Received: 30 March 2017 | Revised: 1 July 2017 | Accepted: 7 July 2017
DOI: 10.1002/we.2132

WILEY

SHORT COMMUNICATION

Wind turbine performance decline in Sweden

Jon Olauson[1] | Per Edström[2] | Jesper Rydén[3]

[1]Division of Electricity, Department of Engineering Sciences, Uppsala University, Uppsala, Sweden
[2]Sweco Energuide AB, Gothenburg, Sweden
[3]Department of Mathematics, Uppsala University, Uppsala, Sweden

Correspondence
Jon Olauson, The Ångström Laboratory, Box 534, 751 21 Uppsala, Sweden.
Email: olauson@gmail.com

Funding information
Vindforsk, Grant/Award Number: 40290-1

Abstract

We show that Swedish wind turbines constructed before 2007 lose 0.15 capacity factor percentage points per year, corresponding to a lifetime energy loss of 6%. A gradual increase of downtime accounts for around one third of the deterioration and worsened efficiency for the remaining. Although the performance loss in Sweden is considerably smaller than previously reported in the UK, it is statistically significant and calls for a revision of the industry practice for wind energy calculations. The study is based on two partly overlapping datasets, comprising 1,100 monthly and 1,300 hourly time series spanning 5–25 years each.

KEYWORDS

downtime, linear regression, performance decline, wind power

1 | INTRODUCTION

Practically all technical systems are subject to deterioration of some degree, and it should come as no surprise that performance of wind turbines (WTs), like, e.g., gas turbines,[1] decline over time. Although a lot of research has been conducted on, e.g., downtime and failing components, surprisingly little work has been devoted to the overall reduction of WT performance with age; the thorough study on UK farms by Staffell and Green[2] is the main exception. The main conclusion from Staffell and Green[2] was that UK farms lose around 1.6% of the output per year in relative terms, with average capacity factors (CFs) declining from 0.285 when new to 0.21 at age 19. If a similar pattern was to be seen outside UK, the assumptions currently used for wind energy calculations would have to be changed considerably. Needless to say, this would have a profound impact on the profitability and may ruin the business case for many projects.

The primary objective with this paper is to present a similar study for Swedish conditions. We however use partly different methods and expand the scope by also considering the evolution of downtime with age and factors explaining differences in trends. The former was made possible by a unique database of hourly observations for almost all Swedish WTs. Much more details are available in the (not yet published) technical report which is provided as Supplementary Material (SM). Here, we abbreviate sections in the report as SM 1.1, etc.

2 | DATA

Two datasets of wind power generation were primarily used in this study: "Vindstat" monthly data and hourly data from the Swedish electricity certificate system "Cesar" (SM 3.1). The former can be accessed from http://vindstat.com/, and the latter can be retrieved by request from the Swedish Energy Agency. The time series and metadata (coordinates, capacity, rotor diameter, etc.) were manually reviewed and corrected when necessary, see SM 3.2. For validation of data quality (SM Appendix) and evaluation of the methodology for detecting downtime, SCADA data were obtained from Vattenfall and OX2.

We refer to the entity for which a measurement is taken as a "unit." In most cases, a unit corresponds to a single WT, but (for Cesar) it can also be a small farm. Only units with measurement periods of 60 months or longer were considered (SM 3.2). In Table 1, the net numbers of units and other summary statistics are given.

In order to remove the effects from wind variability, the monthly time series were long-term corrected (LTC) with output from three different meteorological models: MERRA,[3] ERA-Interim ("ERA-I")[4] and EMD ConWx ("ConWx").[5] A conclusion from the reviewed literature (SM 2.5) is that no model is consistently best in terms of correlation and consistency and that it is probably wise to use two or more independent datasets for LTC; if the results do not differ too much, they can be considered robust.

TABLE 1 Summary statistics for the two datasets of wind power measurements that were analysed as well as the SCADA data used for validation. A “unit” is defined as the entity for which a measurement is taken; most often individual wind turbines but sometimes small farms

	Vindstat	Cesar	SCADA
Units	1103	1317	106
Wind turbines	1103	1537	106
Total capacity	1.2 GW	1.9 GW	222 MW
Data recording period	1990–2015	2003–2015	2012–2015
Temporal resolution	Monthly	Hourly	10 min
Observations	143,000	103 million	13 million

3 | METHODS

Three different methods were used for quantifying the linear change of performance (SM 4.2.2). Most emphasis was put on linear regression of CF on age for individual units:

$$CF_{LTC} = \beta_0 + \beta_1 \cdot age + \beta_2 \cos(2\pi \cdot age) + \beta_3 \sin(2\pi \cdot age) + \varepsilon. \tag{1}$$

The coefficients β_2 and β_3 were potentially included to account for residual seasonal patterns in CF_{LTC}. For the model selection, Akaike's information criterion is useful, and we chose to use the version AICc, with correction for finite samples.[6] Among a set of possible models, the one with the lowest AICc is preferred. The coefficients β_2 and β_3 were included only if AICc was lowered. In any case, β_1 was the coefficient of primary interest. Note that we present slopes in percentage points per year (pp/y) for absolute CFs; if the fitted model for a certain unit is $CF_{LTC} = 0.31 - 0.0013 \cdot age$, the slope is −0.13 pp/y. To determine confidence intervals for mean and median trends , a bootstrap method[7] was used since the data were not normally distributed (SM 4.2.6).

The second method was regression of CF on age for all units in a cohort, i.e., units with start years in a three-year sliding window (1989–1991, 1990–1992, etc.):

$$CF_{LTC} = \beta_0 + \beta_1 \cdot age + \sum_{n=2}^{N} \beta_n I[n] + \varepsilon, \tag{2}$$

where n is the unit number of the N units in the cohort and $I[n]$ is an indicator (dummy) variable taking the value one for observations for unit n and zero for all other observations. An alternative metric (Method 3, SM 4.2.2) was also developed since we feared that violations of the linearity assumption might have a systematic impact on the trends obtained by using Equation 1. The results from Method 3, which are not presented here, were however very similar to those from Equation 1 (SM 5.4).

In order to determine the impact from different variables (start year, manufacturer, latitude, etc.) on the trends, multiple linear regression models were set up. Since we were not very interested in the influence from extreme trends, the data were “winsorised”[8] using limits of ±2 standard deviations from the mean. Interaction terms were calculated with a partial orthogonalisation method, which improved the fits considerably as compared to using “raw” interaction terms. Details are given in SM 4.2.5.

Per definition, a trend in the properly long-term corrected CF time series can stem from a trend in downtime and/or a trend in the efficiency of the WTs. In order to identify downtime periods, “fictive” generation time series were created from ConWx wind speed data. Periods of sufficient lengths when the measured generation was zero and the fictive generation was above a certain threshold were classified as downtime, see SM 4.2.4 for details. This method proved adequate; when comparing to actual downtime records from OX2, there were 9% false negative and 8% false positive classification hours (compared to the true number of downtime hours).

4 | RESULTS

This section begins by a comparison of measurements and outputs from the three meteorological models, which may have some interest in its own; to our knowledge, it is the first time that wind data for LTC is evaluated on this scale. Subsequently, performance declines and evolution of downtime are quantified.

4.1 | LTC data

Correlations between modelled (SM 4.1) and measured generation are presented in Figure 1. For the analyses of hourly data, ERA-I wind speeds were interpolated to hourly resolution using cubic splines. Periods with downtime, unusually low production and measurement anomalies were excluded, see SM 5.1. The results for MERRA and ConWx are very similar, but ERA-I performs slightly worse. Correlations for Cesar monthly data

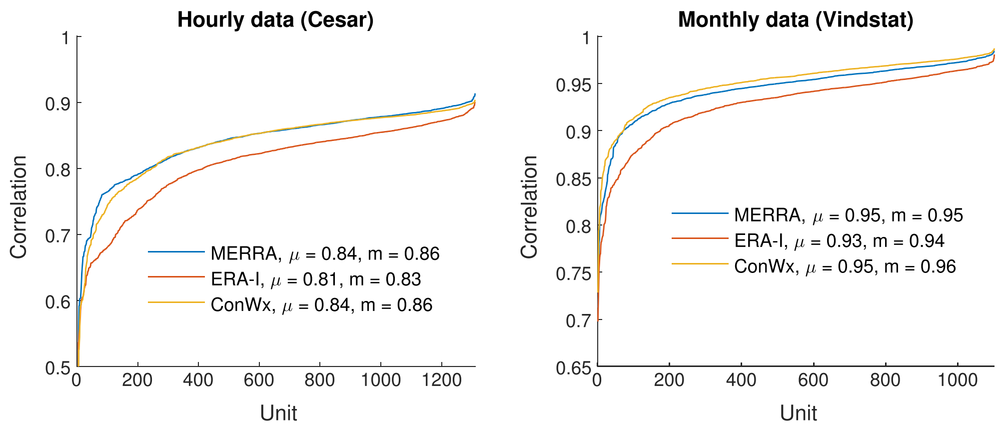

FIGURE 1 Correlations between measured generation and generation calculated from meteorological data (sorted from lowest to highest). The mean (μ) and median (m) values are given in the legends [Colour figure can be viewed at wileyonlinelibrary.com]

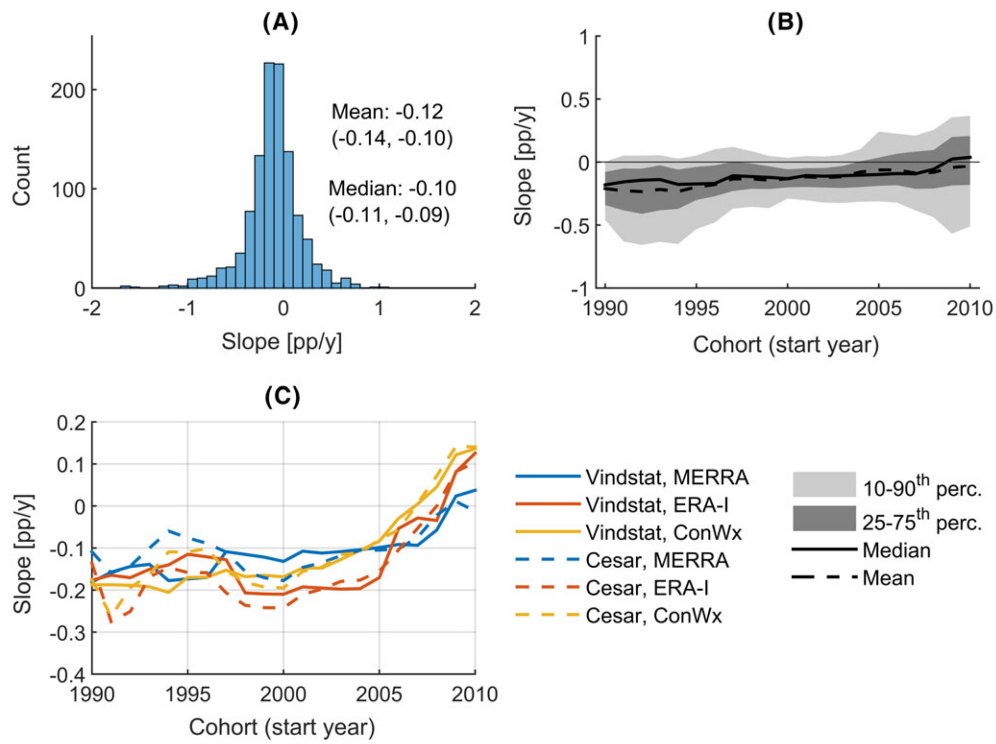

FIGURE 2 Trends in capacity factors based on linear regression for individual units (percentage points per year). Panels A and B only give results for Vindstat data long-term corrected with MERRA (see SM 5.2 for other combinations). A, Histogram and mean/median values (including 95% confidence intervals). B, Distribution of trends for different cohorts. "Perc." is short for percentiles. C, Median trends of different cohorts for the six possible combinations of measurement dataset and data for long-term correction [Colour figure can be viewed at wileyonlinelibrary.com]

(not shown) are very similar to those for Vindstat. Interestingly, the average hourly correlation can be increased to 0.86 if a weighted combination of MERRA, ERA-I, and ConWx is used.

In SM Appendix, seasonal patterns and the magnitude of high-frequency fluctuations of CF_{LTC} are analysed. In conclusion, LTC remove most, but not all, seasonal patterns and high-frequency fluctuations. As for correlations, MERRA and ConWx perform similarly and ERA-I slightly worse.

4.2 | Performance decline

The most important results from linear regression for individual units (Equation 1) are given in Figure 2. Panel A shows the distribution of all slopes and panel B illustrates the distributions for different cohorts. Panels A and B give results for Vindstat data long-term corrected with MERRA. Results for other combinations (SM 5.2) are similar which demonstrates the robustness of the analysis. As an average for all six combinations, the mean and median slopes are both −0.10 pp/y. Figure 2C shows that the slope is generally more negative for older units (units with earlier start years); the median decline for units built before 2007 is 0.15 pp/y. A statistical test revealed that the performance declines were similar for new and old units

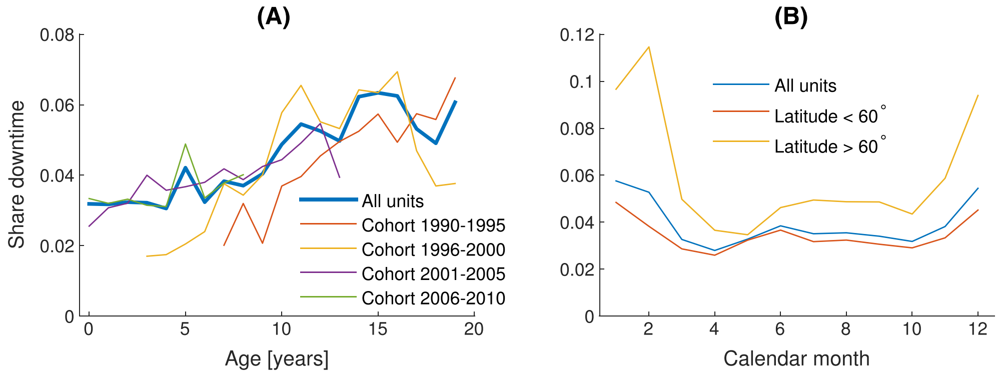

FIGURE 3 Estimated downtime for Cesar units. A, Evolution of downtime with age for all units and cohorts with certain start years. B, Downtime depending on calendar month (1 = January, etc.) [Colour figure can be viewed at wileyonlinelibrary.com]

during the first five years of operation. There are thus strong reasons to believe that −0.15 pp/y is a better estimate of the lifetime performance (although it is of course possible that newer units will have more gentle deterioration also when ageing).

Results from cohort regression (SM 5.3) and equivalent trends (SM 5.4) are similar to those from linear regression for individual units; the differences are generally smaller than those between different combinations of datasets and data for LTC shown in Figure 2C.

As has been shown above, trends are more negative for older units. By using multiple linear regression techniques, it was studied whether other factors impact the trends in a statistically significant way. No other factor could fulfil this requirement for all different analyses performed. There are however relatively clear indications that WTs with higher CFs have more negative trends, that forest farms decline less than farms in open terrain, and that WTs from other manufacturers than Vestas, Enercon, or WindWorld lose performance faster than Vestas WTs (SM 5.7).

4.3 | Downtime

The total downtime for Cesar units was estimated at 4.0%, which is in line with earlier results (3% is often taken as industry standard, see SM 2.3). Figure 3A shows how downtime changes with age, both for all data and for four cohorts comprising WTs with different start years. The downtime generally increases with age, from around 3.2% at age 0–4 years to 5.9% at age 14–19 years (all units). The increases are statistically significant ($P < 0.05$) for all cases but the cohort with start years 2006–2010. From Figure 3B, one can conclude that downtime is higher in wintertime, especially for units in the north. This is most likely due to icing.

Since downtime increases with age, it should come as no surprise that excluding downtime data give less negative trends. This is particularly true for units with a steep decline. By using several different approaches (SM 5.6), we conclude that increased downtime accounts for roughly one third of the observed performance decline, but that large variations exist between units. The remaining two thirds of the performance decline can thus be attributed to reduced efficiencies of the WTs.

5 | CONCLUDING DISCUSSION

Here, it has been showed that Swedish WTs lose around 0.10 CF points per year. For units built before 2007, the median decline is 0.15 pp/y, corresponding to a 20-year energy loss of around 6%. Since the trends for the first five years of operation are similar for new and old WTs, it is reasonable to assume that the latter is a more realistic estimate. Furthermore, there are indications (SM 4.2.3 and SM 5.7) that units with higher CFs lose performance faster in absolute terms. It is thus possible that onshore WTs constructed today (CF around 0.35) will have sharper declines. For wind energy calculations in Sweden (and other countries in cold climate), we recommend decline assumptions in the range 0.10–0.20 pp/y. For a WT with CF 0.35, this corresponds to an energy loss of 2.7–5.4% over a 20-year lifetime; more than what is generally assumed today but considerably less than for UK.[2]

An important continuation of our work is to identify in more detail the factors contributing to particularly negative trends and to improve the strategies for preventing performance loss. The results presented here can potentially be used for benchmarking WT performance changes over time.

ACKNOWLEDGEMENTS

This work was conducted within the StandUP for Energy strategic research framework and was funded by Vindforsk through contract 40290-1. Energimyndigheten, Vindstat, OX2, and Vattenfall kindly provided data. Nils-Erik Carlstedt, Olle Viotti, Mikael Bergkvist, Lasse Johansson, Diego Navarro, Åsa Elmqvist, Jan-Åke Dahlberg, and Martin Löfstrand are acknowledged for their contributions to the technical report which this paper is based on.

ORCID

Jon Olauson http://orcid.org/0000-0003-4921-8345

REFERENCES

1. Kurz R, Brun K. Degradation of gas turbine performance in natural gas service. *J Nat Gas Sci Eng*. 2009;1(3):95–102.
2. Staffell I, Green R. How does wind farm performance decline with age? *Renew Energy*. 2014; 66:775–786.
3. Rienecker MM, Suarez MJ, Gelaro R, et al. MERRA: NASA's modern-era retrospective analysis for research and applications. *J Climate*. 2017;24:3624–3648.
4. Dee DP, Uppala SM, Simmons AJ, et al. The ERA-Interim reanalysis: configuration and performance of the data assimilation system. *Q J R Meteorol Soc*. 2011; 137:553–597.
5. EMD ConWx Mesoscale Data. http://emd.dk/files/windpro2.9/EMDConWx&uscore;MesoScale&uscore;data.pdf (Accessed: 2016-12-22).
6. Hurvich CM, Tsai C-L. Regression and time series model selection in small samples. *Biometrika*. 1989;76(2):297–307.
7. Efron B, Tibshirani R. Bootstrap methods for standard errors, confidence intervals, and other measures of statistical accuracy. *Stat Sci*. 1986;1(1):54–75.
8. Tukey JW, McLaughlin DH. Less vulnerable confidence and significance procedures for location based on a single sample: Trimming/Winsorization. *Sankhya The Indian J Stat Series A*. 1963;25(3):331–352.

SUPPORTING INFORMATION

Additional Supporting Information may be found online in the supporting information tab for this article.

How to cite this article: Olauson J, Edström P, Rydén J. Wind turbine performance decline in Sweden. *Wind Energy*. 2017;1–5. https://doi.org/10.1002/we.2132