e-Prime - Advances in Electrical Engineering, Electronics and Energy 11 (2025) 100901

Contents lists available at ScienceDirect

e-Prime - Advances in Electrical Engineering, Electronics and Energy

journal homepage: www.elsevier.com/locate/prime

A comparative analysis of real and theoretical data in offshore wind energy generation

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ARTICLE INFO

Keywords:
Wind offshore
Renewable energy
Wind energy forecasting
Wind power predictive models

ABSTRACT

Wind energy plays a key role in the global shift towards renewable energy, requiring accurate prediction models for integration with power grids and effective energy distribution. This study validates the accuracy of wind speed forecasts from three widely used sources – European Centre for Medium-Range Weather Forecasts (ERA5), Modern-Era Retrospective Analysis for Research and Applications, MERRA-2 (NASA), and the Wind Atlas – against actual power generation data from the WindFloat Atlantic offshore wind farm near Viana do Castelo, Portugal, over the years 2022 and 2023. The results show that NASA's forecasts were the most precise, with annual relative errors of 5 % for 2022 and 1.6% for 2023, outperforming the other models. This analysis underscores the importance of validated forecasting models to enhance renewable energy management through multi-year data for precise local calibration. The findings also emphasize the necessity of consistent short-term load forecasting models for reliable daily energy production. Overall, this research demonstrates that combining global wind datasets with local validation improves offshore wind prediction accuracy. In this context, NASA's dataset emerges as the most reliable for operational and planning purposes in offshore renewable energy systems.

1. Introduction

Globally, there is an urgent need of transition to sustainable energy to ensure long-term energy security, stabilize prices, and reduce dependence on fossil fuels in power generation [1–3]. Portugal aims to become carbon neutral by 2050, but this transition presents significant challenges [4,5].

Fig. 1a and b illustrate the total installed power by technology in Portugal for the year 2022, highlighting the distribution between renewable and non-renewable energy sources [6].

Fig. 1a shows the total installed power by technology in megawatts (MW). Wind power leads with 8142 MW, followed by hydropower with 5730 MW. Natural gas and solar power contribute with 4918 MW and 2659 MW, respectively. Biomass, biogas, and geothermal power have smaller shares, and coal power has been completely phased out, reflecting Portugal's efforts to reduce carbon emissions [6]. Fig. 1b shows the proportion of renewable versus non-renewable energy sources. Renewable sources account for 75% of the total installed power (17,426 MW), while non-renewable sources make up 25% (5823 MW) [6]. These figures highlight Portugal's progress in integrating renewable energy, with a significant share from wind and hydropower. The elimination of coal power underscores the country's commitment to decarbonization and climate change mitigation. This energy landscape is crucial for this research, which aims to improve wind energy predictions by comparing theoretical models with actual data from the Wind Float offshore wind farm near Viana do Castelo. The present work seeks to enhance forecast reliability and contribute to efficient renewable energy management.

In addition to addressing limitations in the literature, this research provides relevant insights to improve forecasting accuracy and supports operational planning for newly explored offshore regions, thereby contributing to efficient resource utilization and enhanced grid integration.

Wind power is becoming a more and more important source of renewable energy. In a bid to reach a sustainable ecosphere and adopt an eco-friendly attitude, wind power emerges as an excellent option. Offshore wind farms, in particular, generate electricity using the more stable and powerful air currents present at sea. In Portugal, tender is expected to be launched for the installation of offshore wind turbines

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https://doi.org/10.1016/j.prime.2025.100901
Received 8 October 2024; Received in revised form 7 December 2024; Accepted 12 January 2025
Available online 20 January 2025

Abbreviations and Nomenclature

Cp	Performance coefficient
ERA5	European Centre for Medium-Range Weather Forecasts
MERRA-2	Modern-Era Retrospective Analysis for Research and Applications (NASA)
MAE	Mean Absolute Error
MSE	Mean Squared Error
SCADA	Supervisory Control and Data Acquisition
SD	Standard Deviation
Wind Atlas	Long-term averaged wind speed profiles based on climatological models
pu	Per Unit

with an installed capacity of 10 GW by 2030 [7]. As such, wind-energy facilities are a major element of the entire world's renewable energy mix. In this context, the reliability of wind power plants, as well as the accuracy of their predictions, is critical. Effective management and planning depend on accurate forecasts derived from complex mathematical models. Because the abundance of wind patterns continuously returns this power, the prediction is frequently intricate, and forecasting tools must be tested to determine when and where they give rise to mistake. This is precisely the case with the offshore wind farm in Portugal, near Viana do Castelo [8,9]. Equipped with three wind turbines capable of achieving a combined generation capacity of 1 pu (per unit), equivalent to 25 MW [8,10], as demonstrated in 2022 and 2023 through Fig. 2a and b, respectively, this installation represents a crucial component of the solution in understanding wind power's real-world efficacy and predicting accuracies.

Furthermore, other aspects concern the predictability of wind energy, the necessary and optimal calculation when managing grids and investing decisions, and the connection of their prediction with real power output. This forecast is based on several variables and detailed elaboration that are related to the wind speed, turbine types, the environment, and so on. However, the randomness of the wind's patterns to increase this unpredictability in one's possibilities to generate power allows comparing the model of forecast with the actual output to refine the model and use it more reliably.

To address these challenges, it is essential to employ robust error metrics to evaluate the accuracy of wind speed prediction models, such as Mean Absolute Error (MAE) [11], Mean Squared Error (MSE) [12], and Standard Deviation [13] to assess the predictive performance of different models. These metrics are crucial for identifying the precision and reliability of predictive models, as they provide quantitative measures of the discrepancies between predicted and actual values [14,15]. By incorporating these metrics, the study aims to offer a comprehensive evaluation of the models' accuracy and reliability.

Existing scientific literature on wind power forecasting covers various methodologies and approaches. Some of the prominent works include a provided and a comprehensive review of current methods and advances in wind power forecasting, highlighting the strengths and weaknesses of different approaches [16]. The authors in [17] used artificial neural networks for wind power forecasting, showing promising results in short-term predictions.

Recent advancements have focused on offshore wind energy forecasting. In Ref. [18] a novel prediction model integrating Temporal Convolutional Network-Dual Attention Network and Sparse Transformer was developed to address spatio-temporal coupling in clustered offshore wind farms. This approach demonstrated substantial improvements in predictive accuracy by incorporating spatial interactions between adjacent installations. The sensitivity of offshore wind energy forecasts to sea surface temperature inputs, emphasizing the

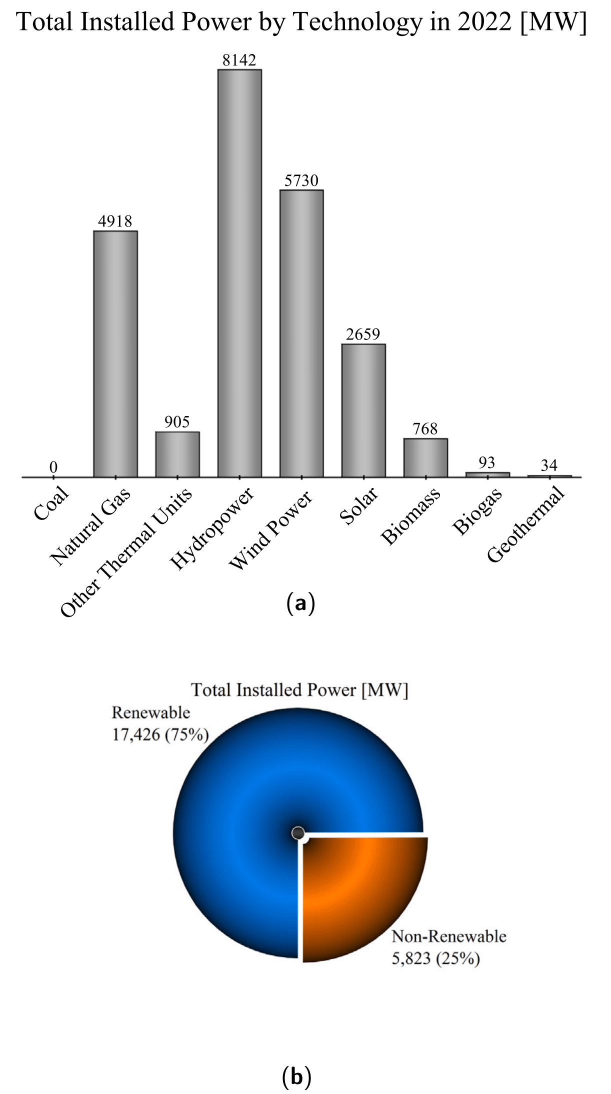


Fig. 1. Variation of energy sources in Portugal in 2022 [6]. (a) Total installed power by technology. (b) Total installed power.

critical role of high-resolution of sea surface temperature data in capturing transient atmospheric phenomena and enhancing hub-height wind characterization in the Mid-Atlantic was analyzed in [19]. The work in [20] shows that methodologies integrating Long Short-Term Memory and Convolutional Gated Recurrent Unit models with clustering techniques have provided a robust framework for categorizing and predicting daily wind power output, supporting grid operation optimization. The Ref. [21] addresses the performance evaluations of datasets such as ERA-5 and MERRA-2 across diverse climatic conditions have underscored their applicability in refining wind energy forecasting models, offering insights into dataset reliability for operational use. These advancements underscore the potential of integrating diverse datasets and innovative techniques to refine predictive accuracy, particularly for applications in complex systems like offshore wind farms.

Despite these advancements, a notable deficiency persists in the direct comparison of theoretical predictions with real-world data, particularly in offshore wind energy. Previous studies have primarily focused on general predictions and theoretical models without validating them extensively against real-world data [22]. On the other hand, innovative methods and technologies are employed to enhance the forecasting accuracy. For instance, the paper in [14] proposed a

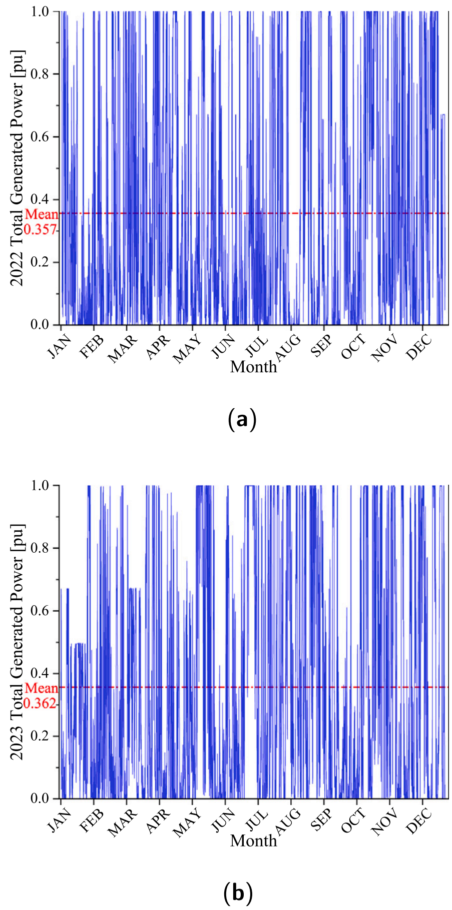


Fig. 2. Total generated power. (a) Year 2022. (b) Year 2023.

wind power ramp prediction method based on value-at-risk to improve operational stability in wind farms. [23] developed a short-term wind power forecasting model using a multi-scale receptive field-mixer and conditional mixture copula, which integrates various scales of meteorological data for improved accuracy. The authors in [15] utilized deep learning techniques to mine wind information, identifying potential sites for offshore wind farms. Additionally, [24] introduced a privacy-preserving and adaptive federated deep learning approach for multiparty wind power forecasting, ensuring data security while enabling collaborative forecasting efforts. [25] proposed a novel stacking ensemble variant based on machine learning for short-term wind speed forecasting, which optimizes the combination of different machine learning algorithms to enhance forecast accuracy.

While previous works have significantly advanced the field of wind power forecasting, they often have notable limitations. Most studies focus on either theoretical models or real-world data in isolation, without comprehensive validation that integrates both perspectives. Additionally, the unique challenges of offshore wind farms remain little explored. This work addresses these gaps by leveraging high-resolution operational data from an offshore wind farm to validate widely used forecasting models – ERA5, NASA, and Wind Atlas – under real operating conditions, offering practical insights to improve forecasting accuracy and reliability.

By integrating real-world data, this research highlights the variability in forecasting accuracy across temporal and spatial resolutions, providing actionable insights for refining and adapting these models to specific offshore locations. Furthermore, the proposed methodology has significant potential for application to other coastal regions, where localized coefficients can enhance daily forecast accuracy. As global offshore wind energy capacity continues to grow – with Portugal targeting 10 GW by 2030 – these findings are essential for improving production forecast reliability, energy management, and grid integration. These insights not only advance scientific understanding but also offer practical guidance for policymakers and grid operators to optimize offshore wind energy utilization.

The research problem in this study is framed by the pressing need to evaluate and validate global wind forecasting models (NASA, ERA5, and Wind Atlas) against real-world data from offshore wind farms. The lack of direct validation using operational offshore data poses significant challenges to the integration of renewable energy into power grids. Importantly, the present work seeks to address the shortcomings in wind energy forecasting by conducting a comprehensive evaluation of these models, comparing their predictions against real power data from an offshore wind farm. By analyzing relative errors on annual, monthly, and hourly levels, this research provides actionable insights to improve wind energy predictions and supports the deployment of offshore wind energy capacity, offering valuable contributions to the scientific community.

The core research question guiding this research is: *"How do widely used global wind forecasting models (NASA, ERA5, and Wind Atlas) perform when validated against real-world data from an operational offshore wind farm, and which model provides the most reliable predictions for integration into the energy grid?"* This question provides the necessary focus and direction to evaluate the accuracy and reliability of these models under real-world conditions.

Although applied to a specific case study, the findings can be generalized to other regions or case studies, contributing to a broader understanding of renewable energy forecasting [26]. Furthermore, the current research compares wind speed data forecasts from three important sources – ERA 5 [27], NASA [28], and Wind Atlas [29] – with the actual power generation data collected from an offshore wind farm named Wind Float near Viana do Castelo, Portugal, over the year 2022. By comparing the theoretical power output obtained through linear interpolation of three different sources' wind speeds with the actual power data from the wind farm, this study aims to evaluate the models over an annual and monthly scale. This research aims to achieve an innovative approach that could fill the gap between theory-based expectations and offshore wind's actual energy production [30,31]. Therefore, a comparison of relative errors in production is carried out both on an annual and month-to-month level, extending this comparison to an hour-by-hour analysis.

In contrast to research that relies solely on theoretical or simulated datasets, this study moves the field forward by incorporating real-world production data into forecasting models. This approach highlights variability in model performance and provides critical insights for adapting these models to localized conditions. As offshore wind energy continues to expand globally, including Portugal's ambitious 10 GW target by 2030, this research supports energy planning, grid integration, and the development of robust methodologies for renewable energy systems.

To support this research, the following conjecture has been established: "*Each global wind forecasting model analyzed (NASA, ERA5, and Wind Atlas) will show varying levels of accuracy when validated against real-world data from the WindFloat Atlantic offshore wind farm. By comparing their performance, we aim to identify the most reliable model for predicting offshore wind energy production"*.

The contributions of this paper are threefold:

1. Evaluation of the accuracy of widely used forecasting models under real operational conditions.
2. Provision of actionable insights for improving wind energy predictions.
3. Support for the integration of offshore wind energy into power grids.

These contributions establish the basis of the study, articulating its purpose, central research assumptions, and main contributions. It highlights how the research unites theoretical prediction tools with real-world validation, addressing a significant gap in the scientific literature while offering practical and scientific value.

This article is organized as follows: Section 2 shows the methodology, starting by characterizing the wind resource and developing the models that support the case study. Section 3 presents the results of the simulations, while Section 4 discusses their implications. Finally, Section 5 summarizes the conclusions and outlines future research directions.

2. Methodology applied to the case study

Portugal became a precursor in deploying wind turbines on floating platforms and currently operates a floating offshore wind farm off the coast of Viana do Castelo. This installation comprises three platforms with a total installed capacity of 25 MW, located approximately 20 km from the coastline. This research conducts a comparative analysis of theoretical and actual power generation by this offshore wind farm and the methodology includes data collection and preparation, theoretical power calculation, and comparison of theoretical values with actual power generation data.

The integrated approach to comparing theoretical and actuality of power generation will be developed based on the data from multiple sources of wind speed, the wind turbines' power curve characteristic, and the linear interpolation method to define theoretical power generation. The comparison focuses on annual and monthly energy production and extends to an hourly analysis throughout the years of 2022 and 2023.

2.1. Data sources and preparation

Wind speed data were collected from three sources: ERA 5 (European Centre for Medium-Range Weather Forecasts), providing hourly global atmospheric reanalysis data since 1970 [27]; the NASA dataset, which refers to the Modern-Era Retrospective Analysis for Research and Applications (MERRA-2), offering high-resolution hourly atmospheric reanalysis data since 1980 [28]; and Wind Atlas, providing long-term averaged wind speed profiles based on climatological models [29]. These datasets were chosen for their accuracy, high resolution, and relevance to the study area. Actual power generation data for 2022 and 2023 were obtained directly from the offshore wind farm's operational records.

The operational phase of the WindFloat Atlantic platform began in 2022, marking the point at which the wind farm reached full installed capacity. Consequently, the analysis in the present work focuses on data from 2022 and 2023, as earlier data from the wind farm's deployment phase does not accurately reflect its operational capabilities. This temporal scope ensures that the analysis represents the wind farm's performance under steady-state and stable operational conditions. Despite the limited time frame, a thorough evaluation was conducted across hourly, monthly, and annual time scales to maximize insights derived from the available data. This approach provides a robust foundation for model validation, even with a shorter data period.

It is important to note that the real data available for this research corresponds to the turbine's power output and does not include direct measurements of wind speed at the site. Consequently, direct comparisons with actual wind speed data could not be performed. Instead, the turbine's standard power curve was utilized to indirectly validate the forecasting models using the provided power output data.

Fig. 3 displays a wind speed comparison between the data extracted from ERA 5, NASA, and Wind Atlas. Fig. 3a and b depict the monthly average wind speed throughout the years 2022 and 2023, respectively, derived from the three sources of wind speed data utilized in this study.

Table 1
Specifications of the wind turbine of 8 MW.

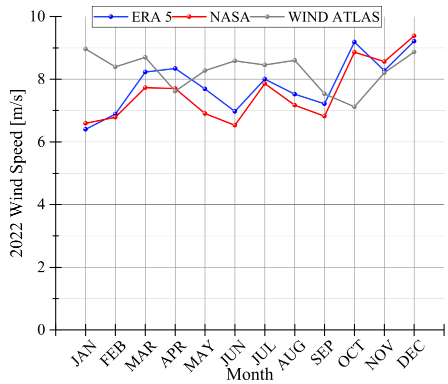
Specification	Details
Manufacturer	Vestas wind systems A/S
Model	V164-8.0 MW
Rated power	8000 kW
Rotor diameter	164 m
Swept area	21,124 m^2
Number of blades	3
Cut-in wind speed	4.0 m/s
Rated wind speed	13.0 m/s
Cut-out wind speed	25.0 m/s
Maximum rotor speed	12.1 rpm
Generator type	Permanent magnet generator
Operating voltage	66,000 V
Grid frequency	50 Hz
Tower type	Tubular steel
Application	Offshore

The variations observed in the ERA 5 and NASA data between the two years can be attributed to the nature of these sources, which provide reanalysis data based on real-time observations and are continuously updated to reflect actual atmospheric conditions. Consequently, these values vary annually, capturing the specific weather patterns of each year. In contrast, Fig. 3c illustrates a comparison among the three wind speed data sources, displaying floating bars that represent the maximum, minimum, and average values of the data collected from these sources. The Wind Atlas data remains constant between 2022 and 2023 because it represents long-term climatological averages rather than annual observations. These data are based on extensive periods, typically 20 to 30 years, and provide a stable profile of wind speed for specific locations, hence do not reflect year-to-year variability.

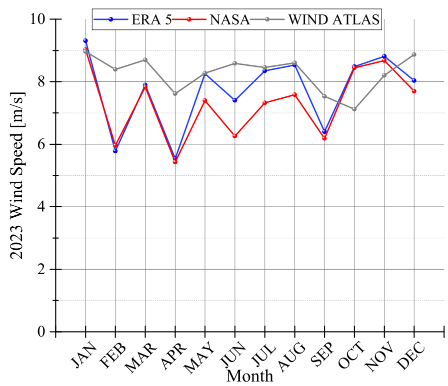
The characteristic power curve of the wind turbines, which depicts the relationship between wind speed and generated power (in kW), was obtained from the manufacturer's specifications. This curve is critical for translating wind speed into potential energy production. It was decided to use a turbine with a unitary power of 8 MW [32]. Fig. 4 presents the features of the wind turbine chosen for this study, including the standard power curve. This curve shows the relationship between power output in kilowatts (kW), the performance coefficient (Cp), and variable wind speeds. It demonstrates a gradual increase in power output as wind speeds rise, up to the turbine's rated speed. Beyond this point, the output levels off, maintaining a constant value. This behavior indicates the turbine's operational maximum, established to safeguard against potential damage in high-wind speed conditions. Table 1 portrays the specifications of the wind turbine of 8 MW. These technical details emphasize the turbine's suitability for offshore environments and highlight its operational capabilities, which are essential for understanding the accuracy of the wind energy predictions evaluated in this research.

Real power generation data for the years 2022 and 2023 were collected directly from the offshore wind farm's operational records, providing an empirical basis for evaluating the accuracy of theoretical power estimations.

The datasets selected for this research – NASA, ERA5, and Wind Atlas – are among the most widely recognized and utilized in wind energy forecasting. These datasets were chosen due to their high temporal and spatial resolution, as well as their established reliability in capturing wind patterns relevant to offshore wind energy applications. While other datasets were initially considered, they were excluded due to limitations such as insufficient resolution or the absence of critical parameters required for comparison with the WindFloat Atlantic data. The selected datasets provide a comprehensive basis for this analysis, ensuring that the conclusions drawn are robust, meaningful, and applicable to the operational conditions of offshore wind farms.



(a)



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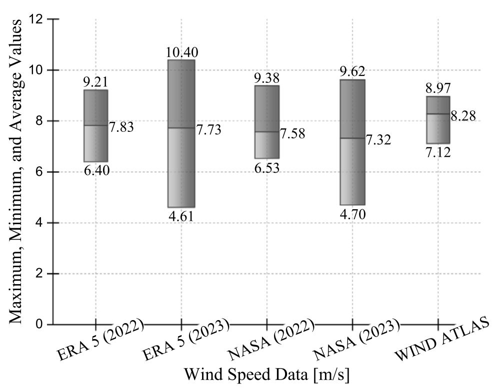


(c)

Fig. 3. Wind speed comparison between ERA 5, NASA, and Wind Atlas. (a) Monthly average wind speeds for 2022. (b) Monthly average wind speeds for 2023. (c) Comparative analysis of wind speed data: maximum, minimum, and average values.

2.2. Theoretical power calculation

Theoretical power generation was estimated using linear interpolation between known points on the turbine's power curve [33,34], as described in step 5 of the flowchart (Fig. 5). The turbine's power curve is illustrated in Fig. 4, which depicts the relationship between wind speed, power output, and the performance coefficient (Cp). Eq. (1) defines the interpolation process mathematically, providing transparency and supporting the accuracy of the theoretical power outputs calculated in this study.

Given a specific wind speed value, the corresponding power output (in kW) was calculated (1).

$$P_{\text{estimated}} = P_{\text{low}} + \left(\frac{P_{\text{high}} - P_{\text{low}}}{V_{\text{high}} - V_{\text{low}}} \right) \times \left(V_{\text{actual}} - V_{\text{low}} \right) \tag{1}$$

where $P_{\text{estimated}}$ is the estimated power output, P_{high} and P_{low} are the power outputs at the higher and lower wind speeds, V_{high} and V_{low} are the corresponding wind speeds, and V_{actual} is the actual wind speed.

This approach was applied to each hourly wind speed value from the three wind speed datasets, generating three sets of theoretical power data for comparison with the actual power production records.

As mentioned, the characteristic power curve of the turbine used in this work was obtained from the manufacturer's specifications, which are widely recognized as reliable and validated for steady-state modeling. Given that the SCADA (Supervisory Control and Data Acquisition) data used are sampled at 15-min intervals, the turbine operates under steady-state conditions during these periods, allowing the use of the manufacturer's power curve as a robust basis for the analysis. This approach ensures that the theoretical calculations align closely with the turbine's actual performance under real-world conditions.

Lastly, the use of the Vestas 8 MW turbine model, directly operational at the WindFloat Atlantic project, ensures that the theoretical analysis reflects real-world operational conditions. The manufacturer's power curve, validated for steady-state modeling, provides a robust foundation for translating wind speed data into power output. This alignment enhances the reliability of the theoretical calculations and supports the accuracy of the forecasting models tested in this research.

2.3. Comparison of theoretical and actual power generation

To evaluate the accuracy of the predictive models, the relative errors in production on both annual and monthly levels were compared, extending the comparison to an hour-by-hour analysis. This analysis helps identifying the bias and accuracy of current theoretical models by comparing them with actual data.

The analysis compares the actual power generation with the theoretical outputs derived from each wind speed data. The primary metrics for comparison were the relative error rates calculated on an annual and monthly basis, as well as an in-depth hourly comparison throughout the year. The relative error was calculated (2) [33,34].

$$\text{Error}_{\text{relative}} = \left(\frac{P_{\text{actual}} - P_{\text{estimated}}}{P_{\text{actual}}} \right) \times 100\ \% \tag{2}$$

where P_{actual} is the actual power generated, and $P_{\text{estimated}}$ is the theoretical power estimated from the wind speeds.

2.4. Statistical analysis

This subsection describes the statistical methods used to evaluate the accuracy of the predictive models. Error metrics were calculated such as Mean Absolute Error (MAE) [11], Mean Squared Error (MSE) [12], and Standard Deviation (SD) [13] to provide quantitative measures of the discrepancies between predicted and actual values. These metrics are crucial for identifying the precision and reliability of the analytical models and present a robust set of statistical indicators to thoroughly evaluate model performance.

2.4.1. Mean absolute error (MAE)

MAE measures the average of the absolute differences between the predicted values and the actual values. It indicates the average accuracy of the predictions (3).

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^{N} \left| P_{\text{estimated},i} - P_{\text{real},i} \right| \tag{3}$$

where:

N is the number of observations (in this case, 12 months).

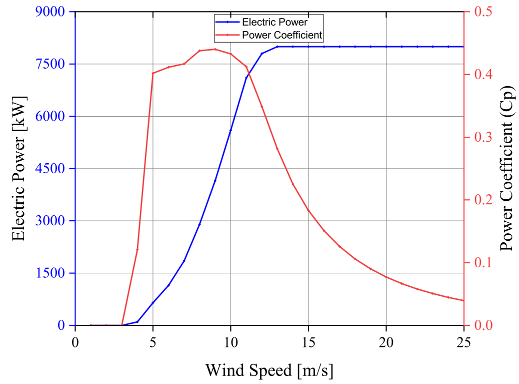


Fig. 4. Standard power curve of the selected wind turbine showing power output and performance coefficient (Cp) across different wind speeds.

$P_{\text{estimated},i}$ is the estimated value for month i.
$P_{\text{real},i}$ is the real value for month i.

2.4.2. Mean squared error (MSE)

MSE measures the average of the squared differences between the predicted values and the actual values. It penalizes larger errors more than smaller ones, providing an indication of the overall accuracy of the predictions (4).

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}\left(P_{\text{estimated},i} - P_{\text{real},i}\right)^2 \tag{4}$$

where:

N is the number of observations (in this case, 12 months).
$P_{\text{estimated},i}$ is the estimated value for month i.
$P_{\text{real},i}$ is the real value for month i.

2.4.3. Standard deviation (SD)

SD measures the amount of variation or dispersion of the theoretical values in relation to the mean of the theoretical values. A smaller standard deviation indicates that the values are closer to the mean (5).

$$\text{SD} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(P_{\text{estimated},i} - \overline{P_{\text{estimated}}}\right)^2} \tag{5}$$

where:

N is the number of observations (in this case, 12 months).
$P_{\text{estimated},i}$ is the estimated value for month i.
$\overline{P_{\text{estimated}}}$ is the mean of the estimated values

2.5. Flowchart of methodology

The flowchart in Fig. 5 summarizes the steps involved in the methodology.

Explanation of Fig. 5 steps:

1. Start: The study begins with the initial setup and planning of activities.
2. Data Collection: Wind Speed Data — The wind speed data is collected from three sources: ERA 5, NASA, and Wind Atlas. Actual Power Data — The actual power generation data is obtained from the Wind Float offshore wind farm near Viana do Castelo, Portugal.
3. Data Preparation: The collected data is prepared to ensure consistency and accuracy. This step involves cleaning and aligning the data to the same time frames, ensuring it is properly structured for analysis.
4. Theoretical Power Calculation: Using the turbine's power curve provided by the manufacturer, the theoretical power output is calculated from the collected wind speed data through linear interpolation.
5. Linear Interpolation: The theoretical power output is estimated through linear interpolation between known points on the turbine's power curve, as detailed in Section 2.2. This step is further supported by Fig. 4, which illustrates the turbine's power curve, and Eq. (1), which mathematically defines the interpolation process. Together, these elements validate the methodology used in this step.
   The theoretical power output is estimated through linear interpolation between known points on the turbine's power curve. This provides a continuous estimate of power output across the range of observed wind speeds.
6. Comparison and Analysis: The theoretical power outputs is compared with the actual power generation data. This comparison is performed on different time scales – annual, monthly, and hourly – to identify trends and discrepancies at various temporal resolutions. Error Metrics — Error metrics are calculated such as MAE, MSE, and SD to quantify the accuracy of the predictive models.
7. Results Interpretation: The results of the comparison and analysis are interpreted to draw conclusions about the accuracy and reliability of the theoretical models. This step involves discussing the findings, identifying potential improvements, and making recommendations for future research.
8. End: The study concludes with the finalization and preparation of the findings.

The research plan outlined in this flowchart integrates the following key aspects:

- **Problem Identification:** The study identifies the need to evaluate and validate widely used wind forecasting models through a comprehensive literature review. This approach addresses critical challenges, such as the integration of offshore wind energy into power grids, resource variability, and the lack of validation using real-world operational data.
- **Proposed Solution:** A comparative evaluation of three globally recognized forecasting models (NASA, ERA5, and Wind Atlas) is conducted using empirical data from the WindFloat Atlantic wind farm. This method aims to determine the most reliable model for practical and operational applications in offshore wind energy forecasting.
- **Validation:** The findings are validated using statistical metrics such as MAE, MSE, and SD. These metrics compare theoretical power outputs against real production data from 2022 and 2023, ensuring a robust evaluation of model accuracy and applicability.

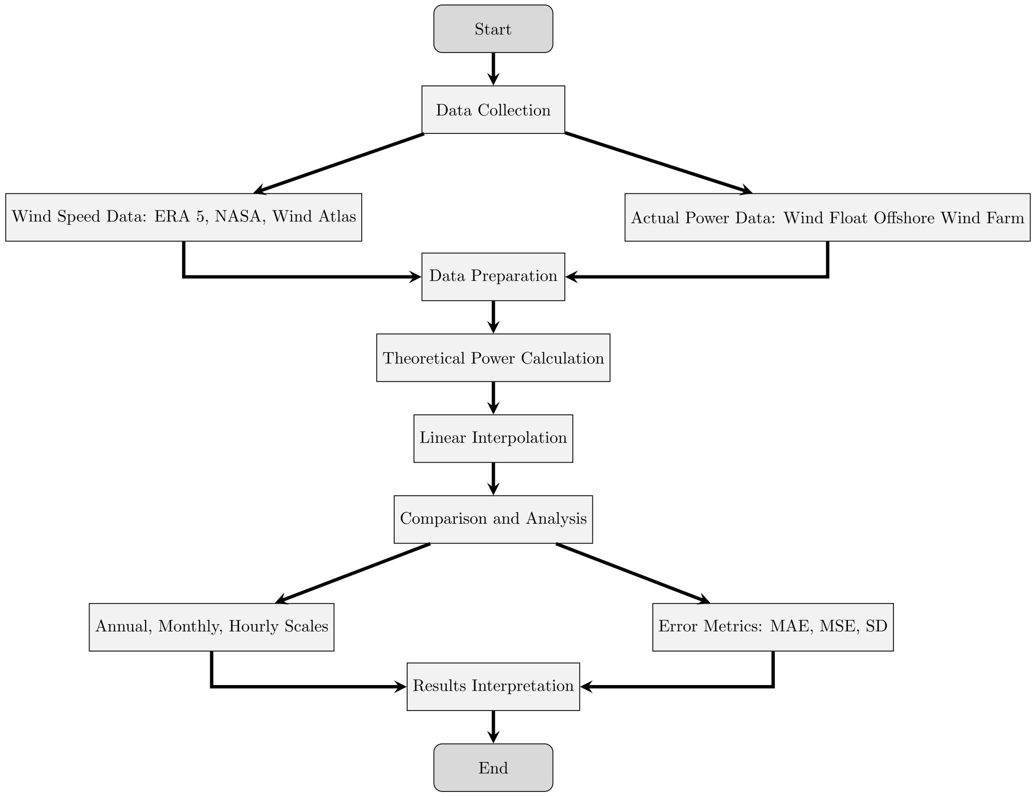


Fig. 5. Flowchart of the methodology.

These elements provide a structured approach to addressing the study's objectives and contribute to improving the accuracy and reliability of offshore wind energy forecasting models.

3. Results

This section compares theoretical models with actual wind power generation data, emphasizing differences in accuracy and practical implications.

The results indicate significant variations between real data and theoretical models on a comparative analysis of theoretical and actual wind power generation data for an offshore wind farm located near Viana do Castelo, Portugal. Utilizing wind speed data from ERA 5, NASA, and Wind Atlas, and comparing these with actual energy production figures, we aimed to assess the accuracy of these predictive models over an annual and monthly basis for the years 2022 and 2023, respectively.

Fig. 6 portrays the comparative study between actual power generation data and the calculations from ERA 5, NASA, and Wind Atlas for the years of 2022 and 2023. Fig. 6a and b provide a month-by-month analysis of the average power generated, offering insight into the temporal variability and forecasting accuracy across different seasons. This visual representation highlights the fluctuating nature of wind power production and the comparative forecasting performance of each data source on a monthly basis.

Fig. 7a and b provide an hourly analysis of average power generation for 2022 and 2023, respectively, offering insights into daily fluctuations in wind energy production. It compares actual output with forecasts from ERA 5, NASA, and Wind Atlas, highlighting the precision of each data source in capturing hourly variations.

Tables 2 and 3 present the monthly relative error calculations for 2022 and 2023, respectively, based on wind speed data from ERA 5, NASA, and Wind Atlas.

Table 2
Relative error calculations for 2022.

Month	ERA 5 [%]	NASA [%]	Wind Atlas [%]
January	4.33	12.45	92.36
February	10.20	3.21	47.03
March	8.85	2.06	14.71
April	5.11	5.47	27.77
May	14.19	4.76	22.14
June	2.06	12.88	50.70
July	33.28	27.86	34.42
August	31.37	25.56	44.45
September	2.58	14.29	20.05
October	4.38	1.71	48.70
November	12.06	21.49	1.03
December	6.86	11.95	5.36

Table 3
Relative error calculations for 2023.

Month	ERA 5 [%]	NASA [%]	Wind Atlas [%]
January	71.20	63.21	64.75
February	7.96	13.97	60.88
March	31.63	29.50	40.80
April	2.90	16.71	48.06
May	5.82	8.88	7.37
June	4.03	25.16	23.65
July	4.67	26.20	8.41
August	4.59	25.50	10.89
September	1.83	12.26	3.44
October	18.35	18.12	36.02
November	30.87	26.67	2.99
December	0.35	8.29	7.14

Is possible to perceive throughout Tables 2 and 3 that ERA 5 shows variability in both years, with significant reductions in some months of 2023. This indicates potential for improvement in the model's accuracy. NASA is consistently the most precise across both years, reinforcing its

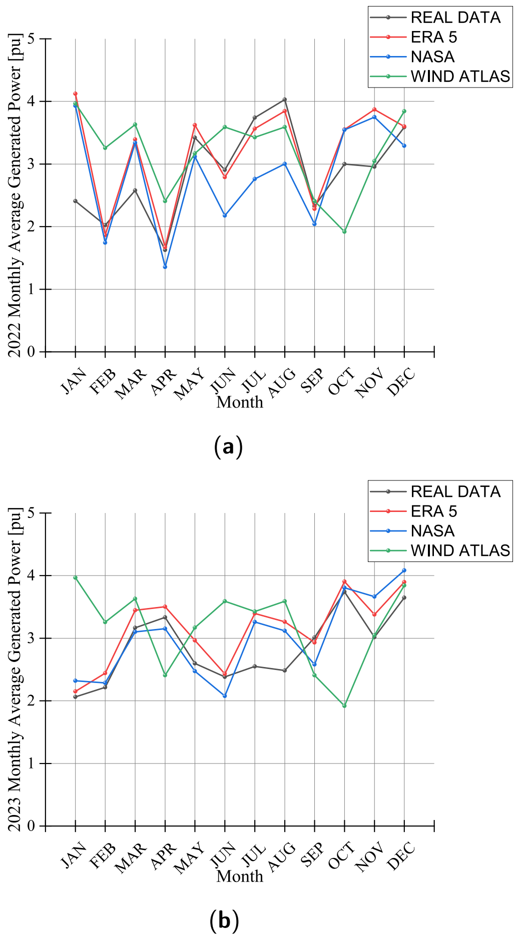


Fig. 6. A comparative analysis between actual data and theoretical data from ERA 5, NASA, and Wind Atlas. (a) Monthly average power generation for 2022. (b) Monthly average power generation for 2023.

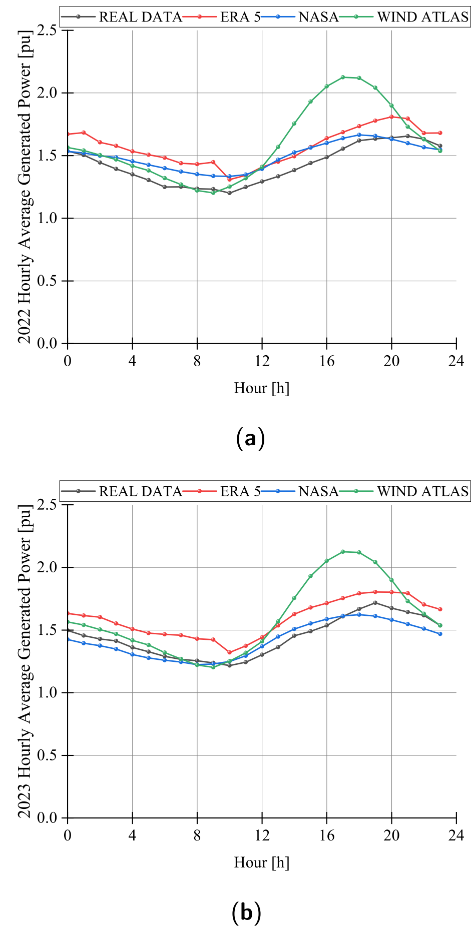


Fig. 7. A comparative analysis between actual data and theoretical data from ERA 5, NASA, and Wind Atlas. (a) Hourly average power generation for 2022. (b) Hourly average power generation for 2023.

Table 4
Error metrics for 2022.

Data source	MAE [MW]	MSE [MW^2]	SD [MW]
ERA 5	12.11	203.56	9.68
NASA	10.12	155.48	13.38
Wind Atlas	20.83	497.24	16.85

Table 5
Error metrics for 2023.

Data source	MAE [MW]	MSE [MW^2]	SD [MW]
ERA 5	14.94	320.39	16.80
NASA	11.66	209.32	18.49
Wind Atlas	18.41	429.36	16.41

reliability for wind speed forecasting. Regarding Wind Atlas, despite some improvements, it still has the highest variability and errors, suggesting a need for significant refinement.

The relative error calculations for the years 2022 and 2023 are presented in Tables 4 and 5, respectively. The error metrics include the MAE, MSE, and SD, providing a detailed view of the accuracy of wind speed prediction data from ERA 5, NASA, and Wind Atlas.

Table 4 shows that for the year 2022, NASA presents the lowest MAE, 10.12 MW, and MSE, 155.48 MW^2, indicating the highest accuracy in predictions. On the other hand, Wind Atlas has the highest MAE, 20.83 MW, and MSE, 497.24 MW^2, indicating a greater discrepancy between predicted and actual values.

Table 5 reveals that for the year 2023, NASA continues to have the lowest MAE (11.66 MW) and MSE, 209.32 MW^2, again highlighting its accuracy. Wind Atlas, although showing some improvement, still exhibits the highest MAE, 18.41 MW, and MSE, 429.36 MW^2.

Fig. 8 shows the annual total average power generated and annual relative error for the years of 2022 and 2023.

Fig. 8a consolidates the monthly observations of Fig. 6 into a single overview, presenting the total average power generated throughout 2022 and 2023. Through this aggregation, it is possible to observe the overall predictive accuracy of the three data sources against the actual yearly production, providing a succinct evaluation of their effectiveness in capturing the annual energy yield from the offshore wind farm.

Fig. 8b displays the annual relative errors between the actual power generation and the predictions considering the wind speed data for the sources ERA 5, NASA, and Wind Atlas for the years 2022 and 2023. Each bar represents the annual relative error for each data source. Consequently, relative errors were found to be 10.3% for ERA 5 for both 2022 and 2023, 5% in 2022 and 1.6% in 2023 for NASA, and 11.9% in 2022 and 10.5% in 2023 for Wind Atlas. In accordance with these results, NASA has the straightest line of approximation, which infers the possibility of predicting wind power generation in the most consistent way.

The findings highlight the superior performance of the NASA dataset in predicting wind power generation under real operational conditions. These results establish a strong basis for refining forecasting models, particularly in the context of expanding offshore wind energy capacity. Further discussion of the practical implications is provided in Section 4.

Furthermore, the results demonstrate distinct performances among the forecasting models analyzed. Key findings include:

- **Performance of Forecasting Models:** The NASA dataset exhibited superior accuracy, achieving relative errors of 5% in 2022 and 1.6% in 2023. These results highlight NASA's reliability for long-term offshore wind energy predictions.
- **Temporal Variability:** ERA5 displayed reasonable accuracy, with particular strengths at shorter temporal resolutions, such as hourly forecasts. This suggests its suitability for operational scenarios requiring finer temporal resolution. Wind Atlas, on the other hand, showed the highest variability and error rates, reflecting its primary focus on long-term climatological averages rather than real-time prediction.
- **Practical Implications:** The results emphasize the importance of validating theoretical forecasting models against real operational data to enhance predictive accuracy and support grid operators in managing the variability of wind resources effectively.

These results underscore the critical role of high-resolution datasets, such as NASA, in improving offshore wind energy management, particularly for regions targeting ambitious renewable energy capacities.

4. Discussion

This section explains the results and highlights the reasons behind the observed discrepancies, discussing their practical and theoretical implications for offshore wind energy.

4.1. Key findings

The findings emphasize the challenges in predicting wind power generation due to the variability of wind speeds. The NASA forecast closely aligns with the actual wind power generated by the turbine configurations used, likely due to its sophisticated atmospheric modeling and higher resolution, which more accurately capture wind production dynamics. Conversely, Wind Atlas shows the highest error rates.

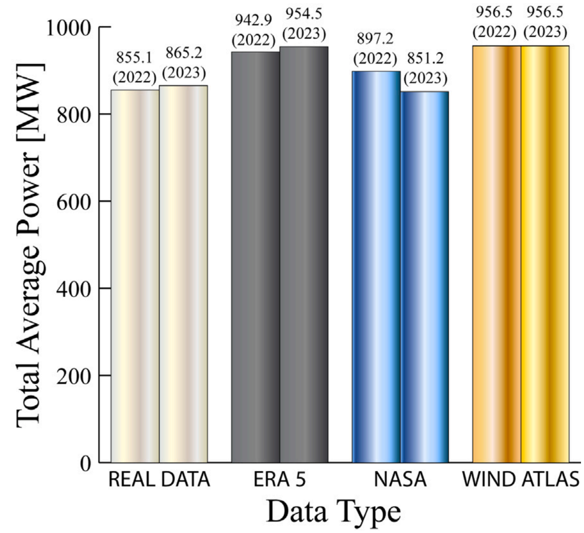
The variations in monthly errors, principally the high discrepancies during the summer, points to the complex interplay between local meteorological conditions and the predictive capabilities of global wind speed datasets. Such fluctuations suggests, in principle, the need for localized corrections in the predictive models and, potentially, the use of multiple data sources for high precision in the results.

Furthermore, the observed differences in forecasting accuracy among the datasets can be attributed to their resolution and methodological approaches. NASA's higher temporal and spatial resolution allows for more precise modeling of wind dynamics, aligning closely with real-world operational data. In contrast, Wind Atlas, while valuable for climatological insights, lacks the level of detail needed for short-term predictions, contributing to its higher error rates. ERA5 demonstrated reasonable accuracy, particularly for shorter temporal resolutions such as hourly forecasts, indicating its suitability for operational scenarios requiring finer temporal resolution.

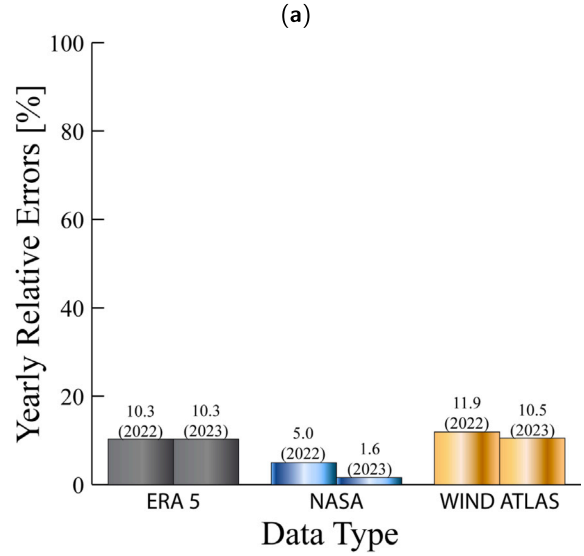
These findings underline the necessity for forecasting models that integrate global datasets with localized corrections to improve predictive accuracy. They also emphasize the importance of validating theoretical forecasting models against real operational data to enhance offshore wind energy management and support grid operators in effectively handling wind resource variability.

It should be noted that this research also underlines the necessity for regular model validation and correction. Given that wind power is a vital part of the renewable energy framework, enhancing the quality of predictive models should be part of energy forecasting, grid maintenance, and the rationalization of power generation.

The insights gained from this validation advance scientific understanding of forecasting accuracy while providing actionable recommendations for grid operators and policymakers to enhance offshore wind energy integration. This is particularly critical as offshore wind capacity continues to expand globally, demanding robust and reliable forecasting methodologies.



(a)



(b)

Fig. 8. Comparison among ERA 5, NASA, and Wind Atlas forecasts versus actual wind farm output for the years of 2022 and 2023, respectively. (a) Annual total average power generated. (b) Annual relative error.

Relative error calculations are crucial for evaluating wind speed prediction models. Identifying the most precise data sources helps to improve forecasting models, enhancing renewable energy management.

The current research uniquely demonstrates the practical validation of forecasting models using real-world data from an operational offshore wind farm, addressing a critical gap in the literature dominated by theoretical analyses. By comparing the performance of ERA5, NASA, and Wind Atlas across multiple temporal and spatial resolutions, it provides actionable insights that extend beyond theoretical frameworks, showcasing the variability in forecasting accuracy and highlighting the importance of model calibration with localized coefficients to improve reliability. These findings are particularly significant as nations like Portugal aim to install 10 GW of offshore wind capacity by 2030. This research offers a robust methodology that not only supports energy planning and grid stability but also enables operational efficiency in maritime zones.

Moreover, the detailed performance metrics analysis provides quantitative evidence for observed trends and discrepancies, reinforcing the practical implications and giving a strong foundation for the development of forecasting models better suited to operational applications.

These findings also highlight their practical implications for offshore wind energy management. By adapting forecasting models to specific offshore locations, operators can address unique environmental and operational challenges, enhancing energy reliability and grid integration. In addiction, the demonstrated accuracy of the NASA dataset positions it as a critical tool for achieving offshore wind energy targets, aligned with Portugal's vision of 10 GW by 2030. These insights provide a strong foundation for improving renewable energy planning and operational efficiency in coastal areas.

4.2. Performance metrics analysis

It is possible to perceive from the simulations results that: ERA 5 offers reasonable predictions but needs adjustments for critical months to improve consistency. NASA, the most reliable source, is recommended for wind speed forecasting due to its consistent accuracy. Wind Atlas requires considerable improvement to become a reliable source for wind speed predictions, due to its high error rates and inconsistencies. This analysis highlights areas for improvement in prediction models, contributing to more efficient and reliable renewable energy forecasts.

Fig. 8b displays the annual relative errors and it is possible to observe that for the year of 2022, ERA 5 presents an annual relative error of approximately 10.3%, indicating good accuracy in wind speed predictions. NASA has the lowest annual relative error of approximately 5.0%, suggesting that NASA's data is the most reliable among the three sources analyzed. Wind Atlas, exhibits an annual relative error of approximately 11.9%, indicating a greater discrepancy between theoretical and actual data. For the year 2023, the annual relative errors show a similar trend. ERA 5 maintains an annual relative error of approximately 10.3%, demonstrating consistency in prediction accuracy. NASA continues to present the lowest annual relative error, 1.6%, reinforcing its superiority in terms of precision. Wind Atlas, despite a slight improvement, 10.5%, still shows the highest annual relative error among the three sources. The results show that NASA's data is the most precise.

Furthermore, the findings of this research highlight significant variations between real data and theoretical models. Specifically, the NASA model provided the closest predictions to the actual wind power generated by the turbines, as indicated by its lower MAE and MSE values. The MAE value of 10.12 MW for the NASA model suggests that, on average, the predicted values are very close to the actual values, indicating high prediction accuracy. Additionally, the MSE value of 155.48 MW^2 further confirms the accuracy by showing fewer large errors.

The SD value for NASA was found to be 13.38 MW, which indicates a moderate level of variability in the predicted values. This is important for understanding the consistency of the model's performance over different periods.

In contrast, the Wind Atlas model exhibited the highest MAE and MSE values, indicating greater discrepancies between predicted and actual values, as well as a higher occurrence of large errors. The SD for Wind Atlas was also higher, suggesting more variability and less consistent performance.

These error metrics are crucial for evaluating the reliability and accuracy of predictive models in offshore wind energy generation. They provide a quantitative basis for comparing different models and understanding their strengths and weaknesses. The lower error metrics for the NASA model suggest that it is more suitable for accurately predicting wind energy output, which is vital for efficient energy planning and grid management.

In accordance with the simulation results, the best solution of the three theoretical models is the NASA model because is consistently the best solution for both years, 2022 and 2023, as it shows the lowest MAE and MSE values, indicating higher accuracy and fewer large errors. Contrariwise, Wind Atlas model is consistently the worst solution for both years due to its higher MAE and MSE values, indicating greater average discrepancy and a higher occurrence of large errors.

These conclusions are based on the analysis of statistical metrics, which provide a quantitative view of the accuracy and consistency of predictions from each data source.

While specific datasets like ERA5 or Wind Atlas may exhibit lower errors at certain temporal resolutions, NASA's dataset demonstrates consistent performance and accuracy across longer timescales, making it a robust choice for forecasting models. This reliability is crucial for day-ahead and step-ahead predictions, which are essential for operational planning and energy management in offshore wind farms.

The relevance of NASA's dataset is further emphasized by the anticipated expansion of offshore wind farms in Portugal, targeting a capacity of 10 GW by 2030. Developing prediction models based on this dataset, calibrated with real-world operational data, offers actionable insights for grid operators. These calibrated models can address the intermittency challenges of wind resources, ensuring effective energy planning and enhanced grid stability.

4.3. Methodological limitations

Critical areas for improvement in offshore wind forecasting are highlighted by these limitations, offering a foundation for ongoing advancements in predictive accuracy and operational efficiency.

The present work acknowledges several methodological limitations that may influence its outcomes and conclusions. First, the use of linear interpolation to calculate the turbine's theoretical power output, while practical and computationally efficient, simplifies the inherently non-linear behavior of turbines under highly variable wind conditions. This approach may not fully capture the dynamic complexities of turbine operations, particularly during periods of significant wind fluctuations.

Second, the resolution of wind speed datasets used in this research is higher than that of the SCADA power data, which is sampled at 15-min intervals. Within these intervals, turbines operate at fixed power levels, justifying the assumption of constant power output and the use of linear interpolation. This simplification aligns with the level of detail of the available data, ensuring consistency in the results.

Lastly, the study utilized three distinct wind speed datasets, each with varying temporal and spatial resolutions. While this provides a comprehensive comparison, it also introduces variability that could affect the robustness of model evaluations. These differences highlight the importance of harmonizing datasets in future studies to minimize uncertainties. Additionally, exploring non-linear interpolation techniques may offer further insights into turbine performance under dynamic conditions.

Although direct real wind speed measurements were not available, this study leverages the turbine's power output data in conjunction with the manufacturer's power curve for robust model validation. These methodological choices are fully acknowledged as part of the study's limitations, ensuring clarity regarding the constraints and assumptions underlying this research.

Furthermore, the temporal scope of this research, limited to data from 2022 and 2023, reflects the operational phase during which the WindFloat Atlantic platform was functioning at its full capacity. Data from earlier years, corresponding to the installation and deployment phases, were excluded as they do not represent the wind farm's steady-state performance. While this focus ensures that the results accurately capture the operational reliability of the wind farm, it also restricts the analysis to a relatively short time frame. Continuous monitoring in subsequent years will be essential for refining the forecasting models and enhancing their robustness over longer temporal scales.

5. Conclusion

Currently, electrical energy system operators face significant challenges related to the decarbonization of the energy production sector. These challenges include the need for rapid adaptation to emerging clean technologies, efficient resource utilization, and compliance with the requirements of a secure and reliable energy system. Producing less polluting electrical energy is essential for achieving global environmental goals, but it encounters operational and infrastructural barriers that must be addressed.

This work examines the accuracy of different wind speed data sources for an offshore wind farm in Viana do Castelo, Portugal. Using a distinctive approach, an analytical comparison is provided between real and theoretical energy generation data from the offshore wind farm, based on three prominent wind speed datasets: ERA 5, NASA, and Wind Atlas. The methodological choice of using the Vestas 8 MW turbine, operational at the WindFloat Atlantic project, aligns theoretical and real-world conditions, strengthening the reliability of the models tested. The findings suggest that NASA's data is the most reliable for predicting wind power generation, emphasizing the need for accurate and specialized prediction models for efficient renewable energy management.

This research aims to contribute further to the field of renewable energy forecasting by providing relevant information and highlighting the strengths and weaknesses of various forecasting models. Additionally, it illustrates how high-quality, high-resolution atmospheric data can enhance the predictability of wind energy. Considering the results presented in Section 3, this research demonstrates that the data extracted from NASA shows great potential as a predictor of actual energy generation, both annually and monthly.

In conclusion, this work has shown the potential of the suggested methodology. However, the authors believe that this model needs to be further explored and calibrated using real data from not only two years, such as 2022 and 2023 in this case, but from multiple years to refine the forecasting models further. Furthermore, we intend to extend this type of study to additional offshore locations.

Limitations and future improvements

This subsection outlines key research opportunities and methodological refinements to enhance the applicability and robustness of the proposed approach.

This research recognizes several methodological limitations that influence its scope and findings. A key challenge lies in the reliance on global datasets (ERA 5, NASA, and Wind Atlas), which, despite their recognized accuracy, may not fully account for localized conditions critical to offshore wind farms. These datasets do not provide the level of detail required to incorporate site-specific factors, such as microclimatic effects, that significantly impact wind dynamics and energy generation.

Additionally, the use of linear interpolation to estimate theoretical power generation, while computationally efficient, simplifies the nonlinear behavior of turbines under variable wind conditions. This assumption, although practical, may lead to discrepancies, particularly during periods of extreme or rapidly changing wind patterns. Addressing these challenges will require future research to explore more advanced interpolation techniques capable of capturing such dynamics.

Despite these limitations, the high-resolution data from the WindFloat Atlantic platform provides a robust foundation for model validation. This approach not only ensures reliability but also supports the adaptation of the methodology to other coastal regions, both in Portugal and internationally. Incorporating localized coefficients and hybrid methods that combine global datasets with localized corrections can further enhance the accuracy of wind energy predictions.

As offshore wind energy continues to expand globally, robust forecasting methodologies will be crucial for grid integration, energy planning, and the development of sustainable renewable energy systems. Consequently, this research provides a solid framework for such advancements, contributing to a deeper understanding of wind energy dynamics and fostering innovations in renewable energy management.

In addition to these limitations, there are several key research opportunities that can enhance the applicability and robustness of the proposed methodology:

1. Expanding the analysis to offshore wind farms in different regions to validate the generalizability of the findings.
2. Refining forecasting models by integrating advanced techniques, such as machine learning, to further improve accuracy.
3. Investigating hybrid methodologies that combine global datasets with localized corrections to account for specific site conditions and improve prediction precision.
4. Developing modified forecasting frameworks to address challenges related to grid integration, leveraging the insights gained in this study.

Addressing these challenges is essential for ensuring that offshore wind energy predictions not only become more exact but also effectively support decision-making processes, such as grid management and renewable energy investments. These future directions aim to build upon the current findings, ensuring the continuous improvement of offshore wind energy forecasting models and their alignment with global renewable energy targets. These advancements are fundamental not only for the advancement of offshore wind energy forecasting but also for supporting global renewable energy targets, such as the 10 GW offshore capacity goal set by Portugal for 2030, contributing to a more sustainable energy future.

CRediT authorship contribution statement

Fernando M. Camilo: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Paulo J. Santos:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Funding acquisition, Formal analysis, Conceptualization. **Armando J. Pires:** Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Funding

This research was funded by Instituto Politécnico de Setúbal and the Portuguese Foundation for Science and Technology under project grant UIDB/00066/2020.

Declaration of competing interest

The authors declare that we have no financial, personal, or professional conflicts of interest that could have influenced the results or interpretation of this study.

This research was funded by Instituto Politécnico de Setúbal and the Portuguese Foundation for Science and Technology under the project grant UIDB/00066/2020, with no influence on the data or results obtained.

All authors have approved the content of this manuscript and agree with its resubmission.

Data availability

The authors do not have permission to share data.

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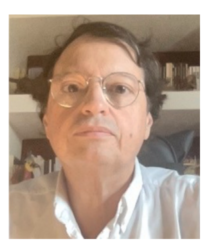

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