sustainability

MDPI

Review

Grid-Friendly Integration of Wind Energy: A Review of Power Forecasting and Frequency Control Techniques

Brian Loza [1], Luis I. Minchala [1], Danny Ochoa-Correa [1,*] and Sergio Martinez [2]

1 Department of Electrical Engineering, Electronics and Telecommunications, Universidad de Cuenca, Ave. 12 de Abril y Agustin Cueva, Cuenca 010203, Ecuador; bandres.lozao@ucuenca.edu.ec (B.L.); ismael.minchala@ucuenca.edu.ec (L.I.M.)

2 Department of Electrical Engineering, E.T.S.I. Industriales, Universidad Politécnica de Madrid, 28006 Madrid, Spain; sergio.martinez@upm.es

* Correspondence: danny.ochoac@ucuenca.edu.ec

Abstract: Integrating renewable energy sources into power systems is crucial for achieving global decarbonization goals, with wind energy experiencing the most growth due to technological advances and cost reductions. However, large-scale wind farm integration presents challenges in balancing power generation and demand, mainly due to wind variability and the reduced system inertia from conventional generators. This review offers a comprehensive analysis of the current literature on wind power forecasting and frequency control techniques to support grid-friendly wind energy integration. It covers strategies for enhancing wind power management, focusing on forecasting models, frequency control systems, and the role of energy storage systems (ESSs). Machine learning techniques are widely used for power forecasting, with supervised machine learning (SML) being the most effective for short-term predictions. Approximately 33% of studies on wind energy forecasting utilize SML. Hybrid frequency control methods, combining various strategies with or without ESS, have emerged as the most promising for power systems with high wind penetration. In wind energy conversion systems (WECSs), inertial control combined with primary frequency control is prevalent, leveraging the kinetic energy stored in wind turbines. The review highlights a trend toward combining fast frequency response and primary control, with a focus on forecasting methods for frequency regulation in WECS. These findings emphasize the ongoing need for advanced forecasting and control methods to ensure the stability and reliability of future power grids.

Keywords: wind energy; grid integration; wind power forecasting; frequency control; energy storage system; review

check for updates

Citation: Loza, B.; Minchala, L.I.; Ochoa-Correa, D.; Martinez, S. Grid-Friendly Integration of Wind Energy: A Review of Power Forecasting and Frequency Control Techniques. *Sustainability* **2024**, *16*, 9535. https://doi.org/10.3390/su16219535

Academic Editor: Firoz Alam

Received: 23 September 2024
Revised: 19 October 2024
Accepted: 28 October 2024
Published: 1 November 2024

1. Introduction

In the last two decades, renewable energy sources (RESs) have significantly increased their contribution to the electrical grid, playing an important role in meeting the growing global energy demand while supporting the urgent need for decarbonization [1]. This shift toward RESs is driven by the escalating environmental concerns associated with fossil fuel consumption, including greenhouse gas emissions, air pollution, and the depletion of non-renewable resources. Governments and energy sectors worldwide have recognized that transitioning to renewable energy is necessary for environmental sustainability and offers opportunities for energy security and economic growth [2]. Among the various RES options, wind energy has emerged as one of the most promising technologies for large-scale power generation.

The preference for renewable energy sources, particularly wind energy, stems from several key factors [3]. Firstly, renewable sources like wind, solar, and hydropower offer the advantage of being abundant and inexhaustible, in contrast to fossil fuels, which are finite and subject to price volatility. Moreover, renewable energy technologies have seen rapid advancements in efficiency and cost effectiveness, making them increasingly competitive with conventional thermal generation. Wind power, in particular, stands out due to its scalability, declining costs, and ability to generate substantial amounts of electricity without emitting carbon dioxide during operation [4]. These characteristics align perfectly with the global push for sustainable energy solutions that can mitigate the impacts of climate change.

Wind energy has gained significant traction over the past few decades among the diverse array of renewable energy technologies. This is primarily due to continuous technological innovation, which has improved turbine efficiency, increased energy capture, and lowered the levelized cost of energy (LCOE) [5,6]. In 2022 alone, new wind power projects contributed 117 GW of additional capacity to the global energy mix, bringing total annual wind power generation to an impressive 544.6 TWh [7,8]. The increasing prevalence of wind power is further supported by the declining costs associated with its deployment. The global weighted average for newly designated onshore wind projects saw a notable decrease of 5% between 2021 and 2022, falling from USD 0.035/kWh to USD 0.033/kWh [9]. This cost reduction is mainly attributable to economies of scale, advancements in turbine design, and more efficient manufacturing processes, all of which have made wind energy more accessible and attractive for large-scale integration into power grids.

The economic viability of wind energy, combined with its low environmental impact, positions it as a key driver in the global transition to cleaner energy systems. As countries increasingly adopt ambitious renewable energy targets and phase out coal and other high-emission generation sources, wind power has become a central component of future energy strategies. The ability to deploy wind farms both onshore and offshore further enhances the flexibility of this technology, enabling it to be tailored to specific geographic and climatic conditions. In regions with favorable wind resources, large-scale wind farms can now provide a substantial portion of the electricity supply, contributing to stabilizing energy prices and reducing reliance on imported fuels.

However, the output power of a wind farm has a stochastic behavior, making it a variable energy source. This variability can cause stability problems in the electrical grid to which it is connected, especially when the penetration level of the RES is high, and the power system has a certain degree of weakness [10]. Modern wind generation, which relies on inverter-based grid connection interfaces, masks its inherent inertia from the grid, thereby diminishing the system's overall inertial response, which is crucial for maintaining stability. This lack of visible inertia seriously challenges grid stability, particularly during disturbances. The main characteristics of a weak power system are the following:

- Few synchronous generator units are connected to the grid.
- Numerous inverter-based resources (IBRs).
- Low short-circuit levels (SCLs).
- Low inertia.

A conventional power generation system is based on synchronous generating units, providing large inertia. Inertia is the kinetic energy stored in the rotating masses of electrical machines. The inertial response is the intrinsic ability of an electrical system to preserve frequency after a disturbance. It is an essential component of the dynamics of the electrical system, mainly when there are numerous disturbances or abrupt changes in the balance between generation and demand of energy. In case of disturbances, synchronous machines absorb the stored kinetic energy. The speed of the generator rotor decreases, which reduces the frequency of the system at a specific rate of change known as the ROCOF (rate of change of frequency). The balance of generated power and demand is closely related to the ROCOF by means of the oscillation equation if the power system is considered as a representation of an equivalent machine [11], where the ROCOF is related to the collective inertia of all the generators connected during the contingency event and the nominal value of the power system frequency.

Power systems dominated by synchronous generators (SGs) are more robust against power imbalances due to high levels of inertia. In a power system where IBRs replace SGs, inertia is reduced. As a result, systems with high IBR integration have lower inertia levels and are more prone to instability [11]. For example, in the case described in [12], the proportion of RESs in a power system should be at most 20% to handle voltage fluctuations appropriately. In another case, the maximum level of wind penetration considered is higher than 40% [13], while an annual RES penetration rate of 35% is reported as technically feasible in [14]. In 2011, the US Department of Energy (DOE) considered a maximum contribution of wind electricity of 20% by 2030 [15]. The simulation results reported in [16] indicate that a penetration level of wind energy of 17.91% combined with an energy storage system (ESS) keeps the frequency fluctuations of the electrical system within the permitted limits. The power system used in this reference is an IEEE 9-bus. The total active power demand of the system is 315 MW, the total apparent power of synchronous generation is 550 MVA, and the total wind capacity is 120 MW. The only country with 100% renewable electricity is Iceland. Other countries with high levels of renewable electricity are Paraguay (99%), Norway (97%), Uruguay (95%), Costa Rica (93%), Brazil (76%), and Canada (62%) [17]. In all the studies mentioned above, the difference in wind penetration levels depends on several factors, such as the availability of wind resources, the resilience capacity of the power system, and the feasibility of reaching the wind contribution levels, among others.

Figure 1 shows the instantaneous power and average annual power levels as a percentage of the load [11,18] divided into three areas: (1) small isolated networks, (2) large isolated networks, and (3) large networks. As seen in Figure 1, as the size of the power system increases, the average annual generation decreases. The instantaneous power exceeds 50%, except for the Western Interconnect power system. Other examples of simulations of power systems with high levels of renewable energy contribution include [19], in which the authors simulate an IEEE-39 bus power system to perform inertia estimation studies with a 30% contribution of wind energy. A similar case is presented in reference [20], where the authors simulate a 27-bus system, where they reach 100% renewable energy and an ESS. The authors of reference [21] analyze the frequency response of the South Australian power system, which has 1200 MW wind capacity and 500 MW photovoltaic generation, to satisfy an average load between 1800 MW and 2500 MW, depending on the time of the year. The research shows that a power system with an average renewable energy penetration level of approximately 80% (depending on the time of the year) can withstand a low-frequency event. An economic impact study is carried out in [22] for the case study of the island of Ponza, Italy. The objective is to obtain an electrical network of 900 kW, 1.16 MW of PV, and 0.1 MW of co-generation, with a total of 2.16 MW of RESs. In addition, feasibility studies of using hydrogen systems to increase wind energy penetration are analyzed in [23–25]. In [25], the authors examine the case study of Anafi Island, Greece, simulating a grid smaller than 150 MW that combines hydrogen, PV energy, and wind energy to reach approximately 84% RES penetration. Another case study is presented in [23] on Flores Island, Portugal, where the wind penetration has increased up to 89% with the implementation of hydrogen energy storage systems. Ghirardi et al. [24] present simulations of 100% RES (wind energy, and an ESS based on Li-ion batteries and hydrogen) in a power system smaller than 150 MW. References [26–28] present different levels of wind energy penetration: 33.3%, 42%, and 30%, respectively.

Identification of the Need for a Review

Nowadays, wind energy conversion systems (WECSs) feature many active and reactive power control systems to manage power system variations. Therefore, a frequency (primary, secondary, and tertiary) and voltage regulation system applied to a WECS must comply with specific power quality parameters, i.e., maximum/minimum values of frequency and voltage variation and the ROCOF, among others, in normal operating modes and contingency events [19,29].

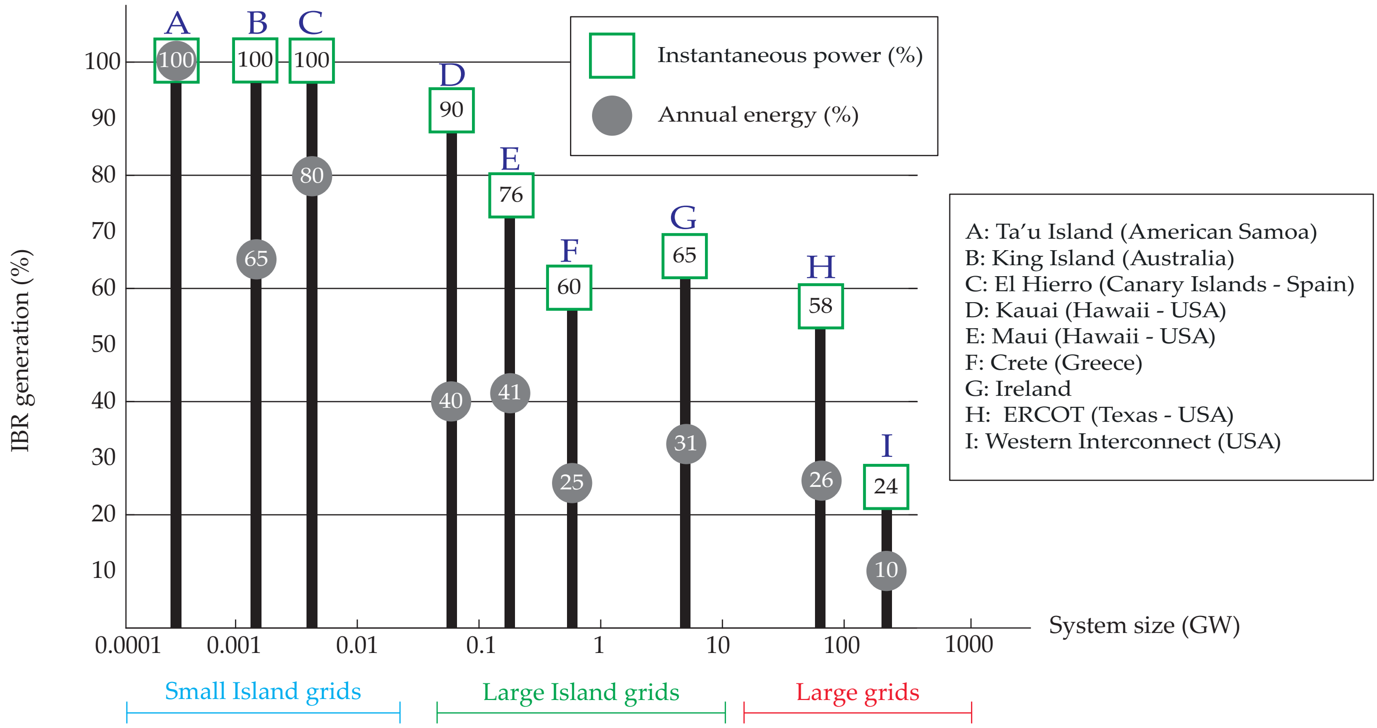

Figure 1. Percentage of IBR generation vs. system size (modified from [18]).

As documented in the literature, many studies have produced a vast miscellany of control strategies that could be used as frequency regulation systems. Ahmed et al. [29] studied the existing challenges for integrating wind energy, such as wind power variability, voltage and frequency stability, reactive power support, fault management capabilities, power quality problems, market, and planning, among others. Additionally, this study reviews methodological solutions such as grid codes, energy storage systems, and wind power policies, as well as the use of an ESS as an auxiliary frequency system in a power grid with high wind energy penetration, as seen in some case studies [20,25]. Ayamolowo et al. [28] analyze the gaps in the integration of renewable energies into the grid, considering different machine technologies that provide synchronous inertia to the grid, including thermal generators, wind turbines connected directly to the power grid, pumped hydroelectric energy storage (PHES), compressed air energy storage (CAES), flywheel energy storage system (FESS), and the implementation of virtual inertia control systems in hybrid systems (wind and solar). In issues related to inertial control and frequency control, hybrid systems were found to offer better characteristics than individual renewable energy systems [28]. The most recent state-of-the-art storage technology choices are studied to reduce the negative impact of the variable nature of wind power on the grid, paying particular attention to the benefits and drawbacks of each technology, such as flywheels, PHES, CAES, different battery storage technology, supercapacitors, and hydrogen [23–25,30]. Aziz et al. extensively review the frequency regulation capabilities of WECSs and inertial control systems, including primary and secondary control. Additionally, the authors state that one of the challenges to increasing wind power penetration is the development of effective wind power forecasting techniques [31].

An overview of the most popular artificial intelligence (AI)-related approaches, their practical benefits when used in various renewable energy sectors, and their practical contribution to improving overall operational effectiveness and optimizing renewable energy control modalities is reported in [32]. Typical approaches to AI techniques are artificial neural networks (ANNs), fuzzy logic control (FLC), particle swarm optimization (PSO), and ant colony optimization (ACO), among others. A comprehensive review of conventional and renewable energy system frequency control techniques is presented in [33]. The authors focused on the latest trends in control systems related to the deviation of active power and frequency from their respective nominal values. The variability in wind power and its impacts on the power system is analyzed in [34]. This review includes a mathematical definition to differentiate between intermittency and wind variability. Shrestha et al. [35] provide in-depth information on the stability problems that contemporary power systems are experiencing due to the widespread use of power electronic converter-based technologies and RESs such as solar and wind energy. Another alternative is using wind energy forecasting methods focused on frequency control tasks or coordinating regulation reserves for contingencies. According to the authors of reference [36], ANN, FLC, support vector machine (SVM), and Kalman filter are the techniques most widely used for wind energy forecasting. Hybrid methods such as ANN combined with wavelet, ANN and SVM, and ANN and FLC were found to be the methods that presented the best results. Yang et al. [37] expand on the technologies used for wind power forecasting reviewed in the previous reference. A critical review of the state of the art of wind energy forecasting methods is presented in [38]. The authors identify which ANN and hybrid methods are the most used. Also, they consider the metrics used to obtain each reported method's performance. They do not mention possible practical applications of the reviewed methods. Tsai et al. [39] present a review of different machine learning techniques and numerical weather prediction (NWP) models applied to wind energy forecasting methods. The authors mention future work such as improving the methods' performance, error reduction, and implementing new techniques to improve the forecast.

Some state-of-the-art reviews relevant to different topics related to wind power forecasting, frequency control systems in WECSs, and the use of different ESS technologies as auxiliary systems for frequency support in networks with a considerable level of wind power penetration have been presented. In the study in [28,29,31,33], all the inertial control techniques and primary and secondary frequency controls available in WECSs are highlighted separately and the authors do not mention the possible combinations of different frequency control systems reported in the literature. The present work reviews different methods (wind power forecasting and frequency control) for integrating WECSs with different wind power penetration levels into a power system. Furthermore, this manuscript highlights the coordination or combination of inertial response with primary and secondary frequency control systems as an opportunity to provide new solutions that optimize reserve resources and provide ancillary services for frequency control. As mentioned in reference [31], developing new wind power forecasting techniques allows for higher wind power penetration levels. This state-of-the-art review presents new wind power forecasting models based on real case studies to provide an auxiliary system for frequency control tasks.

Table 1 summarizes the contributions and limitations of the review articles, and highlights this manuscript's contribution opportunities. The organization of this document is as follows: Section 2 reviews wind power forecasting methods that utilize machine learning techniques. Section 3 examines various frequency control methods from the literature. In Section 4, the findings are discussed. Finally, Section 5 presents the conclusions and potential directions for future research.

Table 1. Contributions and limitations of analyzed review manuscripts.

Study	Contributions	Limitations
[30], 2015	A summary of the most used ESS technologies for integrating variable renewable energy sources is analyzed. The authors conclude that with a 10% penetration level of wind energy, there are no instability problems in the system frequency. With a 20% penetration level of wind energy, additional techniques must be considered to maintain frequency stability in the network.	The article is a specific review on ESS technologies.
[34], 2017	Establishes definitions of wind energy variability and intermittency. The solutions to the problem of wind energy variability are the use of ESS, electric vehicles, wind energy forecasting methods, and wind speed forecasting.	The authors do not discuss frequency control issues. They carry out a general review of wind energy forecasting methods.
[31], 2018	The authors carry out an extensive review of inertial control systems, and primary and secondary frequency control in wind energy sources.	The review article mentions the combination of inertial and droop control without going into other methods of combining different control techniques (contribution option).
[28], 2020	Analyzes conventional and hybrid solutions for integrating renewable sources, with a hybrid system (use of ESS) being the best solution.	The review focuses on different ESS technologies that provide frequency support in renewable energy systems. The article only discusses virtual inertia control techniques in renewable energy sources.
[29], 2020	A detailed review of different solutions for the integration of wind energy sources.	The article suggests that researchers should find the link between wind power forecasting to meet system demand. In this regard, our review can give an overview of the influence of wind power forecasting to maintain the required balance between generation and demand in a power system with considerable wind power levels (contribution option).
[36], 2021	The manuscript points out the advantages and disadvantages of different wind energy forecasting approaches for integrating wind energy sources.	The manuscript analyses and classifies different wind power forecasting methods. The authors highlight the importance of wind power forecasting for resource scheduling tasks one day ahead. However, they do not address the issue of frequency control assisted by wind power prediction.
[35], 2021	The survey highlights the need to coordinate different frequency control techniques for different renewable energy sources.	No reviews has been found that contributes to the topic highlighted above until the review's publication date (contribution option).
[37], 2021	The paper presents a review that expands the approaches applied to wind energy forecasting.	It is a very general review regarding the use of these techniques in frequency control.
[32,33], 2022 (both)	Review of different approaches related to artificial intelligence that could benefit the renewable energy sector and load frequency control systems.	Only artificial intelligence techniques that may be useful are summarized, without considering practical implementations in real scenarios.

2. Wind Power Forecasting

Before presenting the review results on state-of-the-art wind power forecasting methods, a brief description of wind power ramps, the classification of forecasting methods, and the forecast horizon time is presented.

The stochastic nature of wind provokes high variations in wind power. In general terms, these variations in wind power are sudden deviations in the magnitude of wind energy in a given time, defined by (1):

$$|P_w(t + \Delta t) - P_w(t)| > \Delta P_{crit} \quad (1)$$

where $P_w(t)$ is the wind power produced in a specific time, Δt is a time interval corresponding to two consecutive samples, and ΔP_{crit} is a limit value of the variation in the wind power, normally considered as 50% of the wind farm's capacity [40–42]. In another case, in reference [43], ΔP_{crit} is considered to be 3% of the wind farm's installed capacity. Probst O. [44] mentions that a critical variation in wind power is 3 MW/min. Figure 2 illustrates the wind power variation and the limit values that define ramp events. It is possible to identify two types of ramp events: ramp-up events, or an excess of wind power; and ramp-down events, or a lack of wind power. The red dotted line represents the threshold value for a ramp-up event (P_{th}^U), and the blue dotted line represents the threshold value for a ramp-down event (P_{th}^L).

Wind energy forecasting models can be classified according to their time horizons:

1. Short term: from 10 min to 6 h. Applications: regulation actions and real-time operations.
2. Medium term: from 6 h to 1 day. Applications: load dispatch planning and decisions on operational security.

3. Long term: 1 day upwards. Applications: reserve requirements and maintenance schedules.

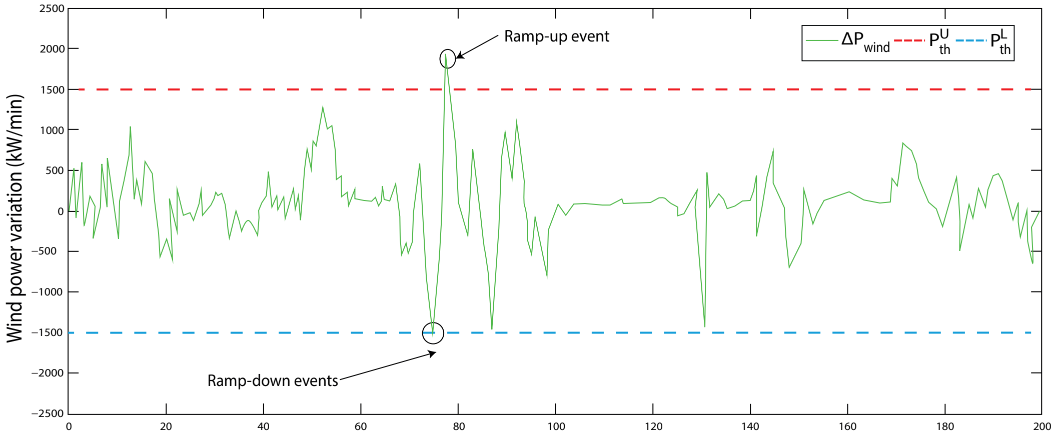

Figure 2. Representation of wind power ramp events.

Table 2 presents the time horizon considered in the studies reported in this review, which are all short term. Short-term forecasts with a time horizon of 1 h were the most frequent option. In the case of the wind farm dispatch schedule, the short-term forecast, between 30 min and 3 h, is the preferred option, according to [40]. The advantage of short- and medium-term forecasts is their greater accuracy and robustness.

Table 2. Wind power forecast model horizon times revised.

Study	Horizon Time/Short Term
[45,46]	10 min to 3 h
[40,47–49]	1 h
[43,48]	10 min to 1 h
[50]	1 h to 6 h
[41]	6 h
[51]	30 min to 1 h
[52]	15 min to 4 h

According to the methodology used, wind energy forecasting methods can be classified into three groups: (1) persistent methods, (2) physical methods, and (3) statistical methods. These can also be combined in hybrid methods. The differences between each method are the variables used, the accuracy, the timescale, and the complexity of the method [38].

- Persistent methods play a key role in comparative studies, as they serve as reference models for measuring the accuracy of new forecasting methods. Their contribution to the analysis of improvements in forecasting methods is significant. A persistent method is a simple model that assumes that the value of a variable in the future will be the same as in the present or recent past.
- Physical methods are NWP models. These methods require large amounts of data, such as wind speed data, wind direction, pressure, and temperature, e.g., to predict wind speed. With physical methods, time horizons of several hours, even days, can be obtained.
- Statistical methods demonstrate high adaptability with their foundation in nonlinear relationships between wind speed and wind power. Adjusting model parameters, such as in auto-regressive (AR) models and ANNs, among others, allows for the training process using historical data to obtain wind power predictions for short periods without compromising accuracy; e.g., in [40], a ramp power forecasting model is proposed.

- Hybrid methods, which are promising combinations of physical and statistical methods or different statistical methods, hold significant potential for the future of wind energy forecasting. Their ability to leverage the strengths of each technique to enhance prediction accuracy is a cause for optimism despite their inherent complexity. For example, in reference [53] a combination of long short-term memory (LSTM) and a convolutional neural network (CNN) is proposed to predict wind energy.

Table 3 summarizes the articles reviewed in this manuscript, with the column labeled "others" highlighting models based on other machine learning techniques such as single-task learning (STL), Kalman filter, random vector functional link network (RVFLN), and random forest regression (RFR), which are used as reference models in a comparative study with the newly proposed models.

Additionally, the seventh column indicates whether the articles implement time-series preprocessing (TS-PP). A "yes" signifies that the article employs a time-series preprocessing technique, while a "no" indicates the absence of such a technique. The eighth column indicates whether the forecasting is about wind power (WP). The ninth column indicates whether the article forecasts wind power ramps (PRs). An "X" marks the type of methods the new forecast model is compared to and whether it predicts WP or wind PRs. All manuscripts on wind power forecasting methods or ramps analyzed in this review involved simulations with real wind farm data.

All studies have a fixed time horizon except for articles [54,55]. The minimum time horizon is 10 min, and the maximum is 6 h. González Sopeña et al. [54] present a method that predicts wind power one step ahead, and Probst et al. [55] present a forecasting wind power method for two time steps ahead.

The methods proposed in [40,41,47,48,51,56] have been developed to increase the efficiency of wind energy/wind power ramp forecasting methods and facilitate the integration of wind farms in different countries, such as the United States, Uruguay, Brazil, Spain, India, and China. References [55,57,58] propose wind energy/wind power ramp forecasting methods to improve the wind energy trimming procedure and increase the lifetime of components of an ESS. It is typical to find an ESS generic model due to its low computational cost, as shown in [52,56,57,59].

The methods proposed in [41,43,45–51,53,54,60,61] use new hybrid topologies of machine learning, support vector regression (SVR), ANN, deep learning (DL), and methods based on LSTM for forecasting wind power ramps and wind power using real data from wind farms from different countries. However, these works focus on testing new wind power forecasting methodologies without visualizing a possible complementary implementation to frequency control systems. Zucatelli P et al. [48] perform wind power forecasting and wind power ramps at different heights (81.8 m, 100 m, 101.8 m, 120 m, and 150 m; which are the heights where the anemometers of the wind farms are located) in tropical and subtropical areas of Brazil and Uruguay. The good results obtained suggest that the proposed method can be used as a tool for power grid operators in the energy supply. Reference [51] concludes that the generalization of a wind power forecasting method is not possible for the continental Spanish region due to several factors intervening during the training process of the extreme learning machine (ELM) network. The main result presented in ref. [46] is the reduction in RMSE and MAE in the wind power forecast using a model based on several "learners" or trees with the adoption of the ensemble approach. The authors also highlight that this type of model can predict the behavior of wind turbines and help prevent failures in the wind conversion system.

Table 3. Summary of wind power and wind power ramp forecasting methods reviewed.

Study	Proposed Method	Comparison Methods				TS-PP	WP	PR	Horizon Time	Description
		ANN	SVR	AR Model	Others					
[59], 2014	Power ramps control and ESS				X	No		X	A 30 min step forward	A wind power ramp control to meet the power ramp limit from power system with the least demand of ESS and least waste of wind resource.
[58], 2014	Dispatch algorithm based on stochastic programming	-	-	-	-	No	X		24 h	Maintain the same charge/discharge cycles of each of the BESS units and provide support for the variability of wind energy produced.
[49], 2017	Auto-regressive logic models			X		No		X	1 to 2 h, 1 h resolution	This study proposed wind power event forecasting based on an auto-regressive logic model with six thresholds.
[57], 2018	Coordination of fast and slow responses through conditional range metric (CRM)	-	-	-	-	No	X		1 h, 1 min resolution	Coordinating the fast- and slow-response ESSs is expected to reduce the variability in hourly wind power generation and maximize the life span of the fast response unit.
[52], 2019	LSTM-ADAM for a coordinated dispatch method	X			X	Yes		X	4 h, 15 min resolution	To guarantee a more accurate and effective dispatch plan, the proposed method resolves the phenomena of over-adjustment and under-adjustment due to huge forecast errors.
[56], 2019	Ramp classification and ESS loading/unloading strategies				X	No		X	24 h, 30 min resolution	With the proposed method and a combination of an ESS, the grid code requirements of China are achieved.
[40], 2019	SVR variants		X			Yes		X	30 min to 3 h, 10 min resolution	The method proposed is used to enhance five wind farms' (sites from USA, India, and Spain) capacities for ramp event short-term forecasting.
[42], 2019	MSAR–swinging door algorithm ϵ method			X		No		X	4 h, 15 min resolution	A wind ramp event forecasting based on an MSAR, the authors present lower power ramp prediction errors and higher correlation.
[53], 2020	Bi-LSTM-CNN	X			X	No	X		10 min, 5 min resolution	Wind power forecasting method based on a hybrid model; Bi-LSTM-CNN has not yet been applied in the application of wind power forecasting.
[41], 2020	Multi-task learning deep neural network (MTL-DNN)				X	Yes	X		A 6 h step forward	This study generates a general prediction of power ramps for all wind farms in Spain.
[51], 2020	ELM and synthetic minority over-sampling technique (SMOTE)	-	-	-	-	Yes		X	6 h	Wind power ramp event detection was applied on three wind farms in Spain. The data used to train the algorithm correspond to different year seasons for each wind farm. This feature does not allow generalization of the method proposed for all wind farms in Spain.

Table 3. *Cont.*

Study	Proposed Method	Comparison Methods				TS-PP	WP	PR	Horizon Time	Description
		ANN	SVR	AR Model	Others					
[43], 2020	OpSDA–CNN–LSTM	X				No		X	10 to 60 min, 15 min resolution	The authors present this new wind ramp forecasting, which improves the mean absolute percentage error by 5% and 22% in comparison with an LSTM and an ANN.
[60], 2021	Discrete wavelet transform (DWT) and twin support vector regression (TSVR)	X			X	Yes		X	A 10 min step forward	Wind ramp event forecasting for onshore, offshore, and hilly sites.
[48], 2021	Wavelet packet decomposition (WPD) and DL+ANN	-	-	-	-	Yes	X	X	1 h, 10 min resolution	The hybrid method can be applied in commercial wind turbines located in tropical and subtropical regions of Brazil and Uruguay.
[50], 2021	Generative adversarial network (GAN)	X	X	X	X	No	X	X	A 15 min step forward	The proposed method solves the over-fitting problem for wind power and ramp event forecasting through a min–max game based on the GAN framework.
[55], 2021	Forecast-based curtailment (FBC)				X	No		X	Two steps forward, 10 min resolution	Compared to traditional approaches, the FBC method offers a wind turbine the ability to self-regulate without the need for an ESS at a lower energy cost.
[46], 2021	Bagged regression trees	-	X	-	X	No	X		10 min, 5 min resolution	New data-driven model of an SCADA system using a decision tree ensemble approach and latent variable regression.
[45], 2022	Evol–CNN	X	X	X		No	X		10 min, 1 h and 3 h, 10 min resolution	Improves the performance of the proposed method through an optimization algorithm to avoid a local minimum of the hyperparameters.
[47], 2022	Gaussian mixed clustering (GMC) + deep neural network	X				Yes	X		1 h, 10 min resolution	Improves the accuracy of WPF, reducing the error by 9.56% in MAE and facilitating the integration of a wind farm into the electrical grid.
[54], 2022	Deep learning spiking neural network (SNN)	-	-	-	-	No	X		A 10 min step forward	Improves computational cost of state-of-art machine learning and deep learning through a new wind power forecasting paradigm based on neuromorphic algorithms.

References [40,41,47,48,50–52,60] implement preprocessing techniques, for example, the synthetic minority over-sampling technique (SMOTE) [51], wavelet transform [40], Gaussian mixture model [47], and discrete wavelet transform [48,60]. This preprocessing of the data with which the forecasting models are trained helps in solving imbalanced data problems. In contrast, reference [43] does not implement a preprocessing of the time series. However, the proposed method can extract four characteristics of ramp events: (1) rate of change, (2) amplitude, (3) onset time, and (4) ramp duration. The proposed method combines a convolutional neural network (CNN) with an LSTM. An artificial neural network with backpropagation and an LSTM are compared with the proposed method. The CNN-LSTM model correctly forecasts 90% of ramps. In reference [47], a Gaussian mixture model-based data preprocessing improves computational efficiency and the accuracy of the probability distribution in probabilistic forecasting is presented. Gonzalez et al. [54] proposed a novel wind power forecasting method based on neuromorphic algorithms that improve the computational cost of prediction. In [57], a method is proposed based on a novel metric (CRM; conditional rank metric). The CRM is a power measurement variability metric that applies probability models to data to quantify short-term power variations empirically.

Figure 3 shows a general distribution of the machine learning techniques applied to forecasting wind power and power ramp events analyzed in this work. Approximately 20% of these papers implemented a variant of SVR or a DL technique, 27% implemented ANN, and 33% applied some variant of supervised machine learning (SML). The combination of SVR and DL to achieve greater accuracy is suggested in [60]. The current trend for handling large amounts of information is big data, according to [56]. Reference [46] presents a new alternative to RFR methods. This paper's main result is the reduction in the root mean square error (RMSE) and mean absolute error (MAE) in the wind power forecast using a model based on several "learners" or trees with the adoption of an ensemble approach. The authors also highlight that this type of model can predict the behavior of wind turbines and help prevent failures in the wind conversion system.

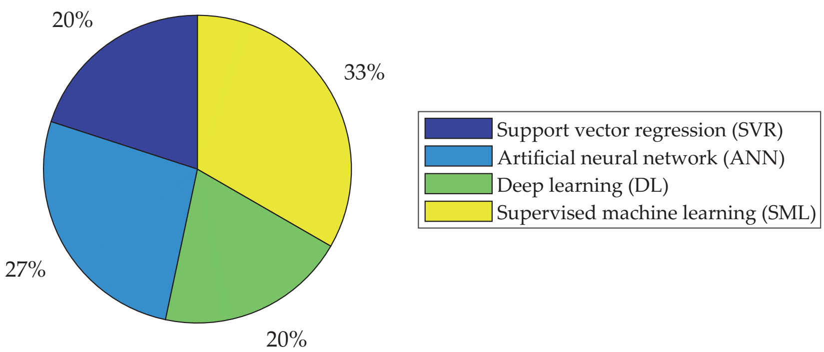

Figure 3. Machine learning (ML) techniques used in forecasting wind power and power ramp events.

3. Frequency Control Review

Figure 4 shows the frequency dynamics of an electrical system when a disturbance occurs. Up to the first 10 s after the disturbance, the frequency reaches a minimum or nadir frequency (NF) value with a high ROCOF. Conventional generators connected during the disturbance reduce the ROCOF and NF because they release kinetic energy stored in their rotating masses. This process is known as inertial response or fast frequency response (FFR). In the case of wind turbines, the inertial response can be emulated by utilizing additional control loops that modify the operating point of the wind turbine to provide inertial support [62,63]. After the inertial response, the primary frequency control (PFC) system stabilizes the electrical frequency at a new stable value. The secondary frequency control (SFC) system uses frequency regulation reserves to reestablish the electrical frequency to its nominal value. Finally, the tertiary frequency control (TFC) system ensures frequency regulation reserves for possible future contingencies.

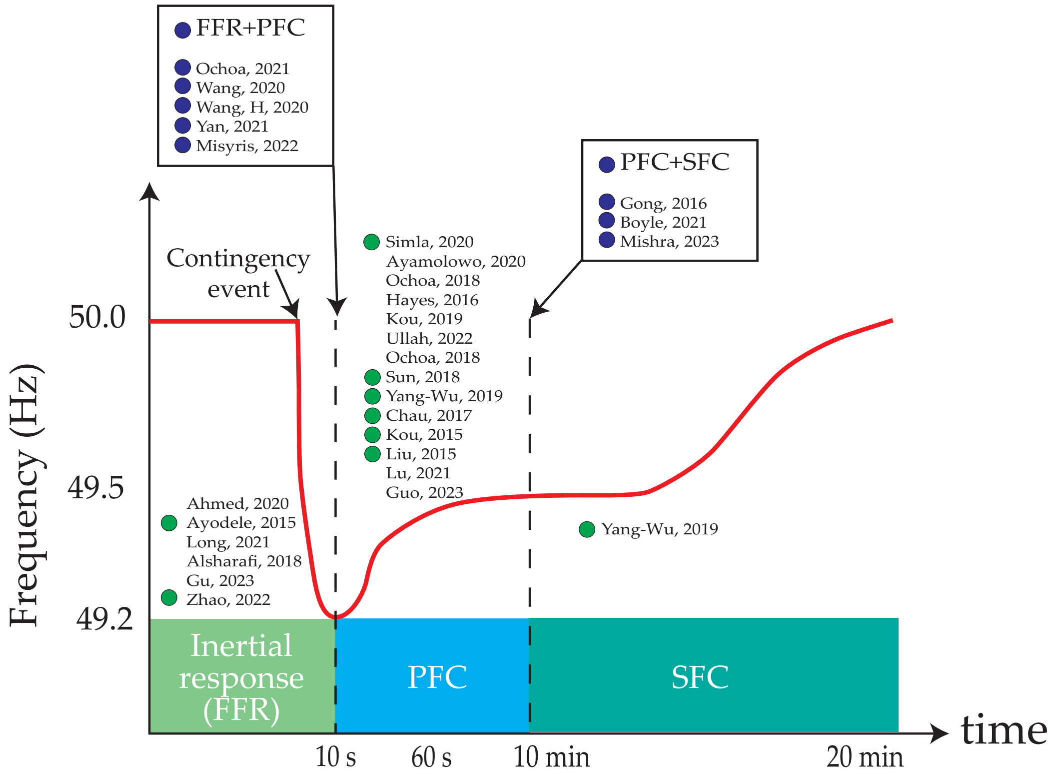

Figure 4. Behavior of the grid frequency during a contingency and location of references according to the frequency control type [27–30,59,62–84].

In the first part of Figure 4 (with a timescale in seconds), the articles focusing on FFR and PFC applications are presented. References [62,64–66] focus on minimizing the ROCOF and the nadir point, while [67,68] emphasize reducing the nadir point of the electrical frequency after a disturbance. On the right side of the figure, the results of novel methods implemented for SFC system tasks are shown. The articles reviewed in this section are categorized as depicted in Figure 4:

- The circles without a background color correspond to works that implement different frequency control techniques, such as adaptive control, droop control, inertial control, and maximum power point tracker (MPPT), among others. For example, Boyle et al. [69] modify the operating point by calculating a new power coefficient (C_p), required each time the frequency variation is greater than or equal to 0.015 Hz. Another alternative is torque limiter-based inertial control (TLIC), which allows for extracting the maximum kinetic energy limited by the wind turbine's maximum torque. Reference [70] presents a modification of a conventional TLIC that delays its response to improve the NF. In addition, the authors conclude that the time of occurrence of the maximum and minimum points of the frequency response is different.
- The green circles indicate works with implemented frequency control systems combined with ESSs.
- The blue circles represent the articles that combine different frequency controls, FFR/PFC or PFC/SFC. Reference [71] presents a coordination strategy between a PFC and an automatic generation control (AGC), which utilizes the storage capabilities of electric vehicles. References [62,67] present a combination of simulated inertia with droop control and optimized power point tracking (OPPT), respectively. The authors of reference [72] present a method of inertial and primary frequency control based on OPPT and pitch control. The objective of the frequency control method is to maintain the rotational speed of the wind turbine within an allowed range and not destabilize it. The disadvantage of this method is the introduction of small torque oscillations in the WECS electric generator, which can produce mechanical fatigue

in the drive-train components. Another common combination is inertial control and droop control. For example, in reference [85], the authors present a combination of inertial and droop control with variable gains as a function of the turbine rotation speed. The inertial control gain has parabolic dynamics, while the droop control gain is linear. At the beginning of a frequency droop event, both gains are set to allow the highest amount of active power injected by the turbine. Finally, these gains decrease their values to ensure that the wind turbine rotation speed is within the operating range and to prevent the turbine from entering a stall state. Sun B. et al., in ref. [73], present a wind power forecasting method for frequency regulation. This method is based on the combination of a distributed model predictive control (DMPC) with a very short-term forecast of wind power (1 min) based on a combination of least squares support vector machine (LSSVM) and extreme leaning machine (ELM). The authors in ref. [74] use a wind power forecast for primary frequency control for four interconnected areas where wind turbines and conventional generators feed the power system. The forecasting method is based on a Kalman filter to modify the reference signal of a conventional PID control, which adjusts the output power of the synchronous generators. The PID controller reference point is modified by a phase compensation link, obtaining a frequency variation less than ± 0.2 Hz (within the allowed range). Chau T. et al., in ref. [75], present a rotor-side controller (RCS) of a modified doubly fed induction generator (DFIG). The proposed method is based on the tie-line power deviation (TLPD) as an input signal, and the authors optimize the controller parameters by means of PSO. One of the advantages of the new method is that it is embedded in the controller and power converters of the DFIG. Therefore, no extra equipment like an automatic voltage regulator (AVR) or flexible alternating current transmission system (FACTS) is required.

Installing large-scale wind farms on weak electrical power systems can lead to imbalances in the electrical grid due to the variability in the wind resources. To address this issue, developing a control system capable of minimizing the negative impact of wind farms on weak electrical grids is crucial to increasing the level of reliability of the wind generation system [32]. In addition, inertial control, droop control, and AGC are some frequency control methods reported in the literature [71]. Further, the most widely used AI techniques for the integration of large-scale renewable sources while minimizing frequency fluctuation can be classified as follows [76]:

1. ANN methods combined with optimization algorithms, e.g., PSO. This combination improves efficiency and reduces computation time.
2. FLC combined with PID controllers improves response time.
3. The use of ACO to solve maximization problems in a hybrid plant (e.g., photovoltaic wind) sizing.

A brief review of contributors to system inertia such as battery energy storage systems (BESSs), supercapacitor energy storage (SCES), superconducting magnetic energy storage (SMES), and CAES, among others, is presented in ref. [61] for more information. For example, a hybrid combination comprising BESSs and SCES could offer a fast frequency response in RESs connected to a weak power system. BESSs based on lead–acid and supercapacitors are the most frequently used storage technologies in the articles found in this work. However, the energy production deficit is covered by implementing other ESSs, such as pumped storage hydro (PSH), CAES, FESS, SCES, and SMES, which are reported in ref. [67]. In this sense, the ESS size and energy dispatch strategies are some challenges encountered. PFC is the most frequent frequency control method in the articles reviewed in this manuscript. Finally, nine manuscripts in the papers examined present combinations of FFR and PFC or PFC and SFC. Table 4 summarizes the frequency control methods analyzed in this review.

Table 4. Summary of frequency control methods reviewed.

Study	Proposed Method	Comparison Methods	Frequency Control	Method of Validation	Wind Penetration
[83], 2015	Stochastic predictive control of BESS for wind farm dispatching	DMPC	PFC	Simulation	Not reported
[84], 2015	A method for sizing ESSs to increase wind penetration as limited by grid frequency deviations	-	PFC	Simulation	10%
[86], 2016	Frequency regulation for hybrid plants	-	PFC	Simulation	10–40%
[87], 2016	Optimised operation of an off-grid hybrid wind–diesel–battery system using genetic algorithm	-	PFC	Simulation	Not reported
[66], 2016	Comparison of two energy storage options for optimal balance of wind farm power outputs	-	FFR	Simulation	Not reported
[88], 2017	Coordinated control strategy of a BESS to support a wind power plant	-	PFC/SFC	Simulation	≈10%
[75], 2017	Schemes for rotor side controller (RSC) of DFIG	No frequency control and TLPD without optimization	PFC/SFC	Simulation	No reported
[67], 2018	Inertial emulation controller and droop controller	Droop control, simulated inertia control, and fast power reserve emulation	FFR/PFC	Simulation	40%
[73], 2018	A frequency control strategy based on model predictive control	Centralized and decentralized MPC	PFC/SFC	Simulation	Not reported
[63], 2018	MPPT gain optimization and inertial control	-	FFR	Simulation Real conditions	≈30%
[89], 2018	Droop coefficient prediction control and PFC (PDC-PFC)	-	PFC	Simulation	≈10%
[72], 2018	Modification of the operating point of the power curve by combining virtual inertia control and pitch control	OPPT, pitch control and OPPT + pitch control	FFR/PFC	Simulation Real conditions	20%
[85], 2018	Inertial control + droop control with variable gains depending on the rotational speed of the wind turbine	Droop control with constant gain	FFR/PFC	Simulation	18.61%
[68], 2019	Nonlinear model predictive control (NMPC)	Frequency control with fixed and variable droop	PFC	Simulation	13%
[74], 2019	Kalman filter + PID	Conventional PID	PFC	Simulation	No reported
[90], 2019	Validating performance models for hybrid power	-	-	Simulation	Not reported
[77], 2020	Droop control under cyber uncertainty	MPPT controller and virtual inertia control	PFC	Simulation	Not reported
[65], 2020	Adaptative PID, differential evolution (DE) algorithm, and load fatigue	-	FFR	Simulation	20–30%
[78], 2021	Frequency controller based on reduced-order virtual machine synchronous machine (VSM)	-	FFR	Simulation	Not reported
[69], 2021	Modification of the power curve tracking coefficient	No frequency control and droop control	PFC	Simulation	No reported
[64], 2021	Fast frequency support using supercapacitors	-	FFR	Simulation	Not reported
[62], 2021	OPPT	-	FFR/PFC	Simulation	20%
[79], 2021	Low-voltage-ride-through (LVRT) control based on speed control	-	PFC	Simulation	Not reported
[71], 2022	AGC to wind farm and an electric vehicle (EV)	-	PFC/SFC	Simulation	≈57%
[80], 2022	Impact evaluation of inverter-based sources on the frequency response of a low inertia power system	-	PFC	Simulation	Not reported
[22], 2023	A full inertia virtual droop control for a BESS	-	PFC	Simulation Real conditions	100% (wind + PV)
[81], 2023	A machine side controller (MSC) and grid side controller (GSC) based on Modular Multilevel Matrix Converters (M3Cs)	DC link voltage control (MSC) and active and reactive power control (GSC)	PFC	Simulation Experimental	Not reported
[82], 2023	A deep learning-assisted adaptive nonlinear unloading strategy	A linear and quadratic unloading strategy	FFR	Simulation	≈30%
[70], 2023	Inertial control based on a torque limiter with delayed response	MPPT and conventional TLIC	FFR/PFC	Simulation Experimental	30%

4. Discussion

The articles reviewed in this document include a wide variety of artificial intelligence techniques, such as convolutional neural networks, deep neural networks, support vector regression techniques, and different machine learning methods such as LSTM, auto-regressive integrated moving average (ARIMA), and ELM. Additionally, fuzzy logic techniques, optimization techniques such as ACO, genetic algorithms, and cuckoo search algorithms, among others, are used to predict wind energy [32]. One of the results of this review indicates that supervised machine learning techniques, such as ELM, are the most used for forecasting wind energy due to the following advantages: computational efficiency, lower risk of adjustment, and effectiveness in noisy data sets compared to other techniques such as ANN and SVR. On the other hand, SVR and ANN are the most used methods with time-series processing techniques to improve their performance. Approximately 50% of the articles analyzed use a time-series processing method. The timescale used for wind power forecasting depends on its application. The analyzed articles report short-term forecast methods (see Table 2) applied for predictive control tasks that aim to minimize wind energy variability. If the forecasting method's time horizon exceeds one day, it can be considered a system complementary to an SFC.

Conventional controls such as inertial and droop control are among the frequency control methods for integrating wind generation systems. It should be noted that these classical controllers have been modified to enable the participation of wind turbines in frequency support tasks. For example, in [62], they modify the operating point of the wind turbine when a frequency variation is detected, enabling frequency support in the wind turbine. In addition, control systems are combined with ESSs and hybrid control methods based on optimization, such as genetic algorithms, particle swarm optimization, firefly algorithm, and differential evolution [33]. For preliminary studies and due to their simplicity, most of the reviewed articles use generic ESS models. However, some researchers propose frequency control methods supported by different ESS technologies, i.e., supercapacitors, lithium-ion polymer-based BESSs, and optimized PSH models. Due to the large energy storage capacities of different ESS technologies, these devices are used as auxiliary systems to extend the frequency support capabilities of a wind farm. In the case of a low-frequency contingency event (e.g., an increase in the load connected to the power system), where the wind turbine controller cannot minimize the adverse effect of the contingency event, the ESS operates in unloading mode and injects active power into the grid according to an energy strategy. In the opposite case, the ESS can operate in loading mode in a high-frequency event, absorbing the surplus wind energy production. In [88], the energy strategy mentioned above is implemented, considering the state of charge of a BESS.

Figure 5 shows a qualitative classification of the techniques used as PFC or SFC analyzed in this work. It can be observed that frequency control methodologies are applied as PFC and SFC [71,73,88], and different frequency control techniques are combined to develop new PFC techniques [63,77].

Hybrid frequency control methods extend the frequency support capabilities of wind turbines compared to a conventional method. These hybrid methods combine different frequency control approaches with or without ESSs. In hybrid methods, the combination of ESSs, minimization of ESS size, maximization of the lifetime of each system element, and selection of ESS technology are the main approaches observed in the articles of this review and the main challenges to be considered in the use of ESSs as auxiliary systems in frequency support tasks assisting large-scale wind farms. As seen in Figure 4, and depending on the technical characteristics (nominal power, response time, power density, and energy), ESSs are applicable in all operating ranges of frequency control, from fast frequency response to primary control and secondary control [61]. References [30,36] analyze all the characteristics of the different ESS technologies and their possible uses in primary and secondary frequency control systems. Other alternatives that have been reported are the development of new control paradigms based on MPPT optimization, droop control, and inertial control systems combined with predictive control systems. These systems are ideal for nonlinear systems and maximize the use of kinetic energy stored in the moving parts of the wind turbine.

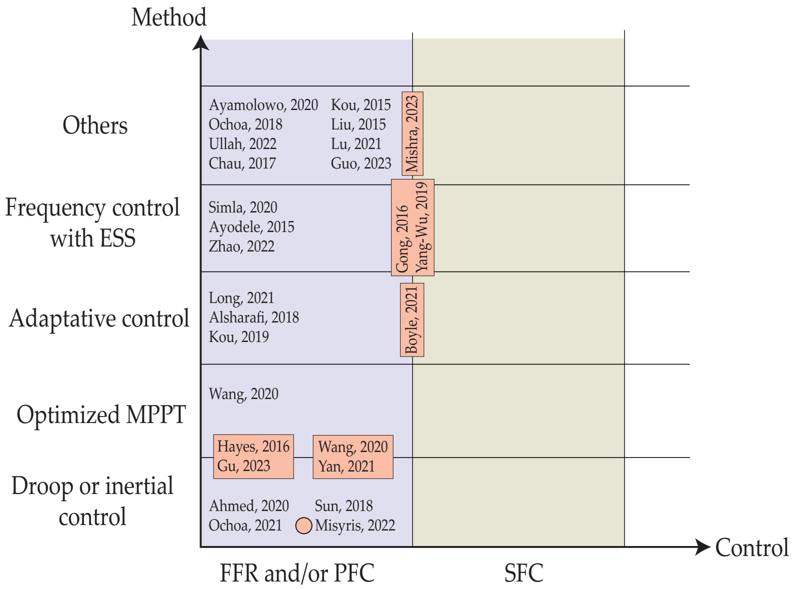

Figure 5. Qualitative classification of frequency control methods analyzed [27–30,59,62–71,73–84].

It should be noted that four investigations coordinate the primary and secondary frequency control strategies and five investigations combine a fast frequency response with primary frequency (see Figure 5). In ref. [71], an AGC for wind farms and combining energy storage systems and electric vehicles is considered. In ref. [73], a predictive control method combined with wind power forecasting with a 1-minute time horizon is presented, and in ref. [88] a BESS as PFC and SFC is proposed through an improved state machine-based control strategy. The method proposed in ref. [88] considers charging/discharging strategies based on the state of charge (SOC) of the BESS and operational constraints, i.e., charging/discharging rate limits and SOC range. The authors conclude that the BESS with the proposed control method can help the wind power plant to provide multi-timescale frequency support, reducing the ESS size and maximizing the lifetime. Reference [73] shows the implementation of wind power forecasting targeting frequency control tasks.

The improvement that exists when frequency control tasks in wind farms are assisted by ESSs or wind power forecasting methods is noticeable. In reference [73], the authors present the combination of a wind power forecast based on LSSVM, an updated SVM variant, and a DMPC control. The simulation setup in this paper is made up of three interconnected areas with a total wind capacity of 951 MW. In each area, there is a total synchronous generation of 1000 MW. The method proposed in this research presents an RMSE in the frequency deviation (from its nominal value) of 1.74% compared to a control method based on DMPC, which presents an error of 3.44%, with both results having a total load change simulation of 110 MW. Furthermore, in the comparison method where wind turbines do not participate in frequency regulation tasks, synchronous generators contribute 8.06 MW on average. In contrast, with the proposed method where wind turbines participate in frequency regulation tasks, the active power contribution by synchronous generators decreases to 7.1 MW. The other case highlighted in this review is reference [74], in which the authors compare the proposed method with a conventional PID controller. The power system frequency with the conventional PID varies between 0.45 Hz and −0.35 Hz, while the method proposed in ref. [74] varies from 0.25 Hz to −0.35 Hz. This result indicates that the proposed method performs better in high-frequency events than the conventional PID controller. But, for low-frequency events, there is no difference.

Accuracy is the biggest challenge when using wind power forecasting to provide frequency support in WECS. Accuracy depends on the data quality and the efficiency of the forecasting method. ELM methods perform best when good quality (noise-free) data are not available. Otherwise, ANN and SVR can give good results, but only with some time-series preprocessing techniques, such as wavelet transform and SMOTE, among others.

Case Studies

Some articles perform case studies with real power system data and hypothetical RES penetration levels for a specific country region to analyze whether control systems can support frequency variations when RESs increase. The results in ref. [13] show that the RES penetration level (wind and solar) should not exceed 10% of Jordan's annual peak demand to avoid grid congestion. It has been proposed that the grid be upgraded to support up to 1600 MW of renewable energy generation by 2020. The authors will not provide further details of the control employed by wind turbines.

ESS use-case studies are analyzed in ref. [20,25]. Le et al., in ref. [20], optimize the ESS controller reference calculation and the charging–discharging strategy of ESS devices. The authors perform simulations of a 27-bus using data from 14 wind farms between 2004 and 2006. The study shows that with the use of ESSs, the level of wind penetration increases from 1.7% to 8%.

The island case studies are the examples with the highest levels of RES penetration due to their geographical location, which makes it difficult to connect to a continental power system. In ref. [25], they integrate an 800 kW wind turbine and a 240 kWh photovoltaic plant into a 91.724 MWh electrolyzer on the island of Anafi, Greece. In this case, penetration reaches 84.68%, where the surplus energy is used to produce 15.3 t of hydrogen per year (the authors do not mention the type of frequency control used in the RES). Another case of an isolated power system is presented in ref. [63], where the authors propose three improvements to the power system of the Galapagos Islands, Ecuador:

1. Modification of the gain of the speed control system controller of the diesel generators of the system.
2. Modification of the MPPT curve of the wind turbines by adjusting the maximum allowed power.
3. Implementation of inertial control based on an extended optimal power point tracker (EOPPT).

The results of the simulations are (1) an improvement in the ROCOF by 89%, (2) a reduction in the ROCOF by 21.66%, and (3) a reduction in the ROCOF by 15%. The result of the third point is obtained from simulations with real data from the wind farm.

In ref. [22], a study is carried out on the island of Ponza, Italy, so that the island's power system is totally renewable. A total of 2.16 MW is divided into 1.16 MW of photovoltaic energy, 0.9 MW of wind energy, and 0.1 MW of co-generation. The authors perform simulations using a full inertia virtual droop control for a BESS.

5. Conclusions

The extensive literature review conducted in this study presents a comprehensive spectrum of solutions pertinent to frequency control and wind power forecasting for the grid-friendly integration of wind energy. The meticulously curated articles substantiate this discernible breadth, as elucidated in Tables 3 and 4. Noteworthy is the robust mathematical underpinning and modeling exhibited by many of these proposed solutions. Most of these methodologies have undergone meticulous scrutiny within computer simulation environments, while a select few have undergone experimental validation. It is imperative to underscore that many authors ardently affirm the broad applicability of their proposed solutions within authentic wind farm settings. Nonetheless, the absence of a rigorously controlled testing environment has impeded a comprehensive evaluation of the practical viability of the entire spectrum of solutions under consideration. This acknowledgment emphasizes the cautious interpretation of the purported applicability of the proposed solutions, signifying the need for further empirical validation and consideration of more realistic conditions for a robust assessment.

A possible idea for future research is made up of two parts. First, a PFC system that reduces the participation of synchronous generators during a contingency event. This PFC is based on virtual inertial control combined with an ESS. This possible solution is chosen since research demonstrates the availability of kinetic energy of the rolling masses of wind turbines can be useful for PFC tasks. Second, implementing a wind energy forecasting method helps establish a minimum amount of regulation reserves to reduce the variability in a variable renewable source and the system's response time to address a contingency event. These two parts must be coordinated by an optimized power management system coordinating the actions between the two frequency control systems. The improvement of a control system assisted by a forecasting method depends on several factors: the quality of data with which the forecasting method is trained, the configuration of the power system of the simulations to be performed, the efficiency of the prediction method, and the simulated contingency cases. Without considering the above, it is observed how the performance of frequency control improves concerning conventional controls according to the references cited in this review. A possible first candidate for a wind energy forecasting method is LSSVR due to its simple implementation and better performance than the other SVR technique variants.

In conclusion, the review presented in this article provides evidence for the need to develop further frequency control systems, energy management strategies, and wind power forecasting methods to provide frequency control at different timescales. To achieve this goal, new control strategies must be developed to coordinate different frequency control systems (primary and secondary) and the availability of regulation reserves and conventional generating resources. The challenge in developing a frequency control technique that includes different controllers operating on different timescales (primary and secondary control or inertial and primary control) is the coordination of the control techniques. For example, in the case of a combination of inertial control and droop control (PFC), the inertial limitations of the wind turbine must be considered to perform the frequency regulation task efficiently. For this case, delimiting the rotational speed variation is essential and requires much attention to prevent the wind turbine from operating in a stall state. In this same sense, an inertial control combined with a droop control can be adapted, with the difference being implementing an adaptive control that modifies the operating point of the wind turbine without following pre-established curves or functions (rotational speed and wind turbine electrical power). Furthermore, further research is necessary to analyze and understand how machine learning methods can be used for primary frequency control and how these methods could be combined with ESSs for improved performance. Finally, more studies are needed to investigate different wind power forecasting techniques and wind power ramp event prediction to improve the system's reliability.

Author Contributions: Conceptualization, B.L., L.I.M., D.O.-C. and S.M.; methodology, B.L., L.I.M. and D.O.-C.; validation, B.L., L.I.M. and D.O.-C.; formal analysis, B.L., L.I.M., D.O.-C. and S.M.; investigation, B.L. and L.I.M.; resources, L.I.M. and S.M.; writing—original draft preparation, B.L. and L.I.M.; writing—review and editing, D.O.-C. and S.M.; supervision, L.I.M. and D.O.-C. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Data will be made available on request.

Acknowledgments: This manuscript is an outcome of the Doctoral Program in Renewable Natural Resources offered by Universidad de Cuenca and Universidad del Azuay. Brian Loza gratefully acknowledges Universidad de Cuenca for funding his Ph.D. scholarship and extends his gratitude to the Department of Electrical Engineering at the Escuela Técnica Superior de Ingenieros Industriales (ETSII) of Universidad Politécnica de Madrid, Spain, for hosting his predoctoral research stay, which was important in the development of this work. The authors also thank Universidad de Cuenca for providing access to the Micro-Grid Laboratory and Faculty of Engineering facilities, which were essential for completing this research.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Saini, D.K.; Yadav, M.; Pal, N. Optimal allocation of distributed energy resources to cater the stochastic E-vehicle loading and natural disruption in low voltage distribution grid. *Sci. Rep.* **2024**, *14*, 17057. [CrossRef] [PubMed]
2. Hashemizadeh, A.; Ju, Y.; Abadi, F.Z.B. Policy design for renewable energy development based on government support: A system dynamics model. *Appl. Energy* **2024**, *376*, 124331. [CrossRef]
3. Tumse, S.; Bilgili, M.; Yildirim, A.; Sahin, B. Comparative Analysis of Global Onshore and Offshore Wind Energy Characteristics and Potentials. *Sustainability* **2024**, *16*, 6614. [CrossRef]
4. Woo, C.K.; Cao, K.H.; Qi, H.S.; Zarnikau, J.; Li, R. Price responsiveness of solar and wind capacity demands. *J. Clean. Prod.* **2024**, *462*, 142705. [CrossRef]
5. Barthelmie, R.J.; Larsen, G.C.; Pryor, S.C. Modeling Annual Electricity Production and Levelized Cost of Energy from the US East Coast Offshore Wind Energy Lease Areas. *Energies* **2023**, *16*, 4550. [CrossRef]
6. IRENA. Future of Wind: Deployment, Investment, Technology, Grid Integration and Socio-Economic Aspects (A Global Energy Transformation Paper 2019), International Renewable Energy Agency, Abu Dhabi. Available online: https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2019/Oct/IRENA_Future_of_wind_2019.pdf (accessed on 26 July 2024).
7. GWEC. Global Wind Report 2022. Available online: https://gwec.net/global-wind-report-2022 (accessed on 6 March 2024).
8. Our World in Data. Annual Change in Wind Energy Generation 2022. Available online: https://ourworldindata.org/grapher/annual-change-wind?tab=chart&country=~OWID_WRL (accessed on 23 June 2024).
9. Renewable Power Generation Costs in 2022. Available online: https://www.irena.org/Publications/2023/Aug/Renewable-Power-Generation-Costs-in-2022 (accessed on 29 February 2023).
10. Abbas, S.; Kazmi, S.; Naqvi, M.; Javed, A.; Naqvi, S.; Ullah, K.; Khan, T.; Shin, D. Impact analysis of large-scale wind farms integration in weak transmission grid from technical perspectives. *Energies* **2020**, *13*, 5513. [CrossRef]
11. Rahmann, C. Power System Stability with 100% Inverter Based Resources (IBRs) [Lecture]. Global PTS, 22 November 2022. Available online: https://globalpst.org/wp-content/uploads/Lecture-2-Stability-With-100-Inverter-Based-Resources-IBRs.pdf (accessed on 30 January 2024).
12. Kroposki, B. Integrating high levels of variable renewable energy into electric power systems. *J. Mod. Power Syst. Clean Energy* **2017**, *5*, 831–837. [CrossRef]
13. Feilat, E.; Azzam, S.; Al-Salaymeh, A. Impact of large PV and wind power plants on voltage and frequency stability of Jordan's national grid. *Sustain. Cities Soc.* **2018**, *36*, 257–271. [CrossRef]
14. Zhou, Y.; Nguyen, D.; Kjaer, P.; Saylors, S. Connecting wind power plant with weak grid-challenges and solutions. In Proceedings of the Power and Energy Society General Meeting, Vancouver, BC, Canada, 21–25 July 2013; pp. 1–7.
15. Marquis, M.; Wilczak, J.; Ahlstrom, M.; Sharp, J.; Stern, A.; Smith, J.; Calvert, S. Forecasting the wind to reach significant penetration levels of wind energy. *BAMS* **2011**, *92*, 1159–1171. [CrossRef]
16. Datta, U.; Kalam, A.; Shi, J. The relevance of large-scale battery energy storage (BES) application in providing primary frequency control with increased wind energy penetration. *J. Energy Storage* **2019**, *23*, 9–18. [CrossRef]
17. Brown, T.; Bischof-Niemz, T.; Blok, K.; Breyer, C.; Lund, H.; Mathiesen, B. Response to 'Burden of proof: A comprehensive review of the feasibility of 100% renewable-electricity systems'. *Renew. Sustain. Energy Rev.* **2018**, *92*, 834–847. [CrossRef]
18. Hoke, A.; Gevorgian, V.; Shah, S.; Koralewicz, P.; Kenyon, R.; Kroposki, B. Island power systems with high levels of inverter-based resources: Stability and reliability challenges. *IEEE Electrif. Mag.* **2021**, *9*, 74–91. [CrossRef]
19. Shen, F.; Liu, S.; Ouyang, G.; Shan, J.; Cao, Y.; Wang, Z.; Zhai, S. Inertia estimation of power system with new energy considering with high renewable penetrations. *Energy Rep.* **2023**, *9*, 1066–1076. [CrossRef]
20. Le H.; Santoso, S.; Nguyen, T. Augmenting wind power penetration and grid voltage stability limits using ESS: Application design, sizing, and a case study. *IEEE Trans. Power Syst.* **2012**, *27*, 161–171. [CrossRef]
21. Yan, R.; Saha, T.; Modi, N.; Masood, N.; Mosadeghy, M. The combined effects of high penetration of wind and PV on power system frequency response. *Appl. Energy* **2015**, *145*, 320–330. [CrossRef]
22. Succetti, F.; Rosato, A.; Araneo, R.; Di Lorenzo, G.; Panella, M. Challenges and Perspectives of Smart Grid Systems in Islands: A Real Case Study. *Energies* **2023**, *16*, 583. [CrossRef]
23. Fragoso, D.; Santos, A.; Fernandes, E.C. Increasing RES penetration through H2 technologies on Flores island, Azores: A techno-economic analysis. *Int. J. Hydrogen Energy* **2023**, *48*, 19846–19861. [CrossRef]
24. Ghirardi, E.; Brumana, G.; Franchini, G.; Perdichizzi, A. H2 contribution to power grid stability in high renewable penetration scenarios. *Int. J. Hydrogen Energy* **2023**, *48*, 11956–11969. [CrossRef]
25. Dimou, A.; Moustakas, K.; Vakalis, S. The Role of Hydrogen and H2 Mobility on the Green Transition of Islands: The Case of Anafi (Greece). *Energies* **2023**, *16*, 3542. [CrossRef]
26. Nguyen, N.; Mitra, J. An analysis of the effects and dependency of wind power penetration on system frequency regulation. *IEEE Trans. Sustain. Energy* **2015**, *7*, 354–363. [CrossRef]

27. Simla, T.; Stanek, W. Reducing the impact of wind farms on the electric power system by the use of energy storage. *Renew. Energy* **2020**, *145*, 772–782. [CrossRef]
28. Ayamolowo, O.; Manditereza, P.; Kusakana, K. Exploring the gaps in renewable energy integration to grid. *Energy Rep.* **2020**, *6*, 992–999. [CrossRef]
29. Ahmed, S.; Al-Ismail, F.; Shafiullah, M.; Al-Sulaiman, F.; El-Amin, I. Grid integration challenges of wind energy: A review. *IEEE Access* **2020**, *8*, 10857–10878. [CrossRef]
30. Ayodele, T.; Ogunjuyigbe, A. Mitigation of wind power intermittency: Storage technology approach. *Renew. Sustain. Energy Rev.* **2015**, *44*, 447–456. [CrossRef]
31. Aziz, A.; Oo, A.; Stojcevski, A. Frequency regulation capabilities in wind power plant. *Sustain. Energy Technol. Assessments* **2018**, *26*, 47–76. [CrossRef]
32. Liu, Z.; Sun, Y.; Xing, C.; Liu, J.; He, Y.; Zhou, Y.; Zhang, G. Artificial intelligence powered large-scale renewable integrations in multi-energy systems for carbon neutrality transition: Challenges and future perspectives. *Energy AI* **2022**, 100195. [CrossRef]
33. Ranjan, M.; Shankar, R. A literature survey on load frequency control considering renewable energy integration in power system: Recent trends and future prospects. *J. Energy Storage* **2022**, *45*, 103717. [CrossRef]
34. Ren, G.; Liu, J.; Wan, J.; Guo, Y.; Yu, D. Overview of wind power intermittency: Impacts, measurements, and mitigation solutions. *Appl. Energy* **2017**, *204*, 47–65. [CrossRef]
35. Shrestha, A.; González-Longatt, F. Frequency stability issues and research opportunities in converter dominated power system. *Energies* **2021**, *14*, 4184. [CrossRef]
36. Singh, U.; Rizwan, M. A Systematic Review on Selected Applications and Approaches of Wind Energy Forecasting and Integration. *J. Inst. Eng. Ser. B* **2021**, *102*, 1061–1078. [CrossRef]
37. Yang, B.; Zhong, L.; Wang, J.; Shu, H.; Zhang, X.; Yu, T.; Sun, L. State-of-the-art one-stop handbook on wind forecasting technologies: An overview of classifications, methodologies, and analysis. *J. Clean. Prod.* **2021**, *283*, 124628. [CrossRef]
38. Hanifi, S.; Liu, X.; Lin, Z.; Lotfian, S. A Critical Review of Wind Power Forecasting Methods—Past, Present and Future. *Energies* **2020**, *13*, 3764. [CrossRef]
39. Tsai, W.; Hong, C.; Tu, C.; Lin, W.; Chen, C. A review of modern wind power generation forecasting technologies. *Sustainability* **2023**, *15*, 10757. [CrossRef]
40. Dhiman, H.; Deb, D.; Guerrero, J. Hybrid machine intelligent SVR variants for wind forecasting and ramp events. *Renew. Sustain. Energy Rev.* **2019**, *108*, 369–379. [CrossRef]
41. Dorado-Moreno, M.; Navarin, N.; Gutiérrez, P.; Prieto, L.; Sperduti, A.; Salcedo-Sanz, S.; Hervás-Martínez, C. Multi-task learning for the prediction of wind power ramp events with deep neural networks. *Neural Netw.* **2020**, *123*, 401–411. [CrossRef] [PubMed]
42. Ouyang, T.; Zha, X.; Qin, L.; He, Y.; Tang, Z. Prediction of wind power ramp events based on residual correction. *Renew. Energy* **2019**, *136*, 781–792. [CrossRef]
43. Han, L.; Qiao, Y.; Li, M.; Shi, L. Wind power ramp event forecasting based on feature extraction and deep learning. *Energies* **2020**, *13*, 6449. [CrossRef]
44. Probst, O. A new strategy for short-term ramp rate control in wind farms. *Int. J. Electr. Power Energy Syst.* **2020**, *120*, 105969. [CrossRef]
45. Jalali, S.; Ahmadian, S.; Khodayar, M.; Khosravi, A.; Shafie-khah, M.; Nahav, I.S.; Catalao, J. An advanced short-term wind power forecasting framework based on the optimized deep neural network models. *Int. J. Electr. Power Energy Syst.* **2022**, *141*, 108143. [CrossRef]
46. Harrou, F.; Saidi, A.; Sun, Y. Wind power prediction using bootstrap aggregating trees approach to enabling sustainable wind power integration in a smart grid. *Energy Convers. Manag.* **2019**, *201*, 112077. [CrossRef]
47. Wang, Q.; Pan, L.; Wang, H.; Wang, X.; Zhu, Y. Short-term wind power probabilistic forecasting using a new neural computing approach: GMC-DeepNN-PF. *Appl. Soft Comput.* **2022**, *126*, 109247. [CrossRef]
48. Zucatelli, P.; Nascimento, E.; Santos, A.; Arce, A.; Moreira, D. An investigation on deep learning and wavelet transform to nowcast wind power and wind power ramp: A case study in Brazil and Uruguay. *Energy* **2021**, *230*, 120842. [CrossRef]
49. Taylor, J. Probabilistic forecasting of wind power ramp events using autoregressive logit models. *Eur. J. Oper. Res.* **2017**, *259*, 703–712. [CrossRef]
50. Zhou, B.; Duan, H.; Wu, Q.; Wang, H.; Or, S.; Chan, K.; Meng, Y. Short-term prediction of wind power and its ramp events based on semi-supervised generative adversarial network. *Int. J. Electr. Power Energy Syst.* **2021**, *125*, 106411. [CrossRef]
51. Cornejo-Bueno, L.; Camacho-Gómez, C.; Aybar-Ruíz, A.; Prieto, L.; Barea-Ropero, A.; Salcedo-Sanz, S. Wind power ramp event detection with a hybrid neuro-evolutionary approach. *Neural Comput. Appl.* **2020**, *32*, 391–402. [CrossRef]
52. Han, L.; Zhang, R.; Chen, K. A coordinated dispatch method for energy storage power system considering wind power ramp event. *Appl. Soft Comput.* **2019**, *84*, 105732. [CrossRef]
53. Zhen, H.; Niu, D.; Yu, M.; Wang, K.; Liang, Y.; Xu, X. A hybrid deep learning model and comparison for wind power forecasting considering temporal-spatial feature extraction. *Sustainability* **2020**, *12*, 9490. [CrossRef]
54. González Sopeña, J.; Pakrashi, V.; Ghosh, B. A spiking neural network based wind power forecasting model for neuromorphic devices. *Energies* **2022**, *15*, 7256. [CrossRef]
55. Probst, O.; Minchala, L. Mitigation of short-term wind power ramps through forecast-based curtailment. *Appl. Sci.* **2021**, *11*, 4371. [CrossRef]

56. Liu, W.; Gong, Y.; Geng, G.; Jiang, Q. Refined ramp event characterisation for wind power ramp control using energy storage system. *IET Renew. Power Gener.* **2019**, *13*, 1731–1740. [CrossRef]
57. Niu, Y.; Santoso, S. Sizing and coordinating fast-and slow-response energy storage systems to mitigate hourly wind power variations. *IEEE Trans. Smart Grid* **2018**, *9*, 1107–1117. [CrossRef]
58. Abdullah, M.; Muttaqi, K.; Sutanto, D.; Agalgaonkar, A. An effective power dispatch control strategy to improve generation schedulability and supply reliability of a wind farm using a battery energy storage system. *IEEE Trans. Sustain. Energy* **2014**, *6*, 1093–1102. [CrossRef]
59. Gong, Y.; Jiang, Q.; Baldick, R. Ramp event forecast based wind power ramp control with energy storage system. *IEEE Trans. Power Syst.* **2016**, *31*, 1831–1844. [CrossRef]
60. Dhiman, H.; Deb, D. Machine intelligent and deep learning techniques for large training data in short-term wind speed and ramp event forecasting. *Int. Trans. Electr. Energy Syst.* **2021**, *31*, e12818. [CrossRef]
61. Zhao, H.; Wu, Q.; Hu, S.; Xu, H.; Rasmussen, C. Review of energy storage system for wind power integration support. *Appl. Energy* **2015**, *137*, 545–553. [CrossRef]
62. Ochoa, D.; Martinez, S. Analytical approach to understanding the effects of implementing fast-frequency response by wind turbines on the short-term operation of power systems. *Energies* **2021**, *14*, 3660. [CrossRef]
63. Ochoa, D.; Martinez, S. Proposals for enhancing frequency control in weak and isolated power systems: Application to the wind-diesel power system of San Cristobal island-Ecuador. *Energies* **2018**, *11*, 910. [CrossRef]
64. Long, Q.; Celna, A.; Das, K.; Sørensen, P. Fast frequency support from hybrid wind power plants using supercapacitors. *Energies* **2021**, *14*, 3495. [CrossRef]
65. Wang, X.; Wang, Y.; Liu, Y. Dynamic load frequency control for high-penetration wind power considering wind turbine fatigue load. *Int. J. Electr. Power Energy Syst.* **2020**, *117*, 105696. [CrossRef]
66. Hayes, B.; Wilson, A.; Webster, R.; Djokic, S. Comparison of two energy storage options for optimum balancing of wind farm power outputs. *IET Gener. Transm. Distrib.* **2016**, *10*, 832–839. [CrossRef]
67. Alsharafi, A.; Besheer, A.; Emara, H. Primary frequency response enhancement for future low inertia power systems using hybrid control technique. *Energies* **2018**, *11*, 699. [CrossRef]
68. Kou, P.; Liang, D.; Yu, L.; Gao, L. Nonlinear model predictive control of wind farm for system frequency support. *IEEE Trans. Power Syst.* **2019**, *34*, 3547–3561. [CrossRef]
69. Boyle, J.; Littler, T.; Muyeen, S.; Foley, A. An alternative frequency-droop scheme for wind turbines that provide primary frequency regulation via rotor speed control. *Int. J. Electr. Power Energy Syst.* **2021** *133*, 107219. [CrossRef]
70. Gu, W.; Chen, Z.; Li, Q.; Yin, M.; Li, Q.; Zou, Y. Torque Limit-based Inertial Control Method Based on Delayed Support for Primary Frequency Control of Wind Turbines. *J. Mod. Power Syst. Clean Energy* **2023**, *12*, 561–570. [CrossRef]
71. Ullah, K.; Basit, A.; Ullah, Z.; Albogamy, F.; Hafeez, G. Automatic Generation Control in Modern Power Systems with Wind Power and Electric Vehicles. *Energies* **2022**, *15*, 1771. [CrossRef]
72. Ochoa, D.; Martinez, S. Frequency dependent strategy for mitigating wind power fluctuations of a doubly-fed induction generator wind turbine based on virtual inertia control and blade pitch angle regulation. *Renew. Energy* **2018**, *128*, 108–124. [CrossRef]
73. Sun, B.; Tang, Y.; Ye, L.; Chen, C.; Zhang, C.; Zhong, W. A frequency control strategy considering large scale wind power cluster integration based on distributed model predictive control. *Energies* **2018**, *11*, 1600. [CrossRef]
74. Yang-Wu, S.; Xun, M.; Ao, P.; Yang-Guang, W.; Ting, C.; Ding, W.; Jian, Z. Load frequency control strategy for wind power grid-connected power systems considering wind power forecast. In Proceedings of the 2019 IEEE 3rd Conference On Energy Internet And Energy System Integration (EI2), Changsha, China, 8–10 November 2019; pp. 1124–1128. [CrossRef]
75. Chau, T.; Yu, S.; Fernando, T.; Iu, H.; Small, M. A novel control strategy of DFIG wind turbines in complex power systems for enhancement of primary frequency response and LFOD. *IEEE Trans. Power Syst.* **2017**, *33*, 1811–1823. [CrossRef]
76. Zhao, E.; Sun, S.; Wang, S. New developments in wind energy forecasting with artificial intelligence and big data: A scientometric insight. *Data Sci. Manag.* **2022**, *5*, 84–95. [CrossRef]
77. Wang, H.; Liu, Y.; Zhou, B.; Voropai, N.; Cao, G.; Jia, Y.; Barakhtenko, E. Advanced adaptive frequency support scheme for DFIG under cyber uncertainty. *Renew. Energy* **2020**, *161*, 98–109. [CrossRef]
78. Lu, L.; Saborío-Romano, O.; Cutululis, N. Reduced-order-VSM-based frequency controller for wind turbines. *Energies* **2021**, *14*, 528. [CrossRef]
79. Yan, X.; Yang, L.; Li, T. The LVRT control scheme for PMSG-based wind turbine generator based on the coordinated control of rotor overspeed and supercapacitor energy storage. *Energies* **2021**, *14*, 518. [CrossRef]
80. Misyris, G.; Ramasubramanian, D.; Mitra, P.; Singhvi, V. Locational Aspect of Fast Frequency Reserves in Low-Inertia Systems–Control Performance Analysis. *arXiv* **2022**, arXiv:2207.08188. [CrossRef]
81. Guo, F.; Yu, J.; Ni, Q.; Zhang, Z.; Meng, J.; Wang, Y. Grid-forming control strategy for PMSG wind turbines connected to the low-frequency AC transmission system. *Energy Rep.* **2023**, *9*, 1464–1472. [CrossRef]
82. Mishra, A.; Mishra, P.; Mathur, H. A deep learning assisted adaptive nonlinear deloading strategy for wind turbine generator integrated with an interconnected power system for enhanced load frequency control. *Electr. Power Syst. Res.* **2023**, *214*, 108960. [CrossRef]
83. Kou, P.; Gao, F.; Guan, X. Stochastic predictive control of battery energy storage for wind farm dispatching: Using probabilistic wind power forecasts. *Renew. Energy* **2015**, *80*, 286–300. [CrossRef]

84. Liu, Y.; Du, W.; Xiao, L.; Wang, H.; Cao, J. A method for sizing energy storage system to increase wind penetration as limited by grid frequency deviations. *IEEE Trans. Power Syst.* **2015**, *31*, 729–737. [CrossRef]
85. Wu, Y.; Yang, W.; Hu, Y.; Dzung, P. Frequency regulation at a wind farm using time-varying inertia and droop controls. *IEEE Trans. Ind. Appl.* **2018**, *55*, 213–224. [CrossRef]
86. Zou, J.; Pipattanasomporn, M.; Rahman, S.; Lai, X. A frequency regulation framework for hydro plants to mitigate wind penetration challenges. *IEEE Trans. Sustain. Energy* **2016**, *7*, 1583–1591. [CrossRef]
87. Gan, L.; Shek, J.; Mueller, M. Optimised operation of an off-grid hybrid wind-diesel-battery system using genetic algorithm. *Energy Convers. Manag.* **2016**, *126*, 446–462. [CrossRef]
88. Tan, J.; Zhang, Y. Coordinated control strategy of a battery energy storage system to support a wind power plant providing multi-timescale frequency ancillary services. *IEEE Trans. Sustain. Energy* **2017**, *8*, 1140–1153. [CrossRef]
89. Zhang, S.; Mishra, Y.; Yuan, B.; Zhao, J.; Shahidehpour, M. Primary Frequency Controller with Prediction-Based Droop Coefficient for Wind-Storage Systems under Spot Market Rules. *Energies* **2018**, *11*, 2340. [CrossRef]
90. Petersen, L.; Iov, F.; Tarnowski, G.; Gevorgian, V.; Koralewicz, P.; Stroe, D. Validating performance models for hybrid power plant control assessment. *Energies* **2019**, *12*, 4330. [CrossRef]