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Review

Ramp Rate Limitation of Wind Power: An Overview

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Abstract: A run for increasing the integration of renewable energy sources in the electricity network has been seen in recent years because of the big concern about environmental issues and pollution from controllable power units. This paper aims to give a general overview of the concept of ramp rate limitation and its principal applications in the literature regarding the field of control strategies, which deal with smoothing the wind power output. Wind power is one of the most-used renewable energy sources, and the objective of limiting the ramp rate of the power output is to produce more stable power. The studies of ramp rate limitation applied in wind power production deal with the definition and detection of this phenomenon in the real data, the methodologies used to forecast it, its application for managing grids and microgrids, the different actions aimed at physically implementing the restriction, and some of the grid code requirements used in different nations.

Keywords: ramp rate limitation; wind power; power smoothing; ramp rate forecast

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1. Introduction

Renewable energy resources represent a valid alternative to the conventional power generation with the aim of increasing global welfare and decreasing pollution and global warming [1]. The goal of reducing the emission of greenhouse gases is a current concern that has led to the necessity of using alternative energy sources to decrease the atmospheric pollution and all the issues related to it [2–4]. Wind energy is one of the most-used renewable energy sources, but it is characterized by a variable and intermittent nature, which causes problems when connected to a grid, damaging its reliability and stability [5]. Wind power tends to be unsteady because of the continuous wind speed fluctuations over time [6]. The use of this renewable source has increased greatly in the last few decades. The installed capacity of wind power generation in the Electric Reliability Council of Texas (ERCOT) passed from 2 GW in 2006 to 16 GW in 2015 [7]. There are many variability-mitigating market rules for wind power production. Among them, we can find the economic curtailment, curtailment to provide a power reserve, or using an energy storage system [8]. In this perspective, the concept of the ramp rate limit is inserted. There is not a unique ramp rate definition in the literature [9]. In general, a ramp event consists of a strong and rapid variation in power, and usually, it can be measured in MW/min or MW/hour. It represents the slope at which power changes, and it can be positive (ramp-up event where the power increases from one time step to the next one) or negative (ramp-down event where the power decreases) [10,11]. When a ramp-up event is limited, the wind power plant produces less power compared to its possibility, and the difference can be stored in a storage system. Conversely, when a ramp-down event is limited, we need a greater amount of power to keep the power profile slope softer. In this case, an additional power source or storage system is strongly needed because they are controllable resources used to supply or store the energy required [12]. The characteristics of the power storage system are also important because it has to provide a fast response to be able to supply or store the right amount of power in a short-term period. In the literature, the choice of a battery can be guided by different aspects, such as capacity, maximum power, life, operating temperature, cost, environmental impact, and efficiency [13].

In [10], the ramp event is considered a critical event because it can be dangerous in terms of the cost associated with an incorrect management and potential damage and deserves particular attention. Moreover, it can be classified according to its magnitude, duration, and ramp intensity, and in the literature, several works performed binary classification in this phenomenon through an indicator function, which can be equal to 1 or 0, depending whether or not a threshold is exceeded. The criterion is based on the variation in power between two time steps, and it is indicated as a percentage of the capacity of the wind turbine. In the literature, the time intervals in which the variation occurs cover a wide range, and they can last from 5 min [14] to 6 h [15]. Relevant attention is also addressed to the forecasting of these chaotic events. An example of a method used to forecast a ramp event is given by numerical weather prediction (NWP) models based on the fact that large ramp events are caused by large-scale meteorological processes. These events were classified into horizontal and vertical atmospheric processes in [16], and their characteristics (such as cold or warm front) can give us information about the type of ramp event (ramp-up or ramp-down event) [17].

The geographical distribution of these events depends on the level of wind power penetration that characterizes the territory. North America with the Electric Reliability Council of Texas (ERCOT) and Bonneville Power Administration (BPA), the Iberian Peninsula in Europe, and Australia are the areas most studied in this field.

The main objective of this paper is to provide an overview of the different fields of study which deal with the ramp rate limitation applied to stabilize wind power output. This control strategy is largely used and has been changed over time thanks to the improvement of technologies, such as the performance of storage systems. The structure of the paper is divided into fours sections. In Section 2, the ramp rate definition and the main methods to forecast it are provided. Section 3 describes the most important control strategies used to implement this kind of limitation. Section 4 provides an actualization of the ramp rate limitation in terms of managing an interconnected network with a high penetration of renewable energy sources. The discussion and the conclusions are presented in Section 5.

2. Ramp Rate Definition and Its Forecast

This section deals with the ramp rate definition and the different methods used in the literature to detect and forecast this phenomenon.

2.1. Ramp Rate Definition

Many studies attempt to give a definition of the ramp rate according to its duration, rate, and magnitude. Generally, the power ramp is a huge power change in a short time horizon [18]. The authors in [19] consider a ramp rate event with an increase in wind power greater than 50% of the maximum capacity of the wind farm within a horizon time smaller than 4 h. In [20], we can find the definition of the ramp event magnitude, which considers all the ramp events with an increase or decrease of power larger than 30% of the capacity of the wind farm as significant, and this is determined with the following equation:

$$|P_{t+\Delta t} - P_t| > P_{val}, \tag{1}$$

where P_t is the wind power output at time t, $P_{t+\Delta_t}$ is the wind power output after a fixed time duration Δ_t, and P_{val} is a cut-off level (a threshold). Furthermore, the authors in [20] also considered the magnitude Δ_t of the initial and final points of the time interval where the ramp change rate occurs and consider that a ramp event occurs when the ratio between the absolute value of the difference between the powers referring to two moments Δ_t are farfrom each other and Δ_t is greater than the threshold power value. This is shown in the following equation:

$$\frac{|P_{t+\Delta t} - P_t|}{\Delta t} > P_{threshold}, \tag{2}$$

where $P_{threshold}$ represents the maximum change rate power. For example, in [21], we have the ramp rate when the change in power is greater than 50% of the wind plant capacity in an interval of time equal to 4 h. We find the same equations in [22].

As follows, it is possible to see the formula used in [5] to modify the wind power output according to a chosen ramp rate limitation.

$$ce(t) = \begin{cases} ce(t-1) + lim & \text{if } e(t) > e(t-1) + lim \\ ce(t-1) - lim & \text{if } e(t) < e(t-1) - lim \\ e(t) & \text{otherwise} \end{cases} \tag{3}$$

where $e(t)$ is the limitless power output, $ce(t)$ is the power output, which is modified according to a limitation, and lim represents the ramp rate limitation chosen, and it is equal to

$$lim = \frac{Maximum\ Installed\ Ramp\ Capacity \cdot Allowed\ Ramp\ Percentage}{100}. \tag{4}$$

In Figure 1, it is possible to see the different profiles of wind production without limitation and production with a ramp rate limitation of 5% in a system with the rated power equal to 2 MW. We also highlight the amount of energy that has to be stored in the battery in green in the case of a ramp-up limitation, and the quantity that the battery has to provide to comply with a ramp-down limitation in red.

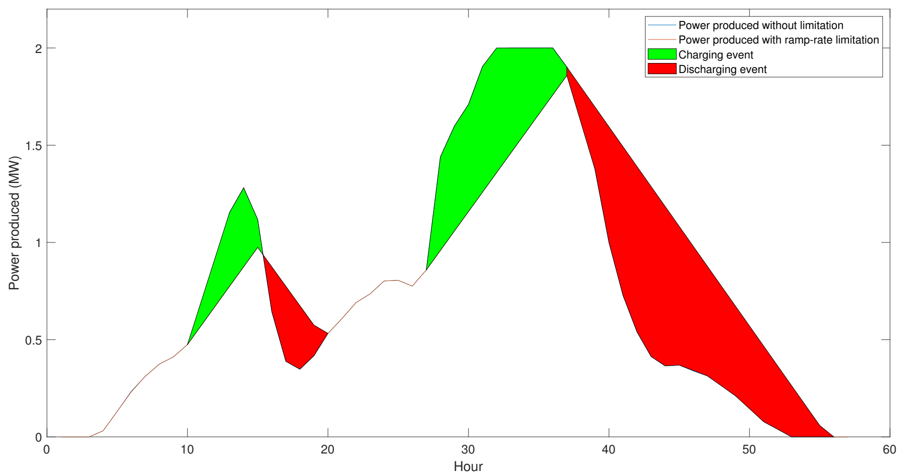

Figure 1. Ramp rate limitation of 5% in wind power output with a rated capacity of 2 MW.

This figure was obtained considering hourly wind speed data from the year 2008 referring to a location in Sardinia with geographical coordinates of 39.5 N latitude and 8.75 E longitude [23]. Once having obtained the wind speed data, we obtain the wind power production from a power curve referring to a wind turbine, which produces power for a wind speed higher than or equal to 4 m/s following a parabolic trend, and it has a constant production equal to its rated power (2 MW) between 13 m/s and 25 m/s. The analytic form of the power curve is shown in the system of Equation (5) in Section 3.2.

What is clear is that the ramp rate definition is strongly affected by the wind characteristics presented in the location under study and by the ramp rate threshold chosen. Establishing the duration of a ramp event is fundamental to properly compute the second step of a typical treatment, which is usually involved in forecasting it to avoid potential damage effects. Very often, works such as [24] choose a definition of the ramp rate to refer to and base the study on it by defining only the time interval.

2.2. Forecasting of Wind Power Ramp Events

The stability of the grid operation is one of the most important issues caused by ramp events, and the harmful effects can be smoothed using different ramp forecasting methods. We can find an example of what can cause a rapid and huge drop of wind power that was not correctly predicted in the strong power imbalance event and the consequent cut out of almost 1.2 GW of power in Texas in 2008 [9,25].

These methods usually are composed by wind speed or wind power forecasts and ramp detection. In the first part, parametric and non-parametric are the two main methods used to model the wind power curve. The former uses linear or polynomial functions to fit the power curve; the latter needs historical data to create data mining algorithms to obtain a power curve similar to the one from the real data. We can find physical models that use physical characteristics, such as meteorological or topological conditions, mathematical statistical models that consider the relation between historical wind power data and forecasting, such as neural networks and auto-regression and moving average (ARMA) models, and machine learning algorithms such as the artificial neural network (ANN), recurrent neural network (RNN), and extreme learning machine (ELM) [26–28]. Recently, a non-parametric approach based on indexed semi-Markov processes proved to be efficient to predict wind power at different time scales [29]. The ramp detection consists of two steps: the definition of the ramp and the implementation of algorithms to detect ramp events [22,30].

The study performed in [31] is interesting, where the authors aimed to forecast the probability of exceeding a power threshold adapting the conditional autoregressive logit (CARL) model previously studied in [32] to model the probability of wind power change overcoming a threshold. They used hourly wind power data of four wind farm on Crete (Greece), where the value of each hour is the average of six wind power readings recorded at the previous hour, and they considered six thresholds (−0.3, −0.2, −0.1, 0.1, 0.2, and 0.3). They developed three new (CARL) models, namely conditional autoregressive multinomial logit (CARML) models. The first aims to estimate the probabilities of exceeding different thresholds by maximizing the likelihood of an expression based on a categorical distribution, which is a generalization of the Bernoulli distribution for a random variable with more than two possible outcomes. In the second one, they considered the spatial modeling using a bi-variate Bernoulli distribution to calculate the probability of a ramp rate event in different locations. With the last model, they estimated the model parameters for fours months, and they performed the probability forecast for the next month. They continued the procedure moving forward by one month. They were interested in forecasting from one to two steps ahead from the multi-step-ahead CARML model. The results show that both predictions are very promising compared to other models.

A different approach is proposed in [30], where a hybrid forecasting model based on a semi-supervised generative adversarial network (GAN) was implemented to forecast wind power and ramp events. The GAN is a class of machine learning frameworks able to deduce the potential statistical distribution of the wind power time series. The merger of the semi-supervised regression with the GAN framework succeeds in decoding the nonlinear behaviors of the wind power data and improving the generated sample quality and decreasing the errors in the forecasting. More specifically, a signal decomposition techniques, variational mode decomposition, was used to divide wind power data into different sub-series with intrinsic mode functions that differ in frequency. Then, the GAN model was applied to generate virtual wind power data with the aim of finding the distribution characteristics of the wind power data. Finally, a GAN discriminative model was used to extract nonlinear features present in the data, and a semi-supervised regression was applied to predict the wind power for the next horizon time. The parameters of the GAN were updated through an alternative training process to minimize the errors of the predictions. The ramp event were divided into five categories according to the nature of the change (up or down event, small or large event, and no ramp event). The authors compared this method with a classical neural network algorithm, deep learning algorithm, and statistical method, showing that it performs better according to different evaluation metrics (MAE, RMSE, and MAPE).

The authors in [33] considered wind data from three different wind farms in Hubei, which are characterized by different capacities. First of all, they used a swinging door algorithm (SDA) to identify the ramp segments. Then, they used a dynamic programming method to identify the ramp trend. Finally, they proposed a new improved dynamic swinging door algorithm (ImDSDA) with dynamic programming, which represents a combination of the SDA and sliding window (SW) algorithm and aims to solve the problem regarding the detection of ramp events and to obtain the optimal door width. This is a two-stage method characterized by high operability. The first stage contains the segment detection and classification. The second stage contains ramp event identification and segment combination. The results show that the this methodology improves the detection accuracy.

In [22], a wind power prediction was obtained in two steps: wind power prediction and ramp detection. In this case, the non-parametric approach was used to build the prediction model and a Markov-switching auto-regression (MSAR) model was used to correct the prediction residual. The MSAR model represents a combination of AR models (which obtain the predictability of the data) and the Markov model (which obtain the randomness of the data thanks to the transition probability of the Markov chain), builds a residual correction model, and incorporates a random residual. At the end, an improved swinging door algorithm proposed in [34] was used to see the linear segment thanks to it being possible to find the ramp event according to the ramp definitions. The authors considered the 15 min wind data of a wind farm located in China. It was shown that this method performs better than the primary model and ARMA model.

A new statistical approach was proposed in [20], where a practical metric based on real data was used to evaluate the forecasting performance of ramp events. The authors calculated the hourly average of wind power and the ramp rate for each month and evaluated the seasonal standard ramp rate values as the input in the algorithm used to predict ramp events. Subsequently, the error metrics were used to evaluate the algorithm, such as BIAS, MAE, NMAE, and SDofAE.

It is also important to correctly choose the prediction time scale, called the time window in [35], which can negatively influence the accuracy of predicting ramps. In this work, the authors focused on optimizing the time window size in order to minimize non-ramp data in the chosen window, and the data analysis that they implemented consisted of extracting the ramp events, selecting the input variables and parameters, and solving the optimization problem through a genetic algorithm (GA) because of the nonlinearity of the objective function [35]. In Table 1, we summarize the different categories and methods of ramp rate predictions according to [10,30].

The indirect method is more easily applicable because it does not require ramp rate data, as opposed to the direct method, which can only be applied by having already adhered to a ramp rate limitation policy. Nevertheless, we recommend implementing the ramp rate forecasting through an optimal mixture of the direct and indirect methods. However, this strategy needs real ramp event data, which are hardly available to researchers, but not to wind farm operators.

The different methods used depend strictly on the skills and means that researchers and practitioners have in their possession. The mathematical statistical methods generally need few resources to be applied as they are based on the analysis of the historical wind power series. Nevertheless, the required skills are advanced. This typology can be improved by adding information from physical methods in the form of covariates. The availability of information necessary to implement the physical methods could be limited to meteorological centers or to the installation of specific meteorological stations near the wind farm. Another relevant aspect in this regard is the time scale of the data provided. Finally, the availability of important computational resources could allow the support of machine learning methods frequently used in the last decade.

Table 1. Ramp rate prediction categories and methods.

Categories		
Indirect forecasting methods: the wind power is forecast, and subsequently, ramp events are detected	Direct forecasting methods: historical ramp events are directly used to obtain parameters to forecast ramp events	
Methods	**Explanation**	**Examples of Models**
Physical methods	Relation between meteorological and environmental characteristics and wind power	Numerical weather prediction systems
Mathematical statistical methods	Statistical methods built on linear and nonlinear functions used to model historical wind power time series	Auto-regressive integrated moving average model, auto-regressive model, Gaussian process
Machine learning algorithms	Computational algorithms to forecast wind energy	Support vector machine, extreme learning machine, neuron-fuzzy network, artificial neural network, genetic algorithm, particle swarm optimization

Increasing importance on ramp rate prediction has been placed in the literature because of the extreme rapidity of this type of event, which does not allow an adequate response of control systems. From this, we have the need of creating ever-more precise forecasting models, which represents the most effective way of dealing with ramp rate events [24]. For this aspect, help could be given by creating a model that takes into account both the historical data available and the production data of already existing wind farms as close as possible to the area of interest. This could help to better understand the nature of the local wind speed.

3. Ramp Rate Limitation Control Strategies

In this section, we present the following two main branches of strategies used to control the ramp rate:

- Using a storage system to supply or store the needed power.
- Controlling the turbine blade pitch and rotor inertia.

3.1. Ramp Limitation Using a Battery Storage System

Many studies deal with the use of a battery storage system to limit and smooth the wind power fluctuation focusing on what type of battery and which size to choose. Obviously, the storage system should be as big as possible to maximize the smoothing of the ramp events. At the same time, the operator wants to minimize the cost, which means minimizing the capacity and the maximum power of the storage system. This is a trade-off that leads to finding the best combination between cost and storage characteristics through a multi-objective optimization approach [36].

The inability to use the battery because it does not have enough space to store all the surplus of power or to supply the right quantity of power to comply with a ramp rate limitation could mean receiving a penalty [5,8]. As follows, a graphic power smoothing algorithm, which is thought of as a modification of the one used in [36], is shown in Figure 2.

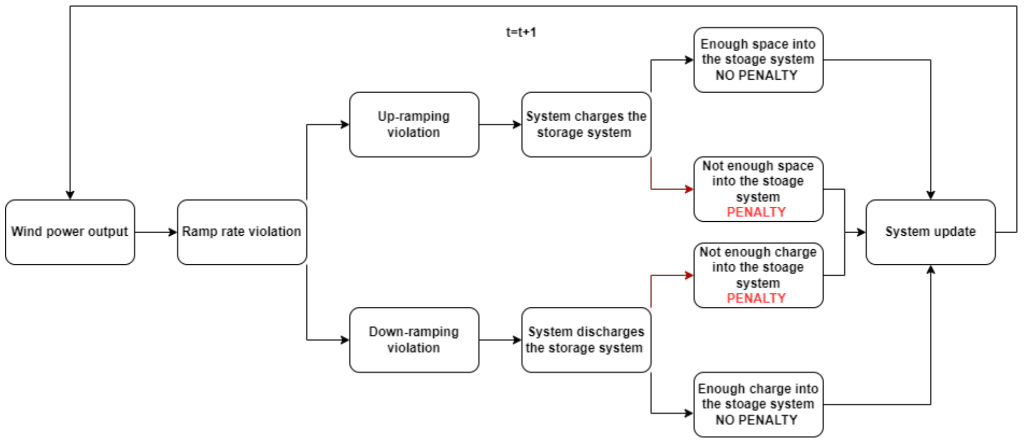

Figure 2. Graphic power smoothing algorithm.

In this case, we added the penalty concept in red, often applied to penalize the wind farm that does not respect the imposed limitation [5,8]. An example of the penalty system is given in [8]. The frequency regulation market in ERCOT is divided into "regulation up" and "regulation down"' prices, and in this study, the penalties for not respecting the ramp-up and ramp-down limits were varied between 0.25- and 5-times the down-regulation price and up-regulation price, respectively.

In Table 2, the main energy storage systems and their advantages and disadvantages are shown.

Table 2. The main energy storage systems with their principal advantages and disadvantages [13,37–40].

Type	Advantages	Disadvantages
Super capacitor	High efficiency, short response time, fast charging time, high energy density	High cost, limited long-term energy storage
Hydrogen-based	Few environmental impacts, moderate efficiency	High capital cost, low storage conversion efficiency
Flywheel	Long life of 15–20 years, high peak power capacity without overheating, insensitivity to depth of discharge, rapid response, very good energy efficiency	Very high capital cost, high rate of discharge in the range of 55–100% per day
Battery	High power density, low-cost materials, high rated pulse power capability, fast response, long life span, effectiveness in small-scale applications	High capital cost, high temperature
Superconducting	High efficiency, short response time	Fuel for maintenance at very low temperature, short-term energy storage
Compressed air	High power capacity, low capital cost, quick startup, moderate energy efficiency	Heat lost for long storage time

Among the types listed in Table 2, the battery (usually indicated with the acronym battery energy storage system (BESS)) is the most popular one due to the small area occupied for installation and its easy implementation. However, their application presents also some problems, such as the need to have a large capacity to cover the wind power fluctuations and the consequent increase of the capital and maintenance costs. In the field of wind power production, for this type of storage system, the most-used technologies are the lead-acid battery characterized by a low investment, easy installation, short lifetime, high maintenance, and poor performance at normal temperature, the nickel-based battery with a long lifetime, low maintenance, higher cost, and high self-discharge rate, and the sodium-sulfur battery with a high efficiency, good power density, high life cycle, considerable power density, thermal management, and low freeze–thaw durability [39]. The important characteristics that a storage system should have for this kind of application are high energy efficiency and fast response [39]. For example, in [8], a NaS battery was used to implement different market policies such as ramp-up and ramp-down limitation. This choice is driven by the fact that this battery has a relatively established storage technology and a power-to-energy ratio suitable for ramp rate limitation. Furthermore, these batteries are modular and can be scaled based on the wind plant's size. In the literature, several studies have investigated the best energy storage system to be coupled with a wind farm. In [36], the authors investigated the capacity of a battery storage system (BSS) to mitigate the ramp rate fluctuations depending on the storage capacity, the power rating, and the threshold chosen. In particular, they compared two different storage technologies and led a technical and economic analysis with a multi-objective optimization strategy to obtain the optimal balance between costs and abatement capacity in a realistic scenario considering maximum ramp rates equal to 5%, 7.5%, and 10%. The storage parameters, the power output from the wind turbine, and the maximum ramp rate represent the input of the model, and a black-box optimization problem was solved through a direct search algorithm implemented in MATLAB.

The minimum storage size to respect the ramp rate limitation was investigated in [41] through an optimization problem implemented in Python and solved using Gurobi. Furthermore, Reference [1] focused on the optimal energy storage system size problem for ramp rate control. This study developed a novel representative day selection technique to select the days on which the optimal operation was based to elect the best size. The procedure was divided into two steps. In the first step, called pre-processing, the data were manipulated to be converted into a one-minute scale and sent to the second step (data clustering), where a set of representative days was chosen. To measure the performance of the selected days in the estimation of the battery size, a ramp rate violation penalty was applied.

Due to the direct proportionality between cost and capacity, it is fundamental to investigate control strategies that aim to optimize the operations of the BESS. Some examples of these methods are listed as follows [39]:

- Wind power filtering such as a low-pass filter, in which the higher elements of the frequency are blocked and the BESS has to store/supply the difference between the power value before and after the filter.
- Charging/discharging dispatch, in which a control system manages the battery operations to obtain the required power to smooth the wind power production. In this context, we find the model predictive control framework.
- Optimization with wind speed prediction, where the predictions are used to improve the control of the BESS.

A penalty can be charged to the wind farm for not respecting the ramp rate limitations [8]. The recent study [5] proposed a new method in which different ramp rate limitations were implemented in a hypothetical wind turbine connected to a battery located in Sardinia. The 10-year data of hourly wind speed were considered, and the battery must provide or supply the quantity of energy needed to comply with the limitation imposed. If the state-of-charge of the battery is not able to do this, the wind farm receives a penalty [42]. The battery operations of charge and discharge are modeled as a discrete-time homogeneous Markov chain in which a state space composed by the following three states is considered: $+1$ for a charge event, -1 for a discharge event, and 0 for the unchanged condition. The aim of this work is to simulate the state-of-charge over time and, consequently, calculate the amount of penalty that the wind farm receives during a given period.

This control strategy is the most used because of its fast response against rapid ramp events. Its applicability is directly connected with the design of increasingly better-performing and less-expensive batteries. Improving the ramp rate forecast can lead to the use of simpler and less-expensive storage system thanks to the possibility of setting the battery conditions (such as its state-of-charge) at the most appropriate state to best respond to the ramp event.

3.2. Ramp Limitation Using Physical Techniques

In this subsection, the main control techniques consisting of directly controlling the wind turbine are presented and explained. In Figure 3, it is possible to see the main components of a generic wind turbine.

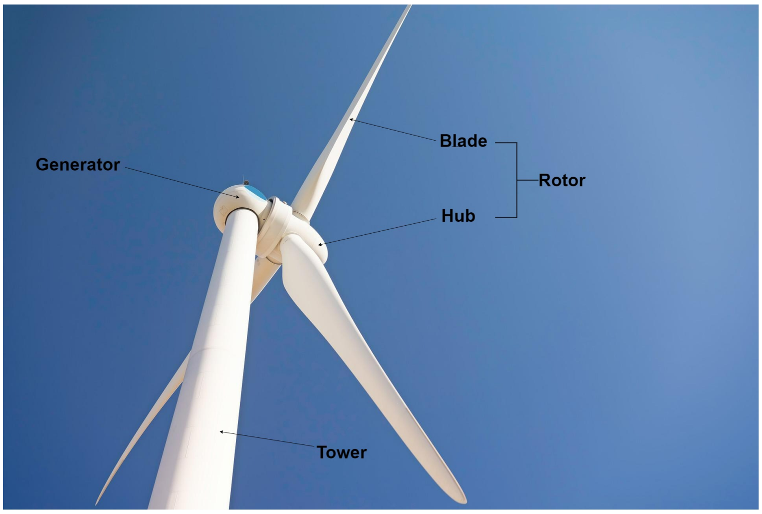

Figure 3. Main components of a wind turbine.

It is also important to remember that the power production of a wind turbine is regulated by a power curve. An example is proposed as follows [5].

$$WT(t) = \begin{cases} 0 & \text{for} \quad v(t) < v_{ci}, \\ P_r \frac{v^3(t) - v_{ci}^3}{v_r^3 - v_{ci}^3} & \text{for} \quad v_{ci} < v(t) < v_r, \\ P_r & \text{for} \quad v_r < v(t) < v_{co}, \\ 0 & \text{for} \quad v(t) > v_{co}, \end{cases} \tag{5}$$

where v_{co} is the cut-out wind speed, v_{ci} is the cut-in wind speed, $v(t)$ is the wind speed at time t, and v_r and P_r are the rated power and the rated wind speed. The wind power production strongly increases with the increase of wind speeds greater than v_{ci} until v_{co} is reached and the turbine has a constant production (P_r). In this way, we can define four different areas in which the power production is differently ruled (in some studies, the authors identify five areas [43,44].

The use of a storage system is not the only approach to cope with the ramp rate of the wind power production [45]. There are several ways to control a wind turbine. One way is represented by the generator torque control, where the controller fixes the generator torque in order to accelerate or decelerate the turbine with the aim of finding the optimal operation point while minimizing the loads [43].

Other less-expensive control techniques consist of controlling the turbine blade pitch and the rotor inertia, but they require advanced control systems and are not suitable for quick responses [46]. In the literature, these two methods of control are called active power control (APC) strategies, and they form two categories: the pitch-angle-regulation-based control (PAC) and the rotor-speed-regulation-based control (RSC) [47]. The pitch control consists of adjusting the blades by rotating them in order to control the aerodynamic efficiency. In this way, it is guaranteed that the right fraction of the current wind power production is exploited and the maximum rotational speed is not overcome [39]. Formerly, the turbines were controlled passively by means of the aerodynamic characteristics of the blades (an example is passive stall control), but this methodology was not very efficient.

Modern wind turbines have active pitch control with electrical or hydraulic actuators [43,48]. The second category consists of smoothing the wind power output by using the large inertia inherent in the wind rotor [47,49,50]. In general, it is possible to have two types of wind turbine generators: constant-speed wind turbines and variable-speed wind turbines. The wind farm can control the frequency using inertia response methods and primary frequency response methods. The first one consists of using the wind farm droop controller and storing its rotational energy in the rotor, and this is possible by controlling the pitch angle [51].

Most of these techniques act directly on the setting of the wind turbine and usually provide a slower response compared with the one provided by a storage system. It is our suggestion that, also in this case, the decision on which control strategy can be used depends on the characteristics of the wind and the ramp events that affect the location under study. For example, ramp events that last hours could be reasonably managed through physical techniques. Conversely, if the duration of the ramp events is of the order of minutes, it might be better to use a battery with a fast response.

4. Challenges in an Interconnected Network and Code Requirements

This section presents the issues that the wind power caused in the managing of an electrical network. Furthermore, some examples of the code requirements are given to show how the ramp rate limitation is regulated.

4.1. Ramp Rate Limitation in the Grid and Microgrid

Electricity systems are currently facing a change due to the desire to reduce carbon dioxide emissions. They are turning into decentralized power grids to increase the penetration of distributed energy resources. The role of microgrids is also crucial, which help in the managing of renewable sources and increase their integration [52–56].

Wind power fluctuations are an important issue also for the management of grids and microgrids, where they cause a change in grid frequency and voltage swing, resulting in instability problems that need voltage control [20,57,58]. In particular, the ratio between reactive power and voltages is reduced, and this fact is accentuated when a rapid change in power occurs [59,60]. Because of this, ramp rate limitations have been introduced by some power utilities to have a more stable power output from RESs [45]. The stochastic nature of the renewable energy sources makes this phenomenon impossible to avoid and difficult to predict with a high level of accuracy. This last aspect was investigated in [31] using autoregressive logit models. In [61], the software OptiWind was used to predict the wind speed in a model predictive control (MPC) framework with the aim of obtaining the optimal wind power dispatch. The objective function of the wind farm consists of minimizing the operation cost, which is the sum of the profit lost led by the cutting off of the wind power, the operation cost of the battery, and the penalty cost due to the violation of a ramp rate limitation equal to 5 MW/10 min.

In [11], the authors studied a methodology to estimate the available reaction time for microgrids facing ramp events caused by renewable energy sources and load changes. The reaction time is the time needed to react to such an event before the system protection mechanisms intervene. This happens when the frequency overcomes its bounds. The rotational velocity of the generators determines the frequency. In a grid/microgrid, the cause of a ramp rate event is not only associated with the wind power variation, but also with the contribution of all the other renewable energy sources connected to the grid and their unified contribution. The authors provided an analytical framework considering the balance between ramp rates and control devices as a function of the inertia of the rotating generators.

A complex problem was solved in [62], where a supercapacitor energy storage system was associated with a 1 MW tidal turbine in an islanded microgrid of Ushant in France to smooth the power fluctuations and keep the state-of-charge in a fixed interval. A methodology was applied to minimize the storage system size and respect a maximum power ramp rate $\Delta P_m/\Delta T = \pm 5$ kW/s, and an original smart power management strategy was applied to manage the energy storage system. The whole tidal energy conversion system was modeled through the energetic macroscopic representation and was controlled through the inversion-based control principle. The authors considered the system constraints and the power balance of the microgrid and gave an original simulation-based algorithm to find the optimum between power flow management and storage system size. The principal steps of the algorithm consists of initializing the parameters of the storage system and turbine, loading the hydroelectric power, and fixing the power integration constraint ± 5 kW/s, starting with an iteration equal to 1 with a required number of modules decided based on the characteristics of this elementary module, applying an original regulation strategy of the state-of-charge to maintain it in a range where it can be properly used to smooth the fluctuations. With the fifth step, a reference power, which feeds the microgrid, is found, and the difference between the hydroelectric power and the reference power represents the power that has to be provided or stored in the storage system. The state-of-charge is updated at each time step, and the algorithm obtains the maximal and minimal state-of-charge values. The iteration continues until the convergence condition is reached. The authors showed that the association of a storage system with a capacity of 2 kwh with a 1 MW turbine succeeds in totally respecting the system constraints and optimizes the energy production, even in a scenario referring to power production and fluctuations from a tidal turbine.

An interesting study was performed in [63], where an active power management scheme in a wind–solar AC microgrid was investigated. The aim was to limit the net output power ramp rate through a computationally efficient variable kernel-width maximum correntropy criterion adaptive filtering methodology, using a battery-energy-storage-assisted ramp rate limit control. In this case, the power ramp events in the microgrid are caused by sudden and large variations of solar irradiation, wind speed, and local load demand.

4.2. Grid Code Requirements

The current high integration of renewable energy sources brings development and change to regulations, standards, and requirements, which are technically and economically justified and, in some case, are not clear. From this point of view, a global harmonization is needed [64]. The Commission Regulation (EU) 2016/631 of 14 April 2016 [65] established technical design and operational requirements to be connected to the electrical system. There are several goals; among them, there is the necessity to facilitate Union-wide trade, secure the system, and encourage the integration of renewable energy sources. To obtain these goals, cooperation between the owners of the power generators and the system operators is strongly needed. The power-generating modules are categorized according to the voltage level of their connection point and their maximum capacity. For example, the power-generation modules that have a connection point below 110 kV and a maximum capacity threshold of 50 MW (Continental Europe) belong to the category called "type C". For this category, the power range referring to the maximum capacity is between 1.5% and 10%. In Denmark, the ramp rate should be between 20% and 1% of the maximum capacity and always below 60 MW/min. In India, the limitation is 10% per minute for plants with a capacity greater than 10 MW connected at $\geq$33 kV. The same requirements are applied for electrical energy storage facilities [66]. In [67], the Puerto Rico Electric Power Authority provides an overview of the minimum technical requirements that the companies must respect to interconnect variable renewable generation to the electric grid. The requirements refer to aspects dealing with the safety, costs, and performance of the system. The voltage regulation system, the reactive power, the power factor requirements, the short-circuit ratio, and the frequency response are only some of the limitations described. The ramp rate control is also included, where a 10% of rated capacity limit on 1-min ramp rates for both photovoltaic and wind generation is required. Other examples are given by EirGrid, which limits positive ramp events up to 30 MW/min, or the transmission system operators in Germany, which limit the ramp-up events at 10% of rated power per minute.

It is evident that unique requirements and regulations do not exist. It would be interesting to think about a general and uniform legislation that could make clearer which rules and limitations need to be observed and could make the work of the manufacturing sector easier, which could design control systems already set to certain limitations.

5. Conclusions

The ramp rate limitation is a control strategy that has been studied extensively over the last few decades. The increasing use of renewable energy sources and, in particular, wind has led to new problems connected to their management and connection to the standard electrical network. From this necessity, the concept of the ramp rate limitation was born with the aim of controlling the rapidity of the change in power production and avoiding problems in terms of network safety and stability.

This paper presented a general overview of the different aspects involving the ramp rate limitation for wind power plants in the literature. Three main study areas can be pointed out, and they are listed as follows:

- The definition and methods of forecasting the ramp rate events underlining the difficulties existing in the literature in finding a homogeneous point of view. This could be due to the fact that this is a relatively new topic and the characteristics of ramp rate events are strongly connected to the characteristics of the wind properties, which differ depending on the location.
- The control strategies used to implement the limitation deal with the use of storage systems or directly controlling the turbine and aim to minimize the costs and decrease the waste of energy.
- The contextualization and application of the ramp rate limitation in the current electrical network with some of the requirements and rules followed in some nations.

The objectives of this paper were to provide a general idea of the ramp rate control strategy to better understand this method and to give guidelines and research directions for future works in a such a new and useful study area, underlining the interconnections that exist among the different research aspects.

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