



HAL
open science

A New Energy Yield Assessment Model with Reduced Uncertainty for Wind Farms Repowering

Paul Mazoyer, Duc Thomas, Andreas Bechmann, Georges Kariniotakis

► To cite this version:

Paul Mazoyer, Duc Thomas, Andreas Bechmann, Georges Kariniotakis. A New Energy Yield Assessment Model with Reduced Uncertainty for Wind Farms Repowering. WindEurope Annual Event 2023, WindEurope, Apr 2023, Copenhagen, Denmark. <hal-04162063>

HAL Id: hal-04162063

<https://minesparis-psl.hal.science/hal-04162063v1>

Submitted on 14 Jul 2023

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire HAL, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



HAL Authorization

A New Energy Yield Assessment Model with Reduced Uncertainty for Wind Farms Repowering

Paul Mazoyer^{a,b}, Thomas Duc^b, Andreas Bechmann^c, Georges Kariniotakis^a

^aMines Paris, PSL University, Centre for processes, renewable energies and energy systems (PERSEE), Sophia-Antipolis, 06904, France

^bEngie Green, 6 Rue Alexander Fleming, Lyon, 69007, France

^cDTU Wind Energy, Frederiksborgvej 399, Roskilde, 4000, Denmark

This paper presents an "adjustment" model [1] and its application for wind plant projects' energy yield assessment (EYA) in a repowering context. Figure 1 illustrates an overview of the proposed methodology graphically.

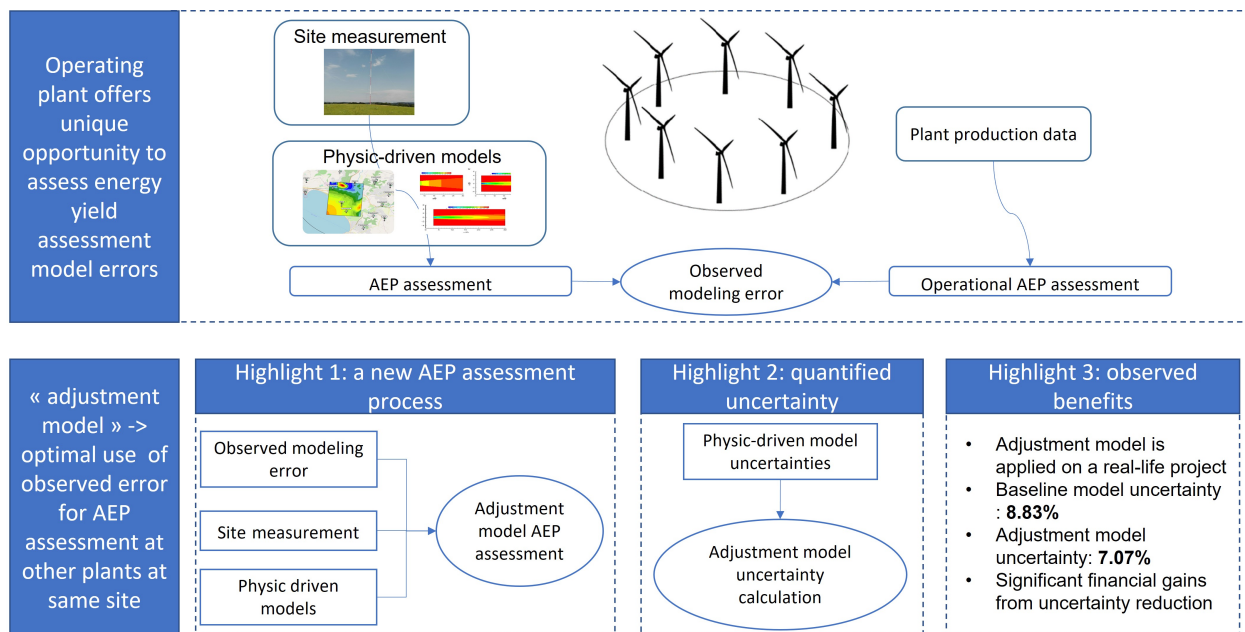


Figure 1: Visual abstract

The outcomes of energy yield assessment (EYA) are critical in the decision process of financial investment in new wind farm projects. In particular, reducing energy yield uncertainty is a lever to improve the project's economic yield [2]. Greenfield wind farm projects have motivated the development of well-established EYA models. These "theoretical" models are based on a sequence of equations that solve the physics, starting from the wind flow modeling to wind turbine power conversion [3]. They are calibrated upon on-site wind measurements. These EYA models can have up to 12% uncertainty in simple terrain in the annual yield prediction [4]. The paradigm of EYA differs for repowering projects since long historical measurements from the operating plant are available. This data can be integrated into the EYA model 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 inputs or outputs [5, 6], calibrating the flow models [7, 8, 9] or replacing the theoretical model with a surrogate machine learning model [10]. The main drawback of such models is the absence of a framework to assess their uncertainty: they only *qualitatively* improve uncertainty. The uncertainty assessment is only possible with extensive testing of models

on a vast, often unavailable database [9]. Besides, the uncertainty models are generally semi-empirical and cannot characterize the added benefit of calibrated parameters or adjusted values [3].

The so-called "adjustment model" proposed here and extensively detailed in [1] solves this issue by providing a *quantitative* assessment of the uncertainty along with an annual energy production (AEP) assessment equation. This paper presents the proposed adjustment model. The adjustment model builds upon the theoretical models. The work demonstrates that the adjustment model consistently outperforms theoretical models regarding uncertainty. We illustrate the adjustment model by applying it to several real-world repowering or extension projects, where we compare AEP established from the theoretical and the adjustment models.

In the following, we introduce the *planned* plant, which is intended to replace the *operating* plant. The adjustment model for the planned wind farm aims to use historical data from the operating one. The various notations involved in the theoretical and operational assessment are described in figure 2.

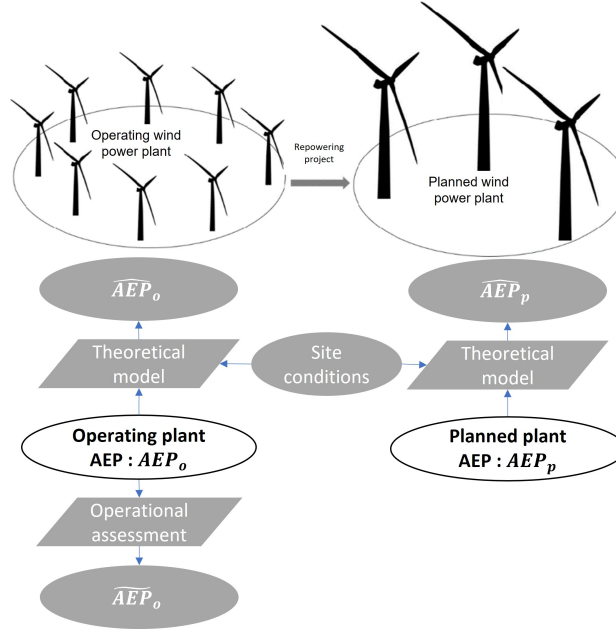


Figure 2: Idealized example of a repowering project. The left side of the figure represents the operating plant that produces a true AEP_o that can be estimated from a theoretical model \widehat{AEP}_o or operational assessment \widetilde{AEP}_o . The site conditions are obtained from site measurements and weather model data. On the right side is the planned project for which no operational data is available. Its future true AEP_o is estimated with a theoretical model \widehat{AEP}_p . This paper presents an alternative model to assess the planned plant.

In the first step, we present the mathematical reasoning of the adjustment model. This model assesses the error of a theoretical model at the *operating* plant by comparing it to the operational assessment with:

$$\widetilde{\epsilon}_{\widehat{AEP}_o} = \frac{\widehat{AEP}_o - \widetilde{AEP}_o}{\widehat{AEP}_o} \quad (1)$$

From this observed error, we intend to model the theoretical model error at the planned plant :

$$\epsilon_{\widehat{AEP}_p} = \frac{\widehat{AEP}_p - AEP_p}{AEP_p} \quad (2)$$

To do so, the adjustment model captures the conditional distribution of $\epsilon_{\widehat{AEP}_p}$ with $\widetilde{\epsilon}_{\widehat{AEP}_o}$ (in mathematical notation: $\epsilon_{\widehat{AEP}_p} | \widetilde{\epsilon}_{\widehat{AEP}_o}$). Especially, the work demonstrates that the latter is normally distributed. The parameters $\mu(\epsilon_{\widehat{AEP}_p} | \widetilde{\epsilon}_{\widehat{AEP}_o})$ and $\sigma^2(\epsilon_{\widehat{AEP}_p} | \widetilde{\epsilon}_{\widehat{AEP}_o})$ of the probability distribution function are derived in [1]. The mean value of the conditional error

is the adjustment factor to apply to AEP established from the theoretical model.

$$\widehat{AEP}_p \leftarrow \frac{\widehat{AEP}_p}{1 + \mu(\epsilon_{\widehat{AEP}_p} | \widetilde{\epsilon}_{\widehat{AEP}_o})} \quad (3)$$

Besides, it is demonstrated in [1] that the distribution of the conditional error is narrower than the distribution of the error: this induces that the uncertainty of the adjustment model is lower compared to theoretical models. These findings assume that theoretical models and operational assessment errors are Gaussian distributed. This is verified either from backcast reports [11, 12, 4, 13] or Monte Carlo simulation [14, 15].

Derivation of the conditional error parameters requires values from the theoretical model and the operational assessment:

1. The uncertainty of the theoretical model applied to the operating and planned plant: the derivation of such values is a common task of wind analyst. It is generally based on empirical models [3].
2. The uncertainty of the operational assessment: when operational data quality is considered reasonable, this can be neglected; otherwise Monte Carlo method (see [15]) is a convenient tool to derive such values.
3. The observed theoretical model error values $\widetilde{\epsilon}_{\widehat{AEP}_o}$, as discussed above.
4. The correlation between the theoretical model errors at the operating and planned plant $\rho_{\epsilon_{\widehat{AEP}_p}, \epsilon_{\widehat{AEP}_o}}$. Unlike previous terms, this term is not a typical outcome of a theoretical model.

We present this correlation coefficient calculation for typical projects in the second step. It consists of evaluating similarities between the errors at each step of the theoretical models at the operating and planned plant. The correlation coefficient captures the similarities. Typically, we would evaluate the correlation of the wind speed estimation errors for each turbine of the operating and planned plant. The wind speed evaluation builds upon on-site wind measurements, wind flow models, and long-term extrapolation models. When similar inputs (measurement datasets) for both operating and planned plants are used, it is expected that errors in wind resource assessment are correlated. It is even more correlated if layouts and hub heights are similar for the operating and planned plants. Conversely, the correlation of the power-curve errors and the power-production-losses-estimation errors may be low.

Unfortunately, there are few scientific articles on such errors correlation models. One of them, [16], describes a model for wind-flow-model error correlation. Future work will build upon this work to create a thorough mathematical model for correlation evaluation. However, we evaluate most of the correlation values from subjective expert elicitation in the present work. In the paper, we present the evaluation of the correlation coefficient for two real-world projects: 1. A repowering project that consists of replacing turbines at the same locations with turbines of a similar hub height in southern France, and 2. a repowering project with a significant modification of the plant layout and turbine hub heights also in France. For the former, the error correlation is around 60%, mainly because the wind speed evaluation errors are highly correlated. Statistically, the observed error at the operating plant can explain 60% of the theoretical model error at the planned plant.

We apply the adjustment model to the above two repowering projects in the third step. We evaluate the uncertainty and compare both models. Uncertainty reductions of 4.05% are obtained compared to theoretical models and it increases P90¹ by 2.37 GWh per year. Finally, we also evaluate the sensitivity of the adjustment model to its various inputs. We identify that the uncertainty of the model primarily relates to the correlation of the wind speed evaluation errors. Indeed, the latter is a prevailing weight in calculating the correlation. We also assess the impact of the operational assessment quality on the adjustment model. For example, old wind plants concerned with repowering can suffer from sub-optimal performances that are difficult to detect. In such cases, the uncertainty of the operational assessment increases, and consequently, the uncertainty of the adjustment model increases.

To the authors' knowledge, this work brings significant innovative contributions to energy yield assessment research because it embeds a framework for uncertainty assessment. The adjustment model can be implemented in an Excel file, making it accessible for most energy yield assessment teams. The underlying models, theoretical and operational assessments, are generally available in commercial software. The adjustment model is agnostic: it works with any theoretical model. For example, it works similarly if an NO Jensen or an Ainslie model is chosen as the

¹Values of AEP that have a probability of at least 90% to be realized, the probability of exceedance at a 90% level

wake model. The elicitation of the correlation coefficient requires a careful assessment based on analyzing the wind resource assessment outputs and other error sources. In any case, a conservative assessment of the correlation coefficient should be preferred. As long as the correlation is non-null, the adjustment model provides benefits compared to theoretical models.

This presentation will provide the audience with the following:

1. An overview of the pro and cons of EYA models for repowering projects
2. An EYA model dedicated to repowering, including a rigorous assessment of its uncertainty
3. Several examples of the application of the adjustment model to typical repowering wind projects

References

- [1] P. Mazoyer, T. Duc, A. Bechmann, G. Kariniotakis, A new methodology for assessing the energy yield of repowered wind plants with quantified reduced uncertainty, Currently in redaction (2022).
- [2] B. H. Bailey, The financial implications of resource assessment, Tech. rep., AWS Truepower LLC (2014).
URL https://www.sewind.org/presentations/2014/2014-07-24s_ECWC_workshop_presentation_-_Bruce_bailey.pdf
- [3] A. Clifton, A. Smith, M. Fields, Wind plant preconstruction energy estimates. current practice and opportunities, Tech. rep., National Renewable Energy Lab. (NREL) (4 2016). doi:10.2172/1248798.
URL <https://www.osti.gov/biblio/1248798>
- [4] J. C. Y. Lee, M. J. Fields, An overview of wind-energy-production prediction bias, losses, and uncertainties, Wind Energy Science 6 (2) (2021) 311–365. doi:10.5194/wes-6-311-2021.
URL <https://wes.copernicus.org/articles/6/311/2021/>
- [5] M. Bezbradica, H. Kerkvliet, I. M. Borbolla, P. Lehtimäki, Introducing multi-criteria decision analysis for wind farm repowering: A case study on gotland, in: 2016 International Conference Multidisciplinary Engineering Design Optimization (MEDO), IEEE, 2016, pp. 1–8. doi:10.1109/MEDO.2016.7746546.
- [6] M. H. Bullard, Getting back in the game, uncertainty in wind speed dating in the repower world, Presentation at the annual conference of American Wind Energy Association, Seattle, USA (09 2019).
- [7] J. Teng, C. D. Markfort, A calibration procedure for an analytical wake model using wind farm operational data, Energies 13 (7 2020). doi:10.3390/en13143537.
- [8] J. Schreiber, C. L. Bottasso, B. Salbert, F. Campagnolo, Improving wind farm flow models by learning from operational data, Wind Energy Science 5 (2) (2020) 647–673. doi:10.5194/wes-5-647-2020.
URL <https://wes.copernicus.org/articles/5/647/2020/>
- [9] R. Braunbehrens, A. Vad, C. L. Bottasso, The wind farm as a sensor: learning and explaining orographic and plant-induced flow heterogeneities from operational data, Wind Energy Science Discussions 2022 (2022) 1–50. doi:10.5194/wes-2022-67.
URL <https://wes.copernicus.org/preprints/wes-2022-67/>
- [10] J. Park, J. Park, Physics-induced graph neural network: An application to wind-farm power estimation, Energy 187 (11 2019). doi:10.1016/j.energy.2019.115883.
- [11] J. Vidal, C. Ziesler, K. Monnich, Wind energy yield methods update a white paper on validation and update of methods for performing pre-construction wind energy yield assessments in the european context, Tech. rep., UL (2020).
- [12] M. Lunacek, M. J. Fields, A. Craig, J. C. Y. Lee, J. Meissner, C. Philips, S. Sheng, R. King, Understanding biases in pre-construction estimates, Vol. 1037, IOP Publishing, 2018, p. 062009. doi:10.1088/1742-6596/1037/6/062009.
URL <https://doi.org/10.1088/1742-6596/1037/6/062009>
- [13] I. Papadopoulos, T. Beckford, C. Ribeiro, Dnv gl energy production assessment validation whitepaper 2019, Tech. rep., DNV GL (2019).
URL <https://issuu.com/dnvg1/docs/7bc75c58ca7643d9b94be2d957a9b9c0>
- [14] N. Bodini, M. Optis, Operational-based annual energy production uncertainty: Are its components actually uncorrelated?, Wind Energy Science 5 (2020) 1435–1448. doi:10.5194/wes-5-1435-2020.
- [15] N. Bodini, M. Optis, J. Perr-Sauer, E. Simley, M. J. Fields, Lowering post-construction yield assessment uncertainty through better wind plant power curves, Wind Energy (2021). doi:10.1002/we.2645.
- [16] A. Clerc, M. Anderson, P. Stuart, G. Habenicht, A systematic method for quantifying wind flow modelling uncertainty in wind resource assessment, Journal of Wind Engineering and Industrial Aerodynamics 111 (2012) 85–94. doi:10.1016/j.jweia.2012.08.006.