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Using One Wind Farm as a Reference to Estimate the Energy Production of Another: Insights from a Probabilistic Analysis

Paul Mazoyer^a, Thomas Duc^a, and Georges Kariniotakis^b

^aENGIE Green, Place Samuel de Champlain, 92400 Courbevoie, France

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

E-mail: paul.mazoyer@engie.com

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1 Introduction

State-of-the-art methods for modeling wind farm energy production follow a two-step approach: modeling the wind resource and then the farm's conversion of wind into power. These models carry uncertainty due to both accuracy limitations and the stochastic nature of wind. Probabilistic modeling addresses this by assigning probabilities to different production levels by propagating error distributions.

We extend this probabilistic framework to two dimensions by examining the joint probability distribution of energy production at two wind farms in the same region but with different configurations. When operational data from one farm is available, it can inform the expected production of the second, quantifying the uncertainty reduction. This is particularly relevant for repowering projects or developments near existing farms.

Existing approaches focus on short-term prediction and rely on operational data, which is unavailable for future farms. Instead, joint production must be estimated using a physics-based a priori approach. While joint distributions of some error sources exist, others remain unassessed, and no model propagates these joint errors to energy production. We address this gap by developing a physics-based framework to propagate joint uncertainties and assess its impact through a case study.

2 Methodology

2.1 Mathematical Framework

The energy production considered in this study is the annual energy production (AEP). The site wind data is a time series of wind speed U , and the power curve is a function $P(\cdot)$. The stochastic equation of the true AEP, \mathcal{E} , consists of calculating the energy production model chain \mathcal{M} , including the wind speed estimation error ΔU and power curve modeling error ΔP :

$$\mathcal{E} = \mathcal{M}(U + \Delta U, P + \Delta P) \quad (1)$$

However, these errors are unknown, and the above equation (1) is solved in the form of a probability density function (P.D.F.) through uncertainty propagation. As in one-dimensional methods, where ΔU and ΔP are sampled multiple times and propagated to obtain an AEP distribution, we jointly sample $(\Delta U_A, \Delta U_B)$ and $(\Delta P_A, \Delta P_B)$ before propagation. Similar to (1), the joint AEP of two wind farms, A and B , denoted as \mathcal{E}_A and \mathcal{E}_B , can be expressed as:

$$(\mathcal{E}_A, \mathcal{E}_B) = (\mathcal{M}(U_A + \Delta U_A, P_A + \Delta P_A), \mathcal{M}(U_B + \Delta U_B, P_B + \Delta P_B)) \quad (2)$$

where subscripts denote variables specific to each wind farm. The joint probability of AEP at farms A and B is estimated using a Monte Carlo approach. Each sample j follows the error distributions:

$$(\Delta U_{A,j}, \Delta U_{B,j}) \sim f_{\Delta U_A, \Delta U_B} \quad (3)$$

$$(\Delta P_{A,j}, \Delta P_{B,j}) \sim f_{\Delta P_A, \Delta P_B} \quad (4)$$

Finally, for each sampling iteration j , we compute the joint AEP sample $(E_{A,j}, E_{B,j})$ as:

$$(E_{A,j}, E_{B,j}) = (\mathcal{M}(U_A + \Delta U_{A,j}, P_A + \Delta P_{A,j}), \mathcal{M}(U_B + \Delta U_{B,j}, P_B + \Delta P_{B,j})) \quad (5)$$

The set of joint samples allows inference of the joint P.D.F. of AEP for the two farms.

2.2 Case Study

The simulated case study involves two wind farms in Northern France: one with five 0.85 MW wind turbines aligned in a single row, and another, located a few hundred meters to the northeast, consisting of three 2.3 MW turbines. The hub heights of the two farms are 55 m and 63 m, respectively. This scenario represents a repowering case, where the operational periods of the two farms do not overlap, ensuring no inter-farm wake effects. Wind measurements are available from a nearby mast to the south, while long-term wind data is derived from a reanalysis dataset at a location a few kilometers from the wind farms. Multi-year operational datasets from both wind farms are available and allow for validation of the probability distribution estimation through a weak statistical test.

2.3 Simulated Model

The wind resource assessment components of the model \mathcal{M} are described in Figure 1. The power curve is modeled from the wind turbine manufacturer specification sheets.

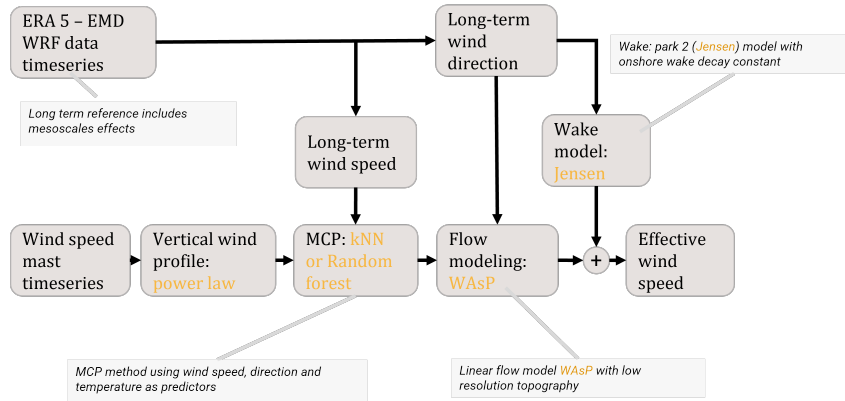


Figure 1: Overview of the wind resource assessment process implemented. MCP stands for *Measure Correlate Predict*, and kNN stands for k-nearest neighbors. The effective wind speed accounts for both the local resource and wake effects.

The joint power curve error $f_{\Delta P_A, \Delta P_B}$ is assumed to follow a bivariate Gaussian distribution, with parameters depending on wind speed. The calculation of $f_{\Delta U_A, \Delta U_B}$ involves another Monte Carlo process: the errors are sampled and propagated through the wind resource assessment model. The vertical extrapolation uncertainty model is an extended version of Kelly's model [1]. The horizontal extrapolation uncertainty model is based on the Clerc model [2]. The MCP uncertainty model is a Gaussian joint distribution, with parameters derived from training residuals. Finally, the wake uncertainty model is a Gaussian joint distribution with variance from [3].

3 Results and Discussion

Figure 2 shows the joint AEP samples of farms A and B (referred to as the existing and repowered farms in the graph), along with a Kernel Density Estimate of their marginal distributions. The results indicate a strong correlation between the AEPs of the two farms, despite differences in turbine types, hub heights, and layouts.

The empirical Pearson correlation coefficient is 84.7%, highlighting the close relationship between their energy production. The joint distribution exhibits a Gaussian-like shape, further validated by a Henze-Zirkler test, which yields a p-value of 19%, supporting the hypothesis of joint normality. Observed wind farm productions from both farms show a good match with the modeled probability distribution.

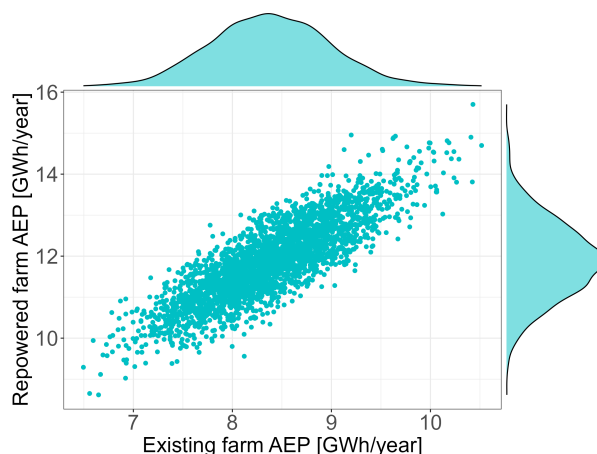


Figure 2: "Joint distribution of annual energy production (AEP) for farms A and B. Marginal distributions on the axes highlight the correlation structure, with farm A representing the existing site and farm B the repowered site.

The correlation value is influenced by the choice of joint uncertainty distribution models. In particular, power curve uncertainty has a significant impact, as observed through sensitivity analysis. Due to the limited literature on joint uncertainty modeling, an expert-based approach is necessary to parameterize the distribution.

4 Conclusion

This work introduces a methodology for modeling the joint probability distribution of energy production at two wind farms in close proximity. The joint P.D.F. is estimated a priori using a physics-based approach, without relying on operational data. Evaluation of the joint distribution in a simple terrain case study reveals a strong correlation between AEPs, despite differences in farm characteristics. The distribution appears Gaussian, which facilitates further calculations based on the estimated AEP distribution.

The joint distribution serves two purposes: it provides the most precise estimate of the AEP of a future wind farm, given that an existing farm has experienced a certain level of production. This estimate comes with a reliable uncertainty quantification. This has key applications in reducing project risks, whether when developing near an existing farm or repowering a wind farm. Despite interesting results of the method, the modeling of the joint AEP distribution is sensitive to the choice of uncertainty models which requires specific care during selection.

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