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An Integrated Methodology for Assessing Wind Power Curtailment Using Anemometric Measurements and Operational Data in the Brazilian Context

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Abstract

The increasing share of wind power generation has intensified the occurrence of curtailment events in power systems worldwide, mainly driven by transmission constraints, operational limitations, and imbalances between generation and demand. In the Brazilian context, this phenomenon has become more pronounced since 2023, highlighting structural challenges of the Brazilian Interconnected Power System and the need for reliable methodologies to estimate curtailed wind generation. This study presents a methodology to estimate wind power potential during curtailment events, aiming to support forecasting models and the economic compensation of affected generating agents. The proposed approach integrates measured power generation data, technical information of wind farms, and anemometric measurements from SCADA systems, combining data filtering and consistency procedures, gap-filling based on spatial correlation among wind farms, and regression models supported by statistical and computational techniques for wind-to-power conversion. The methodology was applied to more than 1,000 wind farms connected to the Brazilian transmission grid and achieved accuracy levels above 95% on a semi-hourly basis and exceeding 99% for annual aggregations.

Keywords: wind power curtailment; wind generation estimation; power system operation; renewable energy integration; SCADA data analysis

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1. Introduction

The continuous growth in electricity demand, combined with the need to reduce greenhouse gas emissions, has driven the expansion of renewable energy sources as a cornerstone of sustainable development [1]. In this context, wind power has consolidated as one of the most attractive options, exhibiting remarkable growth over the past decades [2]. Currently, global installed wind capacity has reached approximately 1 TW, accounting for nearly 25% of the total renewable capacity worldwide [3]. Projections indicate that by 2030 wind power generation will surpass hydropower in terms of global energy production, being exceeded only by solar photovoltaics [4].

Despite this positive evolution, the increasing penetration of wind power introduces significant operational challenges due to its inherent variability and strong dependence on meteorological conditions [5]. Key challenges include the growing need for power and energy reserves to compensate for production fluctuations, as well as increased complexity in power system planning and operation [5–7]. In this context, comprehensive knowledge of wind power generation and accurate forecasting become strategic assets, serving as essential inputs to support operational and dispatch decisions [5–8].

However, as wind power penetration intensifies, the frequency of curtailment events has increased, often associated with transmission constraints, operational limitations, and temporary imbalances between supply and demand. In such cases, the analysis of observed generation alone, even when supported by accurate forecasts, is insufficient to characterize the actual performance of wind farms.

Estimating the potential generation that would have occurred in the absence of constraints becomes necessary to disentangle curtailment effects from natural wind variability, enabling a proper assessment of energy losses, fairer management of operational restrictions, and the evaluation of economic impacts, particularly in compensation processes for affected generators.

In the Brazilian context, where wind power expansion has been rapid and geographically concentrated in regions with structural transmission bottlenecks, reliable estimation of unrealized generation plays a central role in both operational and regulatory analyses. Robust estimation models enhance transparency between market agents and the system operator and provide consistent support for improving planning, operation, and wind power forecasting processes.

Within this framework, this work proposes a methodological development for wind power generation estimation, with a specific focus on identifying and quantifying energy losses associated with curtailment events. The approach accounts for the particularities of the Brazilian power system while incorporating internationally adopted practices and experiences. The proposed methodology is innovative and, although developed for the Brazilian context, exhibits broad applicability, serving as a reference for other system operators and the scientific community. The main contributions of this paper are summarized as follows:

- An objective review of the literature on wind power generation estimation methods and their application to curtailment quantification, covering institutional practices, operational requirements, and experiences from international power system operators.
- An overview of the Brazilian power sector, with emphasis on the specific characteristics of wind power generation and an analysis of curtailment within the Brazilian Interconnected Power System (SIN).
- A novel wind power generation estimation model is proposed, with a strong emphasis on practical applicability for large-scale system operators, particularly the Independent System Operators in Brazil, namely the Brazilian National Electric System Operator (ONS). The methodology adopts a hybrid approach, integrating physical and statistical concepts through the combination of anemometric data from Brazilian sectoral institutions and wind farms. It incorporates advanced techniques for large-scale wind speed–power (W–P) curve construction, a key requirement for systems with a large number of wind farms, while addressing challenges related to the quality and consistency of operational measurements of generation and wind.
- Results obtained to date indicate robust performance of the proposed model in estimating curtailment within the ONS context, highlighting its potential as a significant contribution to the improvement of estimation practices and operational analysis in power systems with high penetration of variable renewable energy sources.

To achieve these objectives, the paper begins by presenting a brief review of curtailment practices on a global scale, approaches used for wind power generation estimation, and an overview of wind power generation in the Brazilian context. Next, Section 2 describes the data used for model development, the methods applied to process these data, and the resulting model. Section 3 then presents the results obtained, including the main discussions. Finally, Section 4 summarizes the conclusions of the paper.

1.1. Curtailment Practices at the Global Scale

1.1.1. Concept and Causes of Curtailment

The increasing share of variable renewable energy sources, particularly wind and solar power, in the global electricity mix has made curtailment an increasingly relevant challenge for power system operation in many countries [9].

Curtailment is broadly defined as the reduction of electricity generation from a power plant to levels below its available potential [10]. In such cases, despite the availability of energy resources—such as wind or solar irradiance—generation is constrained by operational or structural limitations of the power system. These constraints typically arise from transmission congestion, limited grid access, or excess renewable generation during periods of low demand. In addition, operational security considerations, including voltage control, interconnection constraints, and frequency maintenance, may also lead to curtailment, particularly in small or isolated systems [11].

According to [10], curtailment frequently occurs under conditions of transmission congestion or local network constraints, often associated with the violation of thermal or stability limits. In such situations, system operators reduce generation to prevent overloads, voltage instability, or breaches of security criteria. Another relevant cause is related to system balancing, when total generation exceeds demand and insufficient flexibility or storage is available—a common situation in systems with high solar penetration during daytime or high wind penetration during nighttime hours. Curtailment may also be driven by stability requirements, aiming to ensure minimum levels of inertia and adequate system response to disturbances.

Beyond technical aspects, economic curtailment is also observed and is related to dispatch logic and merit-order considerations, including low or negative electricity prices and strategic bidding behavior in energy markets [12].

1.1.2. Evolution of Curtailment in Systems with High Renewable Penetration

At the global level, wind power curtailment has intensified in several regions, including Europe, China, Canada, and the United States, following the rapid expansion of variable renewable energy capacity [9]. This trend reflects not only the growth of these sources but also structural and operational limitations in power systems to accommodate high levels of variability. In this context, [9] analyze curtailment evolution using an international comparative approach that relates curtailment rates to the share of wind and solar generation in national electricity mixes. This framework enables the assessment of historical trends and comparisons among countries with different levels of system flexibility. Based on at least ten years of historical data, the study classifies power systems according to both the magnitude of curtailment relative to renewable penetration and the temporal trend of this relationship. The results indicate that high renewable penetration does not necessarily imply high curtailment levels, highlighting the critical role of infrastructure and flexibility measures. For instance, while curtailment has increased in European countries such as the United Kingdom, Germany, and Ireland, several regions in China have experienced significant reductions in curtailment rates despite rising renewable shares.

Curtailment has thus emerged as a strategic performance indicator for transmission system operators, as it encapsulates both structural and operational constraints of power systems. It signals the need for transmission reinforcements, enhanced operational flexibility, and adequate ancillary services, and it supports regulatory and market-related decision-making, being an integral part of power system modernization under high renewable penetration scenarios [9]. From a technical perspective, insufficient transmission capacity to transport generation surpluses tends to increase curtailment. In Germany and the United Kingdom, for example, higher shares of variable renewable energy have been accompanied by rising congestion management and redispatch costs, reinforcing the role of curtailment as an operational instrument linked to reserve management and ancillary services [13].

1.1.3. Technical and Economic Impacts of Curtailment

From an economic perspective, curtailment reduces the amount of marketable energy and the expected revenue of Variable Renewable Energy (VRE) projects, potentially deteriorating financial performance indicators and increasing perceived investment risk. Empirical evidence indicates that, as the share of VRE in the power system increases, both the economic loss per curtailment event and the marginal cost of curtailment tend to rise [14].

To mitigate these impacts, compensation mechanisms for generators have been adopted, such as payments for non-dispatched energy or revenue risk mitigation instruments. These mechanisms rely on robust methodologies to estimate the generation that would have occurred in the absence of curtailment [15].

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1.2. *Approaches for Wind Power Generation Estimation*

1.2.1. Role of Wind Power Generation Estimation for System Operators

Wind power generation estimation is essential for system operators when assessing curtailment, as it enables the distinction between generation reductions caused by operational constraints and those associated with the natural variability of the wind resource. By providing a reference of the expected generation in the absence of curtailment, these estimates support operational monitoring, post-operational analysis, and the assessment of energy and economic impacts on generation agents. In addition, robust wind power estimates support real-time decision-making and short-term planning, contributing to the transparent application of compensation mechanisms and to the evaluation of the efficiency of system operation.

Different types of modeling and data have been used around the world to estimate wind power generation under curtailment [16]. Methods to estimate generation include data-driven estimation, which often employ meteorological variables to reconstruct power generation, in addition to empirical and statistical models, and models based on machine learning techniques [17].

1.2.2. Models for Wind Power Generation Estimation

This section presents the main models employed for wind power generation estimation, with emphasis on data treatment and gap-filling procedures, as well as on the methodological approaches used to derive potential generation. Spatial and regional techniques for overcoming data limitations are discussed, together with physical, statistical, and machine learning models applied to production estimation.

Wind power generation exhibits strong spatial and temporal dependence, leading geographically proximate wind farms to share similar meteorological patterns. This characteristic enables the use of spatial information to complement incomplete time series, reduce noise, and enhance the robustness of generation estimates [18]. Common approaches include the use of neighboring wind farms as references, spatial interpolation, clustering of plants with similar behavior, and combinations of these strategies for missing data imputation.

Data from nearby wind farms or meteorological stations can be directly used for model calibration or as auxiliary variables. A widely adopted technique is the use of spatial lags, which model spatial dependence between regions through weighted averages [19]. In the absence of local wind measurements, generation can be estimated by combining physical wind–power models with spatial interpolation methods, such as Natural Neighbor Interpolation, based on Voronoi diagrams [20], and Inverse Distance Weighting, which assigns higher weights to closer observations [21].

Wind farms located within the same region and exhibiting similar operational and meteorological patterns can be grouped into clusters, reducing data heterogeneity and enabling the training of cluster-specific models. Clustering can be based on power profiles, wind time series, meteorological forecasts, or inter-farm correlations, supporting more consistent regional analyses [22]. These techniques are particularly relevant in scenarios involving supervisory data failures, commissioning of new wind farms, or limited data availability, providing significant operational gains for wind generation estimation [23].

Estimation models can be broadly classified into physical, statistical, and machine learning approaches [24]. Physical models rely on design and technical information and do not require historical training data, whereas statistical models exploit explanatory and temporal patterns and are suitable for incomplete time series. Machine learning models, in turn, integrate multiple variables and capture both linear and nonlinear relationships with higher accuracy.

Models based on wind–power curves empirically represent the relationship between wind speed and generated power [25] and can be either parametric, such as sigmoid functions, or nonparametric, constructed directly from observed data [26]. Nonlinear regression techniques, including Generalized Additive Models (GAM) and adaptive splines, such as Multivariate Adaptive Regression Splines (MARS) [26,27], are widely applied. Machine learning methods, including Support Vector Regression

(SVR) [28], decision trees, and Gradient Boosting approaches [29], notably XGBoost [30,31], stand out for their robustness and ability to model complex relationships.

1.2.3. Validation, Uncertainty, and Performance Criteria

Validation aims to demonstrate that the estimates are robust, stable, and physically consistent under different operational and meteorological conditions. To this end, criteria based on bias metrics, absolute and relative errors, and the ability to explain variability are employed, explicitly accounting for observational, model-related, and random uncertainties [32]. Isolated performance metrics are generally insufficient to fully characterize model performance; therefore, sets of complementary performance metrics are typically used.

Several metrics are applied to evaluate the performance of estimation models, including Mean Error (ME), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). ME is primarily used to identify systematic bias, MAE assists in detecting outliers, RMSE penalizes large errors, and MAPE expresses the percentage deviation between estimates and observations [33]. Error metrics can also be normalized, such as nME, nMAE, nMAPE, and nRMSE, typically by installed capacity or other scaling factors, allowing comparisons across wind farms with different characteristics [34].

MAPE, however, is not recommended when observed values approach zero, as its normalization may produce artificially inflated errors even for well-performing models. For this reason, analyses of wind power generation commonly adopt the normalized Mean Absolute Percentage Error (NMAPE). The mathematical definitions of these metrics are provided in [35]. In addition to error-based metrics, the coefficient of determination (R^2) is used to assess the degree of model fit to the observed data.

1.3. Overview of Wind Power Generation in Brazil

1.3.1. The Brazilian Wind Power Fleet

For the proper development of wind power generation estimation models, it is essential to consider the specific characteristics of the Brazilian wind power fleet, as well as the different wind regimes that shape the observed generation behavior. Unlike models strictly aimed at forecasting, estimation models primarily seek to reconstruct the counterfactual potential generation that was not realized, particularly under operational constraints such as curtailment events. These models support the assessment of energy losses, the reconstruction of consistent historical time series, and the technical substantiation of economic compensation mechanisms.

Brazil currently has more than one thousand large-scale wind power plants in operation. Figure 1 illustrates the geographical distribution of these plants across the national territory. Red circles represent wind farms, with their sizes proportional to the density of adjacent points, allowing the identification of areas with higher concentration. Density was calculated based on the geographical distances between wind farms, considering plants separated by less than 0.5 degrees as neighboring points.

The Brazilian wind power fleet is composed exclusively of onshore wind farms. Its spatial distribution is strongly concentrated in the Northeast and South regions, as illustrated in Figure 1, highlighted by the areas outlined in green and blue, respectively. Approximately 94% of wind farms are located in the Northeast, a concentration that increases the complexity of power system operation and the management of curtailment events in this region, particularly during periods of high wind resource availability. In contrast, about 6% of wind farms are located in the South.

In addition to differences in spatial concentration, there are relevant structural differences in the wind regimes of these two regions, which are reflected in distinct patterns of observed wind power generation. These differences have a direct impact on the estimation of potential generation, especially in curtailment analyses, where an accurate characterization of the typical behavior and intrinsic variability of the wind resource is essential to avoid biases in the quantification of energy losses.

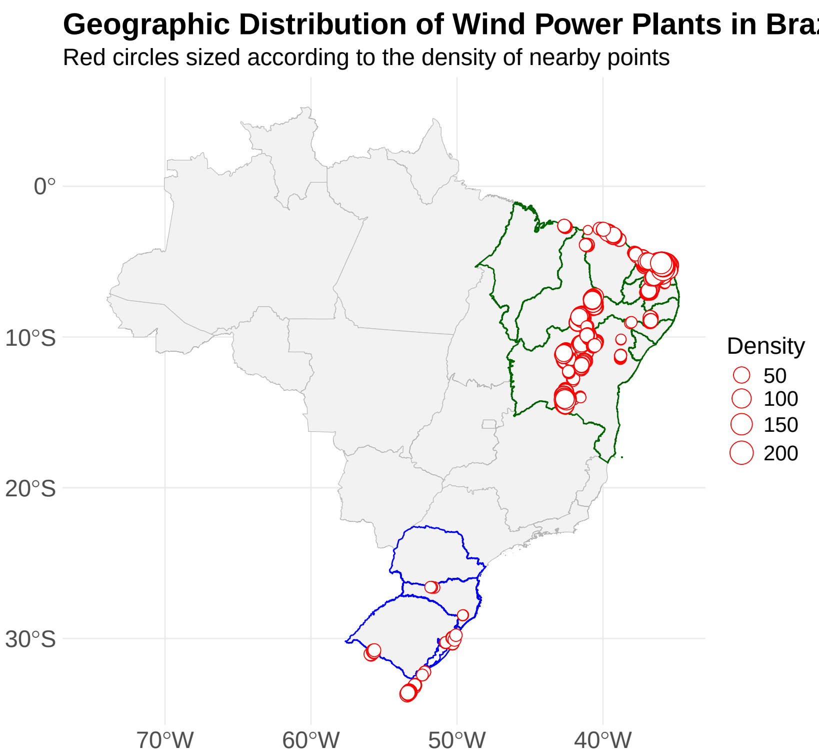

Figure 1. Map of Brazil showing the geographical distribution of wind power plants.

1.3.2. Characterization of Curtailment Events

Energy curtailment primarily arises from transmission constraints and limitations in the balance between load and generation [10,36]. For this reason, system operators classify curtailment events according to operational and security criteria [10].

In Brazil, regulation defines three categories of curtailment: external unavailability, reliability, and energy-based curtailment. These categories are associated, respectively, with constraints external to the power plants, system security requirements, and situations of energy oversupply [36,37].

Between 2022 and 2024, curtailment increased significantly, with a predominance of reliability- and external unavailability–related events. This trend reflects the mismatch between the rapid expansion of renewable generation and the conditions for power evacuation, particularly in the Northeast region [37].

Energy-based curtailment has also intensified, especially during daytime hours, driven by high solar generation and the growing penetration of distributed generation. These factors shift load–generation balancing adjustments toward centralized power plants, with a stronger impact during the wind harvest season [37,38].

In this context, accurate estimation of reference generation is essential to enable constrained-off mechanisms and to ensure adequate financial compensation for power plants affected by operational restrictions [36].

2. Materials and Methods

This study presents a methodology for estimating wind power generation suppressed by curtailment events. The proposed approach integrates technical information and observed generation data with anemometric measurements obtained from the Supervisory Control and Data Acquisition (SCADA) systems of the Brazilian National Electric System Operator (ONS) and the Brazilian Energy Research Office (EPE) [39]. The methodology begins with a wind farm–level data filtering stage, in which measurement errors are identified and relevant information is systematically selected and consolidated from multiple data sources.

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Subsequently, a gap-filling procedure is applied to the wind data time series, using information from nearby wind farms with similar anemometric behavior. Regression models combined with statistical and computational techniques are then employed to convert wind measurements into energy generation estimates, following an approach similar to that adopted in [40]. The methodology further incorporates correction mechanisms designed to mitigate the effects of curtailment events and atypical operational conditions.

The overall structure of the proposed model is presented in Figure 2, which illustrates the information flow underlying the wind power generation estimation process.

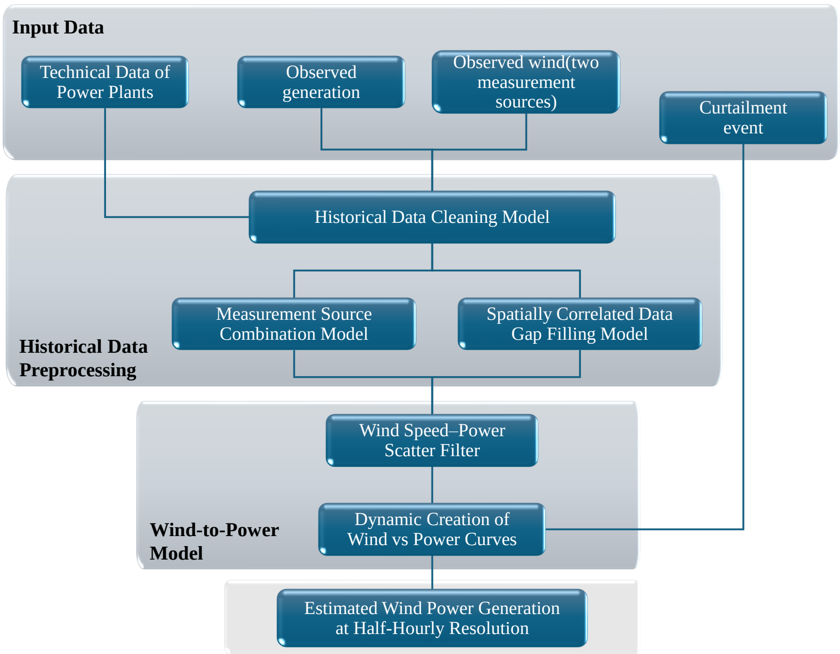

Figure 2. Flowchart of the proposed model.

2.1. Input Data

2.1.1. Technical Data of Wind Farms

Although several technical attributes of wind farms are relevant for power system planning and operation, in the context of modeling aimed at estimating potential generation and analyzing curtailment events, the most essential information is limited to the geographical coordinates of the plants, their total installed capacity, and the commercial operation start date. Other technical characteristics, while important for real-time operation and asset management, are predominantly operational in nature and do not directly influence the ability of estimation models to reconstruct historical time series or to quantify generation losses associated with operational constraints. The technical data used in this study were obtained from the ONS and the Brazilian Electricity Regulatory Agency (ANEEL).

2.1.2. Observed Data

The data used in this study comprise information obtained from the ONS and other institutions within the Brazilian electricity sector. Electric power generation measurements were obtained from the ONS SCADA system. Wind speed anemometric data were collected from both the ONS SCADA system and the Anemometric Measurement Monitoring System of the EPE.

2.2. Historical Data Preprocessing

As mentioned previously, measurements of the same variable are provided by different institutions, and all datasets exhibit issues related to missing data and/or the presence of spurious values (outliers), which are common in real-world data. As a result, the available data may present undesirable characteristics for estimation models and must be properly treated. Furthermore, due to data

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redundancy, it is necessary to construct consistent time series by integrating all available sources. For this purpose, a dedicated data preprocessing methodology was developed, based on the approaches described in [35,41].

2.2.1. Historical Data Cleaning Model

First, the observed wind power generation and wind anemometric data used in this study undergo a systematic quality control, data treatment, and multi-source integration procedure, aiming to ensure temporal consistency, remove spurious measurements, and maximize the use of the available information. Initially, the data are converted to numerical format, and missing values are explicitly identified. Subsequently, physically inconsistent measurements are removed (e.g. generation greater than maximum power of wind farm).

In addition, automated filters are applied to detect frozen sensors, considering both short-term moving windows and temporal persistence at hourly and daily scales. Days with an insufficient number of valid measurements are also discarded, ensuring a minimum level of representativeness of the daily time series.

2.2.2. Measurement Source Combination Model

Next, the processed wind data obtained from different sources (ONS and EPE) are integrated using a hierarchical approach, prioritizing the local source whenever available. When both sources provide valid data, a linear model is fitted between the corresponding time series, and statistical consistency is evaluated using the coefficient of determination (R^2). Data complementation based on the estimated linear relationship is performed only when the model exhibits satisfactory performance. In addition, a geometric criterion based on the distance to the regression line is applied to identify and remove inconsistent observations.

This procedure results in wind time series that are validated, integrated, and fully traceable, with explicit identification of the data source used at each time step, providing a robust foundation for the subsequent modeling stages.

2.2.3. Spatially Correlated Data Gap-Filling Model

Missing wind data are filled using a spatial and statistical approach based on information from geographically proximate wind farms and the integration of multiple observed data sources. Wind time series from neighboring wind farms are individually adjusted to the reference wind farm series using linear models, and the consistency of each adjustment is assessed through the coefficient of determination (R^2). Only wind farms that meet a predefined minimum correlation threshold are considered eligible for data gap filling. Eligible wind farms are then ranked according to the statistical performance of the adjustment, ensuring priority is given to the most representative series.

Missing values are filled hierarchically by replacing only the temporal gaps in the reference wind farm series with estimates derived from the adjusted neighboring series, while fully preserving the originally observed data. Throughout the process, the origin of the data used at each time step is explicitly tracked through dedicated indicators, ensuring transparency and consistency in the construction of the final wind time series.

2.3. Wind-to-Power Model

2.3.1. Wind Speed–Power Scatter Filter

The subsequent stage of the model consists of constructing wind speed–power (W–P) curves. This step requires careful treatment of data dispersion for each wind farm in order to identify and mitigate records that deviate from typical operational behavior. Proper characterization of W–P scatter is crucial for the correction of outliers, as discussed in [42,43].

The adopted methodology, based on [44], employs a robust mathematical formulation for the identification of anomalous points, while preserving, as much as possible, data that are representative of the natural operational behavior of the wind farm. The approach defines upper and lower bounds

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that delimit the typical operating range of the wind power plant, as illustrated by the green and yellow curves in Figure 3. The model proposed in this study advances beyond the original methodology by automating the estimation of the parameters of these boundary curves.

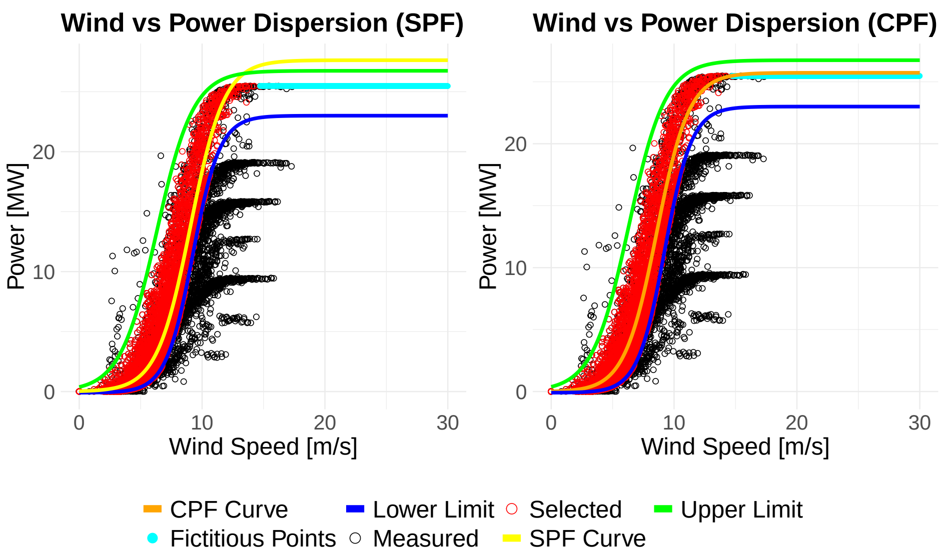

Figure 3. Wind–Power Relationship Curves.

Initially, recent samples of power generation and wind speed are selected, with explicit treatment of null values and restriction to physically plausible ranges. In the absence of predefined limits, the curve parameters are automatically estimated using robust quantile-based statistics, allowing the characterization of cut-in, saturation, and rated power regions. The boundary curves are modeled using logistic functions [44], which provide smooth representations of the lower and upper envelopes of the power curve. The automation of this parameter estimation process is particularly relevant for system operators such as the ONS, which is responsible for supervising a large and heterogeneous wind power fleet comprising more than one thousand utility-scale wind farms.

It is important to note that the exclusion of certain records does not necessarily imply the presence of measurement errors. In many cases, these data are technically consistent but associated with atypical operational conditions, such as scheduled maintenance, equipment failures, or transmission capacity constraints, including curtailment events. As they do not represent the expected behavior of the plant under normal operating conditions, these records are removed from the calibration process of the potential generation estimation models. A similar methodology, with a higher level of detail, is presented in [40].

2.3.2. Dynamic Creation of Wind vs Power Curves

To prevent the estimated wind speed–power curve from violating the physical limits of the wind farm under conditions of low data density in the saturation region, the methodology introduces fictitious points into the wind–power scatter. These points are defined based on robust statistics of the observed data or on previously estimated upper and lower bounds, prioritizing recent measurements and values close to rated power. The inclusion of these synthetic points ensures an adequate representation of the cut-in and saturation regions, stabilizing the curve fitting process and preventing physically inconsistent extrapolations when observations in these operational ranges are scarce.

Finally, the W–P curve is fitted using a logistic function, with parameters estimated through the Gauss–Newton algorithm. Figure 3 illustrates the application of the boundary curves and compares the estimation of the W–P curve parameters (yellow) obtained without the inclusion of fictitious points (No Fictitious Points—NFP) and that derived with their inclusion (With Fictitious Points—WFP).

The experimental results indicate that generation estimation based on aggregated sets of wind farms exhibits higher robustness and accuracy than plant-level estimation, due to the reduction of the intrinsic variability of wind power generation—a phenomenon widely associated with the portfolio effect. This aggregation enhances the statistical stability of the models, which is particularly relevant in curtailment analyses, where distinguishing between the natural variability of the wind resource and operational constraints is essential.

However, aggregated generation time series exhibit a structural upward trend resulting from the continuous expansion of installed capacity. In addition, transmission constraints, often transient in nature, affect these aggregated sets heterogeneously over time, temporarily altering the observed generation patterns. Consequently, the training of estimation models must explicitly account for the dynamics of these time series, whose growth patterns are nonlinear and characterized by discrete increments associated with the commissioning of new wind farms.

To mitigate these effects, a weighted historical average series is constructed based on the number of active wind farms in each time interval, reducing the bias introduced by the expansion of the generation fleet. At the daily scale, a linear regression is applied between the total observed generation and the historical average of the preceding five days, allowing for an indirect capture of the influence of dynamic operational constraints, including curtailment events.

In addition, the dynamic modeling of the wind speed–power curves involves normalizing generation between its extreme values and standardizing wind speed using the historical mean and standard deviation of the series. This procedure leads to the formulation of Equation (1), which establishes the functional relationship between observed wind conditions and the estimated potential generation.

$$
\begin{aligned}
G_e^T = \alpha_{mt}\Bigg(\Bigg(P_{mi} + \frac{(P_{ma} - P_{mi})}{\left(1 + 10^{b\left(V_{mid} - \frac{(V_o - \bar{V}_o)}{\sigma_{V_o}}\right)}\right)^{s}}\Bigg) \\
\cdot (G_{ma} - G_{mi}) + G_{mi}\Bigg) + \beta_{mt}
\end{aligned}
\tag{1}
$$

where G_e^T denotes the total estimated generation of the plant; G_{ma} and G_{mi} are the computed maximum and minimum generation values, respectively; $\bar{V}_o$ and σ_{V_o} represent the calculated mean and standard deviation of the observed wind speed, respectively; V_o denotes the observed wind speed; α_{mt} and β_{mt} are the slope and intercept of the regression that relates the mean to the total generation of the plant; the parameters P_{mi} and P_{ma} represent the lower and upper asymptotic bounds, corresponding to the estimated normalized minimum and maximum power, respectively; b and V_{mid} denote the slope and the x-coordinate of the inflection point, respectively; and s is a coefficient.

3. Results and Discussions

The proposed methodology was applied to a dataset comprising 1043 wind farms connected to the transmission network of the Brazilian Interconnected Power System (SIN).

3.1. Historical Data Processing

As described in Section 2.2, the wind time series data were subjected to a rigorous quality control and consistency assessment process. This process includes the removal of physically inconsistent measurements, the automatic identification of sensors exhibiting anomalous behavior, and the hierarchical integration of multiple observed data sources. In addition, remaining temporal gaps were filled using information from geographically proximate wind farms, selected based on spatial and statistical criteria. Gap filling is performed only when a high level of consistency between the series is observed, thereby preserving the originally measured data and ensuring full traceability of the information used.

Figure 4 presents an example of the application of the wind data selection, treatment, and completion procedures, as well as their relationship with the observed wind power generation. The raw wind series corresponds to the originally available measurements, whereas the filtered wind series results from the application of consistency criteria. In turn, the completed wind series incorporates the filling of the remaining data gaps, producing a signal that is more suitable for use in the estimation models. Observed wind power generation is shown on the secondary axis, allowing for a direct comparison between the relative variations of wind speed and power output, which facilitates the assessment of the physical coherence between the processed wind data and the wind power generation response.

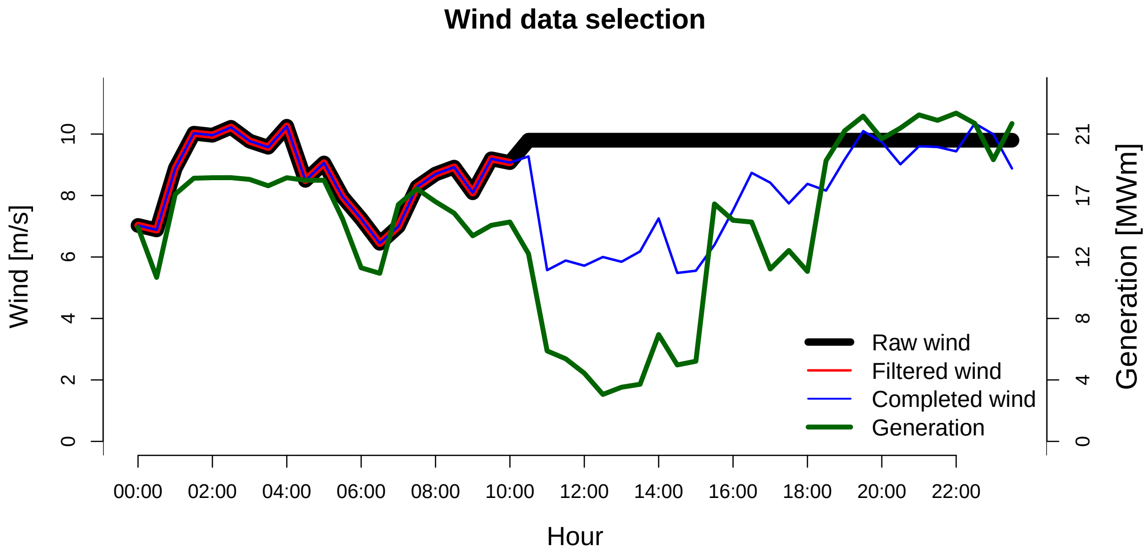

Figure 4. Raw, filtered, and completed wind data, along with the corresponding wind power generation.

Figure 5 shows the distribution of the percentage of wind data failures by wind farm, allowing an assessment of the quality of the time series used in this study. Black markers represent the percentage of invalid data identified in the raw series prior to the application of data treatment procedures, whereas red markers indicate the percentage of remaining gaps after the gap-filling process. Wind farms are ordered according to the percentage of failures in the original series, facilitating the visualization of heterogeneity in data quality across different projects.

It can be observed that, although some wind farms exhibit high percentages of invalid data in the raw series, the data completion procedure significantly reduces the presence of gaps, resulting in more complete time series that are suitable for the application of estimation and forecasting models.

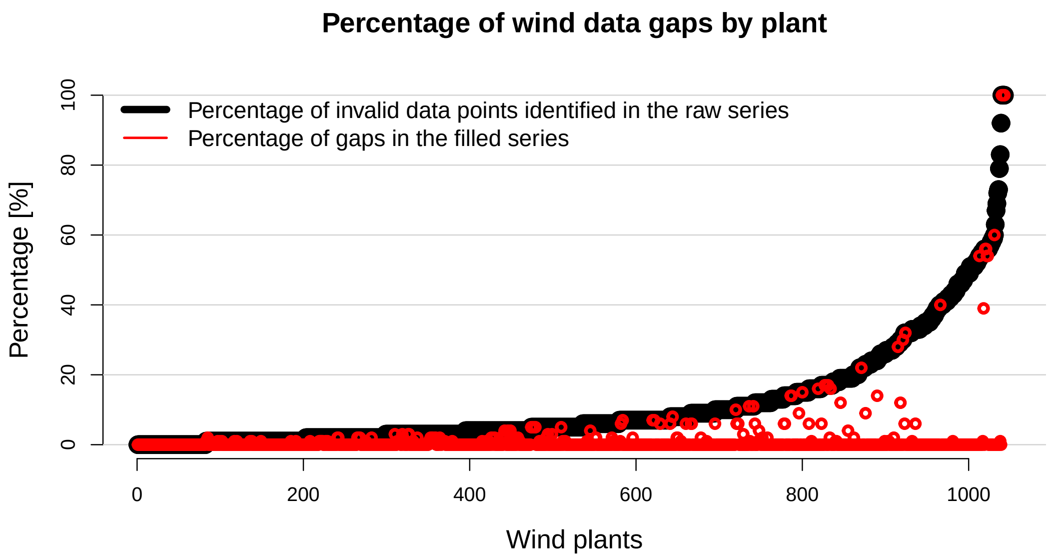

Figure 5. Percentage of missing and invalid wind data by wind plant, before and after the gap-filling procedure.

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As illustrated in Figure 5, some wind farms exhibit high percentages of wind data failures in their original time series. Approximately 42 out of the 1043 utility-scale wind farms considered in the analyses present more than 50% missing or invalid data in their measurement histories, which often hampers the estimation of generation associated with these units. Considering the full set of observations—corresponding to approximately two years of half-hourly data from the 1043 monitored wind farms—about 12% of the records are classified as invalid. After the application of the data treatment and completion steps, this percentage is substantially reduced, resulting in approximately 2% of missing data in the historical series. Although the gap-filling procedure resolves most cases, some wind farms may still exhibit insufficient data quality.

3.2. Results of the Estimation Model Application

As discussed in Section 2.3.2, applying the model to aggregated groups of wind farms, rather than to individual plants, leads to performance gains in the assessment of aggregated generation, which constitutes the primary operational focus of the ONS. The results presented below consider 1043 utility-scale wind farms, totaling approximately 33.5 GW of installed capacity, organized into 153 wind farm groups according to their connection to the SIN. The analysis covers the period from January 2023 to December 2025, using data discretized at half-hour intervals.

Currently, generation curtailment requests issued by the ONS are directed at these wind farm groups, while the operating agents are responsible for allocating the restrictions among the individual plants within each group. In this context, model performance is assessed at the group level. Based on this approach, the following analyses present representative examples of the estimation model performance, highlighting both cases of strong agreement between observed and estimated generation and situations in which limitations in the input data negatively affect the results.

Figure 6 presents two representative cases of wind farm groups exhibiting contrasting performance of the generation estimation model. The left panel shows a case with strong agreement between observed and estimated generation, indicating good explanatory capability of the model for this group. In contrast, the right panel illustrates a poorer performance case, characterized by greater dispersion and systematic deviations. In general, this behavior is primarily associated with issues in the observed generation data itself, as evidenced by the lack of coherence in the dispersion pattern. In addition, in most cases, performance degradation is exacerbated by widespread failures in the wind data of the wind farms composing the group, which are not fully corrected by the data treatment and completion process. As a result, limitations in the input data propagate to the estimation stage, reducing model accuracy in these specific cases.

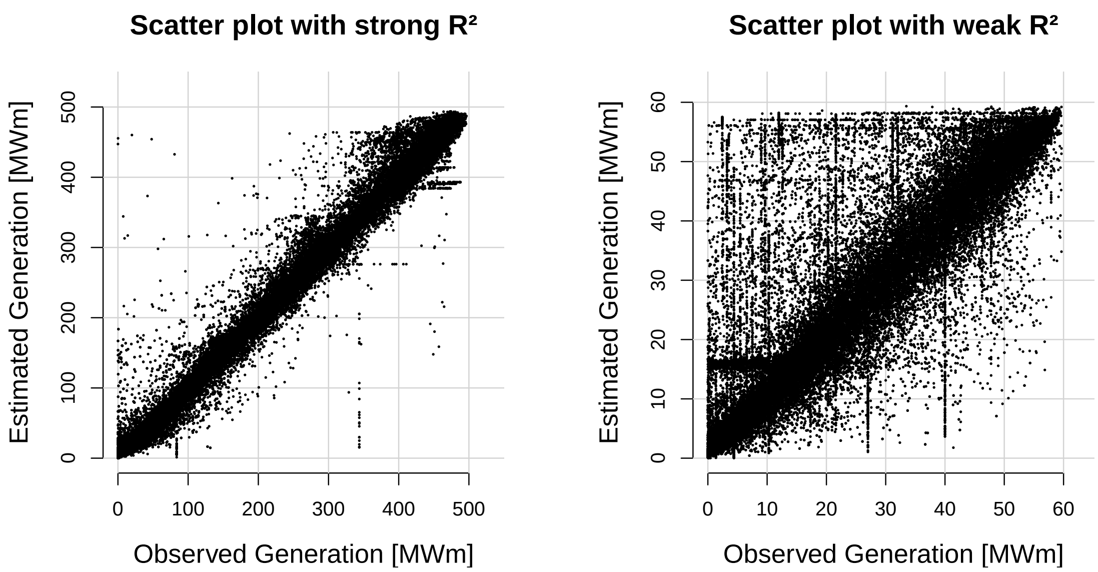

Figure 6. Examples of wind farm groups with strong and weak performance of the generation estimation model.

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Figure 7 illustrates the behavior of the coefficient of determination (R^2, Equation (2)) for each wind farm group, considering the relationship between the observed generation and that estimated by the model. A wide variability in performance across the groups can be observed, where higher R^2 values indicate strong agreement between the observed and estimated series, while lower values reflect a reduced explanatory capability of the model.

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (P_i - \hat{P}_i)^2}{\sum_{i=1}^{n} (P_i - \overline{P})^2} \tag{2}$$

where P_i denotes the observed generation value; $\hat{P}_i$ represents the value estimated by the model; $\overline{P}$ is the mean of the observed values; and n is the total number of observations.

The wind farm groups were ordered to facilitate the graphical analysis of model performance. Among them, 105 groups exhibit $R^2 \geq 0.9$ and are classified as having good performance; 37 groups present $0.7 \leq R^2 < 0.9$ and are considered to have satisfactory performance; and 11 groups show $R^2 < 0.7$, being classified as low-performance cases in generation estimation.

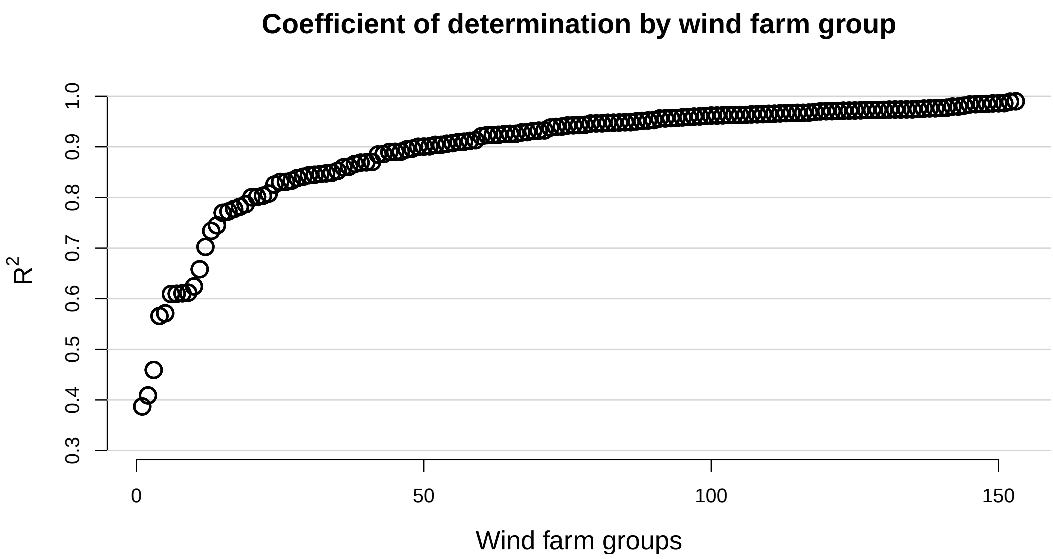

Figure 7. Coefficient of determination (R²) between observed and estimated generation for each wind farm group.

Results at the wind farm group level are particularly relevant for the assessment of generation accounting and are essential in the compensation procedures for affected generation agents. In addition, these results are important for real-time operation, as the estimated generation values can serve as a reference for releasing operational constraints without compromising system security. This is because, if an operator releases a restriction without a reliable estimate of wind power generation, excess generation may occur, potentially leading to overfrequency events and more severe operational issues.

Aggregated results at the electrical subsystem level are also relevant, particularly in the Brazilian context, which is characterized by two major regions with significant installed wind capacity—the South and the Northeast. Such aggregation is important for managing curtailment associated with power transmission between these subsystems. To assess the overall curtailment behavior in the country, even broader aggregations are required, enabling strategic-level analyses. These results are essential for improving system operation planning, reducing economic losses, guiding investments in transmission infrastructure and energy storage, and increasing the effective utilization of clean energy.

Figure 8 presents an example of a comparison between observed and estimated wind power generation for the SIN over ten days, in October 2025, considering a half-hourly temporal resolution. The lower panel shows the evolution of the number of wind farm groups that recorded at least one curtailment request, represented by the blue line. Currently, 153 groups are identified as having experienced operational restrictions, which enables a systematic analysis of the relationship between curtailment events and the aggregated behavior of wind power generation in the Brazilian SIN. This indicator provides an indirect measure of the spatial and temporal extent of the restrictions imposed on wind generation over the analyzed period. The upper panel presents the observed wind power generation (red line) and the generation estimated by the model (black line). A high level of agreement between the two series is observed during periods without curtailment, highlighting the model's ability to consistently reproduce the actual behavior of wind power generation under normal operating conditions. This agreement is a fundamental aspect for the application of the model in counterfactual analyses, as it ensures that differences observed during restriction events can be more confidently attributed to the effects of curtailment rather than to deficiencies in the modeling of potential generation.

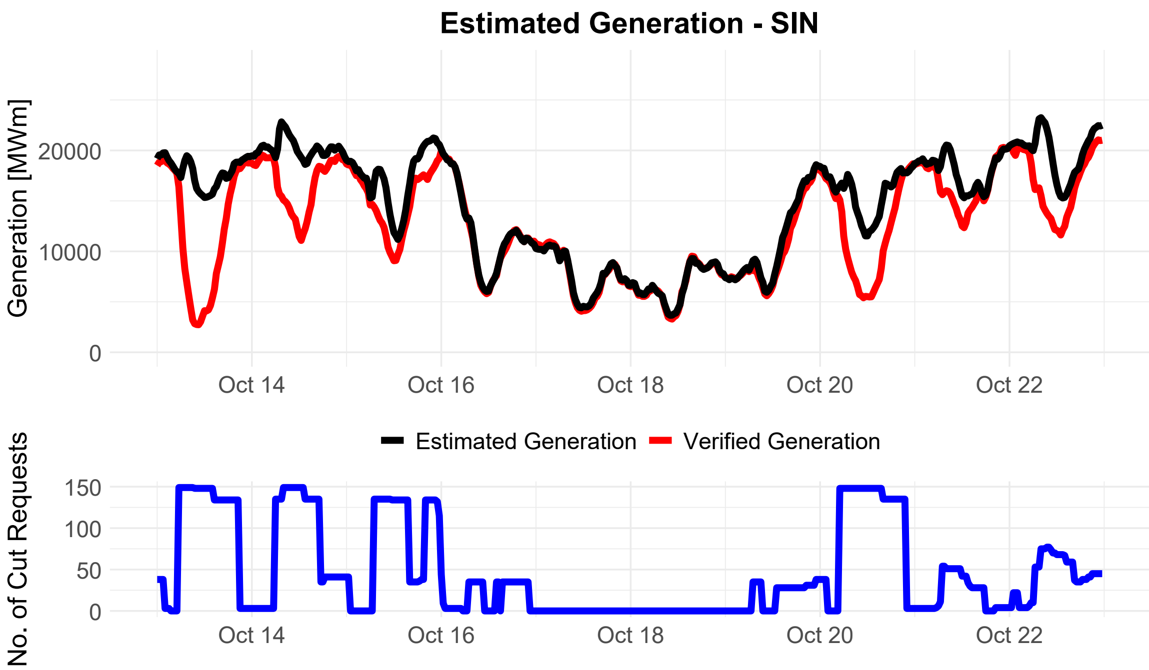

Figure 8. Estimated wind power generation for the SIN at half-hourly resolution.

To enable a more comprehensive assessment of model performance, a set of performance metrics was computed. Due to significant differences in installed capacity between the beginning and the end of the analyzed period—approximately 22.7 GW and 33.5 GW, respectively—raw errors were normalized by the installed capacity at each time step multiplied by the average capacity factor over the period, approximately 33.2% for the SIN. This normalization allows error comparisons under different operating conditions and generation scales, reducing the influence of absolute capacity on the analysis. The normalized performance metrics are presented in Table 1.

Table 1. Error metrics obtained for the evaluated dataset.

	nME	nMAE	nRMSE	nMAPE (%)
Values	-0.0281	0.0401	0.0680	4.0121

The results presented in Table 1 indicate that the normalized Mean Error remains close to zero, evidencing the absence of a significant systematic bias. The small bias observed can be attributed to atypical operational conditions affecting some wind farms, which reduce their generation for reasons not associated with curtailment events. The normalized Mean Absolute Error represents the typical magnitude of deviations, while the normalized Root Mean Square Error, by penalizing larger

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deviations more strongly, highlights the occurrence of occasional higher-magnitude errors. Finally, the normalized Mean Absolute Percentage Error provides an aggregated view of the relative error level, allowing for an intuitive interpretation of estimation performance in percentage terms. Taken together, these metrics indicate a consistent model performance, characterized by low bias and controlled error dispersion.

Finally, the monthly aggregation of estimated generation by electrical subsystem provides a consolidated view of potential generation and the energy losses associated with curtailment events over time. This analysis constitutes a relevant input for medium- and long-term energy planning, as well as for the evaluation of policies and strategies aimed at integrating renewable energy sources into the Brazilian power system.

Figure 9 presents a synthesis of the monthly curtailment analyses. The upper panel shows the monthly average number of curtailment requests, while the lower panel depicts the effectively curtailed energy, obtained by comparing observed generation with that estimated by the model. This approach allows for a direct quantification of the energy impact of operational constraints, highlighting periods in which the gap between potential and observed generation is more pronounced.

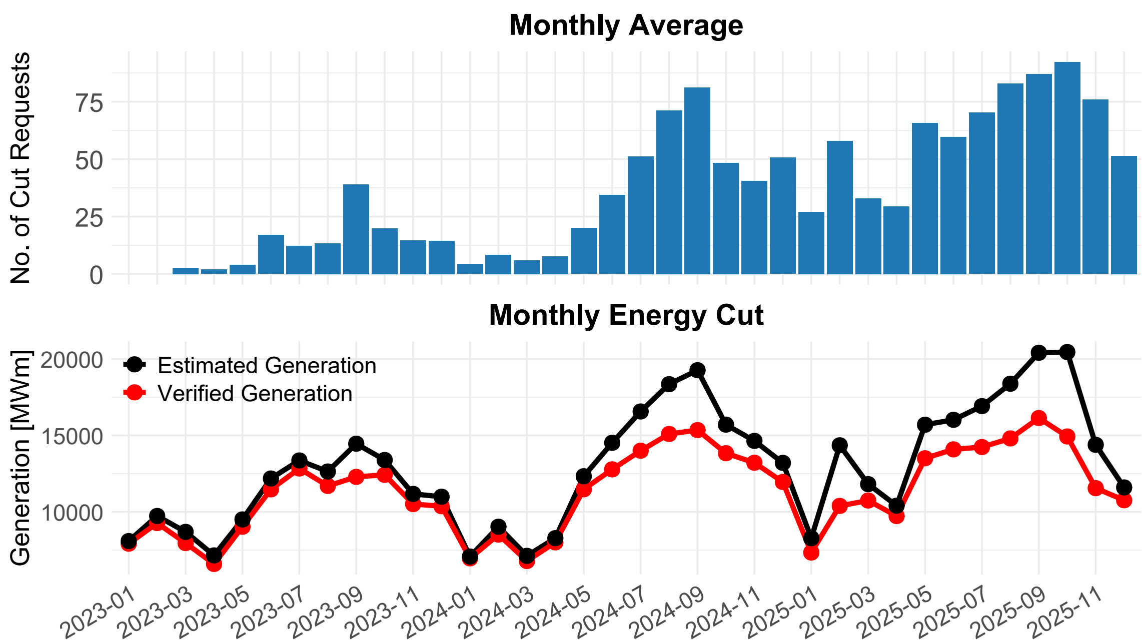

Figure 9. Estimated wind power generation for the SIN at monthly resolution.

Based on the application of the model to periods affected by curtailment, average annual wind power generation losses were estimated at approximately 5% in 2023, 10% in 2024, and 17% in 2025, with indications of a continuing upward trend throughout 2026. These results reflect the increasing frequency and severity of operational constraints associated with the rapid expansion of installed capacity, particularly in regions facing limitations in generation evacuation.

The numerical evaluation of the results confirms the robustness of the proposed methodology. When considering exclusively periods without the occurrence of curtailment, the model achieves an accuracy exceeding 95% at the half-hourly resolution and above 99% when evaluated on an annual aggregated basis.

4. Conclusions

This work presents an innovative methodology for estimating potential wind power generation, designed for large-scale power systems with a high penetration of wind energy. Although developed to address the specific needs of the Brazilian system operator, the proposed approach is general in nature and demonstrates strong potential for application in other power systems, as well as relevance to the academic community focused on large-scale generation estimation techniques.

The main contribution of this study lies in the integrated treatment of wind power generation estimation challenges in complex operational environments, covering data processing, data qualification, and wind–power relationship modeling. Special emphasis is placed on the automatic and dynamic estimation of wind speed–power curves, a key requirement for system operators managing a large number of wind farms with heterogeneous and incomplete datasets.

Despite inherent limitations related to the availability, consistency, and quality of observational data, particularly anemometric measurements, the model demonstrates robust performance in estimating potential wind power generation, enabling the identification and quantification of energy losses associated with curtailment events. The strong agreement between estimated and observed generation during periods without curtailment reinforces the suitability of the adopted approach to represent the physical wind–power conversion process, in line with findings from previous studies employing deterministic models and regression techniques.

In comparison with the existing literature, the results reinforce the importance of employing anemometric measurements and other SCADA data, as well as spatial correlation techniques among wind farms, to address data gaps and inconsistencies, as widely reported in studies on wind power forecasting and estimation. Nevertheless, whereas most previous works primarily aim to minimize forecasting errors, the methodology proposed here specifically focuses on the counterfactual estimation of suppressed generation, an aspect that has received limited systematic investigation, particularly in large-scale power systems such as the SIN.

The large-scale application of the method demonstrates that curtailment events cannot be properly assessed solely on the basis of observed generation, since the latter simultaneously incorporates the effects of operational constraints and meteorological variability. In this regard, the explicit distinction between these factors constitutes a relevant contribution to operational analyses, providing a more consistent technical basis for financial compensation processes and for improving system operation rules.

Beyond its operational use, the proposed methodology stands as a strategic tool for planning and operation studies in power systems with a high share of variable renewable energy sources. The approach enables the reconstruction of historical time series and the technical quantification of energy losses resulting from dispatch constraints. In addition, it provides qualified support for regulatory analyses and economic compensation mechanisms by enabling the transparent, consistent, and reproducible estimation of unrealized generation.

As directions for future research, the proposed methodology can be expanded through the incorporation of additional data sources and its application to other renewable technologies, particularly solar photovoltaic generation, for which curtailment levels have been increasing in Brazil. Furthermore, the integration of probabilistic approaches may allow the explicit representation of uncertainty in wind power generation estimation and the assessment of future curtailment projections under different operational and expansion scenarios. In this context, the integration of stochastic modeling and scenario-based analysis could provide a more comprehensive characterization of curtailment risks associated with transmission constraints, renewable penetration, and demand evolution. Additionally, further developments may address regulatory aspects, supporting the valuation of curtailment and the definition of transparent and consistent criteria for economic compensation mechanisms.

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Data Availability Statement: Some of the data used in this study are confidential and belong to companies in the Brazilian electric power sector. However, most of the data employed in this research are publicly available. Information on wind power plant registration can be accessed through the Brazilian Electricity Regulatory Agency (ANEEL) open data portal at https://dadosabertos.aneel.gov.br/dataset/siga-sistema-de-informacoes-de-geracao-da-aneel. In addition, raw observed wind power data are available from the Brazilian National Electric System Operator (ONS) open data portal at https://dados.ons.org.br/dataset/restricao_coff_eolica_detail. The datasets generated in this study for the purpose of producing the figures are available from the corresponding author upon reasonable request.

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

Abbreviations

The following abbreviations are used in this manuscript:

SIN	Brazilian Interconnected Power System
ONS	Brazilian National Electric System Operator
EPE	Brazilian Energy Research Office
ANEEL	Brazilian Electricity Regulatory Agency
VRE	Variable Renewable Energy
GAM	Generalized Additive Models
MARS	Multivariate Adaptive Regression Splines
SVR	Support Vector Regression
ME	Mean Error
MAE	Mean Absolute Error
RMSE	Root Mean Square Error
MAPE	Mean Absolute Percentage Error
NMAPE	Normalized Mean Absolute Percentage Error
R^2	Coefficient of Determination
W–P	Wind vs. Power

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