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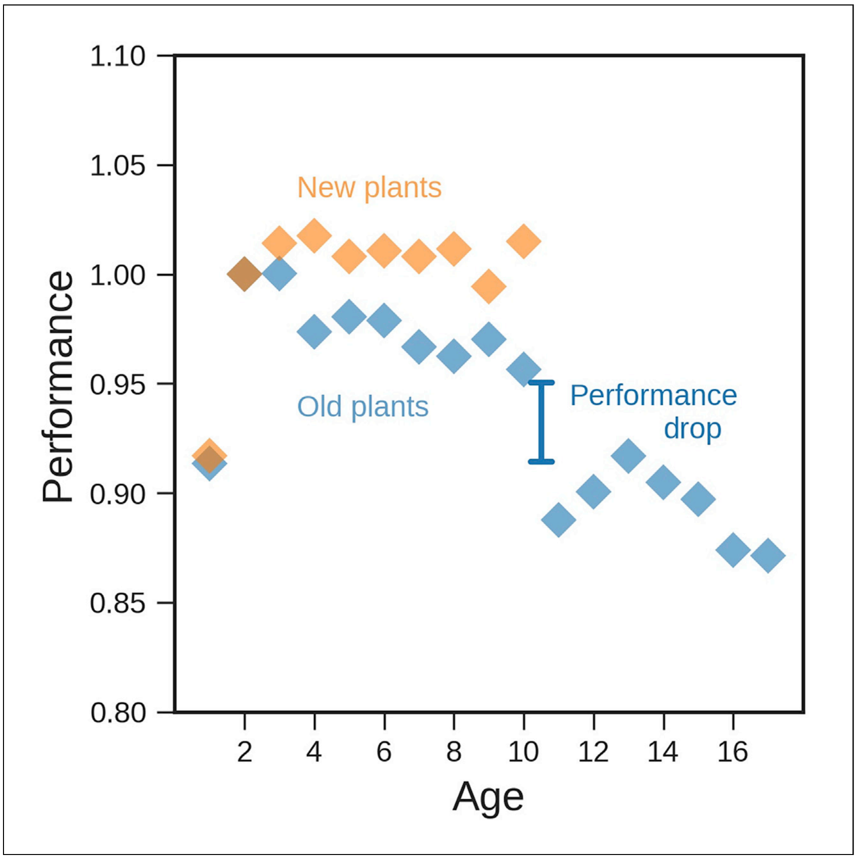

In the United States, wind-plant performance declines smoothly with age, until a stepwise drop in performance occurs when plants age out of eligibility for the performance tax credit. The stepwise change in performance, a pattern not found in other countries, indicates that performance decline can be influenced by policy mechanisms and the cost effectiveness of maintenance and is not an immutable function of physical degradation of the wind turbines. The overall decline rate is on the lower end of estimates from other countries.

Sofia D. Hamilton, Dev Millstein, Mark Bolinger, Ryan Wiser, Seongeun Jeong

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HIGHLIGHTS

We show an analysis of the United States wind-plant performance decline with age

New wind plants show less decline than older plants over their first 10 years

A performance drop occurs when plants lose eligibility for production tax credits

The performance decline rate is sensitive to particular characteristics of wind plants

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How Does Wind Project Performance Change with Age in the United States?

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SUMMARY

Wind-plant performance declines with age, and the rate of decline varies between regions. The rate of performance decline is important when determining wind-plant financial viability and expected lifetime generation. We determine the rate of age-related performance decline in the United States wind fleet by evaluating generation records from 917 plants. We find the rate of performance decline to be 0.53%/year for older vintages of plants and 0.17%/year for newer vintages of plants on an energy basis for the first 10 years of operation, which is on the lower end of prior estimates in Europe. Unique to the United States, we find a significant drop in performance by 3.6% after 10 years, as plants lose eligibility for the production tax credit. Certain plant characteristics, such as the ratio of blade length to nameplate capacity, influence the rate of performance decline. These results indicate that the performance decline rate can be partially managed and influenced by policy.

Context & Scale

The lifetime generation from wind plants is an important input into estimates of wind-plant financial viability and into long-term models of the wind sector. Lifetime generation estimates depend on many parameters, including the rate at which plant performance declines with age. This rate is uncertain and varies by region. Often, this rate is not accounted for by investors, energy modelers, and policy makers.

We evaluate the performance decline rate of the United States wind fleet (most prior research focused on Europe's fleets). We find relatively low performance decline that is sensitive to plant age, tax credits, and certain plant characteristics. The tax-credit sensitivity shows that performance decline is not only a physical process, but is also influenced by maintenance cost-benefit tradeoffs. Thus, performance decline can be partially managed and influenced by policy. These results can be used by investors for financial assessments and can be input into energy system models for policy makers.

INTRODUCTION

Wind power in the United States (US) now supplies an important portion of the nation's electricity (in 2019, wind power supplied 7.3% of the US electricity generation[1] and new wind capacity additions totaled 9,143 MW).[2] Wind power is expected to continue to grow in importance, both in the United States and globally, due to its low cost and the carbon emission reduction goals of many states and countries. To understand wind power's potential growth and impact on electricity systems, it is crucial to accurately estimate the future performance of wind plants. Importantly, wind-plant performance tends to deteriorate with plant age (a characteristic of all engineered systems). Understanding the rate at which wind plants degrade with age is not only necessary to model future growth of the wind sector, but also can impact the expected lifetime energy output, and even financial viability of proposed wind projects. Additionally, the performance of wind plants is an important factor in determining the levelized cost of wind energy (LCOE).[3] Despite its importance, the rate of performance decline is not well established in the United States and a decline in performance due to aging is not typically accounted for in assessments of the LCOE in academic literature,[4,5] government reports,[6,7] or industry publications.[8,9]

The reliability of wind turbines impacts operations and maintenance (O&M) costs and annual energy production.[3] Failure rates for wind turbine components vary over the lifetime of a turbine, with increased failures at the beginning and end of a turbine's lifetime.[10] Failure rates have also been found to vary regionally—in Germany, turbines have exhibited higher failure rates than in Denmark, though the overall fleet-failure rates have been decreasing over time.[10] Recently, the impact of age on the overall performance of wind fleets has been investigated in Sweden,[11] Germany,[12] the United Kingdom, and Denmark.[13,14] These studies consider multiple forms of performance degradation in aggregate, accounting not only for component reliability and downtime, but also aerodynamic and mechanical efficiency losses that tend to grow as plants age, caused by phenomena, such as erosion of the leading edge of turbine blades.[15] Germer and Kleidon[12] found that the energy output of wind turbines in Germany declined at a rate of about 0.6% per year, consistent with similar research on the Swedish wind fleet.[11] Staffell and Green[14] examined the performance of wind projects in the United Kingdom and found a decline in performance of 1.6% per year, a greater rate than in other studies. These studies found performance declining linearly with age, but found a wide range in the magnitude of the estimated performance declines. Differences in technology, terrain, meteorology, fleet vintage, and even regulatory and contractual factors can create differences in how wind fleets age across these regions, so performance change with age must be assessed in different regions separately, with attention paid to the influence of plant characteristics and other regional factors that can impact performance. Despite research efforts in Europe, no study has comprehensively evaluated the impact of age on the performance of the US wind fleet—an important omission—because the US is the second-largest wind power market globally, after China.

This study addresses the research gap identified above by analyzing the performance of 917 onshore wind projects across the contiguous United States (Figure 1). The sample size of wind projects in this study is much larger than the sample sizes in previous work in the European countries, as we analyze a fleet that is roughly an order of magnitude larger, in terms of installed capacity, and which spans a dramatically larger geographic area that encompasses many different climates. It builds on the methods and approaches of the European research efforts to quantify the performance trends of the US onshore wind plants. We pay particular attention to issues that are unique to the US market, such as the effect of policy mechanisms, including the production tax credit (PTC), on performance trends. We were able to remove the effects of the market-based curtailment of wind plants by producing new estimates, informed by market price signals, of plant-level curtailment. Finally, we explored the influence of plant characteristics on the rate of performance decline through a multivariate analysis. The results from this study help clarify the rate of performance decline across the US wind plants, while also providing insight into how the impact of age on fleet performance has changed with newer wind power technology and how policy and market factors can impact performance outcomes.

RESULTS

Fleet-Wide Performance with Age

Following past approaches,[14] we used a fixed-effects regression to determine the average rate of age-related performance decline across the US fleet. The fixed-effects regression was run separately on old and new plants, and we found that the plants that have been operational for at least 10 years had a distinctly different performance than their younger counterparts, see Figure 2. Older plants that became operational before 2008, experienced declining performance over time, but not in a strictly linear fashion. For the first 10 years of operation for older plants, performance decreased at a rate of −0.17 capacity factor percentage points per year (cfpp/year) or a rate of −0.53%/year on an energy basis (note, "capacity factor" is defined in the methods). Between years 10 and 11, a significant drop in performance occurred, at which point performance dropped by about 1.5 cfpp (or 3.6%). Hereafter, we will refer to this drop as the "year-10 drop." After the year-10 drop, performance recovered slightly before a gradual decline resumed (Table 1). The average rate of performance decline for years 11 through 17 is −0.40 cfpp/year

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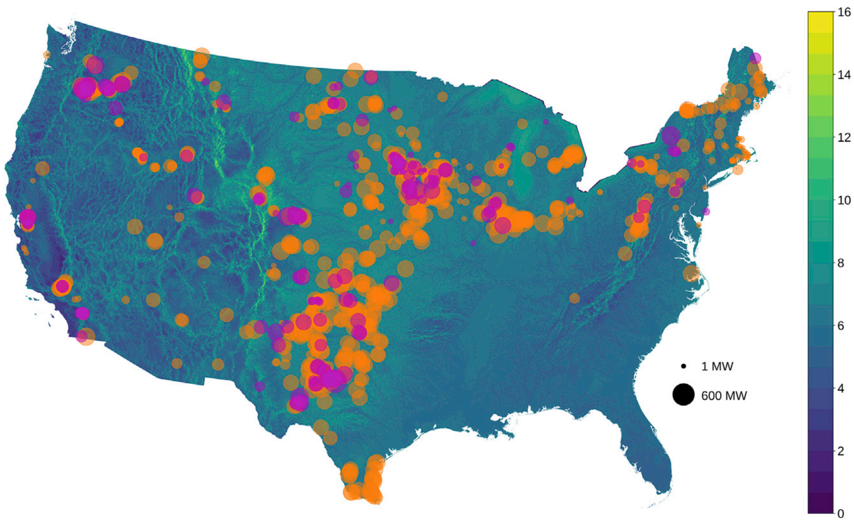

Figure 1. Map of the 917 Onshore Wind Plants Included in the Analysis
Older (pre-2008 commercial online date) plants are shown in pink, and newer plants in orange. The size of each dot is proportional to the nameplate capacity of the plant. The background map shows the annual average wind speed (m/s) at 80 m above surface level.[16]

(−1.23%/year). By 17 years of age, the fixed-effects analysis showed a decline in performance to 87% of year-2 performance. Newer plants are defined here as those that came online in 2008 or later. This cohort of plants experienced only slight, though still statistically significant, degradation at a rate of −0.06 cfpp/year (−0.17%/year). Note, for both the new and old cohort of plants, we avoid comparison to year 1 to avoid issues related to staged construction or other ''teething'' issues. The fixed effects for newer plants show some indication of slight improvement in years 3 and 4, possibly due to extended teething issues through year 2. However, any continued teething issues in year 2 is of much smaller magnitude than the teething issues seen during year 1. This fixed-effects regression included our entire sample of 917 plants.

The most surprising aspect of these results is the abrupt decline in performance found after 10 years of operation. This trait was not found in prior literature. The discrete nature of this event suggests some level of control by the operator, as opposed to maintenance caused by component failure (which one would expect to have somewhat more random timing) or progressive mechanical or aerodynamic efficiency losses. The coincidence in timing between the performance drop and the 10-year window of eligibility for the federal PTC is notable. It suggests that maintenance and operating strategies change when projects lose access to the sizable tax benefits afforded by the PTC. One plausible explanation, noted by Wiser et al.,[17] is that plants that earn sizable profits from power sales and the PTC warrant more intensive O&M activities in order to maximize production and thereby profitability. After the window of PTC eligibility has passed, however, operating profitability declines and, therefore, so does the operational rigor, at least to a degree; it may be more profitable to economize on O&M expenditures after this point, even if it means that performance tends to degrade more with time. A related hypothesis is that, in order to minimize downtime during the period of the PTC, some preventative maintenance may be delayed from the final years of the PTC period to the 11th or 12th year of project life. Another factor at play may be that turbine gear boxes and some other components are often replaced on a roughly ten-year cycle. The fixed-effects model

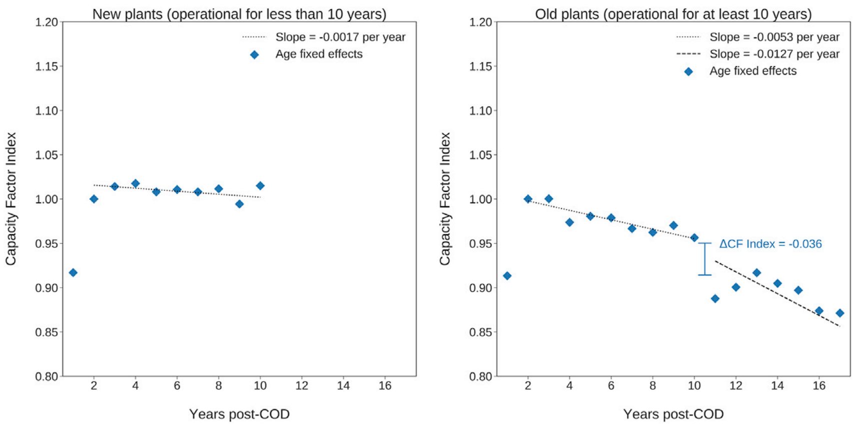

Figure 2. The Results of the Fixed-Effects Regression Shown for Old (n = 186) and New Plants (n = 731) Separately

The fixed effects and trends are normalized by the average capacity factor found for the second year after commercial online date for each cohort. All slopes shown have a p value less than 1E-5.

shows a slight rebound in performance in year 13 relative to years 11 and 12. Thus, perhaps a cycle of component replacement occurs in years 11 and 12, and performance rebounds slightly after this cycle is complete.

Wind plants must sometimes reduce production (a practice commonly called "curtailment") due to electric-grid constraints. In these cases, areas with congested transmission systems or an oversupply of generation can see negative local wholesale power prices. We find that operator choice to curtail is sensitive to these negative wholesale prices and also to the status of the PTC. That is, plants receiving this tax credit would need to see negative prices that are equal in magnitude to the tax credit before it is economically favorable for them to stop generating power, in contrast with plants not receiving the credit, for which it makes sense to stop generation as soon as prices drop below zero. For example, in Electric Reliability Council of Texas (ERCOT) in 2015, plants still receiving the PTC curtailed generation at a rate of 0.5%, while plants no longer receiving the PTC curtailed at 1.7%, and plants that participated in the "Section 1603" grant program instead of the PTC curtailed at 3.2% (we found similar trends in other years). The 1603 grant program operated from 2009–2012 and offered upfront subsidies rather than production-based subsidies. Directionally, these results are intuitive in as much as a plant earning ongoing revenue from the PTC will tend to not want to curtail its output, given the resultant loss in tax benefits. This provides clear evidence that operators are carefully adjusting behavior based on the PTC status to maximize profitability, which provides an additional level of plausibility to the idea that operators would also change maintenance regimes based on the PTC status. However, the PTC-based curtailment changes also add some level of uncertainty to the year-10 performance drop. Though we explicitly consider the PTC status in our plant-level modeling of curtailment, our model of impact of the PTC status on curtailment patterns is based on plant-level data collected in Texas. Our assumption that similar curtailment patterns hold through other regions is untested. If we assume that curtailment is not a function of a plant's PTC status outside Texas, the year-10 drop increases in magnitude to roughly -9%. This change in magnitude demonstrates the sensitivity of the year-10 drop to assumptions about curtailment. So, while we have no explicit reason to doubt our estimates of plant-level curtailment, we note the sensitivity of the year-10 drop to these assumptions.

Table 1. Summary of Performance Trends and Performance Drop for Old (n = 186) and New (n = 731) Plants

Cohort	Metric	%	Cfpp
New	Year 1–10 performance	−0.17 %/year	−0.06 cfpp/year
Old	Year 1–10 performance	−0.53 %/year	−0.17 cfpp/year
Old	Year 10+ performance	−1.23 %/year	−0.40 cfpp/year
Old	Year 10 drop	−3.6 %	−1.5 cfpp

Note the year-10 drop was calculated as the difference between years 8–10 and 11–13 (narrowing the set of years on either side of the drop leads to a somewhat larger calculation of the year-10 drop but does not change the general conclusions, see Table S1).

A second notable, but somewhat less surprising result, is the reduction in performance decline of newer vintages of plants compared with older plants. Staffell and Green[14] found indications that newer plants experienced a lower rate of degradation, but Olauson et al.[11] did not see a difference in the rate of performance decline across different plant vintages. On one hand, the improved performance of newer plants is to be expected given the improvements in controls and technology. On the other hand, the move to progressively larger turbines could have introduced new unanticipated challenges. It seems that, on balance, the newest plants have benefited more (in terms of lower degradation rates) from new controls and technology than they have been harmed by new challenges arising from technology change.

Accurately characterizing the deviation in average wind speeds from the long-term average helps to avoid misidentifying periods with low wind resource as a decline in performance (or identifying high wind resource periods as high performance periods). Wind-plant performance is sensitive to inter-annual variability of average wind speeds, a sensitivity that becomes more important to system-wide operations as wind market share increases.[18] Our goal is to isolate the performance decline that occurs with aging, and that is separate from this inter-annual variability in wind speeds. The level of difference between the new and old plant degradation rates is sensitive to the representation of how wind conditions change over time (i.e., the "idealized wind generation" in Equations 2 and 3, later). In fact, if the idealized wind generation term is excluded from the fixed-effects model, the new plant degradation rate rises to a level comparable to that of the older plants (Figure S1). The idealized wind generation represents the energy that could have been generated at each plant, given the profile of wind speeds at the turbine hub height. The underlying wind speed profile we use is based on re-analysis data (ERA5). There is evidence that re-analysis models do not replicate long-term trends found at surface observation sites. Specifically, Zeng et al.[19] found that surface winds observed at sites across North America had been decreasing through 2012 and increasing since then. If these trends are present at wind sites but not replicated by the re-analysis data, we expect our reported 1-to-10-year degradation rate would be biased low for newer plants and possibly biased high for older plants. However, many of the surface observation sites are far away from wind plants, and there is little evidence that trends at the available surface observation sites are fully representative of trends at the wind sites. Thus, while it is important to note this potential uncertainty, observations of wind speed trends at the wind plant locations are needed before we adjust our estimates.

Individual Plant Performance Trends

Performance trends were calculated for each of the 626 plants (186 old plants and 440 new plants) that had at least 5 years of data. The primary purpose of finding the rate of performance decline for individual plants is to investigate the influence of plant characteristics on the rate of performance decline (next section). We do not rely on the average

Table 2. Performance Trends for the First 10 Years of Operation

Cohort	Mean	95% CI on Mean	Median	95% CI on Median
Old	−0.00301	(−0.00444, −0.00128)	−0.00224	(−0.00370, −0.00102)
New	−0.00014	(−0.00106, 0.00078)	0.00018	(−0.00056, 0.00091)

To reduce the impact of a small number of outliers on the average statistics, outliers with a performance trend that resulted in a z score greater than 3 or less than −3 were removed from the distribution.

of these individual trends to represent the decline in fleet performance for two reasons. First, these performance trends are linear in time, and thus obscure the non-linear results found in the fixed-effects model. Second, the age of each plant varies, and thus an average represents the performance trend across different aged plants. Notwithstanding these caveats, average plant-level trends were broadly consistent with the conclusions from the overall fleet performance trends presented in the previous section. For example, the individual regressions show that new plants have performed better than old plants, see Table 2 and Figure 3. Over the first 10 years of operation, the older plants had higher levels of performance decline with age (mean of −0.301 cfpp/year) than the newer plants (mean of −0.014 cfpp/year).

The average performance rates of individual plants are somewhat sensitive to the particular formulation of the regression model. We investigated this sensitivity across the whole sample, including both new and old plants (Table 3). The regression model chosen to describe the results presented in the above paragraph and in the next section is a function of monthly, plant-level, weather-corrected capacity factors, and includes sinusoidal terms to account for seasonal variation. This chosen regression model produces a fleet-average result of −0.00099 as the trend in capacity factor. This fleet-average value ranges between −0.00029 and −0.00120 depending on whether we examine annual data instead of monthly data, or exclude the weather correction. The long-term weather correction did not significantly shift the center of the distribution of individual performance trends. Staffell and Green[14] found that applying this same type of correction only changed the mean trend by about 0.01 capacity factor percentage points, and here, we find a comparably small shift of about 0.02 capacity factor percentage points. Though there is variation across these methods, they each indicate that a typical plant has experienced a decline in performance over its lifetime and the chosen regression model has a fleet average and median result that falls within the confidence intervals of each of the other formulations.

Degradation Drivers

To investigate if certain plant characteristics could be influencing the rate of performance degradation, metadata for each plant, listed in Table 4, were combined with the individual performance trends. Table 4 also presents the a priori hypothesis on the impact on performance of plants as they age. To focus the analysis on influences that will be most relevant in future years, only new plants (those that have been operational for less than 10 years, but were operational for at least 5 years so that they have a performance trend) were included in the analysis of degradation drivers. Here, linear performance trends were calculated based on the trend in monthly, curtailment-adjusted, weather-corrected, capacity factors (with sinusoidal terms included). The linear trends were then input into a multivariate regression.

Terrain roughness was included as a proxy variable to capture the possible effects of turbulence. To measure terrain roughness, we used a metric for how variable the topography is in the area surrounding each plant, specifically the variance of the sub-grid-scale orography in a grid cell with side lengths equal to five arc-minutes (roughly 10 km), from the static data available from NCAR.[20] The density of nearby projects was investigated to

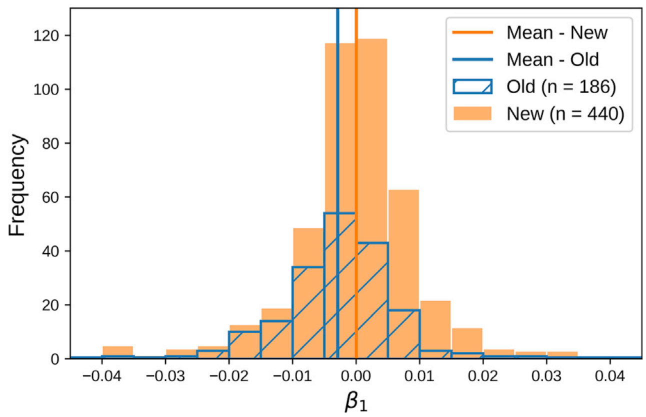

Figure 3. Change in Performance with Age (β_1) from Individual Plant-Level Regressions
Newer plants show little degradation over the first 10 years, in contrast to older plants, which show statistically significant degradation over the first 10 years. Old plant data are overlaid onto new plant data.

look for the influence of neighboring-plant wake impacts and O&M network efficiencies. To capture wake impacts, a proxy variable based on nearby installed capacity and prevailing wind directions was created. The capacity of other wind plants within a 25-km radius of plant X was weighted by the proportion of time it is upwind of plant X and summed. For example, if plant X experiences westerly winds 30% of the time, and less than 25 km due west of plant X there exists one other plant with a capacity of 5 MW, the value of this variable for plant X would be (0.3)(5) = 0.15. For finding O&M network efficiencies, all capacities within 300 km of each plant was summed.

Individual performance trends were regressed on the year of commercial operation, plant size, the two variables for nearby project density, terrain, mean wind speed, turbine manufacturer, turbine specific power, turbine drive-train type, project off-taker, project ownership type and size, and whether a project utilized the PTC. This set of variables is not necessarily complete, but represents the set of plant characteristics for which data are available and for which we were able to hypothesize a mechanism of influence over long-term performance.

The multivariate regression indicated that three characteristics may influence the rate of performance decline over time (Table 5): specific power, terrain roughness, and turbine drive-train type. We caution that the sample size of direct drive turbines (n = 10) was extremely small. While we do not draw definitive conclusions related to direct drive turbines, we do think this finding may be relevant to future research on this topic area. Figure 4 focuses on the numeric variables (not categorical) and shows the impacts of each coefficient on performance trends when combined with values of each variable. For example, though the regression coefficient for terrain roughness is small (on the order of 10^{-8}), we see that it can have an important impact on the degradation rate due to widely varying values of terrain roughness. Specific power likewise has a large impact, though the range is lower, the coefficient is larger.

Additional variables of interest include the year of deployment—plants deployed in 2010 have less degradation than plants deployed in subsequent years. There were some statistically significant differences related to the turbine manufacturers and wind speed, but these results were not significant across the three different samples. Note that these conclusions are not sensitive to whether each plant's degradation rate was normalized by its capacity factor prior to inclusion in the multivariate

Table 3. Performance Trends Calculated from Different Regression Models

Model	Mean	95% CI on Mean	Median	95% CI on Median
Monthly, weather-corrected, with sinusoids	−0.00099	(−0.00170, −0.00028)	−0.00080	(−0.00158, −0.00019)
Without sinusoids	−0.00044	(−0.00113, 0.00026)	−0.00041	(−0.00112, 0.00019)
Without weather correction	−0.00120	(−0.00186, −0.00054)	−0.00141	(−0.00203, −0.00065)
Annual data	−0.00029	(−0.00100, 0.00042)	−0.00056	(−0.00119, 0.00009)

To reduce the impact of a small number of outliers on the average statistics, outliers with a performance trend that resulted in a z score greater than 3 or less than −3 were removed from the distribution. The model "without sinusoids" is based on monthly, weather-corrected data. The model "without weather correction" is based on monthly, raw data. The model "annual data" is based on annual weather-corrected data (and does not include sinusoids).

regression or whether degradation rates were based on monthly or annual data (Tables S2 and S3).

Confirming our a priori hypothesis, lower specific power and direct drive turbines experienced less degradation, while plants located in rougher terrain experienced greater degradation, perhaps due to increased turbulence. Specific power refers to the ratio of turbine nameplate capacity to turbine swept area. In the US, newer plants have tended to have lower specific power as turbine blade length increased more than turbine nameplate capacity. As specific power is driven down so is the minimum wind speed required for turbine output to reach its rated capacity. A lower specific power allows turbines to operate at rated capacity for a greater portion of time, and thus achieve a higher capacity factor. The trend toward low specific power turbines was observed in all regions of the USA, and has not been limited to low wind regions.[21] When a turbine is operating at rated capacity it is less sensitive to some of the mechanisms of age-related degradation. For example, aerodynamic efficiency of blades may decrease over time, but if the wind speed is above that which is required for rated output, then any loss in aerodynamic efficiency can be compensated by simply harvesting a greater portion of the available wind energy (maintaining operation at rated capacity). It is potentially through this mechanism that overall degradation rates were lower for low specific power turbines.

What was mildly surprising was how few of the other variables seemed to have a statistically significant correlation with performance decline. There are a number of possible reasons for this lack of correlation. Some of these plant characteristics may have both positive and negative influences on degradation rates, thus obscuring any measurable correlation. For example, plants in high wind speed locations may spend a greater portion of their time at rated power, reducing the influence of aerodynamic losses and related performance degradation, but, as turbulence is correlated with wind speed, may experience greater degradation related to turbulence. Similarly, larger plants may have access to cheaper maintenance through economies of scale, but may also experience greater turbulence due to intra-plant wake effects. Confounding impacts may also be seen with turbine manufacturers associated with higher than average component failures: problems with equipment may increase the rate of performance decline, but if those equipment problems occur during the first few years of a project but are then fixed, performance may appear to increase over time. In addition to these confounding influences, some of the variables represent proxies for the underlying mechanisms of interest and may not provide adequate fidelity to capture these

Table 4. A Priori Hypotheses About How Project Characteristics Impact Plant Performance Over Time

Characteristic	Hypothesized Impact on Degradation
Project vintage	Newer plants may have improved technology and maintenance regimes and thus lower degradation
Project nameplate capacity	Larger projects may have lower degradation rates due to heightened O&M monitoring and on-site personnel
Project ownership type	Independent power producers (IPPs) with dedicated wind knowledge may establish more effective O&M programs leading to lower levels of degradation, in comparison to utilities, such as investor-owned utilities (IOUs) and publicly owned utilities (POUs), and especially 'Other' owners (e.g., community-owned projects)
Size of project owner	Project owners that own more wind projects may have more experience and economies of scale, leading to lower levels of degradation
Turbine specific power	More time spent at rated power means less time with aerodynamic efficiency losses, leading to lower levels of degradation
Turbine manufacturer	Differences in turbine design, component reliability, and maintenance contracting may lead to variations in performance between turbine manufacturers
Terrain roughness	As a proxy for turbulence, increased terrain roughness (turbulence) may lead to increased degradation due to greater mechanical stresses on the turbines
Average wind speed	Higher average wind speeds (from AWS Truepower data) may also correlate with more time at rated power, and thus lower aerodynamic efficiency losses and so lower degradation; on the other hand, greater wind speeds may increase mechanical and aerodynamic stress, leading to more degradation
Density of new projects within 25 km, weighted by prevailing wind directions	Apparent degradation may increase with nearby projects due to inter-project wake effects as new projects are built upwind
Density of projects within 300 km	Degradation may decline when there are more projects in the larger region, due to maintenance network effects (e.g., cranes in vicinity, spare parts, and personnel)
Merchant plant versus non-merchant	Merchant plants may experience low wholesale prices, leading to less aggressive O&M protocols and therefore higher degradation than plants with long-term power purchase agreement that include performance guarantees
Status of PTC versus 1603 grant	Projects that receive the PTC have higher incentives for aggressive O&M and may therefore have lower degradation than projects that received the 1603 upfront grant
Turbine drive-train type (gear box versus direct drive)	Gear boxes may be more subject to failure, leading to higher levels of degradation

impacts. Finally, there could be other variables that we are unable to capture but that could be driving the results, such as the impact of erosion due to precipitation or wind-blown dust, damage from extreme wind speeds, or a plant's utilization of sensors to optimize plant operations.

Table 5. Multivariate Regression Shows Some Limited Correlation between Degradation Rates and Turbine, Plant, and Site Characteristics

Variable Description	Variable	Full Sample	Central US	Outliers Removed
Numeric	Project capacity	4.96E-06	−6.95E-06	−4.36E-07
Numeric	MW within 300 km	5.66E-07	2.85E-07	1.09E-07
Numeric	Specific power	−2.74E-05**	−1.62E-05	−3.03E-05 ***
Numeric	Terrain roughness	−1.01E-08**	−1.36E-08**	−1.16E-08 ***
Numeric	Mean wind speed	5.63E-04	1.11E-03	9.97E-04**
Numeric	Weighted MW within 25 km	−4.40E-06	−2.15E-05	−2.35E-06
Project vintage	2008	0.00	0.00	0.00
Project vintage	2009	2.65E-03*	1.95E-03	1.78E-03
Project vintage	2010	7.08E-03 ***	4.66E-03*	5.68E-03***
Project vintage	2011	3.35E-03	2.99E-03	2.61E-03
Project vintage	2012	9.03E-04	2.61E-03	−3.16E-04
Drive-train type	Direct drive	0.00	0.00	0.00
Drive-train type	Gear box	−1.07E-02***	−9.85E-03**	−9.23E-03***
1603 grant or PTC	1603 grant	0.00	0.00	0.00
1603 grant or PTC	PTC	1.61E-03	1.46E-03	1.43E-03
Ownership type	IOU	0.00	0.00	0.00
Ownership type	IPP	7.15E-04	1.43E-03	1.37E-03
Ownership type	POU	−3.01E-03	−3.13E-03	−6.36E-04
Ownership type	Other	−3.00E-03	−3.44E-03	−3.24E-03
Owner size	Small owner	0.00	0.00	0.00
Owner size	Large owner	5.53E-04	1.35E-03	3.66E-04
Merchant or not	Non-merchant	0.00	0.00	0.00
Merchant or not	Merchant	3.02E-04	2.15E-04	-6.23E-05
Manufacturer	Vestas	0.00	0.00	0.00
Manufacturer	Clipper	1.60E-03	1.15E-03	1.73E-03
Manufacturer	GE	−2.24E-03	−1.97E-03	−2.63E-03**
Manufacturer	Gamesa	−8.81E-04	−1.13E-03	−6.94E-04
Manufacturer	Mitsubishi	−3.76E-03	−4.37E-03	−3.67E-03
Manufacturer	Repower	8.93E-02	1.11E-02	9.42E-03**
Manufacturer	Siemens	−4.44E-03**	−4.08E-03	−1.85E-03
Manufacturer	Suzlon	1.70E-03	2.80E-04	1.57E-03
Manufacturer	Other	−1.53E-03	−2.14E-03	−3.92E-04

A positive (negative) value means less (more) degradation in performance with plant age. The regression was run on the full sample of new plants with at least 5 years of data, as well as on two smaller samples to test the robustness of these conclusions. One sample included only the central US, since this is where the majority of wind plants are located and is an area with similar site characteristics. The third sample included only plants with performance trends within $\pm$ 0.03, to test a more stringent definition of outliers. Statistically significant results are highlighted according to their p values (see inset legend), where a p value less than 0.01 indicates the strongest evidence of statistical significance.
Note: p value < 0.01 = ***; p value < 0.05 = **; p value < 0.1 = *.

It is interesting to see significant differences between the project vintage years. Our a priori hypothesis was that newer plants might experience lower degradation rates due to new technology and maintenance regimes. We did observe this relationship for pre-2008 and post-2008 plants, as shown earlier. However, within the post-2008

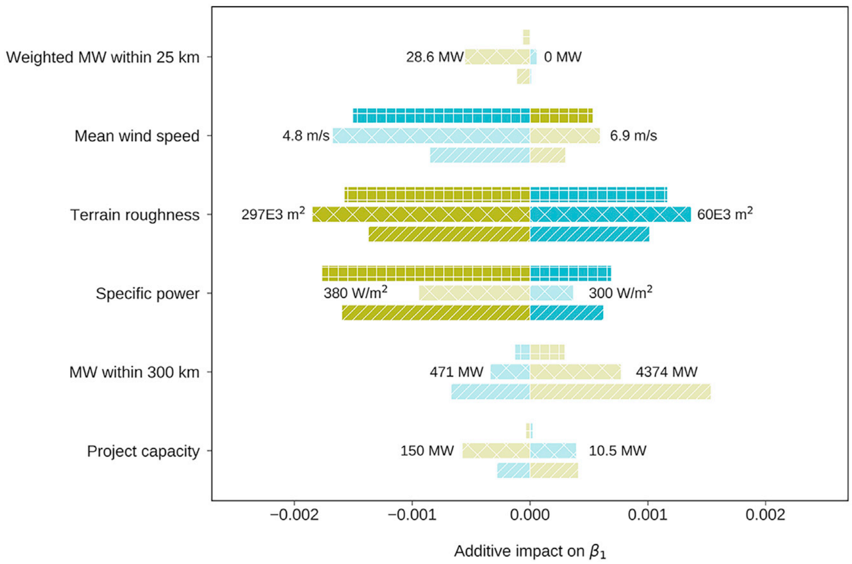

Figure 4. Impact on Performance Trends (β_1) of the Product of the Regression Coefficients and the Typical Range of Values for Numeric Variables

Each bar shows the value of the regression coefficient multiplied by the 20th percentile (olive) or 80th percentile (turquoise) value of the corresponding variable, expressed as an offset from the coefficient multiplied by the median value of that variable. The values of the 20th and 80th percentiles for each variable are displayed as annotations on the figure. Impacts for the coefficients from all three samples tested in the regression are shown, with the full sample at the bottom of each trio (diagonal lines), central U.S. in the middle (intersecting diagonal lines), and with outliers removed on top (intersecting horizontal and vertical lines). Darker bars indicate a p value less than 0.05.

cohort, we did not see a smooth trend in any direction, but instead saw lower degradation rates from 2010 plants and higher degradation rates from 2008 plants; the degradation rates of other vintages fall within the range between 2008 and 2010. One possible explanation for the lack of trend within the post-2008 cohort is that one of the major technology changes since 2008 has been the use of lower specific power turbines, but specific power itself was a variable in the regression, and thus not represented within the vintage variable. Another possibility is that the difference between vintages is related to inter-annual weather variation not captured in the long-term correction process. However, as described in the previous section, we lack an alternate set of wind speed measurements at the plant locations to explore this possibility.

DISCUSSION

Like any engineered system, wind plants experience some deterioration over the course of their lifetime. For the wind fleet in the US, this degradation does not appear to happen smoothly over time, but involves a step-change in performance after 10 years of operation. The majority of wind projects in the US have taken advantage of the PTC, which provides wind plants with a production-based tax credit for their first 10 years of operation. The results described here suggest that, in addition to potentially more frequent component failures and downtime as well as growing mechanical and aerodynamic efficiency losses as plants age, the US plants are operated differently after they age out of the 10-year PTC window. Previous studies on various European wind fleets found linearly declining performance with time.[11,12,14] Different policies for incentivizing the expansion of wind energy in Europe and the United States could be influencing the way in which the US and the European wind plants age differently. In particular, European policies have not generally featured a short 10-year window of eligibility, such as that with the PTC, which could be a reason they did not follow the pattern of the US wind plants. This also implies that wind-plant degradation is not simply a physical process, but is also a function of weighing the costs of maintenance against the value of operation of a wind project. Dao et al.[3] also found that there was a strong relationship between maintenance expenditures and reliability, and thus annual energy production, of wind turbines. It appears that in the US, the PTC makes it cost-effective to both minimize turbine downtime and maintain turbines at a high level while they can still take advantage of the tax credit, but that after year 10, a different maintenance optimization routine is applied.

Overall, the US fleet has experienced levels of performance decline on the low end of the range found in Europe. The fixed-effects regression showed that after 17 years, aging had caused the performance of plants to drop to 87% of their initial levels. This performance decline is less than 1% per year and is closer to the decline of 0.6% per year as described by Germer et al.,[12] than the 1.6% as described by Staffell and Green.[14] Furthermore, the performance of newer plants (i.e., plants that began generating power in 2008 or later) was found to be lower still, with the fixed-effects regression indicating performance declines of only 0.17% per year. It remains to be seen whether this newest set of plants will experience the same sort of drop in performance after their 10 years of PTC revenue ends.

Among newer plants (defined as beginning production during 2008 or later) the rate of performance decline was correlated with a limited number of plant characteristics. Most notably, plants with lower specific power were correlated with lower degradation rates, while plants in rougher terrain were correlated with higher degradation rates. Interestingly, the rate of decline was not found to be correlated with project ownership or plant size. Additionally, characteristics such as average wind speed and the proximity of nearby plants showed little significant correlation with the rate of performance decline. The explanatory power of some of these characteristics may be limited by confounding effects.

The results described here can be used by investors and energy system modelers to refine estimates of wind-plant performance and levelized energy costs. For example, electric sector "capacity-expansion" models, often used by researchers and policy makers to assess how the electricity system will evolve over the next decade, or longer, are sensitive to wind-plant cost and performance assumptions. Additionally, investors could use these results to refine long-term wind-plant performance estimates and associated financial models.

Throughout the paper, we have identified uncertainties to which the conclusions are most sensitive, and we hope that future research will address these challenges and topics. First, in a few years there will be enough data to see if the newer set of plants continues to display the 10-year drop in performance found in the older set of plants. It will also be important to confirm that degradation rates have remained relatively low for the newer set of plants. Future research may also develop a set of more-refined plant characteristics to further diagnose the driving factors of performance decline with age. While terrain roughness was found to be a statically significant indicator of increased degradation, roughness is not a direct measure of turbulence, and so refining this metric in particular could produce valuable results. Also of interest are refinements to metrics related to maintenance network efficiencies and inter-plant wake effects. Finally, it would be useful to develop alternate weather correction methods as the potential exists that wind trends not represented in the re-analysis data may have impacted these results; especially sensitive may be the difference in performance decline between the newest set of plants and the oldest. The challenge here is the lack of publicly available wind speed observations near to wind plants, and at representative heights above ground. The development of improved wind speed estimates could be supported through either improved modeling or measurement campaigns, or, ideally, through large-scale data sharing from wind project operators.

EXPERIMENTAL PROCEDURES

Resource Availability

Lead Contact

Please contact the Lead Contact, Dev Millstein (dmillstein@lbl.gov) for information related to the data and code described in the following experimental procedures section.

Materials Availability

No materials were used in this study.

Data and Code Availability

Data and code will be furnished upon request to the Lead Contact.

Wind Resource Estimates

Estimates of wind speeds at each site of interest were needed to model power generation in order to account for inter-annual and monthly variability in the wind resource. Long-term measurements of wind speeds at each location are typically not available, so previous research efforts have used modeled wind speeds from meteorological reanalyses.[11,12,14] Two methods for obtaining wind speeds from re-analysis datasets were considered for this study. The MERRA2 dataset, which is produced by NASA and provides global hourly wind speeds at ~50 km resolution[22], was downscaled using NREL's WIND Toolkit, which provides 5 min wind speeds at ~2 km resolution over the contiguous United States.[23] The ERA5 dataset[24], a recent product from ECMWF providing global hourly wind speeds at ~30 km resolution, was also tested. When compared with actual wind-plant generation records, ERA5 was generally better able to capture the inter-annual variability in wind resource across the United States and was therefore selected to model wind speeds at plant locations. Earlier studies have also found ERA5 to perform better than other re-analysis products for wind energy applications.[25,26] Wind speeds were vertically interpolated from model layers that surround the hub height for each project (i.e., ~80 and ~120 m). This represents an improvement over previous work[14,27], which used older re-analysis products that required extrapolating wind speeds from one model layer up to typical hub heights.

To convert wind speeds to power, a representative power curve was used for each wind plant. The power curve was chosen based on the predominant wind turbine in use at each wind plant. Most wind plants in the United States only use one type of turbine. Power curves for most turbine models were obtained from "The Wind Power" database.[28] If a plant used a turbine that was not available in the database, the power curve for the most similar turbine was used, based on matching the rotor diameter and capacity. Each power curve is represented as a polynomial with cut in and cut out speed thresholds, below and above which the generation is zero.

Recorded Generation

Recorded generation data for each wind plant was obtained from the US Energy Information Administration, which tracks monthly plant-level electricity generation for over 1,100 wind plants.[29] Monthly capacity factors were calculated from each plant's recorded generation (after adjustments for curtailment, see below) and nameplate capacity. A plant's capacity factor is defined as the ratio of the energy actually produced by a power plant to the maximum amount of energy it could have produced if it had been running at maximum capacity continuously for a given time period. Changes in the nameplate capacity of plants were accounted for in the cases where plant capacity increased due to new turbine addition. However, if the capacity decreased, i.e., because a turbine was removed, this was regarded as performance degradation, and the plant's capacity was held constant; note that there were very few instances of plants with such reported decreases in capacity.

Plant-Level Curtailment

Wind curtailment occurs typically when electric-grid conditions lead to an oversupply of generation locally, resulting in low or even negative wholesale power prices. Wind plants will sometimes reduce output in these conditions below what is technically possible to deliver. This curtailment is a feature of power system conditions, and care must be taken to ensure that one does not count it as part of plant-level performance degradation.

Monthly curtailment on a plant-by-plant level was estimated from a combination of reported curtailment at the regional level and local nodal wholesale prices. Plants were split into three groups: those receiving the 1603 Grant, those receiving the PTC, and those no longer receiving the PTC because they aged out of the 10-year eligibility window. Reported curtailment in each Independent System Operator region (ISO) was distributed to plants where local nodal prices were below a threshold for each group: \$0.0/MWh for 1603-Grant and non-PTC plants, and -\$23/MWh for PTC plants. If there was not enough generation available to curtail at locations below those price thresholds, the thresholds were increased to include more generation (this occurred relatively infrequently). When there was more than enough generation below those price thresholds, the curtailment was assigned in an iterative manner, with a relative weighting toward each group that was determined by finding the ratio that best matched the available plant-level data in the ERCOT ISO, for which actual plant-level curtailment was obtained from ERCOT for a number of years. The curtailment results were not particularly sensitive to the relative weights described above, but are sensitive to the price thresholds assigned to each group.

For plants that are not part of an ISO, plants were assigned the average curtailment for the appropriate group (e.g., receiving the PTC) in the nearest ISO for each month. Since increasing installations of wind power often result in increasing curtailment, when extrapolating curtailment back in time was necessary, we adjusted the oldest available curtailment data by the wind capacity for each year. Specifically, for years that preceded reporting of curtailment data, the curtailment in the earliest available year was scaled by the wind capacity in the year of interest, for each ISO. For example, for a given ISO, if curtailment data began in 2007, the curtailment in 2004 is estimated as:

$$curtailment_{2004} = \frac{capacity_{2004}}{capacity_{2007}} \cdot curtailment_{2007} \qquad \text{(Equation 1)}$$

Reported monthly generation for each plant was then inflated based on the estimated curtailment, so that periods with curtailment would not mistakenly appear as periods of poor performance.

Assessing Performance with Age

The relationship between wind plant age and performance is investigated on a fleetwide basis and on an individual (i.e., plant-by-plant) basis. Assessing this relationship in terms of the entire fleet results in one performance trend that represents the typical performance of all the plants. Determining individual trends produces a distribution of performance trends, which is primarily used to assess how plant characteristics correlate with plant-level degradation rates.

Fleet-Wide Performance with Age

To determine an overall trend for the entire fleet, fixed-effects regression was used, as was done in Staffell and Green.[14] The raw (i.e., reported and adjusted for curtailment) capacity factors, CF, for each site, f, and month, t, were regressed on the ideal capacity factors (i.e., the capacity factors calculated from the modeled generation), with fixed effects for each plant location, s_f, and each whole year of plant age, A_T, using performance at age = 1 year as the reference. Note that "age = 1 year" refers to the 13th through 24th month of reported generation. The variable α represents the intercept, and β represents the regression coefficient on the modeled capacity factors. The term $\epsilon_{f,t}$ represents the random errors between measured capacity factors and our prediction of measured capacity factors from modeled capacity factors and age and site fixed effects.

$$CF_{f,t}^{raw} = \alpha + \beta CF_{f,t}^{ideal} + s_f + A_T + \epsilon_{f,t} \quad \text{(Equation 2)}$$

To calculate an overall slope describing performance with age, γ, the regression was run again with plant age in whole years, A_T, included as a numeric, rather than categorical variable. The first 12 months of operation were excluded from this analysis since most plants are still experiencing teething issues during this time.

$$CF_{f,t}^{raw} = \alpha + \beta CF_{f,t}^{ideal} + s_f + \gamma A_T + \epsilon_{f,t} \quad \text{(Equation 3)}$$

The age fixed effects suggested a drop in performance after 10 years of operation, rather than linearly declining performance. In contrast, Staffell and Green[14] found a linear decline, based on a fixed-effects model, and did not see a non-linear year-11 decline. To test the significance of this year-11 performance drop, another variation on the regression was used. For this regression, only plants that have been operational for at least 13 years were included. A new categorical variable to indicate whether a data point occurs before or after the suspected drop, C_{drop}, was introduced. Data points from years of operation 8, 9, and 10 are assigned as "pre-drop" and data points from years of operation 11, 12, and 13 are assigned as "post-drop." The regression was then run using this new categorical variable in place of the age fixed effects, to test the magnitude and significance of the sudden change in performance observed after 10 years. We tested calculating the drop from only one or two years on either side of the drop, as opposed to three years on either side, and it did not significantly change the result.

$$CF_{f,t}^{raw} = \alpha + \beta CF_{f,t}^{ideal} + s_f + C_{drop} + \epsilon_{f,t} \quad \text{(Equation 4)}$$

Plant-Level Performance with Age

To calculate individual performance trends, monthly reported generation is first adjusted to account for long-term and seasonal variability in wind resource each month. Specifically, modeled generation is used to calculate monthly wind indices for each plant, which are used to normalize the reported generation. A plant's measured, curtailment-adjusted, capacity factors, $CF_{f,t}^{raw}$, are long-term corrected, $CF_{f,t}^{LTC}$, by dividing the monthly capacity factors by the monthly wind index. The wind index, $WI_{f,t}$, for a given month, t, and location, f, is that month's modeled generation, $G_{f,\,t}$, divided by the mean monthly modeled generation for the entire 2007-2017 simulated time period, $\overline{G_f}$.

$$WI_{f,t} = \frac{G_{f,t}}{\overline{G_f}} \quad \text{(Equation 5)}$$

$$CF_{f,t}^{LTC} = \frac{CF_{f,t}^{raw}}{WI_{f,t}} \quad \text{(Equation 6)}$$

The individual performance trend, β_1, for each plant is then determined by regressing the long-term corrected capacity factors on the age of a plant, $a_{f,t}$. The linear regression includes sinusoidal terms to account for any seasonal cycles that were not fully removed by the long-term correction.

$$CF_{f,t}^{LTC} = \beta_0 + \beta_1 a_{f,t} + \beta_2 \sin(2\pi a_{f,t}) + \beta_3 \cos(2\pi a_{f,t}) + \epsilon_{f,t} \quad \text{(Equation 7)}$$

Previous work used a regression model of the nature described here, but that only included the sinusoidal terms if they improved the fit of the model for a given turbine.[11] Instead, we included these terms in the calculation of all the individual performance trends. If there are not lingering seasonal cycles, the coefficients on the sinusoidal terms will simply be very small in magnitude. We also calculated the trends from a simpler regression model without the sinusoids, in order to determine the effect of their inclusion.

$$CF_{f,t}^{LTC} = \beta_0 + \beta_1 a_{f,t} + \epsilon_{f,t} \quad \text{(Equation 8)}$$

Staffell and Green[14] observed that conducting this analysis on the raw and long-term corrected capacity factors produced almost identical values for the fleet-average degradation rate. To assess the impact of the long-term correction in this study, performance trends were also calculated from curtailment-adjusted measured (i.e., uncorrected) capacity factors.

$$CF_{f,t}^{raw} = \beta_0 + \beta_1 a_{f,t} + \beta_2 \sin(2\pi a_{f,t}) + \beta_3 \cos(2\pi a_{f,t}) + \epsilon_{f,t} \quad \text{(Equation 9)}$$

Individual performance trends were also calculated from annual long-term corrected capacity factors (for each year T, where year is defined as beginning in the first month of operation of each plant, not by calendar year), as an alternative method of removing any lingering seasonality. With annual data, there are no longer seasonal cycles present, so there is no need for the sinusoidal terms.

$$CF_{f,t}^{LTC} = \beta_0 + \beta_1 a_{f,T} + \epsilon_{f,T} \quad \text{(Equation 10)}$$

Only plants that have been operational for at least 5 years were included in the calculation of individual performance trends, so that there would be sufficient data to establish a trend. Once again, the first 12 months of data were not used, in order to exclude initial plant teething.

SUPPLEMENTAL INFORMATION

Supplemental Information can be found online at https://doi.org/10.1016/j.joule.2020.04.005.

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AUTHOR CONTRIBUTIONS

Conceptualization, R.W., M.B., D.M., and S.H.; Methodology, R.W., M.B., D.M., S.H., and S.J.; Investigation, S.H., D.M., M.B., R.W., and S.J.; Writing –Original Draft, S.H., D.M., M.B., and R.W; Writing – Review & Editing, S.H., D.M., M.B., and R.W.; Funding Acquisition, R.W. and M.B.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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