Annual Energy Production Loss at US Wind Facilities from Turbine Curtailment for Bats

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ABSTRACT

Wind energy is responsible for hundreds of thousands of bat deaths annually from collisions with wind turbines. To minimize bat deaths, many wind facilities use turbine curtailment (slowing down the rotation of turbine blades) during periods of expected bat activity–mainly at night during the summer and early fall when wind speeds are low. Turbine curtailment effectively reduces bat deaths, however researchers have not examined the implications of curtailment on energy production and wind facility revenue at a national scale. This study simulated wind energy production at existing wind facilities across the contiguous United States (US) under varying curtailment scenarios. We received annual energy production under varying scenarios and analyzed the impact on net present value (NPV) of each wind facility. We found a median 0.12% to 1.91% AEP loss with our low and high curtailment scenarios, corresponding to a -6,262,996 and -101,795,692 kWh loss from curtailment across the US. For many wind facilities, this AEP loss could affect their financial viability, as under high scenarios, curtailment resulted in a negative NPV for over 13% of wind facilities. Our findings suggest that curtailment with low cut-in speeds will not alter AEP significantly, but more stringent curtailment could negatively affect wind facility financials. Future directions for this research may focus on other financial metrics for viability of wind facilities and could examine AEP loss from different smart curtailment technologies to better understand how wind facilities can pursue cost-effective curtailment to reduce bat fatalities.

KEYWORDS

wind energy, conservation, financial viability, smart curtailment, modeling

INTRODUCTION

Wind power is an important energy source in the United States' efforts to decarbonize its energy sector using different forms of renewable energy. As of 2022, wind energy provides energy to meet 10 percent of the United States' electricity demand and accounted for 22 percent of new electricity capacity developed in 2022 (DOE 2023). The Department of Energy continues to have ambitious targets for wind energy growth; the DOE's Wind Vision plan is to provide 20 percent of end-use electricity demand by 2030, and to reach 35 percent by 2050 (DOE 2015). Although wind energy is an important renewable energy, it has some negative consequences for the environment, including the mortality of bat and bird species, which are directly at risk of collisions with active wind turbines (Thaxter et al. 2017). These collisions have become a conservation concern for bats, as there are several endangered species of bats with recorded fatalities at wind farms, and some species have seen population-level declines caused by wind turbine collisions (Allison et al. 2019; Friedenberg and Frick 2021). To minimize bat mortality associated with wind turbine collisions, wind facilities use "curtailment," which is the angling of turbine blades parallel to the wind to slow their rotation down when there is a high risk of collisions (REWI 2022). Studies on curtailment to reduce bat fatality have shown significant reductions in fatality that vary based on species-specific characteristics, the turbine cut-in speed, and other parameters for curtailment (Whitby et al. 2021).

Bats provide several valuable ecosystem services, including pollination, pest control, and seed dispersal, but are facing large population declines due to White Nose Syndrome (WNS) and fatalities due to wind turbines (Kunz et al. 2011). WNS, a fungal disease caused by *Pseudogymnoascus destructans*, has caused significant declines in hibernating bats since its first detection in the US in 2006 (Wibbelt et al. 2010; Blehert et al. 2009). This disease has caused drastic declines in formerly abundant and already-endangered bats. According to the USGS, WNS has killed more than 90 percent of the population of northern long-eared (endangered species), little brown (candidate for endangered status), and tri-colored bat (candidate for endangered status) species (USGS 2021). While WNS has caused the most staggering declines in bat species in recent years, bats are also vulnerable due to wind energy. The hoary bat, which accounts for 31 to 38 percent of all bat carcasses recorded at wind farms (Arnett and Baerwald 2013; AWWI 2020; Thompson et al. 2017), faces severe declines due to wind energy development in the US. There have been evident declines in hoary bat populations, and the hoary bat is expected to experience over a 50 percent decline by 2028 due to turbine collisions, even under conservative estimates (Friedenberg and Frick 2021). Such declines underscore the important role that minimization via curtailment can play in reducing population-level declines in bat species.

Curtailment of wind turbines effectively reduces bat fatalities from collisions with wind turbines (Adams and Williams 2021). There are different forms of curtailment with different parameters and varying cut-in speeds. Two main general forms of curtailment are blanket curtailment and smart curtailment. Blanket curtailment uses only wind speed, the time of year, and time of day as the criteria for when to curtail. Cut-in speed is a significant determinant of the level of minimization; in a meta-analysis by Whitby et al., it is estimated that every 1.0 m/s increase in the cut-in speed would reduce total bat fatalities by roughly 33 percent (Whitby et al. 2021). A 5.0 m/s cut-in speed would be expected to reduce bat fatalities by 62 percent on average (Whitby et al. 2021). An issue with blanket curtailment is that it does not account for other aspects of bat biology and determinants of the likelihood of bat presence, which a smart curtailment approach attempts to better address. Smart curtailment encompasses a broad range of collision minimization techniques that use real-time data to make decisions, such as including the incorporation of precipitation and temperature thresholds (REWI 2022). Other advanced smart approaches include real-time bat call detection and species analysis to decide whether to curtail in more precise increments of time (Hayes et al. 2019). Smart curtailment has the potential to reduce energy loss and revenue loss due to turbine curtailment times while still providing bat conservation benefits (Maclaurin et al. 2022). As wind turbine curtailment has been shown as an effective method of bat fatality reduction and has increased in use due to regulations surrounding bat conservation, researchers have begun to consider the broader implications of curtailment for energy production. AEP loss from bat curtailment has been examined for projected viable wind energy locations in the US and at existing wind farms in Ontario, but there are currently no existing analyses on AEP loss at existing wind farms across the US (Maclaurin et al. 2022; Thurber et al. 2023).

The primary objective of this research was to understand how wind turbine curtailment to minimize bat fatalities affected AEP at existing US wind energy facilities, and the effects of AEP loss on economic metrics for future wind energy curtailment and deployment. To address this objective, we (1) analyzed the AEP reduction at existing wind power facilities under possible curtailment scenarios to identify patterns across scenarios of varying stringency, (2) identified regional differences in AEP loss from curtailment, (3) examined how interannual variation in wind patterns can impact AEP loss, and (4) assessed the economic impact of these curtailment scenarios on the financial viability of wind facilities in the US. Consistent with current research on AEP and bat curtailment, we expected that the specifics of each curtailment scenario will have different associated AEP losses. We expected that some wind farms may be financially unviable under stringent curtailment regimes. To address the goals outlined for this research, our objectives for data collection included gathering data on characteristics of existing US wind facilities and US meteorological data across a defined time series and developing curtailment scenarios.

METHODS

Study site

Our study focuses on currently installed, industrial-sized wind facilities in the contiguous United States (CONUS). To gather data for this study system, we used the most up-to-date data from the 2023 US Wind Turbine Database (USWTDB). The United States Geological Survey, Lawrence Berkeley National Lab, and the American Clean Power Association jointly maintain this database. The latest version of the database when analysis was conducted included 72,731 turbines covering 43 states, plus Guam and Puerto Rico. The most recent turbine additions in the dataset were from the first quarter of 2023. For each wind farm, the USWTDB includes data on location (latitude and longitude), turbine characteristics (height, capacity, year), and size of project in number of turbines and capacity in megawatts (MW).

Meteorological data

To obtain meteorological data necessary to simulate energy production under realistic meteorological conditions, we used the National Renewable Energy Laboratory's (NREL) Wind Integration National Dataset (WIND) Toolkit. The WIND Toolkit gives instantaneous meteorological conditions from a computer model output for the continental United States from

2007 to 2014. It includes wind profiles, atmospheric stability, and solar radiation. We used the wind speeds from the WIND Toolkit to calculate the theoretical AEP. The NREL WIND toolkit only provides modeled meteorological data for CONUS, the lower 48 states. Thus, we limited the turbines covered to these states.

Wind farm characteristics

We made restrictions in our classifications of wind farms to capture only industrial-scale facilities. The goal of this study is to understand large-scale impacts of curtailment on AEP, and many smaller wind farms are not used for maximizing energy production, but rather for research and education purposes. We only included wind farms with over 10 wind turbines, which would remove several USWTDB entries that are experimental farms or research and education farms. We also limited the wind turbines included to wind turbines with a rotor diameter greater than 30 meters, as smaller turbines would not be considered industrial-scale. We also removed entries that lacked information critical to our analysis, such as the rotor diameter and rated power. The majority of wind farms in the USWTDB use a single make/model turbine across the entire wind farm, although a few use multiple turbine types. We simplified the analysis to make the simulation yield per-wind farm AEP by using only a single make/model per wind farm. We selected the first turbine listed for each wind farm in the USWTDB. After removal of entries that did not meet the criteria set above, we had a resulting 983 wind farms with 65,699 turbines included in our analysis.

Modeling of curtailment scenario wind energy AEP loss

In our research, we utilized a modified version of the Electric Power Research Institute's (EPRI) model to assess the AEP loss from wind farms due to bat curtailment practices. To obtain AEP loss consistent with realistic weather and wind patterns, we incorporated datasets from the NREL WIND Toolkit, which provided extensive meteorological data pertinent to our study system. A critical assumption underpinning our model was the standardization of turbine power curves. The U.S. Geological Survey (USGS) database provided the rated power for the wind turbines; however, it lacked specific data on cut-in, cut-out, and rated wind speeds, as well as the power curves. To bridge this gap, we assumed standard power curves for each turbine and scaled them to match the rated power output (Milan et al. 2010). Thurber et al. 2023 used this standard power curve approach, with an expected error margin of less than 5-10%. In our computational analysis, the standard power curve approach also gave a level of error less than 5-10%, which we considered to be within acceptable limits for the purposes of our study. Using the model with these assumptions, we modeled the different curtailment scenarios to give the AEP loss.

Scenarios modeled

We modeled 18 curtailment scenarios that differ based on the curtailment type (smart or blanket), time period for curtailment, cut-in wind speed, air temperature threshold, and precipitation threshold. We received AEP for 2007-2014 for each wind farm location under each strategy. These scenarios are the same ones developed by MacLaurin et al. 2023 to provide consistency for comparison of results (Table 1). For each scenario, curtailment only occurs from thirty minutes before sunset to thirty minutes after sunset when the parameters are met. We chose to analyze smart versus blanket curtailment to see whether the parameters included resulted in a large difference in AEP. It is important to note that smart curtailment has many meanings throughout the literature and wind energy industry. Smart curtailment can be the incorporation of advanced detection technology or inclusion of additional parameters for when to curtail. For this study, we used a simple approach to define smart curtailment based on bat behavior patterns. Bats do not fly at very cold temperatures, so we used an air temperature threshold of 10ºC, whereby the turbines would not curtail if the temperature was below 10ºC (Martin et al. 2017). Bats usually do not fly during heavy rainfall, so we used a precipitation threshold of 1 mm/hr, whereby the turbines would not curtail if precipitation exceeded 1 mm/hr (Voigt et al. 2011)). The time-periods for curtailment reflect seasons where bats are likely to be active. Current curtailment policies include state-dependent time periods and cut-in speeds, which we attempt to reflect through these scenarios. We chose scenarios varying in cut-in speed and time period from the smart and blanket types to represent the low, mid, and high scenario (Table 1).

Table 1. Curtailment scenarios for modeled AEP used in this study. Scenarios used were adapted from Maclaurin et al. 2022. Curtailment is for the time of year in time period, and occurs when conditions are met for periods from 30 minutes before dusk to 30 minutes after dawn. Smart curtailment includes parameters not to curtail if temperature is below 10ºC and if precipitation is greater than 1 mm/hr.

Scenarios	Curtailment Type	Time Period	Cut-in Speed (m/s)	Air Temperature (ºC)	Precipitation Threshold (mm/hr)
1 (low, smart)	smart	July 15-Oct 15	5	10	1
2	smart	July 15-Oct 15	6	10	1
3	smart	July 15-Oct 15	6.9	10	1
4	smart	July 01-Oct 31	5	10	1
5 (mid, smart)	smart	July 01-Oct 31	6	10	1
6	smart	July 01-Oct 31	6.9	10	1
7	smart	April 01-Oct 31	5	10	1
8	smart	April 01-Oct 31	6	10	1
9 (high, smart)	smart	April 01-Oct 31	6.9	10	1
10 (low, blanket)	blanket	July 15-Oct 15	5	-	-
11	blanket	July 15-Oct 15	6	-	-
12	blanket	July 15-Oct 15	6.9	-	-
13	blanket	July 01-Oct 31	5	-	-
14 (mid, blanket)	blanket	July 01-Oct 31	6	-	-
15	blanket	July 01-Oct 31	6.9	-	-
16	blanket	April 01-Oct 31	5	-	-
17	blanket	April 01-Oct 31	6	-	-
18 (high, blanket)	blanket	April 01-Oct 31	6.9	-	-

AEP loss analysis; comparative effectiveness of smart vs. blanket curtailment

In order to ascertain how smart curtailment compares to blanket curtailment in terms of AEP loss, we used the AEP loss data for the different curtailment scenarios. We used statistical analyses to determine variance and significance of differences in AEP loss between smart and blanket curtailment. We used multiple analysis approaches using Python to analyze the effects of smart vs blanket curtailment on the US as a whole, including creating boxplots for comparison (Python 3).

We used an aggregated analysis approach: we calculated the AEP loss for each wind facility under each curtailment scenario, and used a differential calculation to determine the difference in AEP loss between curtailment methods compared to a scenario under no curtailment. We summed all the individual differences to get a total differential value representing the cumulative impact.

Regional responsiveness to curtailment strategies

We conducted a regional analysis of the AEP loss associated with the curtailment scenarios. To do regional analysis, we separated the wind farms based on the regional classifications defined by Maclaurin et al. 2023. We analyzed how each region responds to the different curtailment scenarios, with differences in wind speed, temperature, and precipitation possibly factoring into regional differences in AEP loss. We compared the impact of curtailment scenarios on AEP loss across the different regions to identify regional variations in the AEP loss. We expected variation in AEP based on regional differences in meteorological conditions, along with high site-specific variations that may mediate the regional differences.

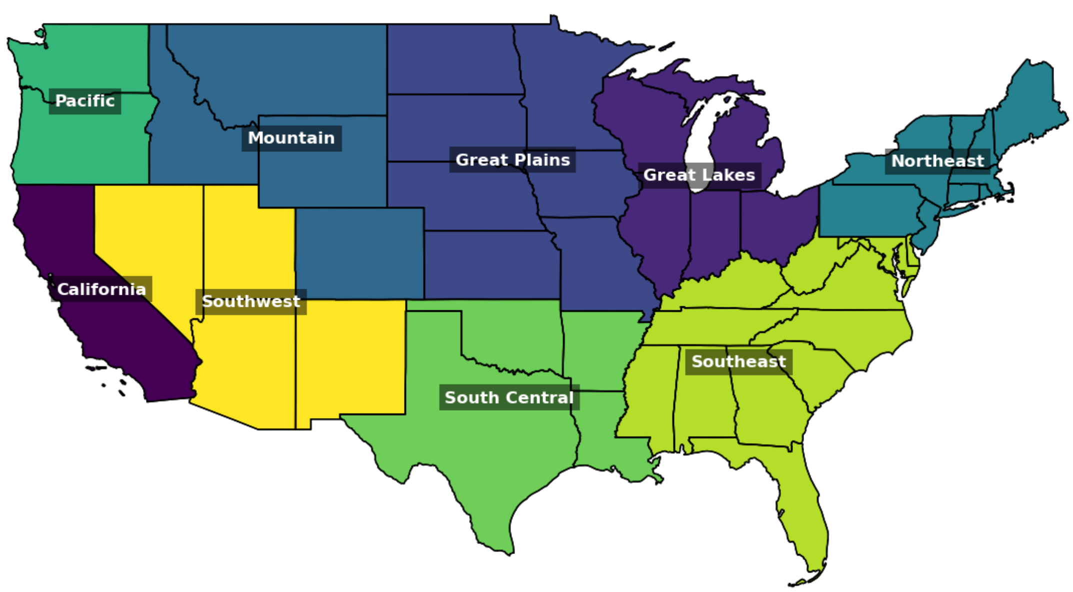

Figure 1. Regional definitions for wind farms in CONUS used for analysis. Regional definitions and groupings taken from the Maclaurin et al. 2023 analysis.

Interannual variation in AEP

We simulated our data in a way that gave an AEP for each wind farm based on the curtailment scenario and wind data for each year from the timeframe of 2007 to 2014. We looked at the differences in AEP based on year by sorting the AEP values. We looked at the differences in average AEP loss by scenario, and the variance of the percent AEP loss by scenario. Further, we looked at whether variation by years was different based on region. We expected that interannual variation in wind could have a strong impact in the amount of AEP loss seen year by year.

Financial costs associated with curtailment

We utilized the Net Present Value (NPV) as a metric to assess the economic potential across multiple scenarios and regional distributions. The NPV approach captures the total value created over the project's life by calculating the difference between the discounted cash inflows and the sum of initial plus operational expenditures. We first estimated the initial capital investment for each wind farm, incorporating the predicted turbine costs and the regionally adjusted balance of system (BOS) costs using estimates from Maclaurin et al. 2023. We predicted turbine costs per kilowatt and BOS costs per kilowatt using the estimates from Maclaurin based on the specific power of the turbines at each wind facility (Figure 2). We applied the same BOS multipliers given in Maclaurin et al. 2023 to reflect differences in costs by region. These were then multiplied by the turbine rated power and the total number of turbines installed.

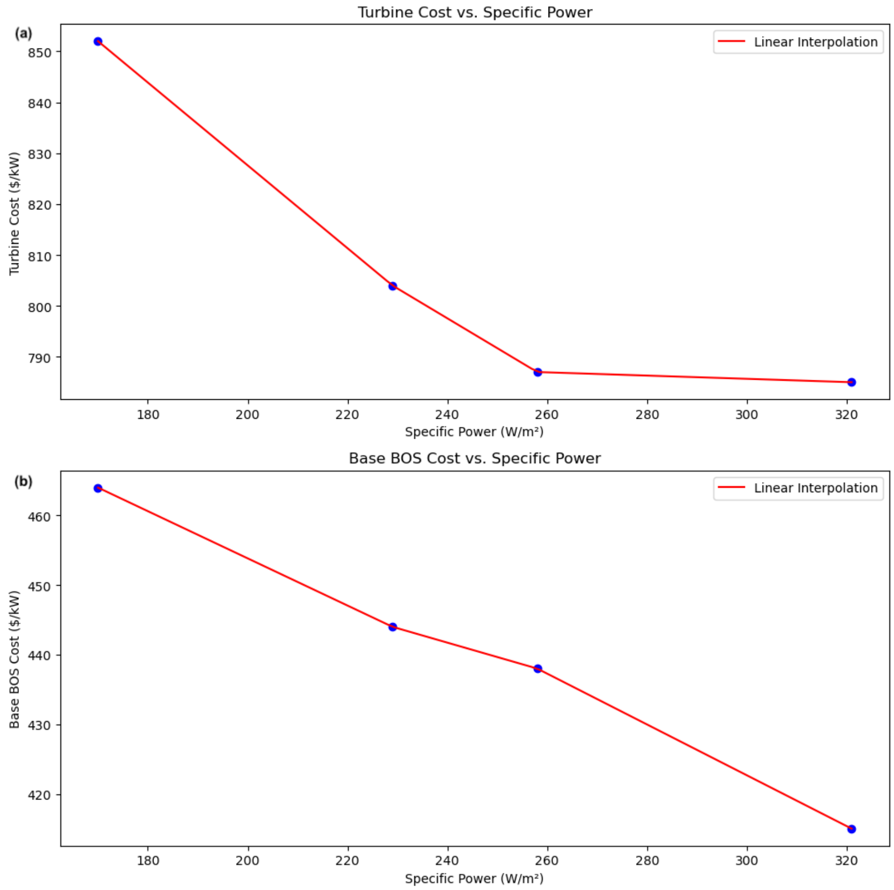

Figure 2. Linear interpolation to predict turbine cost and base BOS cost using specific power. The points in blue indicate the values corresponding to the (a) turbine cost estimates and (b) base BOS costs in $/kWh associated with the specific power values in W/m^2 used in Maclaurin et. al 2023. We estimated predicted costs using specific power following the linear interpolation trendline in these figures.

For the operational expenditures, annual operational and maintenance (O&M) costs, we estimated them based on a fixed rate of $44 per kilowatt of rated power used in Maclaurin et al. 2023. We derived revenue estimations from the site-specific AEP values multiplied by the PPA price. We estimated PPA price using average regional PPA prices for 2021-2022 from the US Department of Energy 2023 Land Based Wind Market Report. Additionally, we included production tax credit (PTC) revenues, amounting to $27.5 per MWh for the initial ten years, reflecting governmental incentives for renewable energy investments.

To compute the NPV, we discounted the net annual cash flows, defined as the total revenues minus the annual O&M costs, over the wind farm's expected operational lifespan of 30 years. We applied a discount rate of 6.7% to reflect both the time value of money and the risk profile of the projects. We calculated NPV for each wind farm under each of the eighteen energy production scenarios by subtracting the total initial capital investment from the sum of the discounted cash flows. These calculations were systematically performed and then aggregated by region to provide a detailed analysis of how varying operational strategies and market conditions impact the financial outcomes of wind energy projects. This approach to NPV is a simplification and cannot definitively determine the true net present value of these wind facilities. The numbers we estimated, such as PPA price, are highly site specific and are outside of the scope of an analysis on a national scale. Further, many factors such as federal, state, and local taxes were excluded, and estimates for turbine and BOS price may not reflect true prices. We expected that less stringent curtailment regimes would not result in negative NPV, however we anticipated that some curtailment regimes would translate to potential significant losses for wind farms.

RESULTS

Our study quantified the impact of curtailment scenarios on existing wind energy facilities at national and regional levels and across years. Our results include measures of expected AEP loss from curtailment scenarios, a breakdown of the sensitivities of AEP to components of curtailment parameters, yearly changes in AEP from curtailment, and an analysis of the economic impact of curtailment scenarios across the US and by region.

AEP loss analysis; comparative effectiveness of smart vs. blanket curtailment

Our study evaluated the AEP loss across 983 wind farms incorporating 65,699 turbines, under different curtailment strategies from 2007 to 2014. The scenarios demonstrated a wide range of AEP loss. We observed that the AEP loss varied significantly between smart and blanket curtailment strategies in the more restrictive scenarios, and had a lesser impact under less restrictive scenarios. The low smart curtailment scenarios (Strategy 1) had an average AEP loss of 0.12 percent, whereas the high blanket scenarios (Strategy 18) showed the most substantial losses with an average of 1.98 percent (Table 2; See appendix for complete Table). Cut-in speed results in consistent patterns between the scenarios; scenarios with a cut-in speed of 5 m/s accounted for all six of the lowest average AEP losses (Figure 3).

Figure 3. Boxplot comparison of Percent AEP loss by Curtailment Scenario.

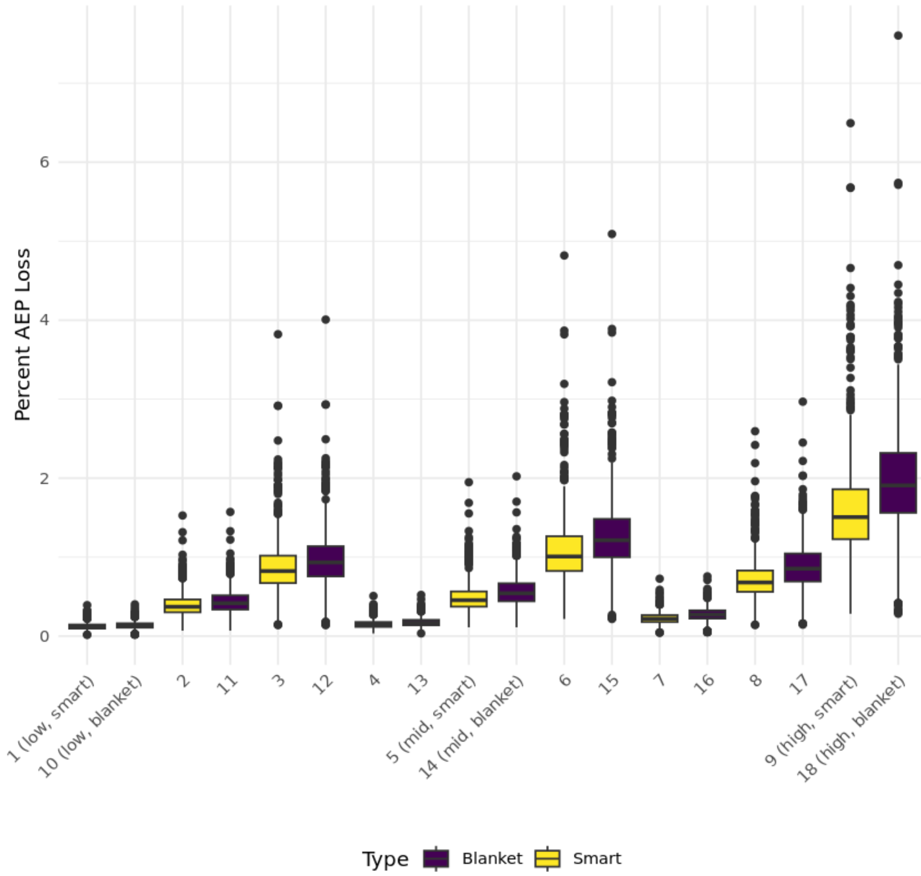

Table 2. Mean, median, minimum, and maximum percent AEP loss under curtailment scenarios.

Scenarios	Mean % Loss	Median % Loss	Min % Loss	Max % Loss
1 (low, smart)	0.121662281	0.116819195	0.01676871	0.392123825
5 (mid, smart)	0.485262071	0.455048442	0.111402442	1.948178113
9 (high, smart)	1.605771555	1.506363251	0.282629256	6.494006522
10 (low, blanket)	0.134919517	0.129777372	0.017487522	0.402139002
14 (mid, blanket)	0.563176719	0.54178994	0.11159781	2.022966083
18 (high, blanket)	1.981849286	1.907314409	0.283377686	7.603024965

As we expected, smart curtailment was associated with lower AEP loss across all scenarios, with varying magnitudes of difference. There is a 0.013% difference under the low scenario and 0.376% difference between smart curtailment and blanket curtailment low scenarios and high AEP scenarios. This result aligns with our hypothesis that smart curtailment, due to its adaptive nature based on real-time environmental data, is more effective in reducing energy loss while mitigating bat fatalities.

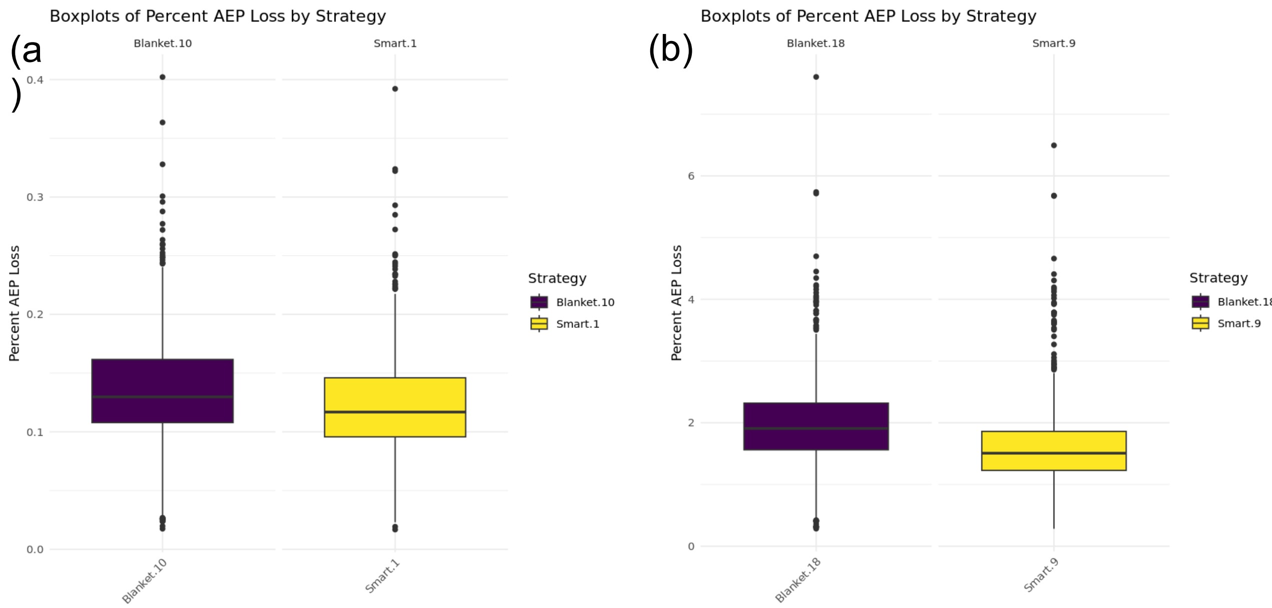

Figure 4. Boxplot comparison of percent AEP loss by smart vs blanket curtailment. The boxplots depict AEP loss under (a) low curtailment scenario and (b) high curtailment scenario.

The analysis of cumulative impacts on AEP due to varying curtailment strategies shows that high curtailment scenarios—both smart and blanket—lead to the most substantial reductions in total AEP, with losses reaching approximately -84,951,566.84 kWh and -101,795,692.12 kWh, respectively (Table 3). In contrast, low curtailment scenarios see much smaller impacts, with the smart strategy recording a loss of -6,262,995.65 kWh compared to the blanket strategy's -6,888,346.01 kWh loss (Table 3). This indicates that while higher levels of curtailment effectively minimize operational output to protect bat populations, they also result in significant decreases in energy production.

Table 3. Cumulative AEP under curtailment scenarios. Total AEP in kWh for low, mid, and high scenarios are shown. Cumulative impact is the difference between total AEP under no curtailment and total AEP under the curtailment strategy.

Scenarios	Total AEP (Strategy)	Cumulative Impact (kWh)
1 (low, smart)	5,064,417,643.29	-6,262,995.65

5 (mid, smart)	5,045,449,808.22	-25,230,830.72
9 (high, smart)	4,985,729,072.10	-84,951,566.84
10 (low, blanket)	5,063,792,292.93	-6,888,346.01
14 (mid, blanket)	5,041,903,887.61	-28,776,751.33
18 (high, blanket)	4,968,884,946.82	-101,795,692.12

Regional responsiveness to curtailment strategies

There was high variation in AEP loss by region. California has consistently low AEP loss compared to the other regions, which may be attributed to meteorological conditions. The Great Lakes and Southwest regions experienced the highest AEP losses, particularly under the high blanket curtailment scenarios, with average losses peaking at 2.63% and 2.42% of total AEP respectively under the blanket high scenario, while California had an average AEP loss peaking at 0.905%. These trends are consistent with our expectations of regional variation and suggest that regional climatic factors can play crucial roles in the efficacy of curtailment strategies.

Table 4. Mean percent AEP loss by region and curtailment scenario (%).

Region	Smart, Low	Blanket, Low	Smart, Mid	Blanket, Mid	Smart, High	Blanket, High
California	0.049475258	0.050894368	0.25626824	0.265509466	0.813473228	0.905107181
Great Lakes	0.155788944	0.171937293	0.632241959	0.737237551	2.067614019	2.63160832
Great Plains	0.117092887	0.133976471	0.434722015	0.536746311	1.427721943	1.873471598
Mountain	0.167019266	0.189413296	0.561500192	0.6822849	1.64924353	2.307391596
Northeast	0.112075417	0.137269091	0.460776362	0.607837098	1.450887233	2.143734689
Pacific	0.111222426	0.122289001	0.442796878	0.527557899	1.330198555	1.77154484
South Central	0.113760108	0.119862288	0.50095216	0.528152146	1.808017741	1.927038604
Southeast	0.12632816	0.140235542	0.508254673	0.600836432	1.662300327	2.097069075
Southwest	0.177908992	0.188502546	0.663509241	0.726762593	2.106306462	2.417699632

Table 5. Median percent AEP loss by region and curtailment scenario (%).

Region	Smart, Low	Blanket, Low	Smart, Mid	Blanket, Mid	Smart, High	Blanket, High
California	0.038347797	0.039401853	0.186865966	0.193141946	0.613963106	0.688529473
Great Lakes	0.156343815	0.174413418	0.648237715	0.753250401	2.096080898	2.651443244
Great Plains	0.114492892	0.131984135	0.430439464	0.530426959	1.399373843	1.879967796
Mountain	0.167814656	0.190843554	0.559248738	0.678388697	1.678279095	2.301074224
Northeast	0.105375571	0.125545957	0.441407895	0.572882163	1.399075523	2.087862561
Pacific	0.104628041	0.114292021	0.406637507	0.462763614	1.252730561	1.615939218
South Central	0.106541405	0.113095372	0.445859657	0.47795422	1.589177766	1.732013196
Southeast	0.107488272	0.122383642	0.442490238	0.536447747	1.453445708	1.897872781
Southwest	0.162892639	0.179080895	0.613334628	0.686150909	2.028975292	2.266983524

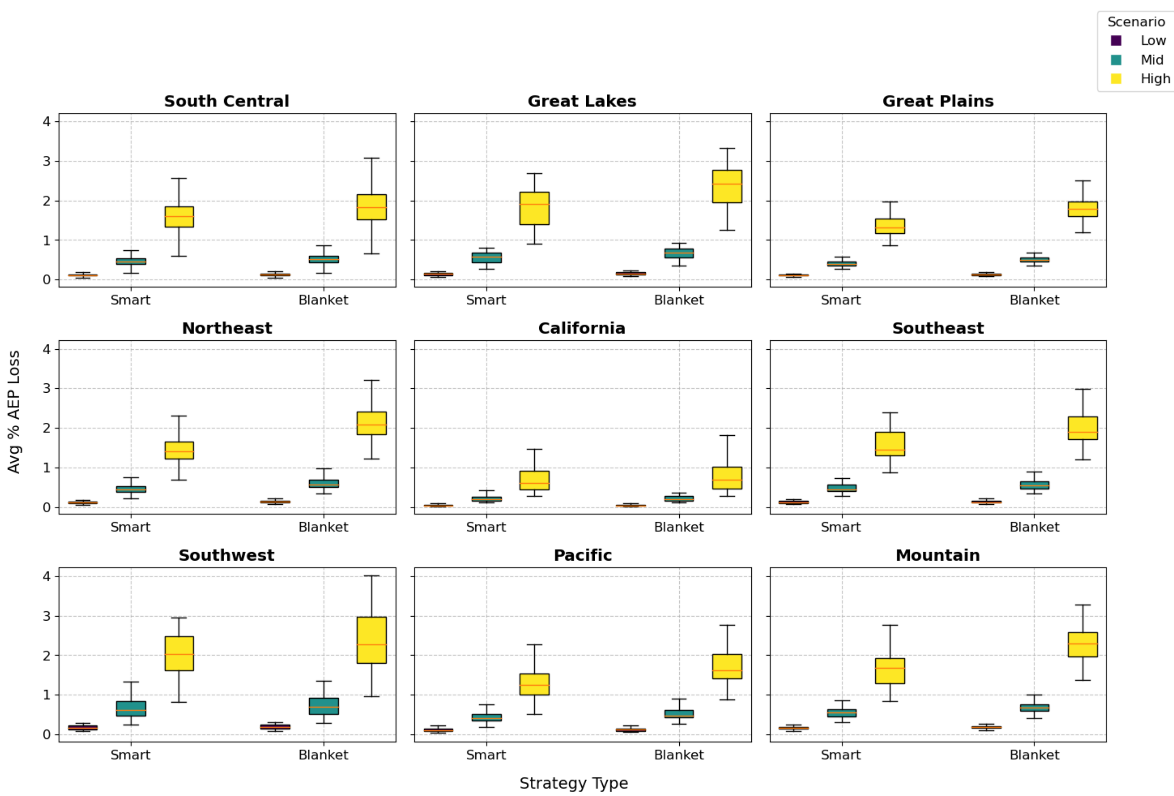

Figure 5. Boxplot comparison of average percent AEP loss for wind farms sorted by region for low, mid, and high scenarios.

The cumulative impact data indicates that more aggressive curtailment strategies lead to disproportionately higher losses in regions with erratic meteorological conditions. For instance, the cumulative AEP loss in the Great Lakes under the high blanket strategy was the highest at approximately -13.74 million kWh, suggesting a significant reduction in energy production capability due to curtailment.

Table 6. Estimated cumulative impact of curtailment strategies on AEP compared to the no-curtailment scenario by region.

Region	Total AEP Baseline	Smart, Low	Smart, Mid	Smart, High	Blanket, Low	Blanket, Mid	Blanket, High
California	206,104,631	-99,833	-507,238	-1,604,999	-102,812	-525,942	-1,782,037
Great Lakes	515,840,445	-825,781	-3,339,046	-10,972,832	-906,064	-3,858,142	-13,736,361
Great Plains	1,418,287,366	-1,726,045	-6,437,449	-21,262,634	-1,965,012	-7,860,570	-27,468,999
Mountain	389,749,421	-639,168	-2,167,808	-6,418,268	-729,569	-2,640,513	-8,994,030
Northeast	166,402,594	-174,252	-724,566	-2,299,310	-215,667	-967,012	-3,419,425
Pacific	215,735,921	-236,791	-959,571	-2,923,558	-259,842	-1,138,197	-3,859,923
South Central	1,910,028,487	-2,168,639	-9,579,627	-34,550,108	-2,289,373	-10,112,043	-36,857,885
Southeast	43,735,485	-57,658	-237,903	-784,957	-63,521	-275,527	-962,751
Southwest	204,796,288	-334,828	-1,277,623	-4,134,899	-356,486	-1,398,806	-4,714,281

Interannual variation in AEP loss

Through our investigation into yearly AEP data, we aimed to determine the impact of interannual variability (IAV) in wind conditions on AEP loss due to curtailment strategies. Our analysis showed significant fluctuations in AEP loss percentages year-over-year, influenced by regional and annual meteorological variations. We found that IAV contributed to variable AEP loss across different regions and years, with variation up to a 0.75% difference in percent AEP loss between years (high, blanket scenario).

Under the mid-level blanket approach (6 m/s cut-in, July 01-Oct 31), California shows relatively stable losses annually, ranging from a low of 0.236% in 2009 to a high of 0.292% in 2011. In contrast, the Great Lakes region exhibits more substantial fluctuations, with the lowest loss at 0.662% in 2008 and peaking at 0.846% in 2014, and the Southwest similarly has losses that fluctuated between 0.664% in 2010 and 0.845% in 2014. While our yearly wind resource data involved simulated wind patterns for 2007 to 2014, this variation suggests that the Great Lakes region may be more susceptible to IAV than California (Figure 6a).

We predicted that smart curtailment would have greater variation between years and regions with lower AEP losses overall, as precipitation and temperature are used as determining factors for curtailment. Under the mid-level smart approach, California showed a slightly narrower range from 0.225% in 2009 to 0.285% in 2011, suggesting a more stable output under smart curtailment. The Great Lakes' AEP loss ranged from 0.573% in 2008 to 0.775% in 2014, which is notably less variation compared to the blanket approach. The Southwest had a high percent AEP loss of 0.811% in 2014 down from 0.654% in 2007, showing that smart curtailment still experiences the impacts of regional and yearly variations (Figure 6b).

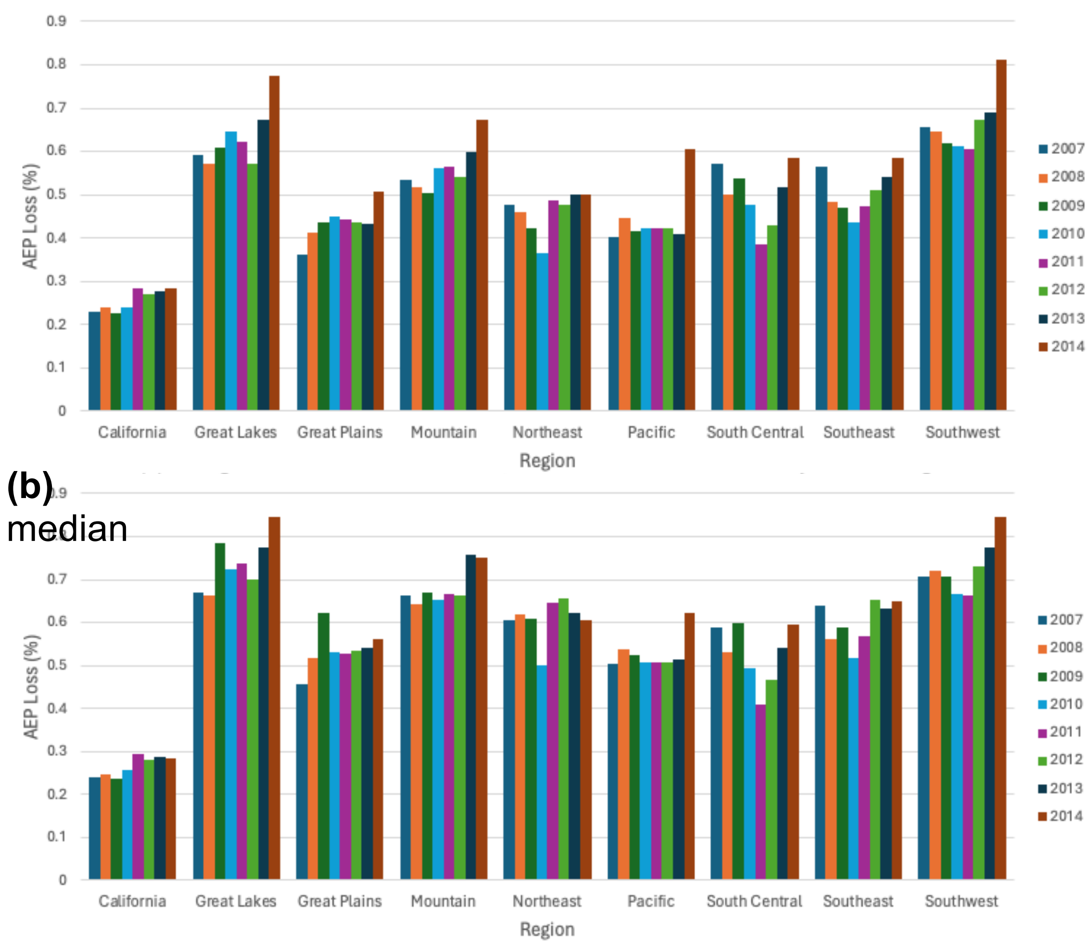

Figure 6. Average percent AEP loss under (a) mid, blanket curtailment scenario and (b) mid, smart curtailment scenario by year and region. The middle scenarios refer to a curtailment time period of July 01 to October 31, with a cut-in speed of 6 m/s.

Financial costs associated with curtailment

We found that many wind farms could be economically infeasible due to AEP loss under more stringent curtailment scenarios and with consideration of our cost assumptions. Due to the competitive nature of power markets, even fractions of a cent can impact power purchase agreements. Under curtailment scenario 5 with mid-smart curtailment parameters and scenario 14 with mid-blanket parameters, we found that 11.5% of wind farms would have a negative NPV (Figure 4). The scenarios show a range of negative NPV counts from 110 to 134 wind facilities with a negative NPV, with 107 facilities having a negative NPV with no curtailment. The assumptions made in the NPV calculations do not reflect true wind facility cost but may show trends in NPV.

Table 7. Count and percent of wind farms with positive vs negative NPV under curtailment scenarios.

Scenarios	Positive NPV Count	Negative NPV Count	Positive NPV %	Negative NPV %
1 (low, smart)	873	110	88.81	11.19
2	870	113	88.5	11.5
3	868	115	88.3	11.7
4	872	111	88.71	11.29
5 (mid, smart)	870	113	88.5	11.5
6	862	121	87.69	12.31
7	872	111	88.71	11.29
8	869	114	88.4	11.6
9 (high, smart)	857	126	87.18	12.82
10 (low, blanket)	872	111	88.71	11.29
11	870	113	88.5	11.5
12	866	117	88.1	11.9
13	872	111	88.71	11.29
14 (mid, blanket)	870	113	88.5	11.5
15	861	122	87.59	12.41

16	872	111	88.71	11.29
17	866	117	88.1	11.9
18 (high, blanket)	849	134	86.37	13.63
No curtailment	876	107	89.11	10.89

Under different curtailment scenarios, some regions do not show large changes in percent of facilities with negative NPV. The Northeast and Southeast had no wind facilities with a negative NPV, while the Pacific had a negative NPV for 64.91% of their facilities. These losses are substantial and show high regional variation in the financial impacts of curtailment.

Table 8. Percent of wind farms with a negative NPV under low, mid, and high curtailment scenarios by region.

Region	No curtailment	Low, Smart	Low, Blanket	Mid, Smart	Mid, Blanket	High, Smart	High, Blanket
California	21.54	21.54	21.54	21.54	21.54	23.08	23.08
Great Lakes	17.9	19.14	19.14	19.75	19.75	23.46	27.16
Great Plains	3.88	3.88	3.88	3.88	3.88	3.88	3.88
Mountain	16.05	16.05	16.05	16.05	16.05	16.05	17.28
Northeast	0	0	0	0	0	0	0
Pacific	57.89	59.65	61.4	61.4	61.4	63.16	64.91
South Central	1.07	1.07	1.07	1.34	1.34	2.41	2.41
Southeast	0	0	0	0	0	0	0
Southwest	29.03	29.03	29.03	29.03	29.03	29.03	29.03

DISCUSSION

This paper gives insights into broad impacts of bat curtailment on AEP, including considerations of how variation in wind resource by year can change the effects of curtailment and discusses the potential economic impact of wind energy curtailment. It is important to consider the different effects of wind turbine curtailment, as bats are experiencing unprecedented threats from disease and wind turbines, which will likely necessitate conservation measures at wind farms in the near future (Allison et al. 2019; Friedenberg and Frick 2021).

AEP loss across the US– scenario analysis

The relative impact of AEP loss across the US varies significantly with curtailment strategy, posing essential considerations for the balance between wildlife conservation and renewable energy goals. Overall, our AEP loss from scenarios do not drastically diverge from the levels given from site-specific AEP reduction research, which give values of AEP loss ranging from 0.06 to 3.20% (Whitby et al. 2021; Arnett et al. 2010; Thurber et al. 2023). We found that Smart curtailment measures have the potential to reduce bat fatalities while having a lesser impact on power generation for wind facilities. This effect is particularly large when the cut-in speeds are 6 m/s and 6.9 m/s, whereas the magnitude of reduction of AEP loss is significantly smaller with cut-in speeds of 5 m/s. While smart curtailment is a broad term that covers many technologies, our smart curtailment scenario for analysis focused on smart curtailment that integrated temperature and precipitation thresholds, using Maclaurin et al. 2022's scenarios for smart curtailment. Other smart curtailment measures may have even greater reductions in AEP loss, such as the Turbine-Integrated Mortality Reduction (TIMR) system which uses acoustic detection of bats to initiate shutdowns, avoiding curtailment when conditions in which bats could fly but are not in the area. (Hayes et al. 2019).

This analysis used the scenarios created in Maclaurin et al. 2022, a paper which approached US-wide AEP reductions through analyzing curtailment across all viable land for potential wind development. Consistent with Maclaurin et al. 2022, we found that the cut-in speed of the scenario had a larger impact on AEP than other factors, including months of curtailment. While general trends were the same, our average AEP reductions were much smaller for the curtailment scenarios than those used in their analysis. This difference is likely due to the intentional siting and planning of existing wind facilities at locations that are less vulnerable to sensitivities of AEP reduction. Extensive planning goes into wind facility development to ensure their financial viability, whereas Maclaurin et al. 2022 used spatial exclusions but did not consider many operational constraints that would make sites unsuitable for realistic wind development.

AEP loss across the US– regional analysis

Regional variability in AEP loss underscores the importance of localized curtailment strategies to mitigate the economic and environmental impacts of wind energy production. Curtailment has varying effects depending on wind farm characteristics, with patterns emerging depending on the turbine characteristics and location of the wind farm, proxied by region in this research. Our results suggest that wind resource patterns can be very regionally and even site-specific, contributing to strong differences in AEP reductions. Moreover, bat patterns can vary by region, so while this research broadly considers scenarios across the United States, curtailment requirements are dependent on the ranges of threatened and endangered bats.

Interannual variation in AEP

Interannual variability in wind patterns significantly influences AEP loss from curtailment, highlighting the complexity of predicting and mitigating the impacts of curtailment on energy. IAV in wind and resulting AEP is a common occurrence, with the eastern US's wind farms' simulated AEP ranging from 0.94 and 1.06 of their long-term averages (Pryor et al. 2018). We found IAV in wind patterns significantly influences AEP loss from curtailment but has a differing impact by region. These trends highlight the complexity of predicting and mitigating the impacts of curtailment on energy production. Our analysis shows that average AEP loss due to curtailment can vary by up to 0.75% between years. Understanding and accounting for this interannual variability is crucial for developing more accurate and efficient curtailment strategies. Such strategies could be flexible and adaptable to changing environmental conditions to ensure that wind farms can operate efficiently while minimizing impacts on bat populations.

The interannual variation in AEP loss underscores the importance of considering regional meteorological conditions when designing and implementing curtailment strategies. It also suggests that adaptability in curtailment protocols, possibly through more dynamic, sensor-based systems, could mitigate the impact of such variations and optimize the balance between wildlife conservation and energy production efficiency.

Financial implications of curtailment on wind energy

The financial impacts of curtailment on wind farms, particularly under stringent scenarios, may pose significant challenges to the economic viability of wind energy projects. Our analysis using NPV suggests that some curtailment scenarios can lead to economic losses, but curtailment regimes with a 5 m/s cut-in speed will likely not confer significant economic losses for most wind facilities. We cannot definitively draw conclusions from this NPV analysis due to the assumptions made and exclusions of important facility-specific data that are outside the scope of this study. Further research including more specific parameters could give a more realistic estimate of the financial impact of curtailment by considering costs for development, site-specific land leasing costs, grid losses, costs for transmission and network costs, as well as tax policies (Krohn et al. 2009).

Synthesis

In this study, we investigated the impact of bat curtailment on energy production at existing wind energy facilities. Several bats are threatened, endangered, or may be listed in coming years across the continental US. Vulnerable bat populations have ranges reaching every state in the continental US, so wind energy facilities will all likely be required to minimize their impact on bat populations in coming years. Depending on the stringency of the curtailment scenario and the wind resources available at the wind facility, each wind farm could potentially face significant AEP loss, translating to considerable financial losses. Wind facility managers should consider their interactions with bat populations and identify potential strategies to minimize harm to bats while maximizing their energy production.

Limitations and future directions

A critical underpinning of this study is the calculation of theoretical AEP the wind facilities, which was limited by lack of information on the power curves for each turbine–a necessary component to compute energy production. We estimated the power curve based on rotor diameter and rated power. Simulations of energy production using NREL WIND meteorological data showed AEP differences of 1.5%-3.5% between using the approximate power curve and the known power curve. This is a low error which leads to the conclusion that provides a reasonable approximation to the actual power curve for the type of analysis performed here.

A future avenue for research in this area could involve considering how AEP loss could differ due to future climate change impacts. Climate change is expected to alter wind resources across North America. These effects include reduced wind power in parts of the Western US and East Coast, while there may be increased wind speeds during certain seasons in the Central US (Chen 2020). Our research looked at AEP with wind data from 2007 to 2014 due to the data availability for these years, however the wind resources could be different today and in future periods due to climate change. By considering both historical variability and future projections of wind resources, wind farm operators can better balance the dual objectives of wildlife conservation and energy production. This approach not only helps in optimizing AEP loss in the face of interannual variability but also prepares wind energy facilities to adapt to potential shifts in wind patterns due to climate change, aiding the long-term sustainability and viability of wind energy as a key component of the renewable energy mix.

To avoid take of endangered bat species, wind facilities that have possible presence of threatened and endangered bats in their project area are legally required to implement operational fatality minimization measures such as curtailment. As of 2024, several bats are listed as endangered or are proposed for listing under the Endangered Species Act across the eastern half of the US (USFWS).

In the coming years, it is likely that bats with ranges across the contiguous US will be listed as threatened or endangered, including the hoary bat and little brown bat. This likelihood necessitates further research into nationwide impacts of curtailment. Possible future research could modify the curtailment scenarios to align with the policy suggestions of the US Fish and Wildlife Service (USFWS) to better understand the impact of real policies on AEP outcomes for wind facilities.

The research presented in this paper provides insight into how curtailment parameters will affect the energy production of wind facilities across regions and with interannual variation in wind resource. With high AEP loss from stringent scenarios, research into operational minimization techniques that also reduce AEP loss will be valuable, especially when cut-in speeds of 6.9 m/s are associated with significant AEP loss. Looking towards the future, wind energy research should consider how innovation can prevent harmful wildlife impacts from collisions while facilitating the deployment of wind energy at a large scale.

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APPENDIX

Table A1. Mean, Minimum, and Maximum percent AEP loss under all curtailment scenarios.

Scenarios	Average % Loss	Median % Loss	Min % Loss	Max % Loss
1 (low, smart)	0.121662281	0.116819195	0.01676871	0.392123825
2	0.39151637	0.371136593	0.069065334	1.526967816
3	0.876096608	0.822931118	0.139291862	3.821565919
4	0.149655158	0.143298959	0.033873659	0.508189829
5 (mid, smart)	0.485262071	0.455048442	0.111402442	1.948178113
6	1.089477114	1.007199087	0.216812507	4.818517582
7	0.223842626	0.219835994	0.042843831	0.726797668
8	0.715264474	0.67941542	0.140914285	2.594017504
9 (high, smart)	1.605771555	1.506363251	0.282629256	6.494006522
10 (low, blanket)	0.134919517	0.129777372	0.017487522	0.402139002
11	0.432427575	0.4160772	0.070234973	1.572001053
12	0.968169391	0.932773767	0.139489036	4.007257368
13	0.17325927	0.168328973	0.034817675	0.521600989
14 (mid, blanket)	0.563176719	0.54178994	0.11159781	2.022966083
15	1.266696773	1.213475494	0.21726177	5.090510758
16	0.273911313	0.271821596	0.047726195	0.756350954
17	0.879247972	0.853831879	0.145406772	2.967813215
18 (high, blanket)	1.981849286	1.907314409	0.283377686	7.603024965

Table A2. Cumulative AEP under curtailment scenarios. Total AEP in kWh for low, mid, and high scenarios are shown. Cumulative impact is the difference between total AEP under no curtailment and total AEP under the curtailment strategy.

Scenarios	Total AEP (Strategy)	Cumulative Impact (kWh)
1 (low, smart)	5,064,417,643.29	-6,262,995.65
2	5,050,407,465.14	-20,273,173.80
3	5,024,742,930.23	-45,937,708.71
4	5,062,956,397.50	-7,724,241.44
5 (mid, smart)	5,045,449,808.22	-25,230,830.72
6	5,013,314,032.69	-57,366,606.25
7	5,058,953,725.93	-11,726,913.02
8	5,033,194,363.09	-37,486,275.85
9 (high, smart)	4,985,729,072.10	-84,951,566.84
10 (low, blanket)	5,063,792,292.93	-6,888,346.01
11	5,048,544,120.40	-22,136,518.54
12	5,020,597,195.15	-50,083,443.79
13	5,061,857,148.22	-8,823,490.73
14 (mid, blanket)	5,041,903,887.61	-28,776,751.33
15	5,005,296,963.61	-65,383,675.33
16	5,056,620,512.44	-14,060,126.50
17	5,025,791,129.48	-44,889,509.46
18 (high, blanket)	4,968,884,946.82	-101,795,692.12