RESOURCE &TECH

NOVEMBER 14–15 | AUSTIN, TX

T. DELMIRO

Casa dos Ventos Energias Renováveis - Brazil

casadosventos

Operational Assessment: Impact of Wind Direction Modeling on Estimating Directional Curtailment Deficit

ABSTRACT

Aiming to expand the market viability of wind farms as sustainable and bankable energy sources, accurate resource modeling, thorough micrositing in complex terrains, and precise energy yield assessment are crucial for maximizing operational performance.

During wind farm development, a common practice to enhance competitiveness is to increase installed capacity by adding turbines or enlarging rotor size for improved efficiency, which frequently involves reducing the spacing between wind turbines within the targeted resource area. However, effective wind sector management (WSM) may be necessary to mitigate fatigue loads caused by ambient and wake-induced turbulence from neighboring turbines over a 20-35 year operational lifetime.

A performance benchmarking of wind direction modeling methodologies for long-term production estimation was conducted and compared with SCADA operational data from an onshore wind farm with closely-spaced turbines located in highly complex terrain in the northeastern region of Brazil. The results validate more suitable methodologies and provide valuable insights into maximizing operational performance and minimizing energy losses.

OBJECTIVES

The variability in the average wind direction within an onshore wind farm arises from terrain complexity and the influence of seasonal along with medium to long-term climatological cycles (1). Considering that, and aiming to optimize micrositing to account for wind direction impacts (besides mean wind speed), it is imperative to adjust the collected wind direction data to accurately reflect the usual 20-35 years of operational lifespan. This imperative is complemented by the need for a wind resource modeling approach capable of spatially extrapolating wind direction statistics or time series from the available measurement coordinates.

Enhancing wind direction modeling can mitigate uncertainties in the estimation of losses associated with WSM strategy, thereby refining the accuracy of wind turbine positioning and quantity selection for the purpose of optimizing energy production.

In this context, the study conducts a comparative analysis of WSM deficits derived from wind direction modeling that, in turn, is based on measured data obtained before the operational phase. Additionally, the study involves spatial extrapolation of this variable achieved via statistical adjustments to wind resource maps from five different sources.

METHODS

According to Figure 1 and the previous study (2), a row of turbines from an operating wind farm in the northeastern region of Brazil was selected to meet the following criteria: having wind turbines with active WSM strategies, being unaffected by the wake effects of neighboring turbine rows, and having local measurements of at least three years before the start of operation.

The operational WSM losses were derived from SCADA (Supervisory Control and Data Acquisition) that were filtered to ensure all turbines were in a fully operational state. These data were collected over a complete year to mitigate seasonal bias. Additionally, residual losses due to WSM curtailment hysteresis were disregarded to ensure a fair comparison with modeled losses.

The comparison contrasts the results of two long-term adjustment methods in the time series of resource variables. Method **LT WS only**: wind speed adjustment for the long-term from a linear regression of a reanalysis series with the best correlation coefficient and simply measured wind direction. Method **LT WS+WD**: full long-term adjustment (speed and direction) using the same reanalysis series that delivers the best Pearson linear correlation to wind speed and Jammalamadaka-Sarma circular correlation (3) to wind direction. The long-term direction adjustment was performed with circular regression (4).

Furthermore, the speed-ups of the long-term adjusted time series to the turbines' positions were carried out using five distinct wind resource maps discretized into 12 direction sectors: 2 mesoscales (**Meso1** and **Meso2**) from different providers, 2 Computational Fluid Dynamics (CFD) models employing different solver parameters and grid systems (**CFD1** and **CFD2**), and a linear extrapolation model (**Linear**). The **Meso2** and **Linear** models were also compared using 36 sectors.

In agreement with the conclusion of a previous study (2), the method for estimating WSM losses was solely based on time series due to its superior accuracy in estimating WSM losses with appropriate computational cost.

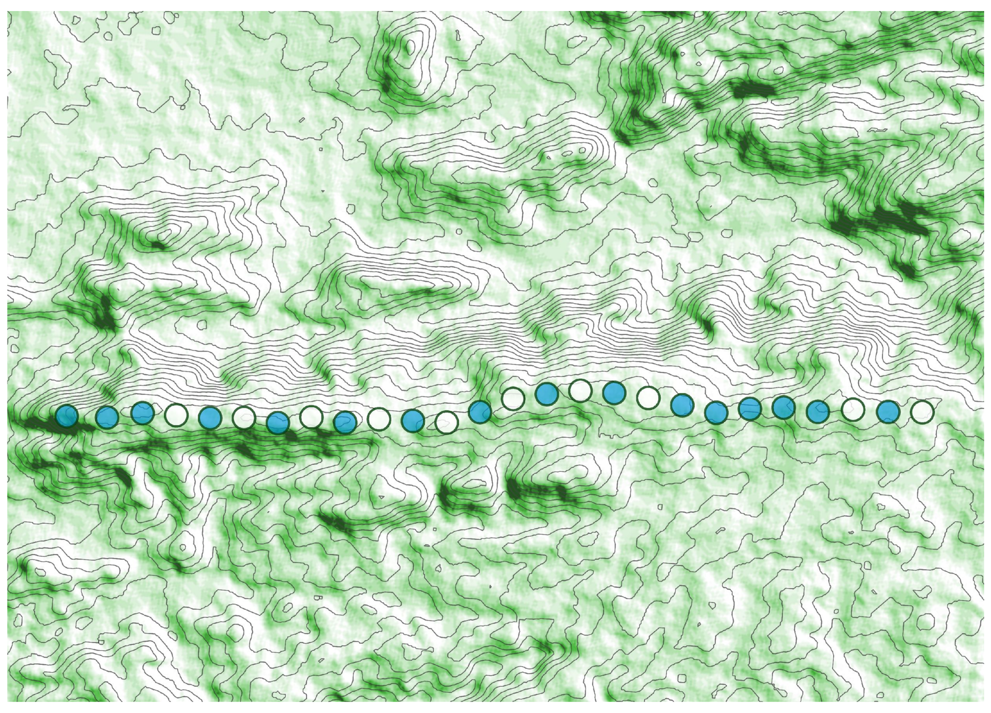

Figure 1: Studied turbine row. Circles filled in blue highlight turbines with WSM enabled: 16 of 25. Note: real north is anonymized.

RESULTS

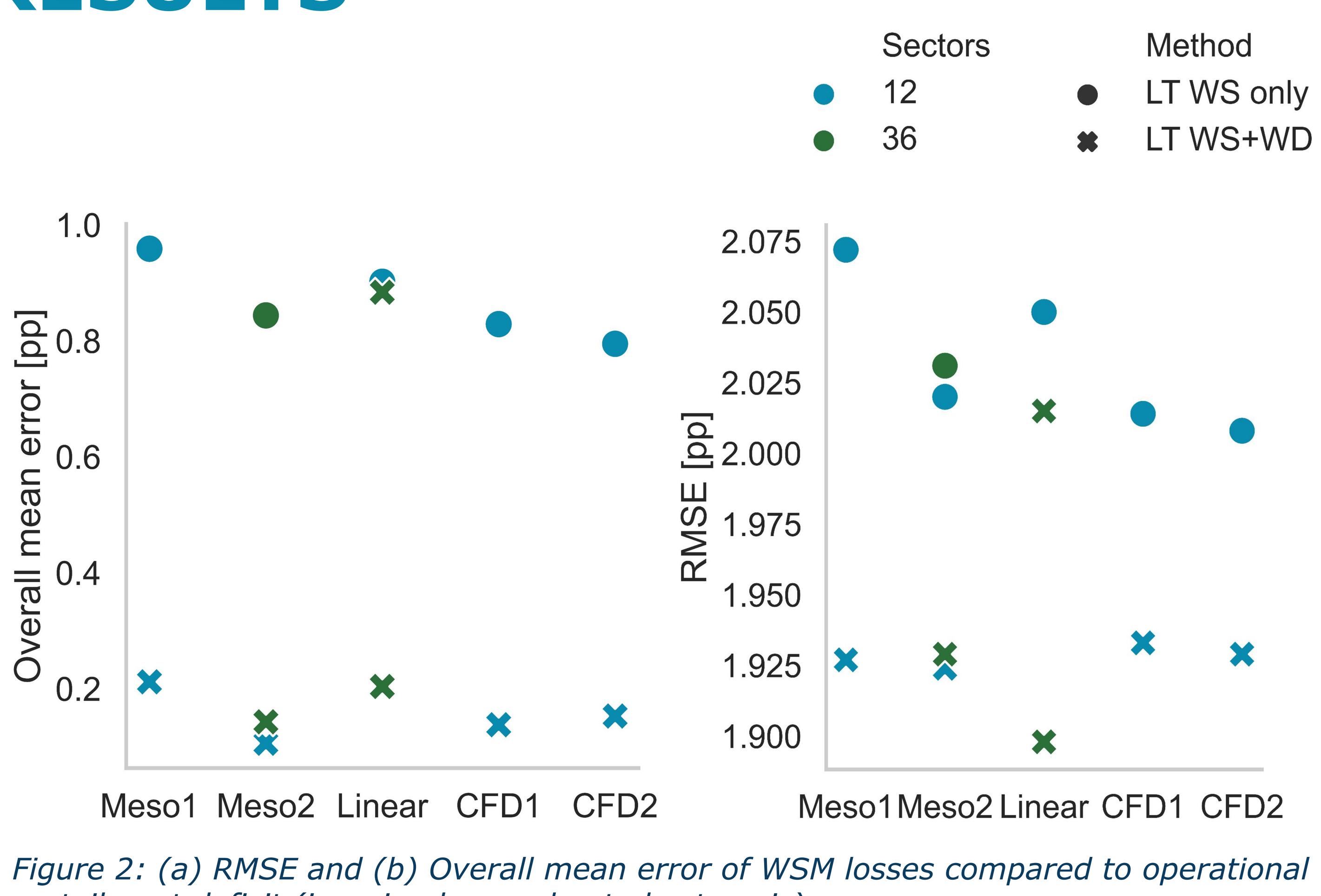

Figure 2: (a) RMSE and (b) Overall mean error of WSM losses compared to operational curtailment deficit (ignoring losses due to hysteresis).

CONCLUSIONS

Figure 2 shows the overall mean error and RMSE (root mean square error) of estimated WSM losses by adopting different long-term adjustment methods and wind resource maps in comparison to the operational data. The following key conclusions can be drawn:

- The **LT WS+WD** method (full long-term adjustment for both speed and direction) consistently outperforms the **LT WS only** method (long-term adjustment of speed only), irrespective of the chosen wind resource map or the number of directional sectors used for resource extrapolations.
- The wind resource model with the lowest overall mean error is **Meso2**, closely followed by the **CFD1** and **CFD2** models when using the **LT WS+WD** method.
- The **36-sector Linear** model displays the lowest RMSE, followed by all other models with a comparable degree of accuracy when using the **LT WS+WD** method. However, the number of directional sectors has a minimal impact, given the WSM loss assessment relies on time series calculation in this study.

Overall, the most cost-effective configuration favors the **LT WS+WD** method in conjunction with the **12-sector Meso2** model. While CFD models are acknowledged for their capacity to describe wind resources in complex terrains (5), they come with higher computational costs. On the other hand, the **Linear** method is unsuitable for evaluating highly complex terrains (6) which tends to impact the wind direction horizontal extrapolation.

The results of this study hold valuable implications for wind farm developers, offering opportunities to improve the accuracy of WSM deficit estimations. This, in turn, can lead to more effective optimization of turbine placement and amount, resulting in increased energy production and prolonged operational lifespans.

REFERENCES

1. **Brower M.** Wind Resource Assessment: a Practical Guide to Developing a Wind Project. Hoboken, N.J.: Wiley; 2012.
2. **Delmiro T.** Operational Asset Analysis: Impacts of Wind Resource Models on Directional Curtailment Losses. WindEurope: Resource Assessment & Analysis of Operating Wind Farms 2023 [Internet]. 2023 Jun 1 [cited 2023 Oct 6]; Available from: https://windeurope.org/tech2023/programme/posters/PO010/
3. **Jammalamadaka SR, Sarma Y.** A Correlation Coefficient for Angular Variables. Statistical Theory and Data Analysis II. 1988;349–64.
4. **Mohamed I, Hussin AG, Hazwan A.** On Simulation and Approximation in the Circular Regression Model. Asian Journal of Mathematics & Statistics. 2008 Apr 15;1(2):100–8.
5. **Dhunny AZ, Lollchund MR, Rughooputh SDDV.** Wind Energy Evaluation for a Highly Complex Terrain Using Computational Fluid Dynamics (CFD). Renewable Energy. 2017 Feb;101:1–9.
6. **Bowen A, Mortensen NG.** WAsP Prediction Errors Due to Site Orography. 2004.