How The Climate Variability Affects Wind Generation in Brazil

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Abstract—**This paper applies statistical and machine learning techniques to investigate the relationship between meteorological variables and wind generation in Brazilian power plants. Public data from INMET, ONS, and ANEEL were used to perform descriptive, inferential, and predictive analyzes. An interactive Shiny application and the REST API were developed to provide real-time predictions and dynamic visualization of results, facilitating practical application of the predictive model for energy planning and operational decision making.**

Index Terms—**statistical analysis, machine learning, energy generation, meteorological data, Shiny, REST API, wind power forecasting**

I. Introduction

The Brazilian energy matrix is characterized by a high share of renewable sources, particularly hydroelectric, wind, and solar power. Although this composition contributes to sustainability, it also introduces a high degree of operational dependency on weather conditions. Among these sources, wind energy has shown remarkable growth in recent years, especially in the Northeast region, due to its abundant wind resources and government incentives. However, the inherent variability of wind generation poses significant challenges for the operation and planning of the National Interconnected System (SIN). Sudden changes in wind speed can lead to fluctuations in energy supply, requiring grid operators to deploy backup generation, often from more expensive and carbon-intensive sources. This volatility directly impacts not only grid stability, but also financial outcomes in the short-term energy markets.

Given this context, accurate wind generation forecasting becomes an essential tool for energy dispatch planning, risk management, and market operations. Although there are global models, the complex topography and diverse climatic patterns of Brazil require localized data-driven approaches that account for regional weather behavior and characteristics of power plants. The motivation behind this work is to address this operational gap by leveraging machine learning techniques to create a accurate and scalable forecasting model tailored to the Brazilian context. Furthermore, by developing an REST API and an interactive Shiny application, this paper is designed to provide practical tools for system operators, traders, and policy makers to make more informed decisions in real time. This approach hopes to not only support operational efficiency but also contribute to a broader goal of decarbonization and energy transition in Brazil.

The purpose of this paper is to quantitatively assess the correlation between meteorological data and wind energy generation, focusing on predictive modeling and the development of an interactive web application with REST API capabilities for real-time wind generation forecasting.

The remainder of this paper is organized as follows. Section II presents a review of the literature on wind power forecasting using machine learning techniques and discusses related work in the Brazilian context. Section III describes the methodology, including data sources, preprocessing steps, and feature engineering. Section IV details the model development process, hyperparameter selection, and the training strategy. Section V evaluates the performance of the model and provides an analysis of the importance of the characteristics. Section VI presents the deployment of the REST API and the Shiny web application developed to operate the forecasting model. Section VII discusses the results, highlighting practical implications and limitations. Section VIII outlines threats to validity. Finally, Section IX concludes the paper and suggests directions for future research.

II. Literature review

The application of machine learning techniques in wind power forecasting has gained significant attention in the past decade. Several studies have highlighted the effectiveness of advanced algorithms in improving forecast accuracy using meteorological and operational data.

Alkesaiberi et al. [1] conducted a comprehensive comparison of multiple machine learning algorithms, including Extreme Gradient Boosting (XGBoost), Random Forest, and Support Vector Regression, for wind power prediction. Their findings suggest that tree-based ensemble models, particularly XGBoost, consistently outperform traditional statistical models due to their ability to handle nonlinear relationships and heterogeneous data.

In the Brazilian context, Gerhardt and Webber [2] explored the application of machine learning models for wind energy forecasting using data from the southern region of Brazil. Their study demonstrated that machine learning techniques can substantially improve predictive performance compared to conventional forecasting methods used in the energy sector.

Farias [3] focused on integrating different numerical weather prediction models with machine learning approaches to enhance wind energy generation forecasts. This research emphasized that hybrid models, which combine meteorological simulations with supervised learning algorithms, can deliver reliable forecasts, especially in regions with complex weather dynamics, such as Brazil.

Couto et al. [4] investigated the relationship between climate variables and wind speed for forecast purposes. Their study highlights the strong influence of atmospheric conditions, including pressure and humidity, on wind patterns, reinforcing the need to incorporate detailed meteorological characteristics into predictive models for wind power.

Cai et al. [5] further validated the effectiveness of XGBoost in wind speed forecasting tasks. Their research demonstrated that XGBoost not only provides high accuracy, but also offers better computational efficiency compared to deep learning models in the context of structured, tabular meteorological data.

From a climatological perspective, Gurgel et al. [6] analyzed the density of wind power in northeastern Brazil using regional climate models. Their results underscore the significant variability in wind potential in different areas, particularly in semi-arid regions, which presents both opportunities and challenges for wind energy forecasting in the country.

Furthermore, geographical and meteorological analyses from journalistic sources, such as Exame magazine [7], confirm that certain regions of Northeast Brazil, like Rio Grande do Norte, experience some of the highest wind intensities in the country. This aligns with scientific findings regarding the region's suitability for wind power generation.

Collectively, these studies establish a solid foundation for the application of machine learning models to wind power forecasting, highlighting the critical role of localized meteorological data and advanced predictive algorithms such as XGBoost. The present study extends this body of work by integrating geographic, meteorological, and operational data into an interactive forecasting platform designed specifically for the Brazilian energy market.

III. Methodology

A. Data Sources

1) INMET – Meteorological Data

The National Institute of Meteorology (INMET) provides hourly and daily records from weather stations throughout Brazil. Data collected include temperature, relative humidity, solar radiation, precipitation, and wind speed.

2) ONS – Power Plant Generation

The National Electric System Operator (ONS) offers files that contain hourly and daily generation figures for each power plant in the country. Variables include plant code, date, time, and generated energy (in MW).

3) ANEEL – Locations of power plants

The Brazilian Electricity Regulatory Agency (ANEEL) maintains SIGA (ANEEL's Generation Information System), which provides latitude and longitude for each registered power plant. These coordinates were used to link the geographical location with local meteorological data.

B. Preprocessing

Data integration involved matching the generation records of the National Electric System Operator (ONS) with the geographic coordinates of each power plant obtained from the Brazilian Electricity Regulatory Agency (ANEEL). These coordinates allowed the identification of the closest meteorological stations of the National Institute of Meteorology (INMET), facilitating the alignment of meteorological data with energy generation data.

Several columns were removed from the data set to improve the performance and precision of the model. Specifically, unique identification columns, nearest station, latitude, longitude, and modality type codes were discarded. Furthermore, the precipitation operation column was excluded due to a significant imbalance. Temperature-related columns were removed because they were considered not to contribute meaningfully to the predictive modeling process [10].

Missing data was managed through critical preprocessing steps. First, all records associated with power plants that lack geographic coordinates (latitude and longitude) in the SIGA system were removed, as these coordinates were essential for associating plants with the nearest meteorological stations. Secondly, numerical columns containing missing values were imputed using the median value method. This choice addressed the data inconsistency prevalent in meteorological records from northeastern Brazil during the year's first quarter, typically characterized by energy outages, limited maintenance, and reduced automation compared to other regions. In particular, the data between 10 AM and 8 PM consistently had fewer missing values, as these hours coincide with regular working periods, which justifies the median imputation approach. The global radiation column was removed due to missing values exceeding 50% of the total entries.

To begin feature selection, the Pearson correlation matrix was computed to assess inter-feature dependencies (see Fig. 1). Based on this analysis, for atmospheric pressure and humidity measurements, only the base measurement columns were maintained; those containing only maximum or minimum readings were discarded.

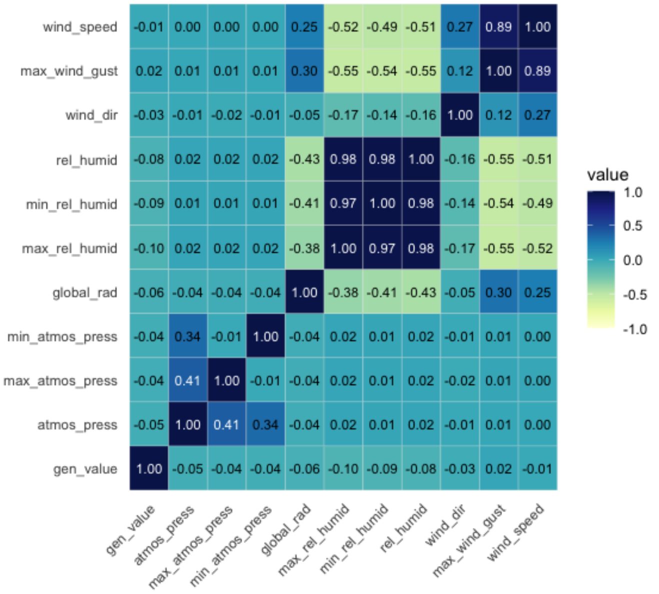


Fig. 1. Pearson correlation matrix of variables considered for feature selection.

Feature engineering efforts included creating a new variable that represents seasonal periods based on the date column. This engineered feature enhanced the predictive capacity of the model by capturing seasonal variations that influence wind energy generation patterns. The data column was subsequently removed because it has no predictive value for the model.
To handle extreme values, box plots were generated for all numerical variables. During this analysis, a large number of outliers were identified in the variable *wind_dir* (wind direction in degrees). Upon further investigation, approximately 45% of these outliers originated from the Calcanhar meteorological station. This observation aligns with a 2017 article published by *Exame* magazine, which reported that this region in the state of Rio Grande do Norte is the windiest in Brazil [7]. Given this context, outliers were treated using the Interquartile Range (IQR) method.

For data normalization and scaling, categorical variables underwent One-hot encoding, converting them into binary vectors. Numerical variables were scaled using the Min-Max scaler technique, standardizing the data to a consistent range and facilitating model performance.

For the development and validation of our model, the data set was segregated into a training set, comprising 70% of the data, and a testing set, containing the remaining 30%. This 70/30 distribution represents a standard trade-off in machine learning, providing a sufficiently large training partition for the algorithm to effectively learn the underlying data distribution without overfitting, while maintaining a large enough independent test partition to reliably evaluate the model's ability to generalize to new, out-of-sample data.

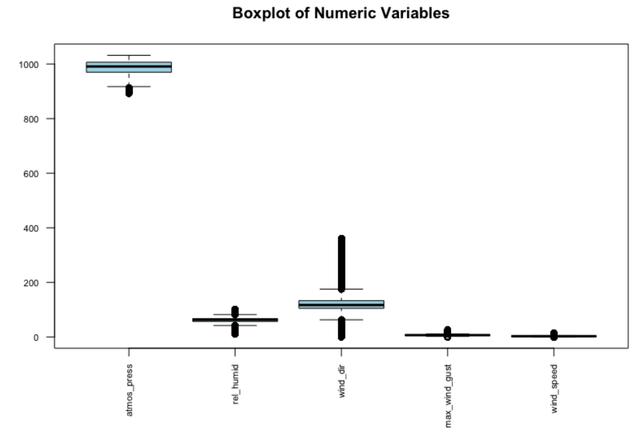


Fig. 2. Boxplot of numeric variables.

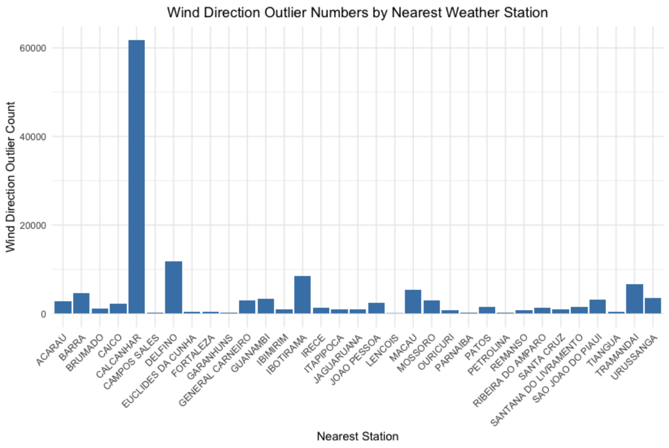


Fig. 3. Wind Direction Outliers.

IV. Model Training

For the predictive task, an Extreme Gradient Boosting (XGBoost) model was implemented, utilizing the xgboost package in R. This algorithm was selected for its high performance and efficiency in handling tabular data for regression problems.

Before training, the data was structured into the DMatrix format, an internal data structure used by XGBoost to optimize memory usage and training speed. The model's behavior was configured through a specific set of hyperparameters. The key parameters included a learning rate (eta) set to 0.1, a max_depth of 6 for individual trees, and both subsample and colsample_bytree ratios of 0.8 to mitigate overfitting by sampling rows and columns, respectively. The learning objective was defined as reg:squarederror, and the root mean squared error (RMSE) was chosen as a metric to evaluate the performance of the model during training.

The training process was executed for a maximum of 100 boosting rounds. To ensure generalization of the model and prevent overfitting, a validation mechanism was used by providing a watchlist that contained both the training and the testing sets. Furthermore, an early stop criterion was instituted to stop training if the RMSE on the test set did not improve for 10 consecutive rounds. The final model retained for evaluation is the one that achieved the lowest RMSE on the unseen test data.

V. Model Performance and Evaluation

Following the training phase, the finalized XGBoost model was evaluated in the unseen test set to evaluate its generalization performance. The predictive accuracy of the model for this regression task was quantified using three standard metrics: root mean squared error (RMSE), mean absolute error (MAE), and coefficient of determination (R²). These metrics were chosen to provide a comprehensive view of the accuracy of the model, with RMSE and MAE indicating the average prediction error in the units of the target variable, and R² representing the proportion of variance explained by the model.

A. Feature Importance Analysis

To interpret the behavior of the model, we calculated the importance of the features using the *Gain* metric, which quantifies how much each feature contributes to the reduction of the loss of the model. As shown in the chart above, `atmos_press` (atmospheric pressure) emerges as the most influential predictor, with the dummy for `state_id_PI` (the state of Piauí) a very close second. Among the categorical variables, site specific flags, especially `plant_name_Conj. Laranjeiras` and `plant_name_Conj. São Roque` rank highly, indicating that generation patterns differ substantially across locations. Seasonal indicators also play a key role: `seasons_Winter` appears within the top five, followed by `seasons_Spring` and `seasons_Summer`, reflecting the impact of time of year on output. Wind–related metrics such as `wind_dir` and `max_wnd_gust` provide additional predictive power, and smaller–effect plant dummies (including `Conj. Monte Verde`, `Conj. Serra do Seridó`, `Conj. Caju`, `Conj. Babilônia Sul`, `Conj. Umburanas`, `Conj. Oeste Seridó`, `Conj. Santa Eugênia`, `Conj. Oitis` and `Conj. Novo Horizonte`) together with `rel_humid` (relative humidity) round out the top twenty. Overall, these results show that the model is heavily based on atmospheric pressure and geographic context (state and plant identifiers), while seasonal and wind factors serve as important secondary signals.

B. Evaluation Results

The model demonstrated moderate predictive capability, achieving the following results in the test data:

RMSE: 51.9328 MAE: 35.8778 R-squared (R²): 0.5925 The R² value indicates that the model explains approximately 59.25% of the variance in the target variable, suggesting a reasonable fit to the data. These results are competitive with existing wind generation prediction models in the literature, particularly considering the complexity and variability of Brazil's diverse wind resource landscape.

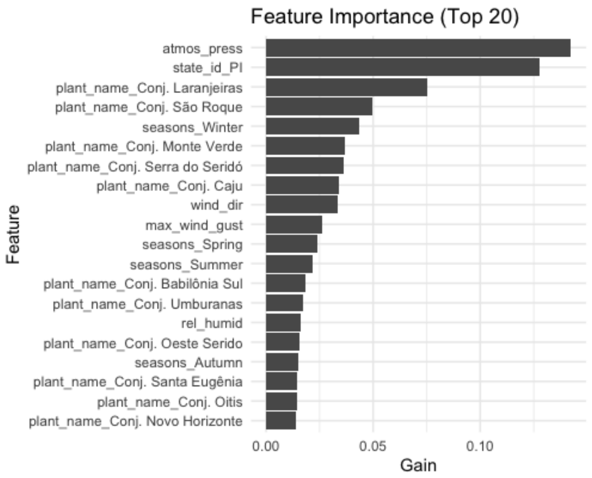


Fig. 4. Feature Importance (Top 20)

VI. API and Shiny Application

A. REST API Development with Plumber

A RESTful API was developed using the R Plumber package to enable programmatic access to the trained XGBoost model [9]. The API provides a standardized HTTP interface for obtaining wind generation predictions, facilitating integration with existing energy management systems, and enabling automated forecasting workflows.

The API endpoint accepts meteorological parameters through POST requests in JSON format, including atmospheric pressure, relative humidity, wind direction, maximum wind gust, wind speed, plant name, subsystem, state, and season. The service performs real-time data preprocessing, including one-hot encoding of categorical variables and normalization of numerical features using the preprocessing pipeline. Error handling mechanisms ensure robust operation, with appropriate HTTP status codes and descriptive error messages for invalid inputs or system failures.

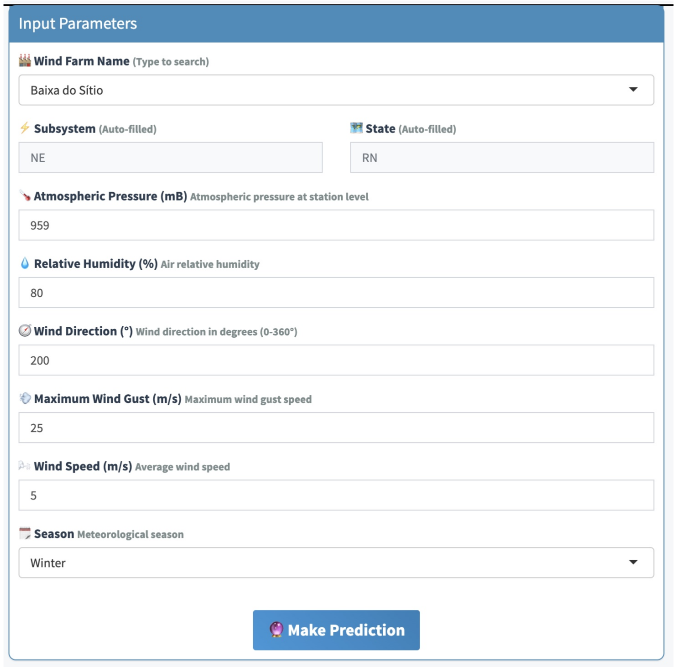
Input validation ensures data integrity by checking parameter ranges (e.g., humidity between 0-100%, wind direction between 0-360°) and verifying plant names against the official wind farm registry. The API returns predictions in a standardized JSON format with the estimated generation in megawatts, along with metadata on the prediction timestamp and input parameters used.

B. Interactive Shiny Application

A comprehensive web application was developed using Shiny in R to provide an intuitive interface for wind generation forecasting [8]. The application serves both technical and non-technical users, offering real-time predictions with rich interactive visualizations that enhance understanding of wind generation patterns and model behavior.

1) User Interface Design: The application employs a modern dashboard layout using the shinydashboard package, featuring a clean and responsive design optimized for desktop and mobile devices. The interface is structured into two main sections: a prediction panel for input parameters and result visualization, and an information panel providing model documentation and technical details.

The input parameters are organized in an intuitive form with descriptive labels and help text for each meteorological variable. Wind farm selection utilizes an autocomplete search feature with alphabetically sorted options, facilitating quick selection from the 136 available facilities in eight Brazilian states. Geographic information (state and subsystem) is automatically populated upon plant selection, using accurate mapping data derived from official ANEEL records.



Input Parameters

Wind Farm Name (Type to search)

Baixa do Sítio

Subsystem (Auto-filled): NE

State (Auto-filled): RN

Atmospheric Pressure (mB) Atmospheric pressure at station level

959

Relative Humidity (%) Air relative humidity

80

Wind Direction (°) Wind direction in degrees (0-360°)

200

Maximum Wind Gust (m/s) Maximum wind gust speed

25

Wind Speed (m/s) Average wind speed

5

Season Meteorological season

Winter

Fig. 5. Shiny Input Parameters.

2) Data Integration and Accuracy: The application incorporates precise wind farm mapping based on official data from the wind farm summary database, ensuring 100% accuracy in state and subsystem assignments. The final distribution includes 129 facilities in the Northeast (NE) subsystem in Bahia (42), Rio Grande do Norte (57), Ceará (18), Piauí (5), Paraíba (4), and Pernambuco (3), plus 7 facilities in the South (S) subsystem in Rio Grande do Sul (5) and Santa Catarina (2).

3) Interactive Visualizations: The application features three complementary visualization components that provide different perspectives on the prediction results.

Generation Gauge: A speedometer-style indicator displays the predicted generation value with a color-coded scale ranging from 0-200 MW. The gauge employs a dynamic color scheme: red for low generation (<30 MW), yellow for moderate generation (30-70 MW), green for high generation (70-120 MW) and blue for very high generation (>120 MW). This visualization provides immediate visual feedback on the predicted generation level.

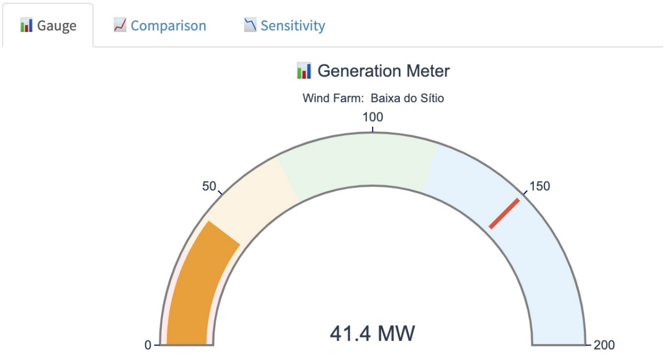


Fig. 6. Generation Gauge.

Wind Speed Sensitivity Analysis: An interactive line plot demonstrates how the predicted generation varies at different wind speeds (3-20 m/s) while keeping other parameters constant. The current input wind speed is highlighted with a distinct marker, allowing users to visualize the impact of wind speed variations on the generation output. This feature is particularly valuable for understanding the model's sensitivity to this critical input parameter.

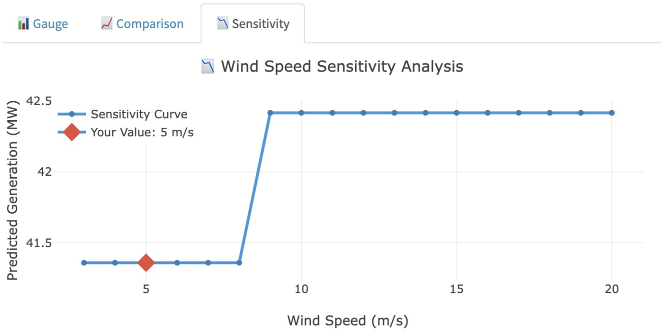


Fig. 7. Wind Speed Sensitivity Analysis.

4) Technical Implementation: The application utilizes several advanced R packages for enhanced functionality: Plotly for interactive graphics, shinyjs for custom JavaScript integration, and DT for data presentation. The interface incorporates real-time input validation, error handling with user notifications, and responsive design elements that adapt to different screen sizes.

Performance optimization includes efficient model loading, cached preprocessing objects, and streamlined prediction pipelines that ensure subsecond response times for typical user interactions. The application supports concurrent users through Shiny's reactive programming model, with automatic updates triggered by input parameter changes.

VII. Results and Discussions

The developed XGBoost model demonstrates competitive performance in predicting wind generation in Brazilian power plants, with an R² of 0.5925 indicating that almost 60% of the generation variance can be explained by meteorological variables and plant characteristics. This performance is particularly noteworthy given the complexity of Brazil's wind resource landscape, which spans diverse climatic zones and topographical conditions.

The feature importance analysis reveals interesting insights about wind generation patterns in Brazil. The predominance of geographic variables (state and plant-specific characteristics) in the top predictors suggests that local microclimate and topographical factors play crucial roles in generation variability. Atmospheric pressure emerges as the most significant meteorological variable, indicating its strong correlation with wind patterns and weather systems that affect wind generation. These results are in line with previous research, such as Alkesaiberi et al. [1] and Farias [3], confirming that meteorological variables, particularly atmospheric pressure and wind speed, are key drivers of wind generation variability."

The interactive Shiny application successfully translates complex machine learning predictions into an accessible interface for energy sector professionals. The automatic plant mapping feature eliminates potential user errors in geographic assignments, while sensitivity analysis provides valuable information for operational planning.

The REST API enables integration with existing energy management systems, supporting automated forecasting workflows and real-time decision-making processes. During validation testing, the API demonstrated robust performance under concurrent load conditions and provided consistent response times that are suitable for operational environments.

VIII. Threats To Validity

Despite promising results, this study is subject to several validity threats that may affect the generalizability and reliability of the findings.

A. Internal Validity

The internal validity is influenced by the presence of missing data, especially from meteorological stations with inconsistent reporting. Although median imputation was applied to handle missing values, this approach may introduce biases, particularly if the missingness is not completely random. Furthermore, the exclusion of temperature-related variables, although supported by correlation analysis and literature, could overlook indirect interactions with other variables that could influence wind generation under specific conditions.

B. External Validity

The developed model is specifically tailored to the Brazilian wind farms and the meteorological characteristics of Brazil. Consequently, its applicability to other geographical regions with different wind regimes, climates, or operational characteristics may be limited. Furthermore, the data set used reflects historical patterns within a fixed time frame. Climate variability and long-term changes, such as those induced by climate change, can reduce the predictive performance of the model in the future.

C. Construct Validity

The selection of features, including the removal of some meteorological variables and the aggregation of categorical variables, may affect the validity of the construct. There is a risk that the features used do not fully capture all relevant factors influencing wind generation, such as orographic effects (local terrain influences) or wake effects between wind farms, which are not directly represented in the dataset.

D. Conclusion Validity

The model achieved moderate performance, with an R² of 0.5925, suggesting that while it captures significant patterns, a substantial portion of the variance remains unexplained. This may be due to the inherent stochastic nature of the wind or limitations in the temporal and spatial resolution of the input data. Furthermore, the model evaluation relied on a random train-test split, which, while standard, does not fully account for temporal dependencies that could impact forecast accuracy in operational settings.

IX. Conclusion

This study successfully demonstrates the application of machine learning techniques for wind generation prediction in Brazil, achieving meaningful predictive accuracy while providing practical tools for energy sector applications. The performance of the XGBoost model, combined with the comprehensive web application and API infrastructure, offers a complete solution to wind generation forecasting needs.

The tools were developed to address real-world requirements in the Brazilian energy sector, providing technical professionals and decision makers with accessible interfaces for generation planning and operational optimization. Automatic wind farm mapping and interactive visualizations improve the user experience while ensuring data accuracy and consistency.

Future work could explore ensemble methods combining multiple algorithms, incorporation of additional meteorological variables such as atmospheric pressure trends, and expansion to include other renewable energy sources. The modular design of both the API and the Shiny application facilitates such extensions while maintaining backward compatibility.

The success of this project demonstrates the value of combining a rigorous machine learning methodology with user-centered application design, creating tools that bridge the gap between academic research and practical industry applications in the renewable energy sector.

Code Availability: The complete R scripts for data processing, model training, REST API, and Shiny app are available in https://github.com/BernardoOliveiraPinto/Machine-Learning-Project.

Acknowledgment

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