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 was used to perform descriptive, inferential, and predictive analyzes. An interactive Shiny application and 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 based on multiple sources and its operational efficiency is subject to external weather conditions. This article investigates how climate variables affect wind generation in different types of power plants in Brazil. With the growing importance of renewable energy sources in Brazil's energy mix, accurate wind generation prediction becomes crucial for grid stability and energy trading operations.

II. Objective

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.

III. Data Sources

A. 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.

B. ONS – Power Plant Generation

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

C. ANEEL – Power Plant Locations

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.

IV. Methodology

A. Preprocessing

Data integration involved matching 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 from the National Institute of Meteorology (INMET), facilitating the alignment of meteorological data with energy generation data.

Several columns were removed from the dataset to improve model performance and accuracy. 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. After consulting with meteorological experts, temperature-related columns were removed, as they were considered not to contribute meaningfully to the predictive modeling process.

Missing data was managed through critical preprocessing steps. Firstly, all records associated with power plants lacking 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. Notably, the data between 10 AM and 8 PM consistently had fewer missing values, as these hours coincide with regular working periods, justifying the median imputation approach. The global radiation column was eliminated due to missing values exceeding 50% of total entries.

To begin feature selection, we first computed the Pearson correlation matrix 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.

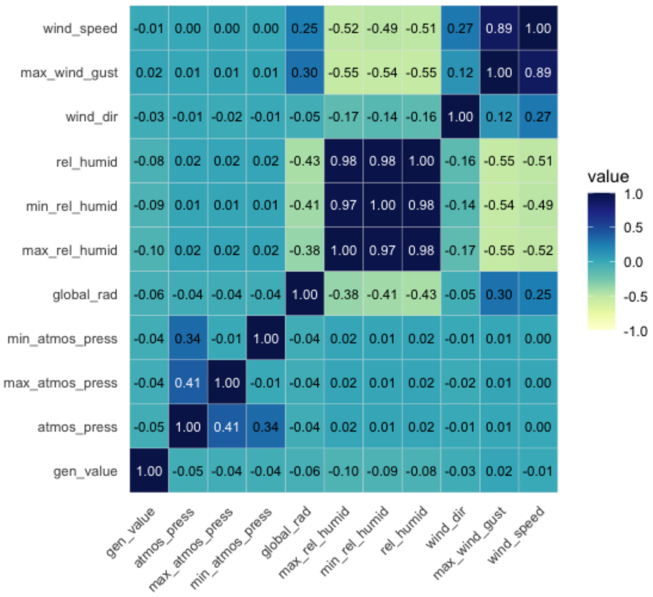


Fig. 1. Pearson correlation matrix of variables considered for feature selection.

Feature engineering efforts included creating a new variable representing seasonal periods based on the date column. This engineered feature enhanced the predictive capability of the model by capturing seasonal variations influencing wind energy generation patterns. The data column was subsequently removed, as it holds no predictive value for the model.

To handle extreme values, we generated boxplots for all numerical variables. During this analysis, we identified a high number of outliers in the variable *wind_dir* (wind direction in degrees). Upon deeper investigation, we found that 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. Given this context, we treated the outliers using the Interquartile Range (IQR) method.

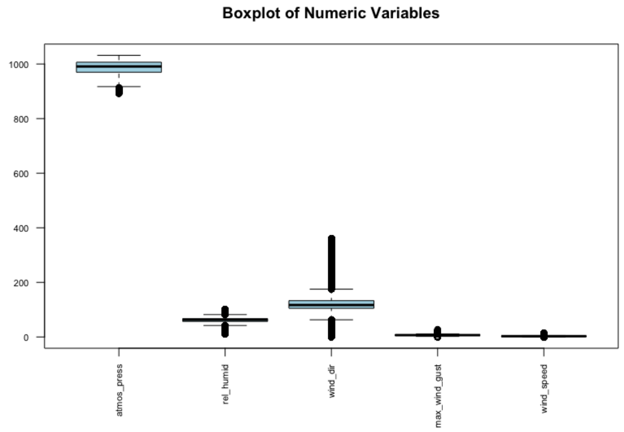


Fig. 2. Boxplot of numeric variables.

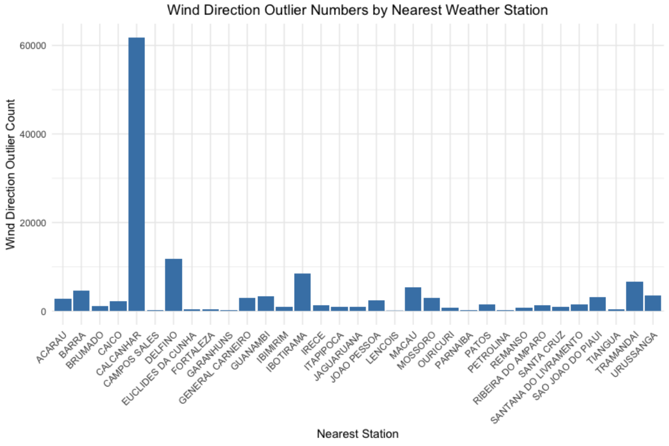


Fig. 3. Wind Direction Outliers.

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 dataset 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.

V. 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.

Prior to 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. 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 the metric for evaluating model performance during training.

The training process was executed for a maximum of 100 boosting rounds. To ensure the model's generalization capability and prevent overfitting, a validation mechanism was employed by providing a watchlist containing both the training and testing sets. Furthermore, an early stopping criterion was instituted to halt 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.

VI. Model Performance and Evaluation

Following the training phase, the finalized XGBoost model was assessed on the unseen test set to evaluate its generalization performance. The model's predictive accuracy for this regression task was quantified using three standard metrics: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R²). These metrics were chosen to provide a comprehensive view of the model's accuracy, 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 model's behavior, we computed feature importances using the *Gain* metric, which quantifies how much each feature contributes to reducing the model's loss. 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 leans heavily on atmospheric pressure and geographic context (state and plant identifiers), while seasonal and wind factors serve as important secondary signals.

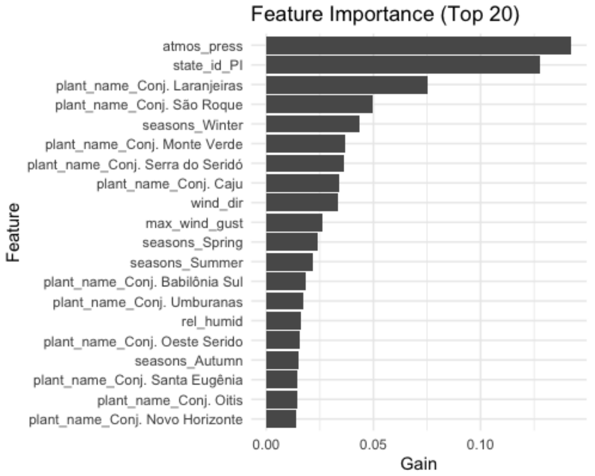


Fig. 4. Feature Importance (Top 20)

B. Evaluation Results

The model demonstrated a moderate predictive capability, achieving the following results on 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.

VII. 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. 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 via 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 pre-trained preprocessing pipeline. Error handling mechanisms ensure robust operation, with appropriate HTTP status codes and descriptive error messages for invalid inputs or system failures.

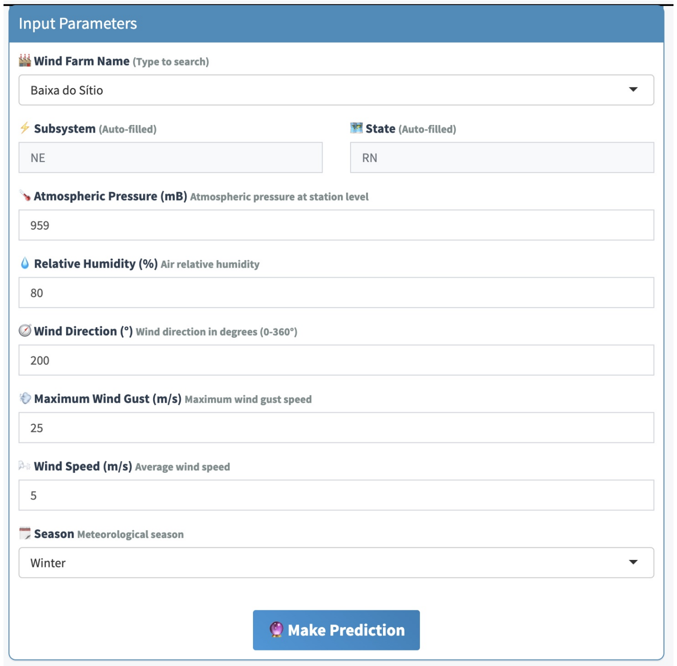
Input validation ensures data integrity by checking parameter ranges (e.g., humidity between 0-100%, wind direction between 0-360°) and verifying plant names against the official wind farm registry. The API returns predictions in a standardized JSON format with the estimated generation in megawatts,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

B. Interactive Shiny Application

A comprehensive web application was developed using R Shiny to provide an intuitive interface for wind generation forecasting. 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.

Input parameters are organized in an intuitive form with descriptive labels and help text for each meteorological variable. The wind farm selection utilizes an autocomplete search feature with alphabetically sorted options, facilitating quick selection from the 136 available facilities across 8 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 farms summary database, ensuring 100% accuracy in state and subsystem assignments. The final distribution includes 129 facilities in the Northeast (NE) subsystem across 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:

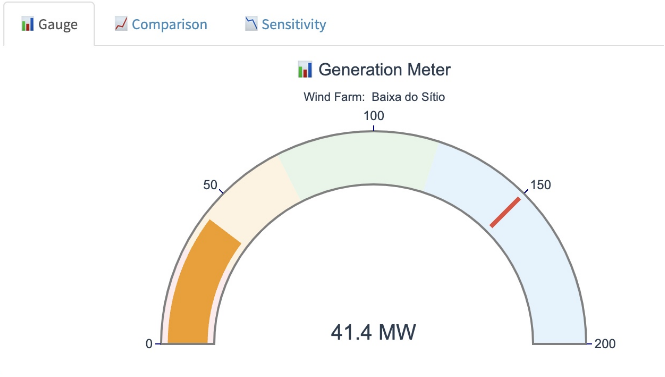


Fig. 6. Generation Gauge.

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.

Historical Comparison Chart: A bar chart compares the current prediction with state-specific seasonal averages and historical maximum values. The comparison incorporates realistic seasonal variations: Bahia averages 85 MW in summer and 55 MW in winter, Ceará shows 75 MW and 45 MW respectively, while other states exhibit 65 MW and 40 MW seasonal patterns. This contextualization helps users understand whether the predicted generation is typical or exceptional for the given location and season.

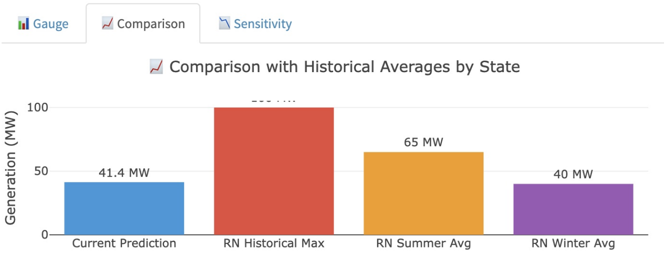


Fig. 7. History Comparison.

Wind Speed Sensitivity Analysis: An interactive line plot demonstrates how predicted generation varies across different wind speeds (3-20 m/s) while holding 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 generation output. This feature is particularly valuable for understanding the model's sensitivity to this critical input parameter.

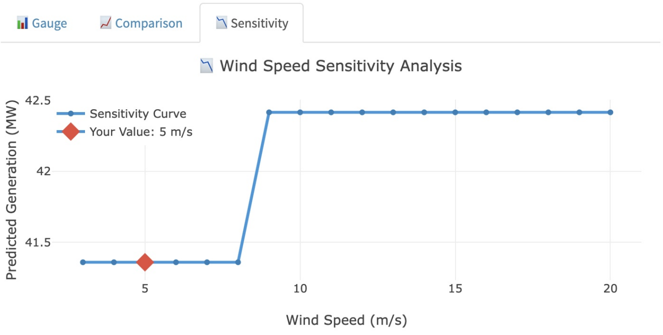


Fig. 8. Wind Speed Sensitivity Analysis.

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 sub-second 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.

VIII. Results and Discussions

The developed XGBoost model demonstrates competitive performance for wind generation prediction in Brazilian power plants, with an R² of 0.5925 indicating that nearly 60% of 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 features) 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 affecting wind generation.

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 the sensitivity analysis provides valuable insights 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 suitable for operational environments.

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 XGBoost model's performance, combined with the comprehensive web application and API infrastructure, offers a complete solution for wind generation forecasting needs.

The developed tools address real-world requirements in the Brazilian energy sector, providing both technical professionals and decision-makers with accessible interfaces for generation planning and operational optimization. The automatic wind farm mapping and interactive visualizations enhance 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 Shiny application facilitates such extensions while maintaining backward compatibility.

The success of this project demonstrates the value of combining 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 on https://github.com/BezimPinto/Machine-Learning-Project.

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