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Simulating the influences of bat curtailment on power production at wind energy facilities

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Abstract

The development and expansion of wind energy is considered a key threat to bat populations in North America and globally. Several approaches to mitigating the impacts of wind energy development on bat populations have been developed, including curtailing wind turbine operation at night during lower wind speeds when bats are thought to be more active. Blanket curtailment approaches have shown substantial promise in reducing bat fatalities at wind energy facilities, but they also reduce the amount of energy extracted from the wind by turbines. A related approach, referred to as smart curtailment, uses bat activity and other variables to predict when bats will be at the greatest risk at a given wind facility. In some contexts, a smart curtailment approach might reduce bat fatalities while also reducing energy loss relative to blanket curtailment. However, it has not been clear how to compare blanket curtailment and smart curtailment approaches in terms of annual energy production at wind facilities. Here, we describe a new approach to simulating the influence of blanket and smart curtailment approaches on energy production at wind energy facilities, and demonstrate the approach using 6 wind energy development areas in the Canadian province of Alberta. We show how stakeholders involved can explore the potential influences of various kinds of bat activity on energy production. We present the results of our Alberta analysis and conclude with some caveats and recommendations for future work on simulating the influences of bat curtailment on energy production at wind energy facilities.

KEYWORDS

annual energy production, bats, echolocation, smart curtailment, wind energy, wind speed

A key current and future threat to bat populations in North America is the broad-scale adoption of wind-generated power (Arnett and Baerwald 2013, Hayes 2013, Arnett et al. 2016, Frick et al. 2017, Friedenberg and Frick 2021). Bat ecologists have become increasingly concerned about the impacts of wind energy development on bats, and numerous research projects and publications have documented impacts and have proposed approaches for mitigation (Arnett et al. 2016, Hein and Schirmacher 2016, Solick et al. 2020, Whitby et al. 2021). One approach to reducing bat fatalities at wind energy facilities is referred to as curtailment, which involves temporarily slowing or stopping turbine blades so they are not a risk to bats that are flying in close proximity to the wind turbines. There are 2 main approaches to curtailment currently used: blanket curtailment and smart curtailment. Blanket curtailment involves curtailing wind turbines at night whenever wind speeds are within a given range when bats are thought to be most active (e.g., curtailing at night when wind speeds are <5.0 m/s; Arnett and Baerwald 2013, Arnett et al. 2016). Smart curtailment, on the other hand, can combine any number of relevant variables to predict when bats either are or might be in the area, and then make automated decisions about when to curtail wind turbine operation only when bats are at heightened risk. For example, in a recent smart curtailment study (Sutter and Schumacher 2017, Hayes et al. 2019), acoustic sensor systems were mounted on a subset of turbines at a wind energy facility to detect bat activity in the area. The acoustic systems were connected to a custom computer server and other hardware and software that processed acoustic data, which in turn combined this information with wind speed data, and then communicated near real-time risk conditions to the wind operator's supervisory control and data acquisition (SCADA) system. In the Hayes et al. (2019) study, the SCADA system initially curtailed turbines for 30 minutes and then the SCADA system evaluated whether to continue curtailment or return to normal operation every 10 minutes thereafter. This approach to smart curtailment resulted in a > 80% reduction in bat fatalities found inside search plots when compared to control (not curtailed) turbines. However, although the Hayes et al. (2019) study resulted in substantially reduced bat fatalities at smart curtailment turbines, the costs and technical complexity associated with the system were not trivial (Hayes et al. 2019). We note that smart curtailment approaches do not assume that all bats are detected, but rather assume that when bats are active around a wind energy facility some of the bats will likely echolocate and produce sounds that are detectable. We also note that smart curtailment approaches have not yet been validated as effective in a variety of environmental contexts and bat species assemblages (Hayes et al. 2019).

It is not clear how blanket curtailment and smart curtailment approaches might influence power production at a given wind energy facility. Thus, it is difficult for wind energy producers, wildlife agencies, and other stakeholders to make decisions about which curtailment approach to use to reduce bat fatalities at wind energy facilities (Arnett et al. 2016, Hein and Schirmacher 2016). Beginning in 2018, we participated in discussions with Alberta Environment and Parks, Electric Power Research Institute (EPRI), and American Wind Wildlife Institute (AWWI) about the possibility of conducting one or more smart curtailment field studies in the province of Alberta, Canada. Based on the Hayes et al. (2019) study and the bat assemblage that occurs in Alberta, we suspected that a smart curtailment approach would likely work well to reduce bat fatalities at wind energy facilities in the province. However, it became clear that we did not know how a smart curtailment strategy might compare to a technically simpler blanket curtailment approach in terms of energy production. The uncertainty resulted in wind energy producers being unwilling to commit to using a smart curtailment approach, such as described in Hayes et al. (2019), until they had a better understanding of the relative energy losses expected to be associated with smart curtailment and blanket curtailment. We decided that a logical next step was to develop a numerical approach that would allow comparison of simulated results of blanket curtailment and smart curtailment, and in particular would allow comparison of the influences of both approaches on energy production at wind energy facilities. Thus, we developed a simulation approach that combined publicly available wind regime data with available bat activity data to compare the potential influences of blanket curtailment and smart curtailment on annual energy production (AEP) at existing wind energy facilities in Alberta and elsewhere. We considered AEP to be the estimated annual energy production for a given wind turbine or wind energy facility, based on the wind speeds experienced at that location over a 1 year period and the wind turbine manufacturer(s) and model(s), using the theoretical power curve for each wind turbine and the wind speeds measured at nacelle height.

While developing our approach, we concluded that simulating the impacts of blanket curtailment and smart curtailment on AEP required an understanding of 6 key variables: (1) the curtailment period or season (e.g., August, September, and October of each year); (2) the wind regime, especially the nighttime winds during the curtailment season, in fine temporal-scale increments (e.g., 10 minute increments); (3) the wind speed curtailment threshold below which curtailment is implemented (e.g., 5.0, 6.0, 7.0 m/s); (4) bat activity patterns during the curtailment season, ideally at nacelle level (e.g., average bat passes detected per night using bat detectors); (5) the turbine model (e.g., Vestas V82 model with 80 m hub-height; Vestas 2005); and (6) the number of turbines at a given wind energy facility. Here, we present the simulation approach we developed to analyze and consider possible influences of curtailment on energy production at wind energy facilities. We use publicly available information about wind energy facilities in Alberta, Canada, as an example to demonstrate the approach, and then discuss how stakeholders can interpret the results from this and similar simulations. We also express caveats and propose suggestions to be considered when simulating the influence of bat curtailment on energy production at other wind energy facilities.

METHODS

We selected 6 wind energy areas in southern Alberta to use in simulating the influences of blanket curtailment and smart curtailment on AEP: Pincher Creek (170 turbines; latitude = 49.486, longitude = −113.950); Fort Macleod (184 turbines; latitude = 49.726, longitude = −113.398); Halkirk (83 turbines; latitude = 52.281, longitude = −112.148); Taber (57 turbines; latitude = 49.785, longitude = −111.151); Irma (22 turbines; latitude = 52.912, longitude = −111.230); and Alder Flats (proposed, number of turbines unknown; latitude = 52.873, longitude = −114.887). We referred to each of these areas as a Curtailment Analysis Area (CAA). The CAAs were each located in an area of wind energy development in Alberta (Figure 1). The Pincher Creek, Fort Macleod, and Taber CAAs are relatively close to one another (<135 km apart) in the southern part of Alberta near the border with the U.S. state of Montana, while the Halkirk, Irma and Alder Flats CAAs are further north of these locations (>280 km; Figure 1). Information on the number of turbines, turbine manufacturer, model, and hub height for the CAAs were extracted from a report by the Canadian Wind Energy Association (CWEA 2018) and from other publicly available sources. For our simulation study, we analyzed the influence of curtailment on a common wind turbine model (Vestas V82 turbine; Vestas 2005), but the approach we developed allows comparison of the influence of different turbine models.

For the purposes of analysis, we considered the wind regime for a given CAA to be the vector of wind speed estimates for each 10 minute increment for the period from 2008–2010 (see below). The wind regime data for a given CAA was then combined with simulated bat activity data to estimate the curtailment status of a hypothetical wind turbine in that CAA during each 10 minute increment of the 3 year period. This information was then used to estimate AEP for each of 3 years for the hypothetical wind turbine in that CAA under the influence of blanket curtailment and smart curtailment. Lastly, we show how the energy production and loss for the various curtailment

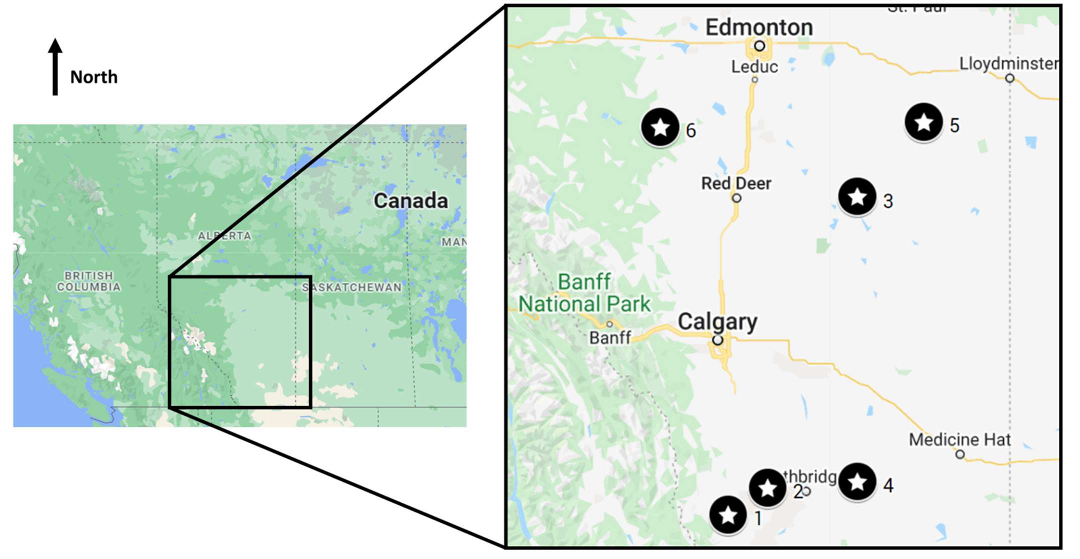

FIGURE 1 Map of Curtailment Analysis Areas (CAA) in Alberta, Canada that were used in this analysis. Approximate locations of CAA's are indicated by numbered black stars. CAA's are: 1 = Pincher Creek; 2 = Fort Macleod; 3 = Halkirk; 4 = Taber; 5 = Irma; and 6 = Alder Flats.

approaches can be compared for a given wind energy facility, using a hypothetical wind energy facility in the Pincher Creek CAA consisting of 170 Vestas V82 wind turbines.

Wind regime data

We extracted wind regime data and environmental conditions at standard nacelle height (80 m) from a publicly available dataset of modeled wind data (wind data; Environment and Climate Change Canada, Modeled Historical Wind Atlas Data, www.windatlas.ca/index-en.php.). The modeled wind data was developed as part of the Pan-Canadian Wind Integration project, which used a 3-dimensional atmospheric model run over a 3 year period (2008–2010) at a spatial resolution of ≈2 km horizontal grid dimension (e.g., ≈4 km^2 grid cells) and 10 minute increments. We concluded that this dataset provided a relatively fine-scale geospatial model of wind speed over all of Canada, including Alberta, that would be useful in curtailment analyses. In our analysis, we used wind datasets to represent past wind regimes associated with each CAA. Wind datasets included estimated average wind speed in meters per second (m/s) in 10 minute increments over 3 years from 2008 to 2010 for each CAA. Wind speed data used for each of these sites consisted of estimated average wind speed for each of 52,704 10 minute increments in year 2008 and 52,560 10 minute increments in 2009 and 2010. The difference in the total number of 10 minute increments in 2008 versus 2009 and 2010 is the result of there being 366 days in 2008, while there were 365 days in 2009 and 2010. The wind data are useful because they provide fine spatial and temporal scale information on how wind speeds vary on annual, seasonal, and daily scales for a given geographic area of interest, and how wind speed trends vary over multiple years. Wind data were available from all areas of Canada, and similar data are publicly available in the United States (https://maps.nrel.gov/wind-prospector). More detail about the statistical downscaling used to produce these wind speed datasets and the relevant citations associated with these approaches can be found at www.windatlas.ca/methodology-en.php.

As a final step of the wind data analysis, we calculated the mean, minimum, and maximum wind speeds for each CAA for each year. We then fit the 2 parameter Weibull distribution to each wind speed dataset, and obtained the

Weibull shape and scale parameter estimates for the best-fitting distribution. Wind researchers commonly use this information to compare wind regimes because it allows quick comparisons among wind regimes in different geographic locations (Wagner and Mathur 2013).

At the outset of analysis, it was unclear how the modeled wind speed data described above (in 10 minute increments) compared to the available historic wind-speeds for a given CAA. Historic wind speed data for Canada is maintained by the Canadian Wind Energy Atlas. However, those data are only available in 1 hour average wind speed estimates, while the modeled wind-speed data is provided in 10 minute increments. Thus, for the Pincher Creek CAA, we used historic wind speed data and compared these data to modeled wind speed data to gain a better understanding of possible differences among the available wind speed datasets for a given area of interest. To simulate 10 minute increments for the historic wind speed data, these 1 hour historic wind speed averages were used for each 10 minute increment in a given hour.

Bat activity data

We compiled acoustic bat activity information from pre- and post-construction acoustic surveys conducted during the summer and autumn (August to mid-October) at wind energy facilities associated with CAAs in Alberta that Alberta Environment and Parks had access to and made available for use in our analysis. The bat activity data included information on average bat passes detected at nighttime during summer and autumn months at 21 locations (mean calls/night = 8.6; minimum calls/night = 1; maximum calls/night = 47). Alberta Environment and Parks was not able to provide information on how the bat activity data were collected, or at what height above the ground. We assumed that the data were collected at near-ground level, and a more refined analysis would benefit from bat activity data collected at hub height and using standardized procedures and equipment. Bat activity at these locations is important for smart curtailment analysis because the amount of activity recorded at wind energy facilities will influence how often a smart curtailment model using acoustic information will trigger curtailment and thus influence the energy produced at the facility. As a simplified example, 5 bat call sequences (i.e., passes) detected uniformly throughout a given night might result in a smart curtailment model triggering curtailment 5 separate times. On the other hand, 5 passes that occur within a short period might only trigger curtailment once or twice for a shorter total curtailment time. Figure 2 shows simplified examples of bat call data (0 = no bat detected, 1 = bat detected) with low, medium, and high bat activity levels distributed at uniform and random intervals in the call data. We did not have empirical data to suggest which approach, uniform or random, would provide a closer approximation to the actual bat activity occurring at these Alberta wind energy facilities.

Numerical simulations

We generated simulated bat activity data to represent different activity patterns that might be expected to occur at Alberta CAAs, based on the acoustic bat activity data available at the time we developed this analysis. Most bat fatalities at wind energy facilities in Alberta and elsewhere in North America occur between mid-July through October (Arnett and Baerwald 2013, Arnett et al. 2016, CWEA 2018). For analysis, we assumed that curtailment would only take place during August, September, and October, and defined this period as the curtailment season. Next, we determined the number of 10 minute increments for each night during this 3 month curtailment season. We defined the potential curtailment period for each night as 30 minutes before sunset on a given day to 30 minutes after sunrise on the following day. For the 3 month curtailment season in southern Alberta this resulted in 6,874 10 minute increments over 91 nights. Using these data, we estimated the probability (from 0 – 1) of a random bat call occurring during a given 10 minute increment, and we then estimated the maximum, minimum, and mean probabilities that a 10 minute increment contained a bat pass, which would then in turn trigger smart

Temporal Uniformity ↑	Low (0.01 probability)	Medium (0.10 probability)	High (0.50 probability)	
	1000000000 0000000000 0000000000 0000000000 0000000000	1000000000 1000000000 1000000000 1000000000 1000000000	1010101010 1010101010 1010101010 1010101010 1010101010	Uniform
	0000000000 0000000000 0000001000 0000000000 0000000000	0000000100 0001000000 0000000001 0010000000 0000001000	1001100011 1100101010 1010100110 0000110111 0011001101	Random

Bat Activity →

FIGURE 2 Simple examples of bat activity and temporal distribution patterns using low, medium, and high levels of bat activity distributed at uniform and random intervals. Each of the 6 cells in the figure represents 50 10 minute nighttime intervals. A 1 indicates that bats were detected during a given interval, while 0 indicates bats were not detected. On the horizontal axis, bat activity increases to the right. On the vertical axis, uniform indicates bat activity that is equally spaced for each of the 3 bat activity levels and random indicates random patterns of bat activity for the 3 bat activity levels. Note that due to space constraints the Low (0.01 probability) cell only shows 50 numbers, but it would require 99 0's to accurately represent the 0.01 probability.

curtailment. For simplicity, we rounded estimates to nearest fractions, such that the curtailment probabilities for individual 10 minute increments were 0.50 (maximum; high simulated activity), 0.01 (minimum; low simulated activity), and 0.10 (mean; average simulated activity).

We then spread uniform and random bat activity patterns across the 6,874 10 minute increments for each activity scenario (Figure 2). For example, one bat pass was created for every other 10 minute increment for the uniform high activity scenario, for every hundredth 10 minute increment for the uniform low activity scenario, and for every tenth 10 minute increment for the uniform average activity scenario. For the random bat activity patterns, we programmed R (version 3.5.1; R Core Team 2018) to choose a 1 (bat activity) or 0 (no bat activity) for each 10 minute increment using the maximum, minimum, and mean probabilities for high, low, and average bat activity scenarios. We followed this approach for each CAA assuming high, medium, and low simulated bat activity and random and uniform bat activity patterns.

We conducted analysis using the 6 bat activity pattern scenarios for each CAA using wind data assuming high, medium, and low simulated bat activity and random and uniform activity patterns. We used 11 possible operational scenarios as follows: (1) no mitigation, which assumed that at all times during the year turbines produced energy at the expected rate for the geographic location; turbine model; hub height; and current average wind speed for a given time increment (e.g., 10 minute increment); (2) and (3) blanket and smart curtailment at night during August–October at wind speeds < 5.0 m/s; (4) and (5) blanket and smart curtailment at night during August–October at wind speeds < 5.5 m/s; (6) and (7) blanket and smart curtailment at night during August–October at wind speeds < 6.0 m/s; (8) and (9) blanket and smart curtailment at night during August–October at wind speeds < 6.5 m/s; and (10) and (11) blanket and smart curtailment at night during August–October at wind speeds < 7.0 m/s.

We conducted simulations for the years in which data were available in the wind data (3 concurrent years, 2008–2010), which provided insight into inter-annual variation in wind speeds and how this variation might influence annual energy production. We concluded that simulations based on these 3 years of wind data should be sufficient to provide us with enough information to complete a preliminary analysis of the impacts of various curtailment scenarios at these CAAs in Alberta, and suggest directions for future analysis and work.

We developed our simulation code in the R statistical computing environment. The code combined the wind speed and simulated bat activity data into data frames for analysis. We estimated sunset and sunrise times to the nearest minute for a given CAA and day (see below). This, in turn, facilitated calculation of other variables needed for the analysis, including estimated wind energy production for each increment of time. We used this information to estimate annual energy production given the wind regime and a standard wind turbine model (Vestas V-82) at each CAA in Alberta, as well as the operational time and energy production lost as a result of the various curtailment scenarios. Each of these simulation scenarios included an analysis of wind speed along with an energy analysis in Megawatt-hours produced per annum (MWh/a) for each site.

We used the package suncalc (Thieurmel and Elmarhraoui 2019) to calculate sunset and sunrise times for each day of 2008, 2009, and 2010 for each of the CAAs. The sunset and sunrise times of a given location in geographic space will vary depending on the time of year and the latitude and longitude of the location. The sunset and sunrise calculations used the central latitude and longitude of each CAA in decimal degrees to estimate the sunset and sunrise time for each day during the 3 year period analyzed. We used the package bReeze (Graul and Poppinga 2018) to analyze and visualize wind data and calculate estimated energy production based on wind speed and wind turbine manufacturer and model, using the theoretical power curve for a Vestas V82 turbine with 80 m hub height (Vestas 2005). We used the package MASS (Modern Applied Statistics with S; Ripley et al. 2022) to fit Weibull distributions to the wind speed datasets and obtain Weibull shape and scale parameter estimates for the best-fitting Weibull distribution for each CAA and year. The R code and wind speed data used for this analysis are posted and freely available online: https://github.com/mark-a-hayes/curtailment.

RESULTS

The maximum, minimum, and mean bat passes per night for 21 wind energy facilities in Alberta was 47.0, 1.0, and 8.6, respectively. Histograms for wind regimes for each CAA for years 2008–2010 are shown in Figure 3. The mean, minimum, and maximum wind speed estimates for each CAA for each full year are shown in Table 1 (Hayes et al. 2021). The shape and scale parameter estimates for the best-fitting 2 parameter Weibull distribution are also shown for each dataset. Across the 6 CAAs analyzed over 3 years, average wind speeds ranged from 5.5–7.0 m/s. Annual, seasonal, and nocturnal wind speed trends and AEP estimates based on these modeled wind speeds for each year tended to be similar for the same CAA. However, there were differences in wind speed averages and trends among years and CAA locations, and the estimated AEP for the same site varied among years.

Under normal operation from 2008 to 2010, the mean AEP for CAAs in this study ranged between 3,538.0 (Alder Flats) and 5,904.0 MWh (Megawatt-hours; Halkirk) per turbine, with a mean ± standard deviation of 4,888.0 ± 840.0 (Table 2). Variance in AEP per turbine (as measured by standard deviation) was greater between years than between CAAs (Table 2). Mean AEP per turbine for blanket curtailment across CAAs and years ranged between 4,806.8 MWh at a wind speed threshold of 7.0 m/s and 4,877.8 MWh at a wind speed threshold of 5.0 m/s, corresponding with mean AEP losses of 1.7% and 0.2%, respectively (Table 2, Figure 4).

Annual energy production loss using smart curtailment across CAAs and years was less than AEP losses using blanket curtailment, ranging from a mean minimum loss of 0.0% at a curtailment treatment of 5.0 m/s (range = 0.00 to 0.01%) to a mean maximum loss of 0.9% at a curtailment treatment of 7.0 m/s (range = 0.56 to 1.25%), resulting in a mean difference in energy savings of 0.9% between smart curtailment treatments (Figure 4). This corresponded with mean improvements in AEP over blanket curtailment from a minimum of 49.6% at 5.0 m/s to a maximum of

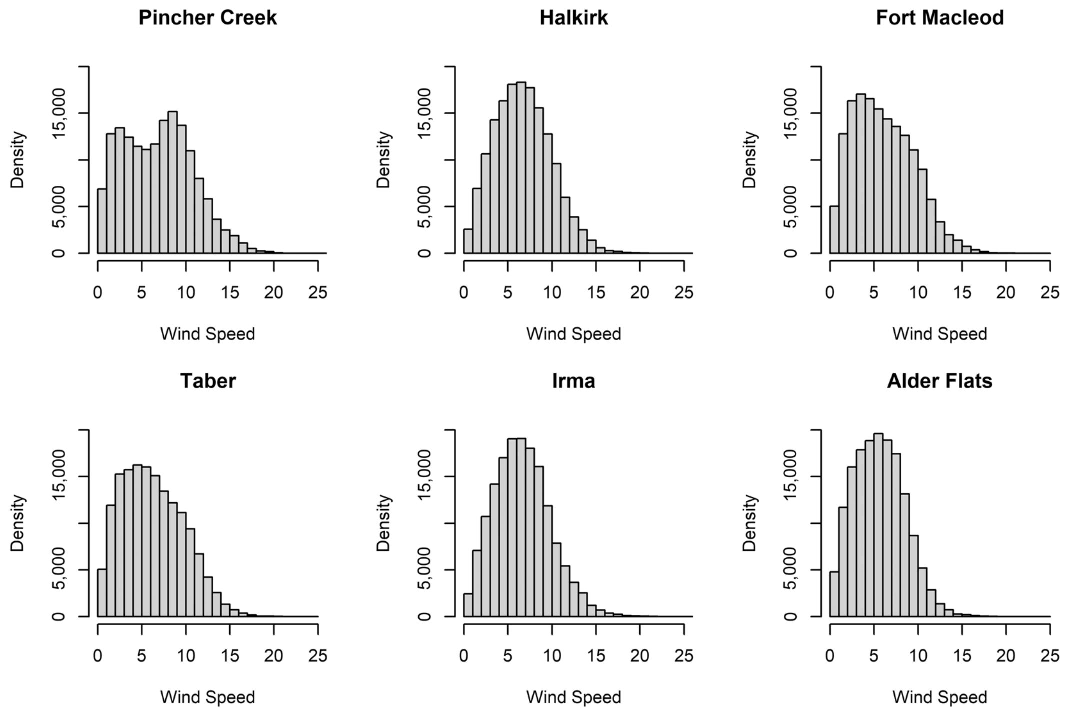

FIGURE 3 Histograms of estimated wind speeds (m/s) at 80 m in 10 minute increments for years 2008–2010 for each Curtailment Analysis Area (CAA). The x-axis indicates wind speed and the y-axis is density of the histogram across the wind speeds.

99.1% at 7.0 m/s for smart curtailment treatments. Thus, smart curtailment ranged from approximately 50 and 100% better than blanket curtailment in terms of reducing AEP loss.

Mean AEP was similar between uniform (4,797.78 MWh) and random (4,797.74 MWh) modeled temporal bat distribution patterns across CAAs and curtailment treatments (Figure 4). We conducted a paired t-test comparing AEP loss between uniform ($\bar{x}$ = 0.247%) and random ($\bar{x}$ = 0.249%) distributions and found that bat activity pattern did not have a significant impact on loss of AEP ($P = 0.052$ at $\alpha = 0.05$). These results, however, suggested some evidence for a difference between uniform and random bat activity; scenarios with uniform bat activity tended to result in slightly higher AEP loss, especially when the curtailment threshold was at higher wind speeds. In contrast, AEP loss was substantially different between low ($\bar{x}$ = 0.02%) and high ($\bar{x}$ = 0.61%) bat activity levels across CAAs and curtailment treatments (Wilcoxon sign rank test; $P < 0.001$ at $\alpha = 0.05$; Samuels et al. 2012), suggesting that the level of bat activity at a wind energy facility has a significant influence on AEP loss.

Mean percent AEP loss was negligible (<0.03%) across all smart curtailment treatments when simulated bat activity levels were low, and ranged between 0.03 and 0.21% for average bat activity levels across all treatments (Figure 4). Annual energy production losses for smart curtailment were greater when bat activity levels were high, ranging between 0.13 and 1.08%, but were still generally half the AEP loss incurred under blanket curtailment across all treatments (0.26 to 2.13%; Figure 4). The difference between percent AEP loss under blanket curtailment and smart curtailment became more pronounced at greater wind speed curtailment thresholds, with the greatest energy savings at 7.0 m/s curtailment for facilities with relatively low bat activity levels (Figure 4).

Energy production differed between modeled and historic wind speed data for Pincher Creek. Average and maximum wind speeds varied between the 2 datasets, which affected the Weibull shape and scale parameters

TABLE 1 Mean, minimum, and maximum wind speed, and Weibull shape and scale parameter estimates for each curtailment analysis area (CAA) for each full year (2008–2010). Abbreviations: Min = minimum; Max = maximum; PC-historic = historic wind data for Pincher Creek. Mean, Min, and Max are in m/s. Shape and Scale are Weibull shape and scale parameters.

CAA	Year	Mean	Min	Max	Shape	Scale
Pincher Creek	2008	6.6	0	21.2	1.95	8.08
	2009	7.0	0	25.5	1.70	7.85
	2010	6.6	0	21.2	1.69	7.31
PC-historic	2008	6.6	0	29.4	1.71	7.57
	2009	6.2	0	27.8	1.61	7.16
	2010	5.7	0	24.7	1.59	6.63
Fort Macleod	2008	6.1	0	21.1	1.88	6.87
	2009	6.2	0	24.8	1.86	7.01
	2010	6.1	0	22.9	1.81	6.88
Halkirk	2008	6.9	0	21.4	2.25	7.78
	2009	6.9	0	26.0	2.26	7.72
	2010	6.6	0	27.8	2.19	7.38
Taber	2008	6.3	0	23.9	1.89	7.14
	2009	6.5	0	24.3	1.92	7.29
	2010	6.1	0	23.2	1.81	6.90
Irma	2008	6.8	0	20.9	2.20	7.68
	2009	6.8	0	25.1	2.26	7.64
	2010	6.5	0	25.4	2.19	7.30
Alder Flats	2008	5.7	0	19.6	2.10	6.44
	2009	5.8	0	24.5	2.13	6.54
	2010	5.5	0	24.8	1.99	6.21

(Tables 1 and 2). The historic dataset produced markedly lower megawatt-hours of energy each year of the analysis under normal operations compared to modeled Pincher Creek data (Table 2).

Average annual energy production and loss over 3 years (2008–2010) for 170 theoretical Vestas V82 wind turbines at the Pincher Creek CAA are shown in Table 3. Total average energy loss for this hypothetical wind energy facility ranged from 1,417 (5.0 m/s) to 10,823 (7.0 m/s) MWh per year using blanket curtailment and 331 (5.0 m/s) to 2,116 (7.0 m/s) MWh per year using smart curtailment. The average estimated energy production and loss for a full hypothetical wind energy facility using blanket curtailment and smart curtailment under a range of assumed wind speed thresholds can be calculated once the energy production and loss under those same scenarios are known for a single wind turbine of the same model (Table 3). We note that Table 3 does not calculate the impacts of blanket curtailment and smart curtailment on revenues at the full wind energy facility, as was calculated, for example, in Hayes et al. (2019) and Rabie et al. (2022). These revenue calculations require information about daytime and nighttime energy spot prices in a given region, how these prices change seasonally and annually, and the availability of tax credits to wind energy producers (Hayes et al. 2019).

TABLE 2 Annual Energy Production (AEP) in megawatt-hours for one Vestas V82 turbine in each Curtailment Analysis Area (CAA) under normal operation for each year of the analysis, based on modeled wind speed data. Pincher Creek historic data are not included in the overall mean.

CAA	2008	2009	2010	Mean
Pincher Creek	6,041	5,719	5,185	5,648
PC-historic	4,824	4,407	3,759	4,571
Fort Macleod	4,743	4,786	4,551	4,693
Halkirk	5,927	6,111	5,674	5,904
Taber	4,664	4,864	4,420	4,649
Irma	5,126	4,996	4,577	4,900
Alder Flats	3,547	3,691	3,376	3,538
Mean	5,008	5,027	4,630	4,889
Standard deviation	921	840	778	840

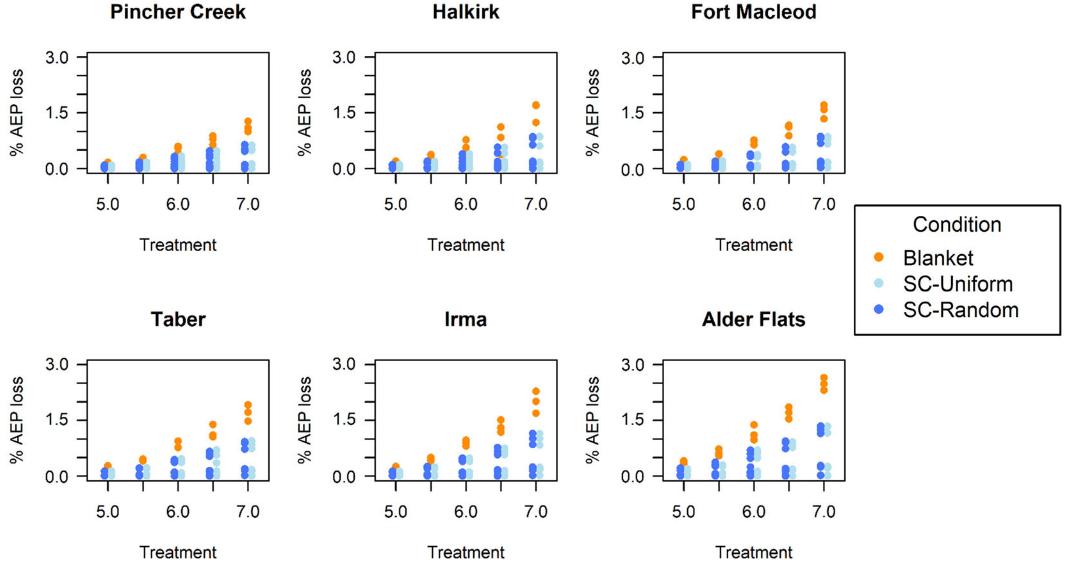

FIGURE 4 Percent Annual Energy Production loss (% AEP loss) for the 6 Curtailment Analysis Areas (CAAs) across curtailment treatments and bat activity level scenarios. The x-axis indicates the curtailment treatments, from 5–7 m/s. The y-axis indicates percent AEP loss relative to normal operations without curtailment. Orange circles indicate simulations using blanket curtailment (Blanket). Light blue circles indicate smart curtailment using uniform bat activity scenarios (SC-Uniform) and dark blue circles indicate smart curtailment using random bat activity scenarios (SC-Random).

DISCUSSION

The use of smart curtailment shows considerable promise in reducing bat fatalities at wind energy facilities (Hayes et al. 2019). However, due to uncertainties associated with the relative costs of smart curtailment and blanket curtailment, it has been difficult for wildlife management agencies, wind energy producers, and other stakeholders to understand the probable energy losses associated with these approaches. Our analysis represents the first

TABLE 3 Average annual energy production and loss over 3 years (2008–2010) for a hypothetical wind energy facility consisting of 170 Vestas V82 wind turbines located in the Pincher Creek Curtailment Analysis Area, using modelled wind speed data. All energy values are in megawatt-hours. Abbreviations: normal = normal operation; blanket = blanket curtailment; SC = smart curtailment. For blanket values, the 2008–2010 values were averaged. For SC all simulations for the 3 years were averaged.

Curtailment (m/s)	Action	Energy/turbine	Total energy	Average energy loss	% Loss
N/A	Normal	5,648	960,217	0	0
5.0	Blanket	5,640	958,800	1,417	0.148
5.0	SC	5,646	959,886	331	0.034
5.5	Blanket	5,635	957,893	2,323	0.242
5.5	SC	5,644	959,518	699	0.073
6.0	Blanket	5,619	955,173	5,043	0.525
6.0	SC	5,642	959,008	1,209	0.126
6.5	Blanket	5,605	952,850	7,367	0.767
6.5	SC	5,639	958,432	1,785	0.186
7.0	Blanket	5,585	949,393	10,823	1.130
7.0	SC	5,636	958,101	2,116	0.220

simulations that compare the potential use of smart curtailment and blanket curtailment strategies using fine-scale wind speed data and simulated bat activity data. The approach we used here required prior wind speed data (e.g., using modeled and/or historic wind speed averages), bat activity data, and a model of how a given wind turbine extracts energy from the wind at given wind speeds (e.g., a power curve relating wind speed to energy extraction; Wagner and Mathur 2013). The results we present here were for a single hypothetical Vestas V82 turbine with 80 m hub height under the influence of the wind regime for a given year, simulated bat activity patterns, and operational scenario used, and for a hypothetical wind energy facility consisting of 170 Vestas V82 turbines located in the Pincher Creek CAA.

The wind regimes were similar among the 6 facilities in southern Alberta, but estimated AEP varied among facilities and between years within facilities, likely due to differences in the wind regimes and inter-annual, seasonal, and nighttime wind conditions at these locations. We found that both blanket and smart curtailment resulted in relatively low AEP loss across all facilities and treatments, ranging between 0.23 and 1.73% power loss for blanket curtailment and between 0.00 and 0.87% for smart curtailment. The simulated losses may appear relatively small, especially when comparing differences between curtailment strategies, but it is possible that even 1% power loss may be economically infeasible for some facilities. Likewise, despite these differences, smart curtailment reduced AEP losses incurred by blanket curtailment by 50 to 100%. Assuming that bats frequently echolocate during migration (but see Corcoran and Weller 2018, Corcoran et al. 2021), and are only at risk of collision when exposed to rotating turbine blades (Peterson 2020, Peterson et al. 2021), smart curtailment appears to be a promising strategy for maximizing energy production and minimizing potential bat fatalities. However, we did not attempt to estimate the cost of implementing and maintaining a smart curtailment system, which may be non-trivial to some wind energy producers.

The distribution of simulated bat activity did not substantially affect AEP across treatments in our study. We assumed that random activity would be more clustered in time than uniform activity, and therefore more representative of real bat data, triggering smart curtailment less frequently than uniform bat activity would. In future simulations, we recommend striving to clearly understand real-world bat activity patterns at nacelle heights and incorporating this information into analyses, if possible. This information would help clarify the influences of bat activity patterns on AEP for a location of interest.

The quantity of bat activity was the main driver of AEP differences comparing blanket and smart curtailment simulations. Under conditions of low bat activity, AEP loss for smart curtailment was negligible across all curtailment thresholds (5.0 to 7.0 m/s) and nearly identical to AEP under normal operating conditions, and much less than AEP loss under blanket curtailment. Annual energy production loss under conditions of average bat activity was also relatively small, ranging between 0.03 and 0.21% for 5.0 and 7.0 m/s curtailment thresholds, respectively (Hayes et al. 2021). Thus, we conclude that smart curtailment may represent a reasonable curtailment approach at Alberta facilities with lower bat activity levels, such as locations typically experiencing less than 10 bat passes per detector-night (Baerwald and Barclay 2011). Smart curtailment might also be a promising strategy for facilities located in other areas with relatively low bat activity, such as throughout much of the western United States, where the number of bat passes per night tend to be relatively low (Hein and Schirmacher 2016, Solick et al. 2020), and in areas that tend to have lower average nighttime wind-speeds. Low nighttime wind speeds would be expected to typically result in longer curtailment times and greater AEP loss under a blanket curtailment strategy (Hayes et al. 2019). Thus, our analysis suggests that the value of smart curtailment could be greatest in regions with lower bat activity and relatively low nighttime wind speeds.

It is not entirely clear to us why the Pincher Creek CAA scenarios using historic data resulted in much lower energy production when compared to the Pincher Creek CAA using modeled wind speed data. The historic wind speed data was only reported in 1 hour time increments, while the modeled wind speed data was reported in 10 minute increments. Thus, the historic wind speed measurement for a given hour represented the average wind speed for that hour. In these cases, if the wind speed was within the curtailment range for any given hour, the simulation would curtail for the entire hour, not in 10 minute increments. This may have resulted in simulated turbines staying in a curtailment condition for longer periods than they would have if the wind speed was measured for every 10 minute increment. This is an area of continuing inquiry; the relative influences of modeled versus historic wind speed data are not yet clear to us. The differences in average wind speed measurements for modeled and historic wind speed data at the Pincher Creek CAA highlight the importance of using high quality wind speed data measured in small time increments (e.g., 10 minute) for a given location. Recently measured wind speed data from reliable and well-calibrated instruments at nacelle height in 10 minute increments would likely be superior to the modelled and historic data used here.

We also recognize that the wind data we used here were derived from weather forecast models that include necessary simplifications of reality and that these data were developed using one of several possible approaches to wind regime modeling. The modelled wind data we used were developed using the Global Environmental Multiscale Model (GEM) using a limited-area modeling approach (LAM), which is referred to as the GEM-LAM model approach. Furthermore, the predicted wind speed conditions for a given location did not necessarily reflect the wind conditions that a given wind turbine would have been exposed to if located in that area in the timeframe considered. Numerous variables influence the wind speeds experienced by an individual wind turbine at any time during a given year (Wagner and Mathur 2013), including: large-scale weather patterns, such as El Niño-Southern Oscillation (ENSO) and annual polar vortex influences; topographic position where a turbine is located, such as the slope and aspect of the location, along with the adjacent topography; biotic conditions, such as the vegetative groundcover, habitat type, and associated roughness of the land surface and resulting turbulence at turbine hub height; and anthropogenic variables, such as the relative locations of nearby wind turbines, roads, and buildings. We therefore viewed the wind datasets used in our analysis and the analysis itself as a retrospective first approximation analysis of the wind speeds experienced by a hypothetical wind turbine and a hypothetical wind energy facility, and the AEP the turbines would be expected to generate if exposed to these wind speeds given the wind turbine model's theoretical power curve.

When possible, we suggest using long-term wind speed data (e.g., collected over at least 2 years) collected at nacelle heights for a given area of interest, ideally in combination with bat activity data also collected at nacelle heights over multiple years. However, when such data are not available, our assumption is that using modelled datasets and a simulation approach similar to what we describe here can help clarify the possible impacts of various curtailment strategies on wind energy production, and this understanding can then be a foundation for more advanced analyses at the wind energy facility and regional scale, as needed. For example, wildlife agencies, wind energy producers, and environmental consultants could use the simulation approach we describe here to make empirically informed inferences about which curtailment strategies might help individual wind energy producers meet the long-term objectives of stakeholders. We conclude that using modeled and historic wind speed data, as used in this analysis, ideally combined with high-quality bat activity data collected at nacelle height, should result in an improved understanding of the relative influences of bat curtailment approaches on energy production at sites of interest to wind energy developers, wildlife agencies, and others.

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CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The R code and wind speed data used for this analysis are posted and freely available online: https://github.com/mark-a-hayes/curtailment.

ETHICS STATEMENT

No ethical information provided.

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