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Uncertainty evaluation of an alternative energy yield

assessment method for repowering projects

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Repowering consists of replacing a plant reaching end of life with a new one (figure 1). Between 40 GW to 80 GW of wind capacity are expected to be reach end of life by 2030 in EU countries and at least half is considered suitable for repowering. The energy yield assessment (EYA) of the new plant is a critical component of the profitability study and risk assessment of the project. EYA of repowering projects are usually carried out using similar methods as those used for greenfield projects, neglecting the SCADA datasets of the existing plant. We present a method, called repowering AEP prediction model, that makes use of SCADA dataset of the existing plant. We model its uncertainty and compare it to the greenfield model uncertainty. The repowering model outperforms the greenfield models for several use cases. It is a simple and efficient method that achieves significant gain in the EYA accuracy and thus in the AEP probability of exceedance values (such as the P90).

Monte Carlo simulation of the error model

Several studies showed that $\delta \widehat{AEP}^g$ and $\delta \widehat{AEP}^s$ are centered normal random variables with variances that depend on inputs properties ([2],[3],[4]). Equation (1) does not permit to deduct the properties of $\delta \widehat{AEP}_n^r$ and must be simulated. Monte Carlo is well adapted for such simulation. In [1], we demonstrate that greenfield model can be represented with a wind to power conversion model that takes as inputs the estimation of long-term wind resource, the power curve, the wake losses and the plant losses. The drawing of random samples of the terms of (1) requires to model the error correlation of these estimates for pairs of turbines of the new and existing plant. In [5], we detail a model for error correlation.



Repowering model

The SCADA datasets contain the power production of each wind turbines of the existing plant. The AEP of the existing plant can be observed and compared to the greenfield model AEP prediction : the error of greenfield model can be estimated (figure 2). The greenfield model error inferred from existing plant data is used as a correction factor for the new plant AEP prediction (figure 3).



Simulation

A simulation is carried out for an EYA of a repowering project that consists of a replacement of a single turbine wind plant of 80 meters hub height with a 100 meters hub height. The global details are given in table 1: the column *correlation* describes the Pearson correlation coefficient expected between the estimates for the new and existing plant (arbitrary chosen). We simulated case 1 where the plants are similar and case 2 where they are not. Figure 2 shows the fitted histogram of the simulation outputs for case 1. Table 2 gives the estimated uncertainty.

	Estimates			Correlation	
	Evicting	Now			
Input	plant	plant	Uncertainty	Case 1	Case 2
Weibull scale factor -c	6	6.5	3.87%	80%	20%
Weibull shape factor-k	2.5	2.5	3.87%	80%	20%
Power curve	1	1	3.00%	100%	20%
Availability	98%	98%	2.00%	60%	20%
Wake losses	100%	100%	0.10%	50%	20%
Performance turbine losses	97%	99%	2.00%	20%	20%
Electrical losses	98%	98%	2.00%	50%	20%
Curtailment losses	98%	98%	2.00%	50%	20%
Environment losses	98%	98%	2.00%	50%	20%



Figure 4: AEP probability density function for case 1. The distribution of AEP estimate is narrower for repowering model than for greenfield model.

	Case 1	Case 2
Repowering model	9.20%	16.10%

Figure 2 : estimation of the greenfield model error. $\widehat{AEP_e}^g$ is the AEP estimation from a greenfield model (index « g ») applied to the **existing** plant (index « e »). $\widehat{AEP_e}^s$ is the AEP observation from SCADA data (index « s »).



Figure 3 : prediction of the new plant AEP. $\widehat{AEP_n}^g$ is the AEP estimation from a greenfield model applied to the **new** plant (index « n »). $\widehat{AEP_n}^r$ is the AEP obtained from repowering model (index « r »).

Error model

Errors are denoted with a δ (for example $\delta \widehat{AEP_n}^r$). They correspond to the relative difference between an estimated AEP and the true AEP. The error of repowering model is calculated in [1] by :

Table 1: EYA inputs for two cases. Wake losses are neglected since it is a single turbine wind plant. Hub height of new plant is higher and thus the scale factor is higher. Losses are expected to be lower for new plant since turbine are more recent.



Table 2: uncertainty evaluation (k=1) from Monte Carlo simulation.

In case the existing and new plant are very similar (estimates error strongly correlated): a gain of 2.6% of uncertainty is observed. The method turns out ineffective in case there is little correlation between the estimates : the repowering is 4.3% more uncertain than the greenfield model in case 2.

Conclusion

The repowering model for EYA can significantly decrease the uncertainty of AEP prediction in case a plant is replaced with a plant that have similar characteristics such as similar layout, similar turbine hub height and similar turbine technology.

The method for uncertainty evaluation relies on the estimation of the covariance of errors of the wind resource, power curve, wake speed deficit and plant losses estimates. While models exist for estimating errors, they are generally limited to the evaluation of the error variance. The investigation of the errors covariance is a new area of research.

References

$$\delta \widehat{AEP_n}^r = \frac{\delta \widehat{AEP_e}^{s} + 1}{\delta \widehat{AEP_e}^{g} + 1} \left(\delta \widehat{AEP_n}^g + 1\right) - 1 (1)$$

Equation (1) permits to compare the greenfield model error $\delta \widehat{AEP_n}^g$ with the repowering model error $\delta \widehat{AEP_n}^r$.

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