Abstract Title: Repowering Potential Unveiled: Assessing Capacity Factor Improvements and Predicted vs. Actual Performance in Wind Energy Underwriting using PLUSWIND, NREL SAM, and EIA Generation Data

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Track 22: Wind Plant and Wakes Modeling

Introductory Summary

The performance of wind energy projects significantly influences investment decisions, making accurate capacity factor predictions crucial for underwriting processes. This study explores the impact of repower projects on capacity factor increases and the discrepancies between predicted and actual performance, offering insights to improve the underwriting process.

Keywords: Wind Energy, Underwriting, Repower Projects, Capacity Factor, Wind Farm Performance, Energy Modelling

Introduction

The success of wind energy projects depends on accurate capacity factor predictions, which play a crucial role in investment decisions and underwriting processes. Understanding the factors that contribute to underperformance and exploring the impact of repowering projects on capacity factor improvements can provide valuable insights for enhancing the underwriting process. This study aims to investigate the performance of wind farms, analyze the discrepancies between predicted and actual capacity factors, and assess the influence of repowering initiatives on capacity factor increases. By examining data from the Berkeley Labs' PLUSWIND database and employing advanced analysis tools, this research offers valuable insights for investors, developers, and policy-makers in the wind energy sector.

Methods

The focus of this study was to analyze the performance of wind farms in the United States, with a specific emphasis on those that underperformed relative to expectations and those that underwent repowering projects. The Berkeley Labs' PLUSWIND database served as the primary data source, providing comprehensive information on various parameters, including the turbine make and model, ownership and development details, geographical location, and reported and measured energy production data.

To investigate the impact of repower projects on capacity factor increases, a detailed analysis was conducted. The capacity factor (CF) was calculated for each wind farm using equation (1), representing the ratio of actual energy output to the maximum potential output over a specific period.

CF = (Actual Energy Output / (Installed Nameplate Capacity * Time)) * 100% (1)

The actual energy output refers to the total energy produced by the wind farm during the designated period, installed nameplate capacity represents the maximum power output the wind farm could achieve if all turbines were operating at their maximum capacity, and time denotes the length of the considered period.

To evaluate the performance discrepancies, the actual capacity factors were compared to the modeled capacity factors obtained from the PLUSWIND database. This analysis allowed for the identification of significant variations between the predicted and actual performance of wind farms, providing insights into the accuracy of capacity factor predictions.

Furthermore, the study specifically focused on wind farms that underwent repowering projects. The capacity factor increase (CFI) resulting from repowering was calculated as the difference between the capacity factor after repowering (CF_post) and the capacity factor before repowering (CF_pre), as shown in equation (2):

Capacity Factor Increase (CFI) = CF_post - CF_pre (2)

To identify the onset of repowering for each wind farm, a change point detection algorithm was applied to the time series of capacity factors. The Pelt method from the ruptures library was utilized, which assumes a Gaussian distribution with constant variance. The algorithm identified the indices corresponding to the change points, with the second change point indicating the repower onset. The repower onset date, pre-repower average capacity factor, post-repower average capacity factor, and capacity factor increase were determined for each wind farm.

Data processing and analysis were conducted using Esri ArcGIS, a powerful Geographic Information System (GIS) platform. ArcGIS provided a robust and integrated environment for a comprehensive examination of various factors influencing wind farm performance. Its GIS capabilities allowed for the seamless integration and visualization of geographical characteristics, environmental conditions, and technical specifications.

By leveraging the capabilities of Esri ArcGIS, this study benefited from its advanced geospatial analysis tools, which enabled the assessment of wind resource potential, identification of suitable wind farm locations, and evaluation of environmental factors that may impact wind energy generation. The integrated GIS platform facilitated the efficient processing and visualization of complex spatial data, supporting informed decision-making and enhancing the overall accuracy of the analysis.

In addition, the wind speed data used in the analysis were obtained from three state-of-the-art meteorological models: MERRA2, ERA5, and HRRR. These models provide hourly wind speed estimates at different heights, allowing for the derivation of hub-height wind speeds for each wind farm. The wind speed data were further processed to calculate density-adjusted wind speeds and to estimate the corresponding density-adjusted capacity factors.

By conducting a thorough analysis of the repower capacity factor and comparing the results to the PLUSWIND data, this study aimed to provide valuable insights into the performance of wind farms, the accuracy of capacity factor predictions, and the impact of repowering projects on overall energy generation. The integration of MERRA2, ERA5, and HRRR data within the PLUSWIND database allowed for a comprehensive evaluation and comparison of wind speed estimates from different meteorological models, enabling a more robust assessment of wind farm performance and underwriting processes in the wind energy sector.

Results and Conclusions

Significant discrepancies were found between actual and predicted capacity factors across different owners, developers, and turbine makes/models. While some companies like Orsted Wind Power North America LLC and NextEra Energy Resources adhered closely to the modeled forecasts, many wind farms generated less energy than what was initially predicted.

Companies such as BP, NextEra Energy Resources, and MidAmerican Energy Company showed substantial average capacity factor increases post-repowering. The turbine makes/models, particularly GE Renewable Energy's GE 1.5-91.5 and Vestas North America's V100-2.0, showed notable capacity factor increases.

The investigation revealed notable discrepancies between actual and modeled capacity factors, emphasizing the importance of a rigorous review in the underwriting process, particularly for repowering projects. Utilizing comprehensive wind resource analysis tools and acknowledging the unique performance enhancements that repowering brings can enable stakeholders to make more educated decisions and mitigate risks tied to capacity factor predictions.

The data indicate that companies like BP, NextEra Energy Resources, and MidAmerican Energy Company experienced substantial average capacity factor increases following repowering. In terms of turbine make and model, GE Renewable Energy's GE 1.5-91.5 and Vestas North America's V100-2.0 showed considerable increases in capacity factors.

The outcomes of this study offer vital insights for multiple stakeholders, such as investors, developers, and policy-makers in the wind energy sector. Improving the accuracy of capacity factor forecasts can enhance the overall efficiency and profitability of wind energy projects, driving forward the transition to renewable energy sources.

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