based on spatial correlation, which are used to build forecasts for wind speed and energy generation on different time scales: from a few minutes to several hours. At the same time, there is evidence [85] proving that physical models are aimed at medium- and long-term forecasts, while they are more prone to calculation errors when making short-term forecasts.

The general algorithm of the forecast action when using numerical weather prediction is shown in Figure 4 [86].

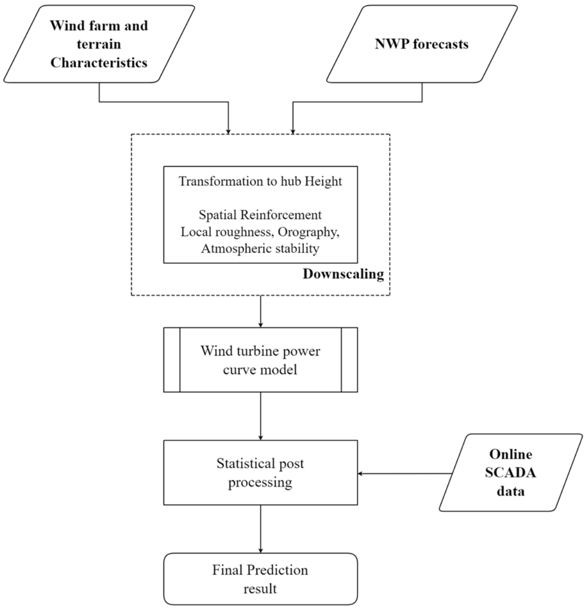

Figure 4. Prediction steps of a wind farm with NPW.

3.2. Statistical Methods of Wind Energy Forecasting

Existing statistical methods for wind energy forecasting are usually based on various time series models to characterize existing trends in the data under study based on the maximum likelihood method or the least squares method. Historical wind speed data are often used to build such models, without taking into account the various meteorological information that is used when building physical forecasting methods.

The following approaches are used as basic statistical prediction models [73]:

- Autoregression;
- Stationary time series model;
- Moving average method;
- Markov chains;
- Autoregressive integrated moving average;
- Simple autoregressive moving average;
- Vector autoregressive moving average.

The main advantage of this approach is its low computational complexity and the low requirement for input parameters (often, we need only wind speed data obtained over a period of 12 months). However, we should also note a significant disadvantage of this approach. These models do not always give adequate and satisfactory results, which is most pronounced when the data are complex and purely nonlinear [87]. To solve this problem and improve the overall accuracy of forecasting, classical statistical methods are often used together with various filtering methods [88,89].

The most common approach to time series modeling is autoregressive moving average (ARIMA), used for forecasting based on historical data, consisting of the autoregressive (AR) model and moving average (MA) [90]:

$$\psi(B)(y_t - \mu) + \xi_q(B)a_t \quad (t = 1, 2, \dots, m), \tag{28}$$

where y_t is the actual values and a_t is the white noise at time t.

In [91], the ARIMA time series analysis model for short-term forecasting is presented. The authors' innovation is the use of an indirect approach to forecasting the amount of energy produced, since initially the value of the wind speed forecast is determined, on the basis of which the model of energy production is built. As a result, it is possible to reduce the number of necessary input data for the model operation, but as a comparative study showed, the use of the direct approach provides greater accuracy than the use of the indirect approach.

In a study [92], the authors propose the creation of a model for time series estimation based on the autoregressive moving average model (ARIMA) and neural networks. To do this, they conducted a study of five combinations of models: ARIMA; ARIMA + wavelet transform; ARIMA + NN1 (neural network); ARIMA + NN1 + NN2; NN. The block diagram of the model proposed by the authors is presented in Figure 5.

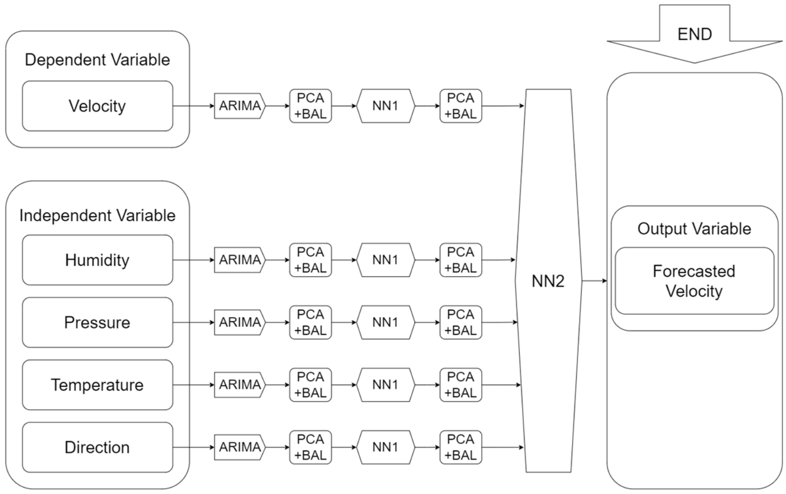

Figure 5. Statistical prediction model ARIMA + NN1 + NN2.

Forecasting was carried out on four forecast horizons, which were previously presented in this work in Table 1; as a result, it was found that the combined model shows acceptable results for all forecast horizon options, and the smallest contribution was obtained when using the wavelet transform, in combination with which the model is little different from the usual ARIMA model.

There are a large number of works based on the use of autoregressive methods: in [93], the authors use the ARMA-GARCH model (generalized autoregressive with heteroscedastic process), for interval wind estimates, which leads to improved overall model accuracy; in [94,95], various approaches to wind energy forecasting based on historical data, including the use of autoregressive methods; research [96] is devoted to considering different models to work with linear and nonlinear time series: MSARIMA, ARIMA-GARCH, MSARIMA-GARCH and MSARIMA-EGARCH. As a result, it was found that the ARIMA-GARCH model provides the highest accuracy; researchers in [97] performed a combination of the ARIMAX model with a machine learning model, resulting in the realization of monthly and hourly wind speed forecasts; in [98], a hybrid regression-based model (sARIMA) was proposed, which allows for analysis of seasonal features in historical data, applied in conjunction with an artificial neural network designed for complex evaluation of non-stationary components; in [99,100], a large comparative analysis of the performance of classical methods of time series analysis and new intelligent approaches such as deep learning and artificial neural networks was presented, as a result of which it was determined that new intelligent approaches are extremely promising methods of forecasting and estimation of time series.

In addition to such regression approaches, one can quite often find models using different filters in the literature. In particular, the Kalman filter, which allows for reducing the level of Gaussian noise in the studied variables and input data [101]: in [102], an approach using the Kalman filter was proposed, which allows for improving the quality of forecasts in numerical weather modeling; in [103], the Kalman filter was applied as a tool for reducing potentially possible errors when making a regional forecast; in [104], two models, namely, the ARIMA model and its modification with the joint application of the

Kalman filter (ARIMA-KF) are considered, as a result of which it was determined that the hybrid model based on the use of an autoregressive model and additional filtering allows us to obtain a more accurate prediction and has better computational power.

3.3. Intelligent Models for Wind Energy Prediction

Recently, intelligent methods have been gaining popularity in all fields, allowing, with proper tuning and optimization, one to ensure a high probability of solving the problem and achieving better performance compared to traditional approaches [105,106]. The field related to wind energy forecasting is not an exception, since the application of approaches based on artificial intelligence technologies allows for solving one of the main problems arising when using statistical approaches—the nonlinearity of the data [107].

The use of artificial intelligence technologies in modern systems based on renewable energy sources is important at all stages of system design and operation [108]:

- Prediction of energy potential;
- Analysis of the stochastic uncertainty inherent in RES;
- Intelligent control of the entire energy system;
- System fault detection;
- Multipurpose optimization.

All AI methods used for solutions with RES can be divided into three main classes of tasks: data processing, building predictions about the amount of theoretical energy values and the amount of energy produced using specific conversion technologies [109], and practical methods for the management and optimization of energy systems used, which is shown in Figure 6.

Compared to physical and classical methods of statistical forecasting, which were discussed earlier in this paper, methods based on artificial intelligence technologies and, in particular, based on neural networks, allow for obtaining more accurate results, especially when forecasting the amount of electricity generation and determining the performance of a power plant based on RES [110].

Among the variety of such methods, let us mention the most common ones:

- Support Vector Machine (SVM);
- Back-propagation neural networks (BP);
- General Regression Neural Networks (GRNN);
- Radial Basis Function Neural Networks (RBFNN);
- Extreme Learning Machines (ELM);
- Deep and convolutional neural networks;
- Fuzzy logic.

A distinctive feature of such approaches is the ability to work with large data sets, as well as the ability to generalize and identify hidden dependencies [111], but there are a number of problems associated with overtraining, problems with convergence and the emergence of local optima to eliminate, which requires much attention being given to the process of forming an intelligent model for a particular problem and its training parameters.

Figure 7 presents a basic classification of intelligent methods that can be used for wind energy prediction [112].

Table 4 shows some of the smart approaches for predicting wind speed and power.

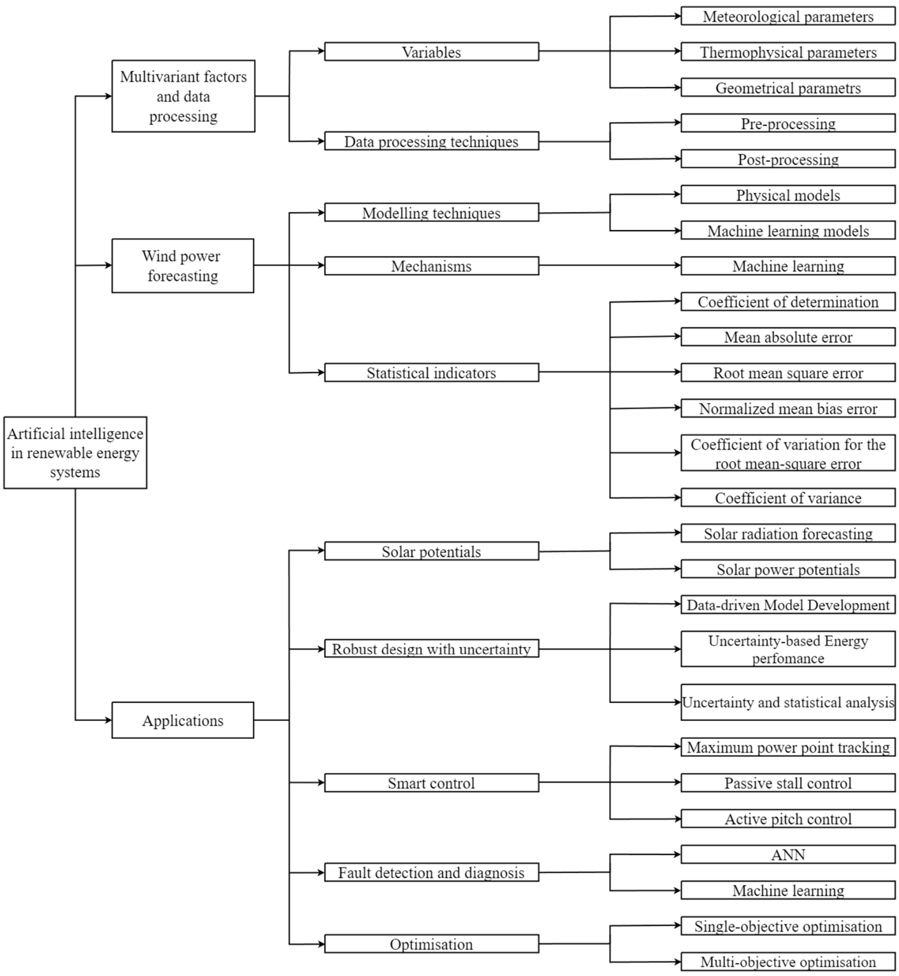

Figure 6. Classification of AI approaches used in the implementation of energy systems based on RES.

Table 4. Methods based on artificial intelligence technologies for wind energy forecasting.

Proposed Model	Data Used	Calculation Index
Artificial Neural Network (ANN) [113]	Average 10 min wind speed data	Average hourly wind speed
Back propagation neural network (BP) [114]	Wind generation data from a wind turbine	Wind speed and power
Artificial Neural Network (ANN) [115]	Humidity, temperature, pressure information	Wind flow energy
Artificial neural network with direct connection (ANN) [116]	Meteorological data	Wind power
Artificial neural networks with forward and backward feedback [117]	Wind speed data (retrospective)	Wind speed
An ensemble recurrent neural network [118]	Wind speed data at 15 min intervals, obtained at 50 m altitude	Probabilistic wind speed prediction
Extreme learning machines [119]	Historical time series with wind or solar energy data	Solar radiation and wind speed
Wavelet transform and neuro-fuzzy logic inference [120]	Wind speed data, weather forecasts based on NWP	Generation of amount of energy by a wind farm
Variational decomposition model and convolutional neural network [121]	Wind speed observation data, at 30-min intervals (5760 observation points)	Wind speed (medium-term forecast)
Support vector machine (SVM) [122]	Data sets from three wind stations	Wind speed (short-term forecast)
Neural networks with memory (LSTM) [123]	Data from a wind farm	Wind speed and wind power output (long term prediction up to 72 h)
Machine learning algorithms [124]	Historical wind speed data	Wind power (long-term prediction)
Deep neural networks [125]	Wind speed data from four wind farms	Wind speed

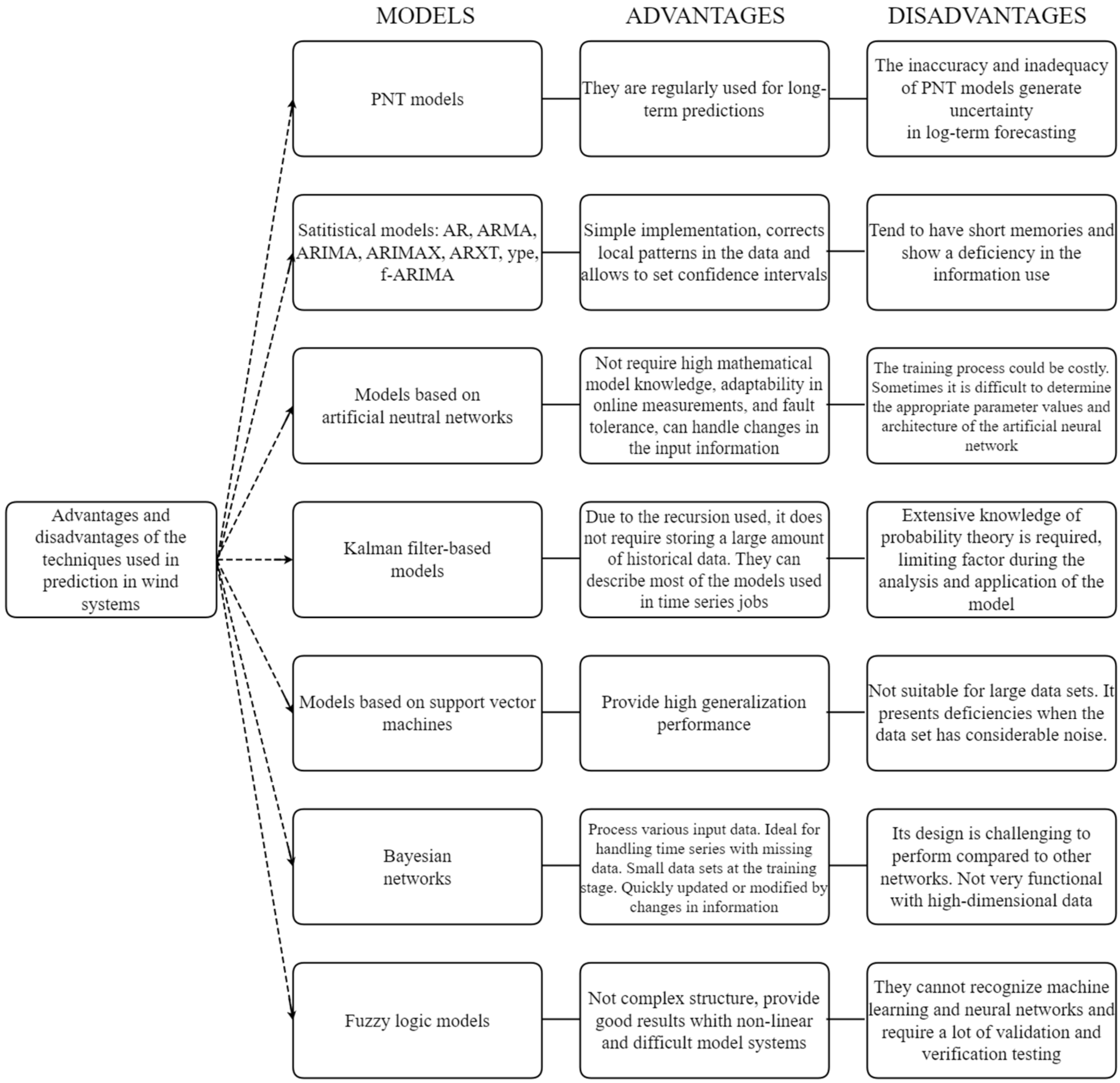

Figure 7. Classification of intelligent methods for predicting wind energy potential.

3.4. Hybrid Models for Wind Energy Forecasting

Hybrid forecasting methods refer to the ability to use different physical, statistical, and intelligent methods together. This combination of methods makes it possible to increase the accuracy of forecasting, which cannot be achieved using standard approaches, be it probabilistic or statistical methods for time series analysis [69]. Figure 8 presents a classification of different hybrid model structures for wind energy forecasting:

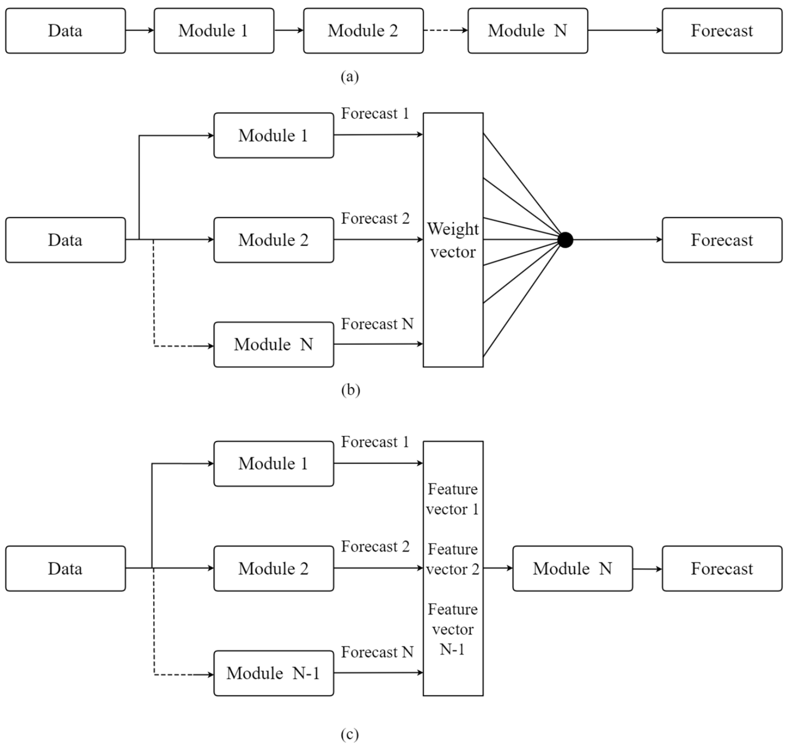

Figure 8. Model structures: (**a**) sequential; (**b**) parallel; (**c**) sequential-parallel.

According to a study [21], hybrid prediction models can be divided into two large categories: models based on metaheuristic optimization and models based on ensemble learning.

Table 5 presents some of the hybrid wind energy estimation methods.

Table 5. Hybrid methods for estimating wind energy potential and predicting wind flow capacity.

Proposed Model	Data Used	Calculation Index
Regression model based on fuzzy logic [126]	Time series with data and wind speeds	Wind speed and direction
Neural networks and the k-nearest neighbor method [127]	Incomplete time series with chaotic behavior	Wind speed
Linear regression and nonlinear machine learning algorithm [128]	Hourly meteorological records 9(from three different cities) wind direction, temperature, dew point, atmospheric pressure, humidity	Wind speed
Empirical mode decomposition combined with autoregressive integrated moving average and generalized autoregressive estimation [129]	Time series	Wind speed
Wavelet packet decomposition, full ensemble empirical decomposition with adaptive noise and artificial neural networks [130]	Time series	Wind speed and wind flow energy
Decomposition methods and artificial intelligence (ANN), an artificial neuro-fuzzy inference system [131]	Historical wind speed data	Forecasting wind power one hour ahead
Time series analysis and multi-criteria optimization by differential evolution algorithm [132]	Fuzzy time series	Wind speed
Jensen's mathematical trace theory, stochastic reliability model and failure tree [133]	Given from a wind power plant	Predicting the amount of energy generated
ARIMA- ANN [97]	Wind speed, pressure, temperature, precipitation	Wind speed
Holt-Winters model, ANN [97]	Wind speed data	Wind speed
Long-term short-term memory neural network (LSTM), enhanced variation mode decomposition (IVMD), and sampling entropy (SE) [134]	Historical wind speed data	Short-term wind energy prediction
ARIMA-KalmanARIMA-ANN [135]	Wind speed data	Wind speed
Weibull-ANN [136]	Monthly wind speed data	Seasonally wind speed data

4. Conclusions

In this work, different types of existing models were considered, which can be divided into probabilistic models based on different types of distributions, physical models designed to accurately estimate and model physical processes in the distribution of wind flows, statistical models that allow one to determine trends based on historical time series, models based on artificial intelligence methods aimed at predicting the amount of wind energy and wind speed in different geographical regions, and hybrid models. It is also possible to define the main distinguishing features of the models considered, depending on their type:

- Physical: They are based on different meteorological values (wind direction and speed, temperature, humidity, pressure, etc.), allow medium- and long-term forecasting, but require sufficient computing power and are very complex, but provide high accuracy.
- Statistical: They use different time series (wind velocity, wind flow energy, amount of generated energy, etc.), allow for making forecasts for all considered horizons and are the simplest to implement, but have a large forecasting error, reaching values of 20–40%.
- Probabilistic models: They use different kinds of distributions in their basis and allow for determining theoretical values of wind velocity for a selected point and wind flow power, and with the right choice of scale parameters allow for achieving high accuracy in calculations.
- Models based on machine learning: They are based on different artificial intelligence methods taking wind speed and wind flow power data (including chaotic time series with incomplete data) as input, are able to make forecasts for all forecast horizons, but show the best results for short-term forecasts.
- Hybrid methods: They are based on a combination of different methods, are able to realize any forecast horizon on available data and provide the best forecast accuracy compared to all other approaches.

Separately, we note that these estimation and forecasting models were considered for the cases of designing power plants, and they differ from the approaches used to assess the potential of power plants located at sea, since additional fluctuations in atmospheric flows are introduced by the movement of sea waves [137].

These models are often used to implement forecasting systems that allow for estimating the amount of energy production, which is presented in various software products for assessing the energy potential of RES [138]. However, given the current trends, the forecasting subsystem can be reorganized into a digital twin [139], designed for the integrated modeling of various systems, including energy systems using RES [140]. Thus, a completely different system is obtained, which significantly expands its functionality, allowing the transition from simple forecasting to comprehensive modeling and testing of the energy system to determine the efficiency of its functioning.

The digital twin includes several different subsystems [141], such as the control system, data acquisition and processing system, data transmission system and the system of modeling and forecasting, the implementation of which is exactly what the models discussed in this paper require. Since the digital twin can have different levels of representation, such as prototype, instance, and aggregated twin [142], it is necessary to form the most appropriate combination of the models used, which allows one to implement the necessary structure of the implemented digital twin.

Thus, this work allows researchers to get acquainted with existing developments in the field of modeling and forecasting wind energy and to choose the most appropriate models for their research. Of course, this work does not cover the whole list of existing models and approaches, but it describes all the main types of existing models and describes their main characteristics and merits, allowing one to determine the most appropriate type of model for a particular study.

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Abbreviations

$f(v)$	the probability of wind speed;
v	the wind velocity (m/s);
k	shape parameters;
c	scale parameters (m/s);
Γ	gamma function;
$F(v)$	the wind speed repeatability;
$\overline{v}$	average speed (m/s);
A	the scale parameter (depends on the average wind speed, A ~ 1.13 v);
$P(V)$	defined as the wind power (in watt);
P_D	defined as the power density of the wind (watt per square meter);
ρ	is defined as the site density of air that is assumed to be 1.225 kg/m^3;
T	the specific period of time;
v_0	defined as wind speed original height (h_0);
θ	the shift or location parameter (m/s);
$u_1 u_2$	weighted coefficients such that $u_1 + u_2 = 1$;
P_{max}	maximum output power (Wt);
P_{min}	minimum output power (Wt);
$\ln f(P)$	self-information $f(P)$.

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