Article

Evaluation of AEP Predictions for Commercial Wind Farms in Sweden

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Abstract: Based on data from 1162 wind turbines, with a rated power of at least 1.8 MW, installed in Sweden after 2005, the accuracy of the annual energy production (AEP) predictions from the project planning phases has been compared to the wind-index-corrected production. Both the production and the predicted AEP data come from the database Vindstat, which collects information directly from wind turbine owners. The mean error was 7.1%, which means that, overall, the predicted AEP has been overestimated. The overestimation was higher for wind turbines situated in open terrain than in forest areas and was higher overall than that previously established for the British Isles and South Africa. Dividing the result over the installation year, the improvement which had been expected due to the continuous refinement of the methods and better data availability, was not observed over time. The major uncertainty comes from the predicted AEP as reported by wind turbine owners to the Vindstat database, which, for some cases, might not come from the wind energy calculation from the planning phase (i.e., the P50-value).

Keywords: energy assessment; validation; wind power; Sweden; P50; AEP; WCP

1. Introduction

Wind power is likely to play a key role when replacing conventional power production with renewable alternatives. Moreover, when installing the large number of wind turbines needed for this transition, it will be a challenge to gain public acceptance. Wind turbines will probably have to be largely located at inland sites, which typically experience lower overall wind speeds compared to coastal sites. This also means lower margins and thus increased demands for reliable prediction regarding the annual energy production (AEP) for planned wind energy developments. The inland sites can often be on more complex terrain—for example, forest areas—which also means greater uncertainty [1].

Sweden had an early ambitious wind energy program with large multi-megawatt prototypes built in the early 1980s [2]. Although Sweden has no wind turbine industry today, wind power currently comprises more than 10% of Swedish electricity production [3]. With Swedish nuclear power likely being phased out over the coming decades, and with the probable electrification of the transportation sector, a large amount of new power production must be installed. This will increase the demand for accurate and reliable AEP predictions, especially because most future wind energy developments are likely to be on forest terrain.

When developing a wind farm, a crucial step is making an AEP prediction, which typically is made using wind-farm project planning software, for most cases using a linear flow model (for more complex terrain, CFD models are recommended). The chosen model evaluates wind data (e.g., from measurement masts), which can be used to predict the AEP for a normal wind year for a

planned wind farm if long-term correlated. From these calculations, a P50 value (50th percentile), which by definition has 50% probability of being exceeded for a real normal wind year, can be acquired. According to the standard [4], the predicted AEP (P50) is calculated as a mean value. This can be explained by the fact that the mean and median values coincide when under a normal distribution of AEP over time, which is reasonable to assume here. From the P50 value and expected uncertainties from different parameters, different p -values can be estimated. The wind resource evaluation and subsequent AEP prediction is an uncertain process, and a proper assessment of the uncertainty is critical for evaluating the risk with a planned wind energy development [5].

It is reasonable to assume that the accuracy of AEP predictions should improve with time. This is due to improvements such as access to better long-term corrected wind data, improved flow models with more advanced wind-shear calculation models, more detailed terrain data, improved tools for sector-based zero-plane displacement, refined measurement methods, improved standards, and a better understanding of cold-climate effects.

In [6], a DNV GL validation between pre-construction AEP predictions and the outcome is presented for Great Britain, Ireland (including Northern Ireland), South Africa, and the UK offshore. For Great Britain, the AEP predictions were shown to have been overestimated by 3.1% based on data from 87 wind farms. Based on a smaller amount of data, Ireland and South Africa had 4% to 5% overestimation, whereas the offshore UK wind farms were only 0.4% under target. The pre-construction predictions were adjusted to comply with the latest methodology, independent of the construction year, making the results valid for projects developed in 2019. According to DNV GL, the overestimations are most likely linked to shortcomings at the pre-construction energy assessment stage. In [7], the neglect of the wind-farm blockage effect (i.e., that not only downstream turbines but also upstream turbines suffer from reduced wind speeds) is suggested to be a key reason for overestimating AEP predictions. Furthermore, AEP predictions have been compared to actual production data for individual wind farms [8–10], and the uncertainty of wind power AEP predictions have been the subject of several studies [5,11–13].

In this study, production data from numerous existing wind farms in Sweden are compared with the pre-construction AEP predictions to evaluate their agreement and to determine whether the overestimations of the British Isles and South Africa cases are representable for Sweden as well. Time trends regarding the installation year have been analyzed to determine whether expected accuracy improvements with time can be observed. The results have also been divided by the terrain type to determine whether the complexity of the terrain affects the accuracy. Few available studies on the accuracy of AEP predictions are based on data from numerous wind turbines. This work is likely unique for the case of Sweden, and it also adds to the general knowledge base of the performance of AEP predictions for wind turbines.

2. Wind Turbine Production Data

The data in this study come from the database Vindstat, which has been gathering production data, including downtime, from Swedish wind turbines since 1988 [14]. Vindstat data have previously been used for evaluating the wind turbine performance decline in Sweden [15]. Until 2016, most Swedish wind turbines were included but when the Swedish energy agency withdrew its financial support in 2017 and Vindstat introduced a member fee, several of the large wind turbine owners stopped reporting, limiting the included wind turbines to around half for the subsequent periods. Besides production data, Vindstat includes some general information about each wind turbine—for example, the predicted AEP as reported by the owner. This AEP was assumed to correspond to a normal wind year and comes from the wind energy calculation from the planning phase (i.e., the P50 value).

For this study, all Vindstat reporting wind turbines installed after 2005 with a rated power of at least 1.8 MW were available, totaling 1162 turbines. The geographical spread of these turbines is illustrated in Figure 1. After excluding turbines according to the criteria described in Section 3.3, the number of wind turbines used in the results was decreased to that listed in Table 1. The locations

of the wind turbines have been divided using satellite imagery into three terrain types, open terrain, forest areas, and offshore, with the number of turbines in each category also presented in Table 1.

Table 1. Vindstat data used for this study. In the columns to the right, the wind turbines after data exclusion are divided into three terrain types.

	No Data Exclusion	With Data Exclusion	Open Terrain	Forest Areas	Offshore
Wind turbines	1162	880	309	493	77
Total capacity (GW)	2.68	1.98	0.67	1.12	0.19
Observations (months)	83,278	49,375	19,307	24,615	5416

Figure 1. Locations of wind turbines included in this study (green). Locations of index sites used for normal wind-year normalization (red); see Section 3.2.

3. Methods

To be comparable with the given AEP (P50) predictions, the wind turbine production data must first be normalized to correspond to the availability counted on the P50 prediction and the wind energy available for a normal wind year. The monthly production data were re-calculated to the wind-index corrected annual production (WCP) and compared to the P50 values.

3.1. Normalization to Wind Turbine Availability and Transformer Efficiency

The P50 value corresponds to the availability that the owner can count on (i.e., the manufacturer guaranteed availability, which is typically 97% [15]). The time-based availability is the percentage of a given period that a wind turbine is available for operation, and for a given month, was calculated as follows:

$$A_t = \frac{T_m - T_d}{T_m} \quad (1)$$

where T_m is the total number of hours for the given month and T_d is the downtime in hours for the same month. The availability for the same month was used to calculate the electricity yield normalized for the typical industry standard of 97% availability (A_{std}):

$$E_a = \frac{E \cdot A_{std} \cdot \eta_t}{A_t} \quad (2)$$

where E is the electricity yield for the given month, and η_t is the transformer efficiency, which must be accounted for because the P50 value refers to the electricity measured at the grid connection point. The transformer efficiency is assumed to be comparable to the modern multi-megawatt wind turbines investigated in this study and is set to 99%, which is typical for Swedish AEP calculations.

3.2. Wind Index Correction and Comparison with Predicted P50

Due to the interannual variations in wind speed, the typically short-term wind measurement data available when calculating the predicted annual electricity yield of a proposed wind turbine must be correlated using a long-term wind dataset [16]. For a sufficiently long time series, the insecurity of the correlation may surpass that of the confirmation between the data and a normal wind year [17]. However, when comparing a vast number of wind turbines, they must have data for the same sufficiently long period. If using different periods for different wind turbines, as in this study, the production data must be individually correlated before comparing.

The normalization was performed by extracting the monthly correlation indices for 77 sites spread across Sweden. For the location of these index sites, see Figure 1. The correlation indices were calculated using the ERA5T reanalysis, which was shown to perform well for the often complex terrain sites of Swedish wind turbines in [18]. For each site, they correspond to the wind energy at 100 m in height for the actual month, compared to the same month for a normal wind year. The mean distance from a wind turbine to its closest index site was 30 km and the maximal distance was 70 km. The yearly mean of all 77 indices together is listed in Figure 2. For an individual wind turbine, all monthly production data normalized for availability (E_a) were plotted against the correlation index for the same month with the index site closest to the specific wind turbine (I_n). This is illustrated in Figure 3 for one of the wind turbines. From a linear regression line, the wind-index-normalized production per month (E_n) was attained for $I_n = 1$. The wind-index-corrected annual production (WCP) was calculated as follows:

$$WCP = 12 \cdot E_n \quad (3)$$

The error between the production-based WCP and the predicted P50 (AEP) from the project developing phase can then be calculated as:

$$error = \frac{P50 - WCP}{WCP} \quad (4)$$

A positive error means that the P50 value was an overestimation of the actual AEP, whereas a negative error indicates an underestimation. To evaluate the magnitude rather than the placing of the error, the absolute error could instead have been used. However, because the predicted AEP reported to Vindstat for some wind turbines is presented as a fraction of the AEP for an entire wind farm, the mean absolute error is enlarged; therefore, it was not used in this study.

Figure 2. Yearly mean of the ERA5T correlation indices for all 77 sites.

Figure 3. Monthly production plotted against the ERA5T correlation index for the corresponding months with the closest index site to one of the wind turbines. The red values have been excluded by the WCP filter.

3.3. Data Exclusion

To avoid reporting errors from Vindstat, the months in which the sum of the downtime and the reported operation time of the generator were greater than the hours of that month were excluded. Months with availability below 90% were also excluded from further analysis. To remove the influence of corrupted data, the outliers in the production-index plot must be removed. This was done using a WCP filter set to $\pm 15\%$, where the index-normalized individual monthly production is compared to the WCP and excluded according to the following:

$$0.85 \cdot WCP > 12 \cdot \frac{E_a}{I_n} > 1.15 \cdot WCP \quad (5)$$

The WCP was recalculated without the filtered values (see Figure 3). If the remaining month-production values were fewer than 12 or if their coefficient of determination (r^2) was below 0.85, the wind turbine was removed from further analyses.

4. Results

For each wind turbine, by normalizing and re-calculating the monthly wind power production data according to Equations (1)–(3) and comparing them to the given P50 in Equation (4), the errors of the pre-construction AEP predictions compared to production-based WCP were calculated. The mean error was 7.1%, which means that, overall, the predicted AEP from the planning phases of the studied wind turbines was overestimated. The mean overestimation is larger for Sweden than that previously shown for the British Isles and South Africa [6]. Dividing the results by terrain type, the error becomes 9.5% for open terrain, 6.3% for forest areas, and 2.0% for offshore turbines. This indicates that the higher complexity of the forest terrain is not the main reason for the error.

Figure 4 presents the error divided by the installation year of the wind turbines. The predicted AEP was most accurate for wind turbines installed from 2011 to 2013, whereas it was slightly underestimated for wind turbines installed in 2013 and 2016 (only four wind turbines installed in 2016 were used in the analysis). In summary, accuracy has not improved over time. This contradicts improvements such as access to better long-term corrected wind data, improved flow models (including improved wind-shear calculation models), more detailed terrain data, improved tools for sector-based zero-plane

displacement, refined measurement methods, improved standards, and a better understanding of cold-climate effects.

To gain an indication of whether the wind-farm blockage effect is the main contributor to the overestimations of AEP predictions in this work, the results could be divided depending on whether evaluating a single wind turbine or a wind farm (and by the wind farm size). This is a possible continuation of this work. The assumption that the predicted AEP reported by the owners to Vindstat comes from the project planning phase adds some uncertainty to the results. However, this is likely to be the case for most multi-megawatt wind turbines installed after 2005. A more thorough study, although based on fewer data, could be performed by collecting individual reports of the predicted AEP from the project planning phase of several projects.

Figure 4. Error of P50 evaluations compared to the production-based WCP depending on the installation year plotted with the standard deviation (blue) and number of wind turbines (red).

5. Conclusions

Compared to the wind-index-corrected and availability-corrected production, the predicted AEP from the planning phase of the wind turbines installed in Sweden after 2005 with a rated power of at least 1.8 MW was overestimated, on average, by 7.1%. This is higher than the previously proven overestimated AEP predictions for projects in the British Isles and South Africa. Dividing the results by terrain type, the error is larger for wind turbines in open terrain than in forest areas, indicating that the more complex forest terrain is not the reason behind the error. Dividing the results by installation year, improvement, which had been expected due to continuous refinement of methods and better data availability, was not observed over time. The major source of error is regarding whether the predicted AEP reported from the wind turbine owners to Vindstat comes from the wind energy calculation from the planning phase (i.e., the P50 value). However, this is likely to be the case for most multi-megawatt wind turbines installed after 2005.

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