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Analysis of the systematic errors of energy yield assessment in the context of wind farm repowering

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Abstract. The repowering of wind farms is a rapidly developing area of research and is expected to represent 40 GW of wind projects by 2030 in the European Union. This has led to the emergence of energy yield assessment methods that incorporate operational data from existing farms with the aim of surpassing traditional methods that rely solely on physical modelling and onsite measurements. The current literature on repowering relies upon the assumption that learning from operational farm data applies to the future farm. Indeed, calibration and adjustment methods assume that physics-driven models (PDMs) have spatially and temporally correlated errors. This study investigates this assumption by analysing PDM errors for 25 pairs of nearby wind projects. A statistically significant correlation is observed. We discuss whether it is reasonable to utilise operational data from existing farms, which possess different characteristics, to improve the long-term production prediction of a repowered farm.

1. Introduction

The outcomes of energy yield assessment (EYA) are critical in the decision process of financial investment in new wind farm projects. In particular, reducing the uncertainty in predicting long-term annual energy production (AEP) is a lever to improve a project's economic yield [1]. Greenfield wind farm projects have motivated the development of well-established EYA models. These models are based on a sequence of equations that solve the physics, from wind flow modelling to wind turbine power conversion [2]. We refer to them as "Physics-Driven Models" (PDM). These models can have up to 12% uncertainty in the long-term AEP in simple terrains [3].

In Europe, 80 GW of wind power will reach its end of life by 2030. This opens the door for an alternative to greenfield development: repowering. The latter involves replacing an existing farm with new wind turbines and infrastructure. Repowering projects avoid the hurdles of greenfield projects as they benefit from existing permits, better local acceptance, and installed grid connexion. The paradigm of EYA differs for repowering projects since long-term historical measurements from the operating farm are available. This data can be integrated into the EYA process to estimate the annual yield contributing to the otherwise limited history of wind campaigns used in greenfield projects.

In the literature, this is done through either adjusting models' outputs [4], calibrating the flow models [5, 6], or replacing the PDM with a surrogate machine learning model [7]. The author are also aware that a common industry practice consists in calibrating the long- term mean wind speed at a site to the power production of an existing nearby farm, as done in [8] and in commercial softwares [9]. The surrogate machine learning models suffer from poor generalization performance [7], and the calibration models still face challenges due to the multicollinearity of parameters [6]. The adjustment models are promising as they quantify the uncertainty associated with the prediction, thus capturing the generalization skills of a model. They are single-parameter models, thus avoiding issues of multicollinearity.

Adjustment models assume that the data from an existing farm can be used to train a predictive model. Specifically, the training set comprises a predictor variable, which is the long-term AEP of the existing farm predicted using a PDM, and a response variable, which is the observed AEP of the same farm from operational data. An adjustment model learns a PDM error at one existing farm and then corrects the PDM prediction at the future farm using this learned error, either employing a linear model [4] or more sophisticated methods [10].

The error learned at the existing farm applies to the planned farm (to a certain extent) because both farms are similar: they are located on the same site. Some site-specific PDM errors are known to correlate: (1) the historical weather data, used to capture inter-annual variability of wind, have a spatially correlated error that allows for correction using the Kriging method [11, 12, 13], and (2) the local wind flow models, used to model the impact of obstacles, roughness, and topography, have a spatially correlated error in simple terrains [14]. On the other side, the farms have different operation periods, wind turbines, layouts, and hub heights, so that the same PDM applied with the two different farm characteristics over the two different periods may not make the exact same error.

To use the existing farm data, the PDM error correlation should be non-negligible; in other words, the farm-specific errors should not prevail over the site-specific errors. However, this correlation structure has not yet been quantified or observed. This paper bridges this research gap by providing experimental values of the correlation of PDM errors. The methodology involves the application of a PDM to pairs of nearby wind farms. The PDM errors are obtained by comparing the predictions to the actual power production data.

The rest of this paper is organized as follows. In section 2, the datasets used for the study are described, along with the methodology applied for assessing the PDM errors. The correlation results are shown and discussed in section 3. Finally, section 4 concludes the paper and offers some perspectives about future work in this domain.

2. Methodology and datasets

We had no access to datasets of repowered wind farms; instead, we had access to datasets from 18 wind farms located within a maximum distance of 7.50 km from at least one other wind farm. We applied the same PDM to both wind farm characteristics for each pair over two distinct periods of similar duration. We then compared the PDM results to production data to evaluate the PDM error for each pair: we obtained two values of errors that we also compared. We expected these values to be statistically correlated, but with a different level of correlation for each pair. Indeed, the correlation values depend on the degree of similarities between the two farms. The latter depends on the distance between the farms, the layout, the hub height, and the wind turbine type similarities.

2.1. Wind farms

The 18 selected wind farms are all located in the north of France, as shown in Figure 1. They were divided into six groups, each labelled with a letter, and are located within a 7.5-kilometre radius of each other. Within each group, the wind farms were labelled with a number. Table 1 describes the selected wind farms' characteristics, including the wind turbine generator (WTG) specifications. Each group comprises wind farms that feature different types of WTG, and

Figure 1: Location of the selected wind farms

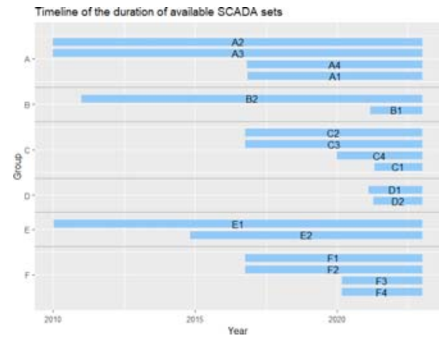


Figure 2: Timeline of available datasets

Group	Wind farm	Average distance to closest farm [m]	WTG type and number	Rotor diameter [m]	Hub height [m]	Rated power [MW]	Reanalysis dataset
A	A_1	660	3 Senvion MM92	92	80	2.05	ERA5
	A_2		14 Gamesa G58	58	65	0.85	
	A_3		5 Gamesa G58	58	65	0.85	
	A_4		4 Vestas V90	90	80	2.05	
B	B_1	1860	3 Vestas V110	110	80	2.2	EMD-WRF Europe+
	B_2		14 Senvion MM92	80	80	2.20	
C	C_1	592	25 GE X 77	80	65	1.5	EMD-WRF Europe+
	C_2		4 Senvion MM82	80	59	2.05	
	C_3		4 Senvion MM82	80	59	2.05	
	C_4		3 Vestas V105	105	80	3.45	
D	D_1	2265	6 Enercon E-92	92	98	2.35	EMD-WRF Europe+
	D_2		4 Senvion MM92	92	80	2.05	
E	E_1	706	5 Gamesa G52	52	55	0.85	EMD-WRF Europe+
	E_2		3 Enercon E70	87	57	2.30	
F	F_1	2540	7 Senvion MM82	80	80	2.05	EMD-WRF Europe+
	F_2		6 Senvion MM82	80	80	2.05	
	F_3		6 Gamesa G90	80	78	2.00	
	F_4		3 Gamesa G90	80	78	2.00	

Table 1: Description of the 18 selected wind farms.

simulated a typical repowering project for which the existing farm WTGs are generally no longer available. The repowered farm is equipped with a newer type of WTG. Groups A and E represented a repowering project with significantly improved rated power. In contrast, the other groups represented projects with significantly improved capacity factors, which is common in repowering projects [15]. Groups A, C, and D have WTGs with significantly different hub heights, enabling them to harvest a higher, and thus better, wind resource. These groups simulated repowering projects where the WTG tip height is increased. However, in cases where regulations impose a maximum height, the hub height remains constant, as simulated by projects B, E and F. Group B represented a scenario where the rotor diameter increases, resulting in an improved capacity factor. Group F corresponded to a repowering scenario with WTGs of identical characteristics.

2.2. Wind farm data

The operational datasets utilized in this study were collected from SCADA systems at a 10-minute resolution and include various turbine-specific parameters. The data were obtained from different SCADA systems, providing a diverse range of parameters such as wind speed measurements using a nacelle anemometer, active power readings, and corresponding timestamps. Additional parameters such as rotor speed, average blade angle, turbine heading, and wind direction were also available in some datasets. The duration of the datasets varied, as depicted in Figure 2. For instance, Group A provided an opportunity to investigate the correlation of PDM errors for long-term AEPs, with wind farm A_2 and A_3 covering the period from early 2010 to mid-2016, and with wind farm A_1 and A_4 covering the period from mid-2016 to early 2023. This allowed for the simulation of an ideal case of repowering, where the wind power farm is repowered after 6.5 years. Group E also permitted similar simulations. Similarly, Group C and F simulated periods of approximately three years, Group B represented a simulated farm repowered after two years, and Group D evaluated a short period of approximately two years.

2.3. Evaluation of power production from operational data

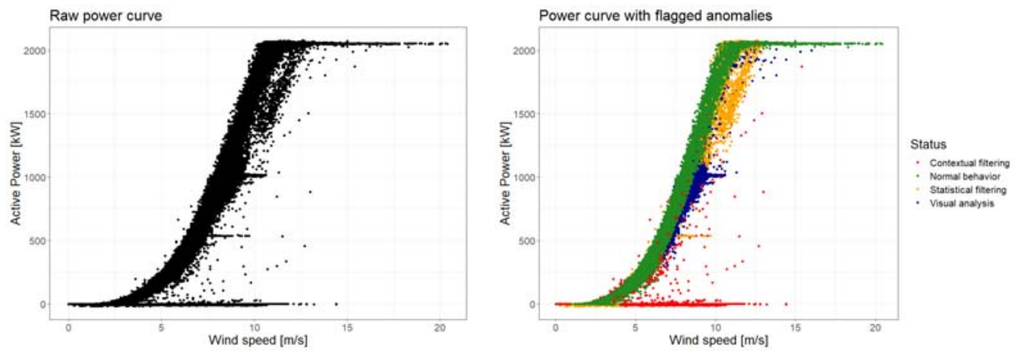
To evaluate power production using operational data, removing points unrelated to nominal farm performance, known as ”anomalies”, is necessary. According to ref. [16], anomalies can be classified into three categories: (1) type 1 anomalies correspond to turbine parking/idling while wind speed is above the cut-in wind speed due to external constraints such as a request from the grid operator, (2) type 2 anomalies correspond to production significantly below the power curve values, which are generally due to curtailments such as noise reduction at night for farms close to inhabited areas, and (3) type 3 anomalies correspond to isolated power production readings, which can be due to sensor failures or turbine starts and stops. Although anomalies represent only a small portion of points in a dataset, they must be filtered out to obtain meaningful results. Data treatment is essential for a WTG with many anomalies, as no treatment can result in a 5.2% difference in estimated AEP compared to treated data [17]. We processed data in three steps, running analysis on each WTG independently :

- Contextual filtering: we filtered points corresponding to power production close to zero while measured wind speed is above cut-in values. We also filtered when the wind speed or power production values were obvious outliers or were identical six times consecutively (frozen data).
- Statistical filtering: we used an isolation forest method to identify isolated points. We identified that the optimal parameters are 100 trees with two dimensions and a threshold of 0.55. The isolation forest tends to produce false positives at the tails of skewed distribution. We manually selected a maximum wind speed for outlier searching (typically 11 m/s) to avoid this effect for high wind speed points. The isolation forest method showed better results than the four other methods (not shown here) suggested in [16].
- Visual analysis: we identified the noise and grid operator curtailments with a visual inspection of the power curves with wind speed, rotor speed, and mean blades angles. We delimited the points corresponding to curtailment manually. We also manually filtered points that appeared as outliers on power curves.

Figure 3 shows the observed power curve before and after all these filtering steps for one example turbine in the dataset. Finally, the data are averaged to an hourly resolution to be compared to the PDM time series.

2.4. PDMs

To use the errors learned at the existing farm for the repowered farm, the PDM for the existing and repowered farm must use as much similar information as possible. Consequently, we used the same reanalysis dataset for a given group of farms as input for the wind flow modelling and



(a) Initial scatter plot. (b) Post-processed scatter plot.

Figure 3: Example of power curve filtering for one WTG of wind farm D_1. The points corresponding to the turbine's nominal behaviour are shown in green, while the others emphasise the effect of each data processing step.

kept the same flow and wake model parameters. The reanalysis datasets considered in this study were either ERA5 or EMD-WRF Europe+, depending on the wind farm (see Table 1). The grid point closest to the wind farms was used, and a logarithmic wind profile calibrated on reanalysis data was used to model wind speed at hub heights [9]. An hourly time series of power production data was generated for each turbine on the farms. We used the softwares WindPRO 3.6 and WAsP 12 and the warranted power curves provided by the turbine manufacturer for each WTG. We disregarded the simulation of technical losses such as curtailment, unavailability, or environmental losses since those anomalies are filtered in the operational data.

2.5. *Comparison of PDM results and operational data*

The errors of the PDM are assessed at hourly intervals by comparing the PDM time series with the power production time series from operational data. These errors were then summed and normalized by the total power production. In backcast studies, the operational data is often reconstructed using historical weather data, as described in studies [18, 19, 20], to calculate the AEP and facilitate comparison with the PDM predictions. However, to improve the accuracy of the error analysis and avoid the confounding effect of long-term extrapolation in the PDM, we only considered valid operational data for comparison. This avoided the use of historical weather data and ensured that, for the operational data, the synthetic power production points generated from such data were not conflated with the PDM predictions. On the other side, using only filtered points prevented us from evaluating the PDM error for certain circumstances, such as wind sectors and the time of the day. Indeed, we filtered noise curtailment in the datasets that generally correspond to a wind sector at night time. We plotted wind roses (not shown here) and compared the wind conditions before and after filtering. We verified that the remaining data points were representative of the long-term climate.

3. Results

Figure 4 depicts the X-Y plot of the PDM errors for the first and second periods: these correspond to the distinct periods, so that the first periods simulate the existing farm and the second periods simulate the repowered farm. The periods depend on the available operational data for each farm. In the first periods, the PDM error ranges from -14% to 55% and the standard deviation is 16%. In the second period, it ranges from -11% to 53% and the standard deviation is 17%.

The PDM error sets have a good amplitude to evaluate the correlation. The PDM error sample correlation coefficient is 89%, evaluated on 25 points. The p-value of the correlation coefficient test is $1*10^{-7}$%, implying that the correlation is statistically nonnull.

Figure 4: Comparison of PDM errors for each possible pair in each group. A pair is composed of two farms over two distinct periods. The first and second periods correspond to the selected distinct periods. For example, A_2 from 2010 to mid-2016 corresponds to the first period, and A_1 from mid-2016 to early 2023 corresponds to the second period. Therefore, one point corresponds to the PDM errors for the farm A_2 from 2010 to mid-2016 (x-axis) and for the farm A_1 from mid-2016 to early 2023 (y-axis).

PDM errors extracted from group F show little consistency. The PDM error evaluated on farm F_2 from 2016 to 2019 is 33% higher than the PDM error evaluated on farm F_4 from 2019 to 2023. We could not determine if this point is a statistical outlier or whether it could be explained by the farm and site characteristics. Farms F_2 and F_4 have very similar hub heights (78 vs 80 metres) and the same rotor diameter (80 meters). The centre of the farms are 2.8 kilometres apart. However, we did not identify a significant decrease in the error differences with distance, as seen in Figure 5. Farms F_2 and F_4 are located on two sides of a small valley with up to 15% slopes; this is likely to disrupt the similarities of site conditions and results in poor error correlations. This issue is left for further investigation.

With pairs corresponding to two sides of the valley removed in group F, the distribution of the error difference has a mean of 1.6%(+/- 0.8%) and a standard deviation of 7.7%. Besides,

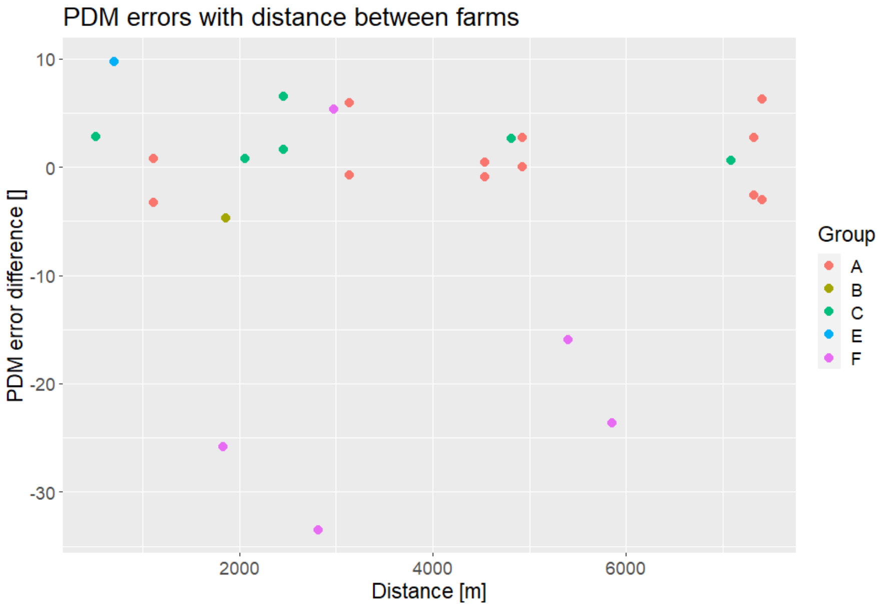


Figure 5: PDM errors difference with the distance between the two farms of the corresponding pairs.

the sample passes a Shapiro normality test with p-scores higher than 50%. This infers that correcting the PDM for the second period using the observed PDM errors for the first period would result in a 7.7% prediction uncertainty of long-term AEP (as long as we consider that bias is negligible). This is a significant reduction compared to the uncertainty of PDM, which is 17% when calculated on observed errors.

4. Conclusion

In the present investigation, our findings indicate that PDM leads to comparable long-term AEP assessment errors for two wind power farms in close proximity, despite being assessed on two separate periods. To assess the existence of a statistically significant correlation structure, we analysed the PDM errors for 25 pairs of wind farms over different periods. The correlation coefficient of long-term AEP assessment error is 89%. This implies that the AEP prediction uncertainty reduces by more than 9% when incorporating the observed errors at nearby farms. It should be noted that the quality of observation impacts the correlation evaluation, especially for older datasets that can be difficult to analyse. Ref [10] presents an EYA repowering method that includes the uncertainty of operational assessment in evaluating repowered farm AEP.

In the context of repowering or wind farm extension, using operational data from existing farms to calibrate or adjust a PDM approach is common practice. This practice assumes that PDM errors exhibit spatial and temporal correlation. We observed a statistically significant correlation between PDM errors calculated over distinct periods. However, the correlation appears to drop to zero in certain complex conditions. To generalize these findings and avoid the potential pitfalls of relying on nearby operational data when no correlation exists, a model of PDM error correlation should be developed. This model should consider variables such as distance, time difference, and terrain complexity, among other farm characteristics. Ongoing research is currently being conducted on this topic. Finally, it is important to note that while operational data improves AEP prediction for the studied wind farms, these represent a degraded case compared to repowering due to their non-negligible distance from each other. Consequently, a greater reduction in uncertainty is expected when operational data are used for repowering purposes.

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