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Bat Detection and Shutdown System for Utility-Scale Wind Turbines

Bat Detection and Shutdown System for Utility-Scale Wind Turbines

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Abstract

At utility-scale wind energy facilities, blanket curtailment of turbines in response to wind speed minimizes bat fatalities, but sacrifices generation and revenue by remaining in effect even when bats are absent. We Energies, EPRI, and its member companies funded a study to develop a turbine curtailment approach that minimizes such economic costs while ensuring lower fatality rates for bats. Turbine-Integrated Mortality Reduction (TIMR^{SM}) is a Smart Curtailment hardware and software system that runs real-time bat activity and weather data in predictive models that link these parameters to bat mortality and issue a current risk value (red/curtail, green/resume, or yellow/override) used to drive turbine operation. Because the TIMR system does not curtail when bats are absent, it frees up turbine operating time for generation.

We Energies chose to implement a predictive model based on descriptive statistical cost–benefit analysis at its Wisconsin Blue Sky Green Field (BSGF) wind energy facility in 2015. During fall bat migration, 10 turbines were operated normally and 10 were model-operated with a 30-minute curtailment period. Real-time data for the study were supplied by acoustic monitoring of bat activity (calls) and wind speed recordings at the turbine nacelle. Bat carcass counts for three species and the *Myotis* family provided evidence of bat mortality. Study results showed a strong correlation between bat activity and mortality, validating the use of activity data to drive curtailment. This is the first study to demonstrate a reduction in mortality for any *Myotis* species; some members of this family are endangered. The study presents an economic analysis of generation and revenue under Smart Curtailment at BSGF, as well as other factors affecting facility operations.

TIMR could be implemented at a new site in weeks, since there is no need to reprogram the core Supervisory Control and Data Acquisition (SCADA) and the communication and alerting interface with SCADA is readily transferred to new users with minimal customization.

Keywords
Bats, Bat mortality, Wind energy facilities, Curtailment, Supervisory control and data acquisition

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PRIMARY AUDIENCE: Owners and operators of utility-scale wind energy facilities.

SECONDARY AUDIENCE: Professionals engaged in the design and installation of turbine curtailment systems and utility or regulatory personnel responsible for bat conservation.

KEY RESEARCH QUESTION

Blanket curtailment of utility turbines in response to wind speed minimizes bat fatalities, but sacrifices generation and revenue by remaining in effect even when bats are absent. This study tested the hypothesis that real-time bat activity at the turbine nacelle, where fatality risk is high, can be used to predict and control bat fatality rates. Predictive models based on real-time bat activity plus wind speed would fine-tune turbine operation, curtailing or resuming rotation in response to risk calculations based on monitored local conditions.

RESEARCH OVERVIEW

We Energies, EPRI, and its member companies funded a study to develop a curtailment approach that minimizes economic costs while ensuring lower fatality rates for bats. Turbine-Integrated Mortality Reduction (TIMR[SM]) is a Smart Curtailment hardware and software system that runs real-time bat activity and weather data in predictive models that link these parameters to bat mortality and issue a current risk value (red/curtail, green/resume, or yellow/override) used to drive turbine operation. The predictive models considered in this study used inferential statistics or descriptive statistics. We Energies chose to implement a predictive model based on descriptive statistical cost–benefit analysis at its Wisconsin Blue Sky Green Field (BSGF) wind energy facility in 2015 at the same time that We Energies implemented a bat mortality study at the facility. During fall bat migration, 10 turbines were operated normally and 10 were model-operated with a 30-minute curtailment period. Real-time data for the study were supplied by acoustic monitoring of bat activity (calls) and wind speed recordings at the turbine nacelle. Bat carcass counts for three species and the *Myotis* family provided evidence of bat mortality. The study presents an economic analysis of lost generation and lost revenue due to Smart Curtailment at BSGF, as well as other factors affecting facility operations.

KEY FINDINGS

- Study results showed a strong correlation between bat activity and mortality, validating the use of activity data to drive curtailment. Bat activity alone predicted 60% of fatalities per week.
- Smart Curtailment at BSGF reduced overall bat fatalities by 83% and little brown bat (*Myotis lucifugus*) fatalities by 90% at model-operated turbines compared with normally operated turbines. The reductions are statistically significant at $\alpha = 0.05$.
- This is the first study to demonstrate a reduction in mortality for any *Myotis* species; some members of this family are endangered. Higher-than-expected *Myotis* fatalities had previously been seen at BSGF.
- Under Smart Curtailment, lost generation was 90 MWh per turbine for the study period from July 15 through September 30, 2015, at a site with relatively low wind speed and a fairly low capacity factor (26.9).

- Lost revenue for the same period was $3,592 per turbine, or $316,082 for all 88 turbines at BSGF, if all turbines were controlled under Smart Curtailment.
- The TIMR system does not curtail when bats are absent; bats can be absent for 25–42% of curtailment hours. Thus, implementing Smart Curtailment frees up turbine operating time for generation.
- TIMR communicates curtailment commands to turbines without altering the core Supervisory Control and Data Acquisition (SCADA) system. Implementation at a new site could be achieved in weeks, since there is no need to reprogram the core SCADA.

WHY THIS MATTERS

Wind energy facilities that implement TIMR Smart Curtailment may benefit in the following ways:

- Reduce bat fatalities, including fatalities of protected species that incur fines or other penalties.
- Free up turbine operating time for generation, increasing energy output and revenue.
- The TIMR communication and alerting interface with SCADA is readily transferred to new users with minimal customization.

HOW TO APPLY RESULTS

EPRI is interested in deploying the TIMR Smart Curtailment system at additional wind energy facilities to further test the efficacy of the technology to reduce bat mortality and to collect additional economic data. Ideally, deployment would be for three years, with at least one year devoted to a bat mortality study.

LEARNING AND ENGAGEMENT OPPORTUNITIES

EPRI has made this report freely available in order to engage companies that build and operate wind energy facilities. EPRI is working with the America Wind Wild Institute (AWWI) to conduct third party evaluations of the TIMR Smart Curtailment system, and EPRI will attend various wind energy forums and conduct webcasts to provide information on the system.

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PROGRAM: Transmission and Distribution and ROW Environmental Issues, Program 51.

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List of Terms

BSGF	Glue Sky Green Field
DNP3	Distributed Network Protocol
EPFU	*Eptesicus fuscus* (big brown bat)
EPRI	Electric Power Research Institute
FERC	Federal Energy Regulatory Commission
ft	foot
GAM	generalized additive model
GLM	generalized linear model
GLMM	generalized linear mixed model
HMI	Human Machine Interface
IED	Intelligent Electronic Device
IJI	Interspersion and Juxtaposition Index
km	kilometer
LABO	*Lasiurus borealis* (eastern red bat)
LACI	*Lasiurus cinereus* (hoary bat)
LANO	*Lasionycteris noctivagans* (silver-haired bat)
LCOE	levelized cost of energy
LMP	locational marginal price
m	meter
m/s	meters per second
MISO	Midcontinent Independent System Operator
mph	miles per hour
MW	megawatt
MWh	megawatt hour
MYLU	*Myotis lucifugus* (little brown bat)
MYSE	*Myotis septentrionalis* (northern long-eared bat)
MYSO	*Myotis sodalis* (Indiana bat)
NB	negative binomial
NERC	North American Electric Reliability Corporation

NOAA	National Oceanic and Atmospheric Administration
P/A	presence/absence
PSC	Public Service Commission (of Wisconsin)
PTC	production tax credit
REC	renewable energy credit
rpm	revolutions per minute
RSZ	rotor swept zone
RTO	Regional Transmission Organization
RTU	Remote Terminal Unit
SCADA	Supervisory Control and Data Acquisition
SSH	Secured Socket Shell
TIMR[SM]	Turbine Integrated Mortality Reduction
Tri-colored bat	*Perimyotis subflavus*
USFWS	U.S. Fish and Wildlife Service
VOB	Vestas Online Business (server)
ZANB	zero-altered negative binomial
ZAP	zero-altered Poisson
ZINB	zero-inflated negative binomial
ZIP	zero-inflated Poisson

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Section 1: Patterns Linked to Bat Mortality at Utility-Scale Wind Turbines

Introduction

An estimated 1 million bat fatalities occur at U.S. wind energy facilities each year at a rate of 13–17 bats per megawatt of installed capacity.

In a review of bat fatalities at wind energy facilities across the United States, Arnett and Baerwald (2013) estimated that cumulative bat fatalities ranged from 0.8 to 1.7 million between 2000 and 2011. Hayes (2013) and Smallwood (2013) estimated bat fatality rates of 13.4 to 17.2 bats/megawatt (MW)/year. At the end of 2015, there were 73,992 MWs of installed capacity in the United States (AWEA 2016), resulting in an estimated 991,493 to 1,272,622 bat fatalities annually. These estimates should be used with caution, as study design varies among the sites evaluated.

From the first studies, scientists observed patterns of bat activity and/or mortality (Fiedler 2004, Kerns and Kerlinger 2004). Although there are exceptions to these observed patterns (Baerwald and Barclay 2011), recurring themes suggest that bat mortality at wind energy facilities is nonrandom. Thus, it may be possible to predict and manage fatality rates.

Linked to bat mortality:

- bat species
- timing of bat activity
- level of bat activity
- meteorological conditions
- turbine operating conditions

Patterns Linked to Bat Mortality

Bat Species

Three bat species, representing 7% of the species in North America, account for more than 75% of bat mortality (Johnson 2005, Kunz *et al.* 2007, Arnett *et al.* 2008, Arnett and Baerwald 2013). These three species are migratory tree-roosting bats with similar life histories and behaviors: hoary bat (*Lasiurus cinereus* or LACI), eastern red bat (*Lasiurus borealis* or LABO), and silver-haired bat (*Lasionycteris noctivagans* or LANO).

A substantial number of fatalities involve species being considered for federal protection, such as little brown bat (*Myotis lucifugus*).

Another 18 species account for the remainder of bat mortality (Arnett and Baerwald 2013). Relatively few fatalities involve federally protected species such as Indiana bat (*Myotis sodalis* or MYSO), northern long-eared bat (*Myotis septentrionalis* or MYSE), or Hawaiian hoary bat (*Lasiurus cinereus semotus*; Arnett and Baerwald 2013, O'Shea *et al.* 2016), but a substantial number of fatalities involve species being considered for listing, such as little brown bat (*Myotis lucifugus* or MYLU; O'Shea *et al.* 2016).

Timing of Bat Activity

The fall migratory season (mid-July to late September or early October) accounts for nearly all of the annual bat mortality in North America (Fiedler 2004, Johnson *et al.* 2004, Johnson 2005, Arnett and Baerwald 2013, Arnett *et al.* 2008, Baerwald and Barclay 2011, Martin 2015). A similar temporal pattern is seen in a single state, Wisconsin (Howe *et al.* 2002). Nightly fatality rates are highly episodic (Arnett *et al.* 2008) with a few nights accounting for most of the fatalities.

Level of Bat Activity

Nightly bat activity levels (Hayes 2000, Erickson and West 2002) are also episodic; on many nights no bats are detected (Reynolds 2006, Baerwald and Barclay 2009).

Predicting bat presence could improve the efficiency of turbine curtailment over scenarios based solely on wind speed.

Higher rates of bat activity at or near the rotor swept zone (RSZ) are associated with higher fatality rates (Fiedler 2004, Johnson *et al.* 2003, Johnson *et al.* 2004, Jain 2005, Baerwald and Barclay 2009, Baerwald and Barclay 2011, Jain *et al.* 2011, Korner-Nievergelt *et al.* 2013). Kunz *et al.* (2007) found that 62% of the variation in bat fatality rates was explained by activity, and Baerwald and Barclay (2009) found that 31% of the variation in fatality rates was explained by activity at 30 meters above ground level. Fiedler (2004) and Baerwald and Barclay (2011) reported that daily mortality and activity rates were similar, but that pattern disappeared when data were averaged across multiple days.

Other studies (*e.g.*, Johnson *et al.* 2004) have not found an association between activity and mortality, but many of these studies relied on ground-based measures of activity or averaged data from multiple days. Fielder (2004), Jain (2005), Baerwald and Barclay (2009), and others have cautioned against inferring bat activity levels at higher altitudes based on data collected at ground level because it is well known that bat activity is vertically stratified (Bradshaw 1996, Lance *et al.* 1996, Kalcounis *et al.* 1999, Hayes and Gruver 2000, Menzel *et al.* 2005, Jung *et al.* 1999).

Meteorological Conditions

Lower wind speeds and warmer temperatures are consistently associated with higher bat activity rates (Arnett *et al.* 2006, Arnett *et al.* 2007, Arnett 2008, Fiedler 2004, Cryan and Brown 2007, Redell *et al.* 2006, Weller 2007, Reynolds 2006, Horn *et al.* 2008) as well as higher fatality rates (*e.g.*, Fiedler 2004, Kerns *et al.* 2005, Arnett *et al.* 2006, Reynolds 2006, Arnett *et al.* 2008, Baerwald *et al.* 2009, Arnett *et al.* 2009, Kerns *et al.* 2005, Young *et al.* 2011, Weller and Baldwin 2012, Martin 2015). Strong winds can influence the abundance and activity of insects, which in turn influence bat activity, and bats are known to suppress their activity during periods of rain, low temperatures, and strong winds (Erkert 1982).

Turbine Operating Conditions

The earliest studies of bat fatalities at wind energy facilities reported no fatalities at nonmoving turbines (Arnett *et al.* 2005) and reduced numbers of fatalities at curtailed turbines. Curtailment may refer to either of the following conditions:

- Turbine blades are pitched out to minimize wind capture, resulting in very low blade rotation rates—less than 2 revolutions per minute (rpm)—compared with the high rotation rates (typically between 2–22 rpm) of blades pitched to capture the wind.
- Turbine blades are pitched to capture the wind below the cut-in speed (more than 50 rpm), but the cut-in speed is raised—typically 5.0 to 6.5 meters per second (m/s) above the rated cut-in speed, which is typically 3.5 m/s. At full speed, the blade tips reach speeds well over 100 miles per hour (mph), depending on the turbine model and the wind speeds involved.

"Blanket curtailment" of turbines in response to wind speed minimizes bat fatalities, but sacrifices generation and revenue by remaining in effect even when bats are absent.

Howe *et al.* (2002) reported a 30% reduction in bat fatalities when turbines were curtailed at a wind energy facility in Wisconsin. Baerwald *et al.* (2009) reported a more than 50% reduction in migratory tree bat fatalities when turbine blades were pitched out (to avoid catching the wind), when wind speeds were below 4.0 m/s, or when operations were delayed until wind speeds were at least 5.5 m/s. Arnett *et al.* (2011) reported a 72–82% reduction in migratory tree bat fatalities when cut-in speeds were raised to 6.5 m/s. However, none of these studies was able to demonstrate that curtailment is effective in reducing mortality of *Myotis* species, some of whom are federally protected.

The economic impacts of curtailment have been documented in only a few instances (Baerwald *et al.* 2009, Arnett *et al.* 2011, Martin 2015). These studies reported a loss of 1–5.3% of annual revenue at a given wind farm.

Implications of Observed Patterns

Consistent bat activity and mortality patterns suggest underlying drivers that can be used to predict high-fatality events. Weller and Baldwin (2012) concluded that predicting bat presence could improve the efficiency of curtailment over curtailment scenarios based solely on wind speed.

We Energies, EPRI, and its member companies funded a study to develop turbine Smart Curtailment—an approach that minimizes economic costs while ensuring lower fatality rates for bats.

Recently, German researchers successfully predicted bat collision levels using weather and bat activity data collected across Germany in a variety of habitats and landscapes (Korner-Nievergelt *et al.* 2013).

In Europe, operational algorithms incorporating information on bat activity (thermal or acoustic data), timing (seasonal and nightly), weather conditions (temperature and wind speed), and turbine height are used to predict collision risk and inform turbine curtailment. The use of these algorithms has resulted in a 60–97% reduction in fatalities at regulated turbines (Lagrange *et al.* 2013, Behr *et al.* 2014).

The Present Study

In 2008, We Energies proposed construction of the Glacier Hills wind energy facility in southern Wisconsin. As part of the order issued by the Public Service Commission (PSC) of Wisconsin, We Energies was required to partially fund a study to minimize bat fatalities. We Energies partnered with the Electric Power Research Institute (EPRI), and EPRI subsequently engaged We Energies, Duke Energy Corporation, Exelon Corporation, and Alliant Energy Corporation in a collaboration to fund the study. The objective of the study was to develop a smarter approach to turbine curtailment that minimized economic costs while ensuring a high conservation benefit (lower fatality rates) for bats. The study required developing an approach, then creating hardware and software to implement that approach at an operating wind energy facility.

Researchers tested the hypothesis that real-time bat activity at the turbine nacelle is positively correlated with bat fatality rates.

Researchers tested the hypothesis that real-time bat activity is positively correlated with bat fatality rates such that Smart Curtailment strategies considering real-time activity at the turbine nacelle will result in optimal curtailment scenarios. Optimal curtailment will maximize operating time (as measured in power generated and revenue) while significantly decreasing (but not eliminating) bat fatalities.

Section 2: The BSGF Study—Facility and Tasks

Introduction

The study was conducted at We Energies' Blue Sky Green Field (BSGF) wind energy facility in Wisconsin.

The study to develop a smarter approach to turbine curtailment was conducted at We Energies' Blue Sky Green Field (BSGF) wind energy facility in the townships of Calumet and Marshfield in Fond du Lac County, Wisconsin. BSGF is located along the Niagara Escarpment, the steep sloped edge of a bedrock ridge that runs from southeastern Wisconsin through northern Michigan; Ontario, Canada; and New York.

BSGF, which came on-line in May 2008, operates 88 Vestas model V82 1.65-MW turbines (We Energies 2016) (Table 2-1) distributed across a landscape dominated by corn, soybean, and alfalfa fields, interspersed with a few woodlots (Figure 2-1).

A 2008–2009 study at BSGF documented a higher-than-expected rate of bat fatalities. A third of the fatalities were little brown bats (*Myotis lucifugus*) under consideration for federal protection as an endangered species.

A post-construction bat fatality study—conducted from July 21 to October 31, 2008, and March 17 to June 4, 2009 (Gruver *et al.* 2009)—documented 247 bat carcasses at BSGF (242 in 2008, 5 in 2009). Over that study period there were an estimated 35.6 bat fatalities per turbine and 21.6 bat fatalities per MW (excluding incidental finds). Little brown bats (*Myotis lucifugus*) accounted for 28.7% of all carcasses found. The large number of fatalities and the high incidence of fatalities for *Myotis lucifugus*, a bat under consideration for federal listing, made this an ideal location for developing and testing a Smart Curtailment system.

Table 2-1
Operating specifications for Vestas V82 turbines

Specification	U.S.	Metric
Hub height	262 ft	80 m
Blade length	134 ft	41 m
Tip height	397 ft	121 m
Cut-in wind speed	8 mph	3.5 m/s
Rated wind speed	30 mph	14 m/s
Cut-out wind speed	54 mph	24 m/s
Maximum tip speed	138 mph	62 m/s

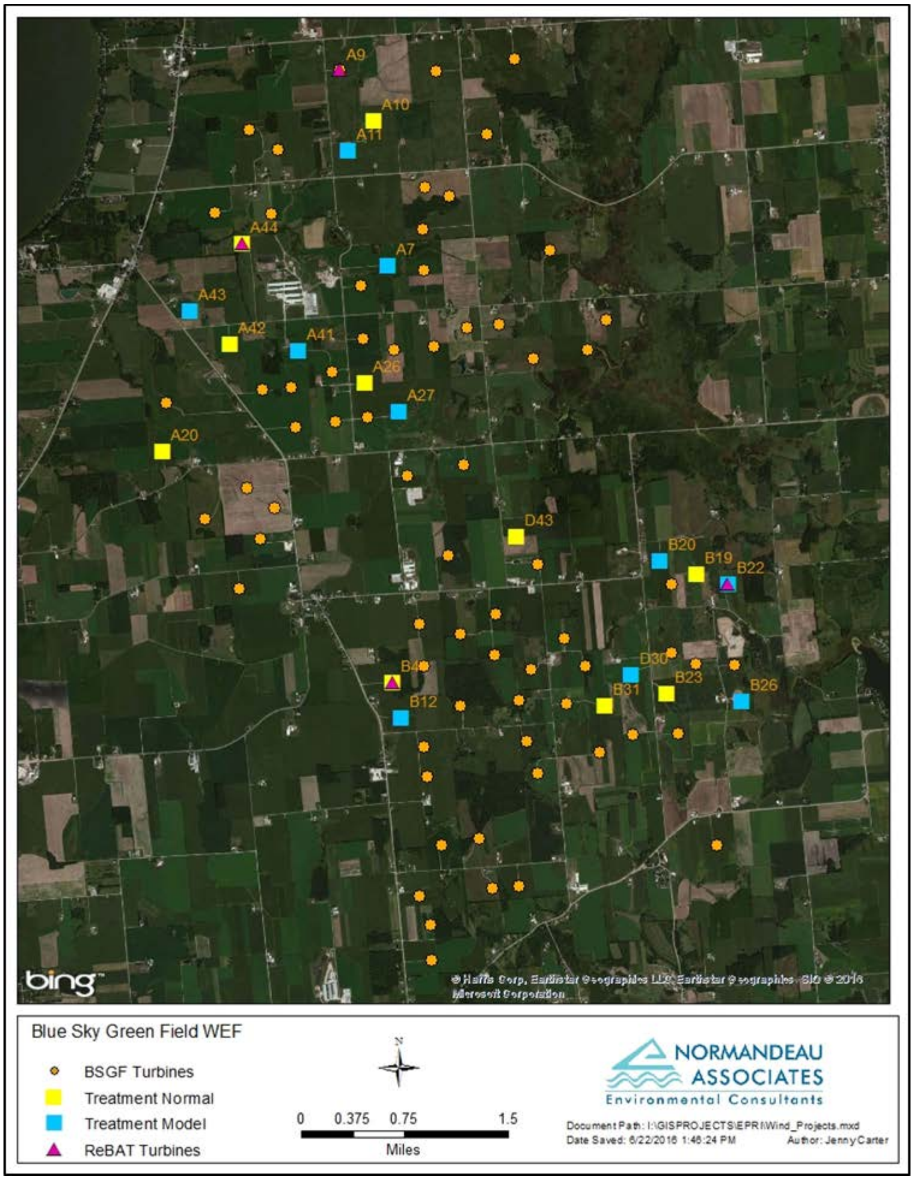


Figure 2-1
Blue Sky Green Field (BSGF) study area with turbine locations

Study Tasks

This study included several major tasks, as follows:

- Develop an automated bat species identification process;
- Develop an automated turbine shutdown system based on Supervisory Control and Data Acquisition (SCADA) remote monitoring;
- Develop predictive modeling of bat activity and mortality; and
- Test and validate the predictive model chosen, and test the shutdown system at BSGF.

Develop an Automated Bat Species Identification Process

Due to the species-specific differences in bat activity and mortality at wind energy facilities (see Baerwald and Barclay 2011, for example), the plan was to build separate risk models for each of the eight species potentially involved: hoary bat, eastern red bat, silver-haired bat, big brown bat, Indiana bat, northern long-eared bat, little brown bat, and tri-colored bat. Development of individual risk models requires real-time classification of echolocation calls for each species—precluding time-consuming manual classification by an expert. A third party contractor was unable to provide this capability after nearly 2 years of collaboration.

Develop TIMR—a SCADA-Based Automated Turbine Shutdown System

The TIMR Smart Curtailment system integrates real-time bat activity data with real-time weather data to provide a current risk value used to drive Vestas V82 turbine operation.

Turbine-Integrated Mortality Reduction (TIMR[SM]) is the Smart Curtailment system developed in this study. It processes weather and bat activity data in real time, calculates the risk of fatality, and communicates this value to the Supervisory Control and Data Acquisition (SCADA) remote monitoring system. After initial processing (*e.g.*, removing noise files), these data sets are transmitted via an external communication system (*e.g.*, cell or satellite network) to a server, where they are processed before being input to the risk model. Once the model calculates a risk value, that risk value is communicated to the SCADA system as an alert status.

The SCADA system responds to a low risk value (green or yellow alert status) by continuing normal turbine operations. It responds to a high risk value (red alert status) by pitching the turbine blades to slow the rotation of the turbine—remaining in that condition until it is safe (green or yellow alert status) to restart the turbines. A detailed description of the TIMR Smart Curtailment system is provided in Section 5.

Develop Predictive Modeling of Bat Activity and Mortality

A detailed description of this task is provided in Section 3.

Test and Validate the Predictive Model Chosen, Test the Shutdown System

A detailed description of this task is provided in Section 4.

Section 3: The BSGF Study—Develop Predictive Modeling of Bat Activity and Mortality

Introduction

ReBat® acoustic detectors were deployed at the nacelles of four turbines to record bat calls indicating exposure to the rotor swept zone, where bats are at high risk of fatality.

Initially, the study proposed simultaneous collection of bat activity and mortality data in 2012. These data would then be used to model mortality in relation to activity and weather conditions. Due to funding limitations, this approach became infeasible; only bat activity and weather data were collected in 2012. Acoustic monitoring systems using full-spectrum ultrasonic detectors (ReBAT®; see Section 5 for details) were deployed on the nacelles of four turbines at BSGF to collect data on the bats' exposure to the rotor swept zone (RSZ), where they are at high risk of fatality. There were two detectors per nacelle (Figure 3-1): one without a reflector plate that sampled the area below the nacelle and one with a reflector plate that sampled the area above the nacelle. In combination, they covered all or nearly all of the RSZ. The detectors recorded from 1 hour before sunset until 1 hour after sunrise each night from July 1, 2012, through October 31, 2012.

Bat activity levels were modeled in relation to weather parameters using two approaches: Inferential Statistical Modeling and Descriptive Statistical Analysis Modeling.

These data were used to model bat activity levels in relation to weather parameters. Multiple avenues of predicting bat activity and fatalities were explored, but most methods were discarded because they were unsuccessful. Those failed modeling efforts, as well as the two successful modeling efforts, are described below.

Figure 3-1
ReBAT® acoustic detectors deployed on a wind turbine nacelle at BSGF showing the reflector plate on the upward looking detector

Inferential Statistical Modeling

Weather variables were selected based on knowledge of bat behavior and common sense. Previous studies (*e.g.*, Weller and Baldwin 2012, Baerwald *et al.* 2009) showed that bat activity and mortality can be correlated with wind speed, temperature, and various other parameters. To ensure the closest possible correlation between bat activity and weather parameters, the following weather data were collected at the nacelles of the four turbines with ReBATs:

- Temperature
- Wind speed
- Wind direction

However, additional weather variables known to influence bat activity and mortality (Arnett and Baerwald 2013, Baerwald and Barclay 2011) were not available from the nacelle-based weather stations. Therefore, the nacelle data were supplemented with data from the weather station closest to BSGF. The following weather data were gathered from the Fond du Lac Airport, approximately 20 kilometers (km) southwest of BSGF:

- Precipitation
- Relative humidity
- Barometric pressure
- Cloud cover

Weather data were correlated with bat activity data (as measured by bat calls) to create 10-minute, hourly, and nightly time-scale data sets used for Inferential Statistical Modeling.

Cloud cover data were combined with information about the phase of the moon and its rise time to create a measure of ambient light during each hour of the night. The data were split into four categories: dark, semi-dark, semi-bright, and bright (Table 3-1). Similarly, precipitation was categorized as no rain, light rain, and rain (Table 3-1).

Table 3-1
Variable definitions for ambient light and precipitation

Ambient Light (0–1)				**Precipitation (inches)**		
Dark	Semi-dark	Semi-bright	Bright	No rain	Light rain	Rain
≤ 0.2	> 0.2, ≤ 0.5	> 0.5, ≤ 0.8	> 0.8	0	> 0, < 1.0	≥ 1.0

Weather data were correlated with bat activity data (as measured by bat calls) on several time scales: every 10 minutes, every hour, and all night (Table 3-2). These time-scale data sets were used for the modeling process described below.

Table 3-2
Bat activity and weather time-scale data sets used for inferential statistical modeling

	10-minute Data	Hourly Data	Nightly Data
Bat Activity	Sum of bat calls within 10-minute increments, per turbine	Sum of bat calls within each hour, per turbine	Sum of bat calls over all hours between sunset and sunrise, per turbine
Tower Weather	Measurements every 10 minutes	Average (median and mean) of each 10-minute period for each hour, per turbine	Average (median and mean) over all hours between sunset and sunrise, per turbine
Local Station Weather	Hourly weather measurements divided by 6 (to achieve 10-minute periods) Same data used for all turbines	Measurements every hour Same data used for all turbines	Average (median and mean) over all hours between sunset and sunrise Same data used for all turbines

Many iterations of the Inferential Statistical Modeling process were performed to look at the data in a variety of ways.

Average values were calculated for each variable; the change in each variable over an hour or night was also calculated. Precipitation was based on the total precipitation in an hour or night.

For the nightly data, the mean and median of the 4 hours following sunset were calculated for each variable. For both the hourly and nightly data, the average wind direction values were converted into four cardinal directions (north, east, south, and west) and four intercardinal directions (northeast, southeast, southwest, and northwest).

To assist with data analysis and modeling, Normandeau contracted with Alain Zuur at Highland Statistics Ltd., a United Kingdom-based ecological statistical consultancy that specializes in complicated data sets and works on the cutting edge of advanced ecological statistical modeling. Many iterations of the modeling process were performed to look at the data in a variety of ways (Figure 3-2, Table 3-3).

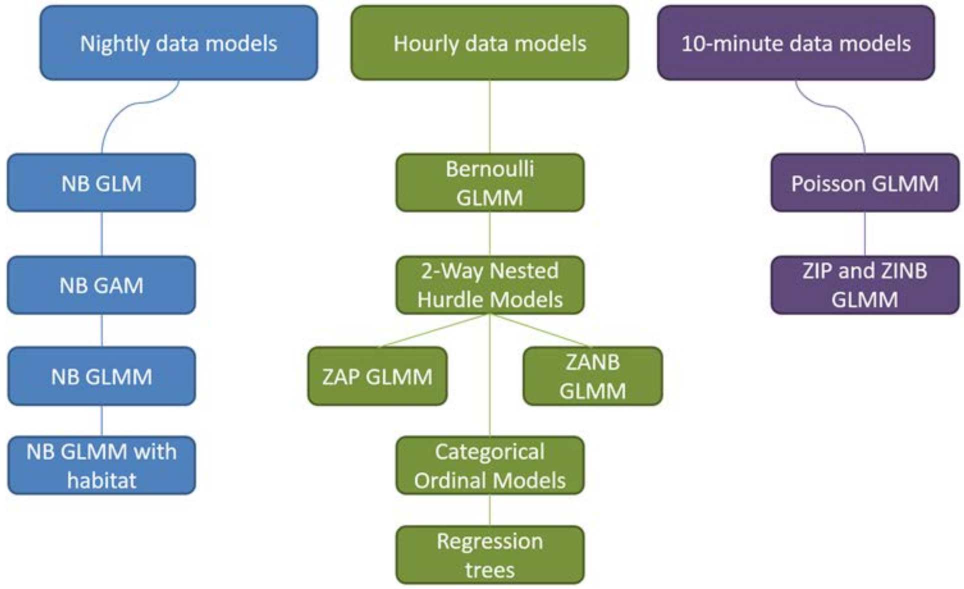


Figure 3-2
Types of inferential statistical models explored for each type of data set

Table 3-3
Acronyms for iterations of the inferential statistical modeling process shown in Figure 3-2

Acronym	Definition
NB	Negative Binomial
GLM	Generalized Linear Model
GAM	Generalized Additive Model
GLMM	Generalized Linear Mixed Model
ZAP	Zero-altered Poisson
ZANB	Zero-altered Negative Binomial
ZIP	Zero-inflated Poisson
ZINB	Zero-inflated Negative Binomial

Scatterplots, Pearson correlation coefficients, variance inflation factors, and principal component analysis bi-plots were used to determine the presence of collinearity within the data. Collinearity is a correlation between covariates that causes problems in data analysis, such as increasing standard errors (Zuur and Ieno 2014). After collinearity evaluation, the following set of covariates was used to build the models:

- Days since July 15
- Precipitation
- Barometric pressure (mean)

- Change in pressure (mean)
- Ambient light
- Temperature (mean)
- Change in temperature (mean)
- Wind speed (mean)
- Change in wind speed (mean)
- Wind direction (mean, categorized)
- Standard deviation of mean wind direction

Models were run for hoary bat, eastern red bat, silver-haired bat, and the species group *Myotis*.

Temperature and day are also correlated (temperatures decreased as the season progressed), but day had to be included in the models to control for temporal correlation (bat activity from Day X is correlated with Day X–1, *etc.*). All numerical weather covariates were standardized prior to modeling.

Models were run for three species—LACI (*Lasiurus cinereus*, hoary bat), LABO (*Lasiurus borealis*, eastern red bat), LANO (*Lasionycteris noctivagans,* silver-haired bat)—and the species group, *Myotis*. Explanations of the different models, including why each one was tried along with its pros and cons, are given in Tables 3-4 through 3-6.

Nightly Data Models

Nightly data models were good at showing the weather variables important to bats, but were not good at predicting bat activity

Nightly data were analyzed using several different models (Table 3-4). These models were good at showing which weather variables (*e.g.*, temperature and wind speed) were important to bats, but were not good at predicting; the 95% credible intervals were large (Figure 3-3), the residual autocorrelation had a greater influence on the predicted values than the actual covariates, and the predicted values obtained by using just the covariate effects (P2) ranged from 0 to approximately 5, whereas the observed number of calls per night was much higher. Finally, the decision was made to model bat activity on a shorter time scale because it would be more informative to know the exact weather conditions at the exact time that bats were being detected at the turbines.

Figure 3-3 shows the large credible intervals that were present for most nightly data models, resulting in poor predictive power.

Table 3-4
Explanation of each inferential statistical model used to analyze nightly data

Nightly Model Type	Why We Tried It	Results
NB GLM	Simple/easy (no random effects).	**With autocorrelation:** When the predicted (fitted) values were generated using the latent autocorrelation, Pearson correlation, and Spearman rank correlation values, comparing the predicted and observed values indicated that the models for each species were a good fit. Although the correlation values were fairly high, the 95% credible intervals were very large—too large to be useful for predictions (Figure 3-3). **Without autocorrelation:** When the predicted values were generated based only on the covariate effects, there was a poor fit between the predicted and observed values for all species. This means that the results using the P1 predictions were driven mainly by the autoregressive correlation process (Zuur and Ieno 2014). The 95% credible intervals were very high.
NB GAM	There appeared to be some nonlinear trends in the GLMs (above), particularly between LACI and temperature and LABO and wind speed.	▪ Similar to NB GLM, the models were a poor fit. ▪ In addition, the nonlinear patterns were not very strong and thus linear patterns, which are easier to compute and interpret, were preferable.
NB GLMM	Included week as a random effect to control for correlation between bat activity observations from the same week. By using the same week value for all four turbines, can also control for correlation among all four turbines.	Some significant parameters, but poor agreement between fitted and observed values, and large credible intervals.
NB GLMM with habitat	Decided to look at the potential effects that habitat around the turbines might have on bat activity. Used Fragstats (McGarigal *et al.* 2012) to determine the amount of wetlands, forest, woody wetlands, and open water within 1 km of each of the four turbines with detectors.	▪ A few habitat variables had an effect, but they were highly correlated. ▪ The three that were not highly correlated were % Open Water, Forest IJI, and Total Edge of Woody Wetlands. ▪ Any of these variables could be used in place of tower in the model (the benefit of this is having models that are not just applicable to one tower). ▪ Also explored and found that some interactions (*e.g.*, Temp*WSpeed) made the models slightly better. ▪ Models, however, were still not good for prediction.

Note: GLM = Generalized Linear Model, GAM = Generalized Additive Model, GLMM = Generalized Linear Mixed Model, LACI = *Lasiurus cinereus*, LABO = *Lasiurus borealis*, IJI = Interspersion and Juxtaposition Index, Temp*WSpeed = notation for the interaction of temperature and wind speed in the model.

Using hourly data has greater behavioral significance, since weather can change dramatically within one night. Hourly presence/absence models were the best predictors of bat activity.

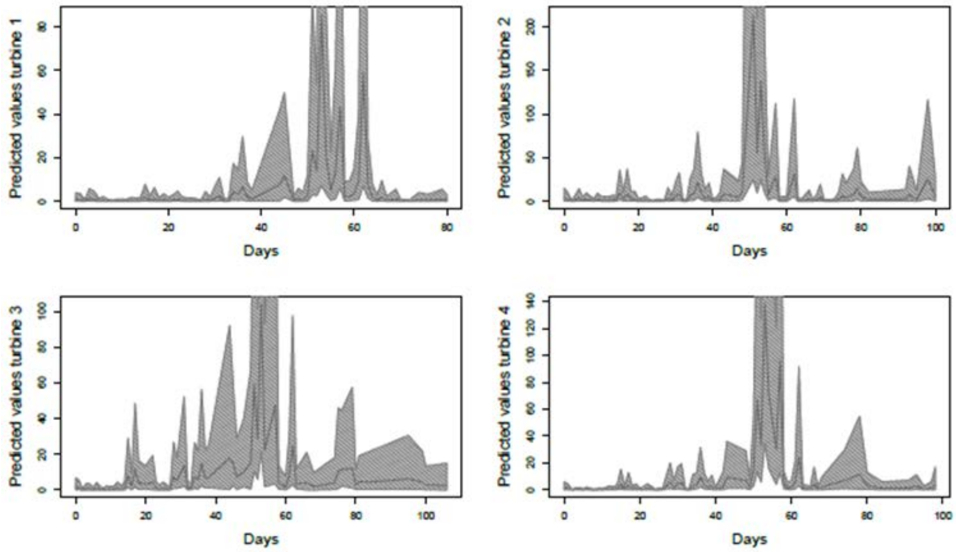


Figure 3-3
Predicted values and 95% credible intervals (grey area) for silver-haired bat (LANO) for each turbine.

Hourly Data Models

Using hourly data has greater behavioral significance, since weather can change dramatically within one night and researchers needed knowledge of the specific weather conditions during which bats were active. Various ways to model the hourly data were tried, including a new method known as regression trees (Sela and Simonoff 2011, De'Ath and Fabricius 2000; Table 3-5). Habitat variables were also included in some of the models to see if predictions could be improved.

Hourly presence/absence models were the best predictors. Like nightly data models, these hourly data models outlined covariates that were important to bat activity.

Table 3-5
Explanation of each inferential statistical model used to analyze hourly data

Hourly Model Type	Why We Tried It	Results
Bernoulli GLMM	▪ To avoid problems similar to those encountered in the nightly models, the hourly data were viewed in terms of presence/absence. The data were placed in a binomial format with values of 0 and 1. ▪ Used a binomial GLMM with a Bernoulli distribution and a logistic link function to model the probability of the presence of bat activity. ▪ Used week as a random effect to control for inherent correlation between all activity observations made within the same week. Used night within a week as a random effect to model correlation between observations made in the same night.	▪ Models showed reasonable agreement between observed and predicted values. ▪ For example, the LACI model was 41% accurate at predicting LACI activity, and 89% accurate at predicting that there would be no LACI activity within a given hour.
Zero-Altered GLMMs (Poisson and Negative Binomial Distributions)	▪ Zero-altered models first model presence/absence and then fit the nonzero data (count data separately). ▪ Given the success of the Bernoulli GLMMs, wanted to try adding the actual activity levels (*i.e.*, non-presence/absence data).	▪ The presence/absence portion of the models could predict fairly well, but the actual counts (data > 0) could not.
Categorical Ordinal Models	▪ To take a step beyond the presence/absence model, the data were placed in the following categories: o Absent (0 calls) o Low activity (-1 standard deviation up to mean activity) o High activity (≥ +1 standard deviation above mean activity)	▪ Models were good at predicting the absence of bats, but fell apart when predicting both low and high activity levels. ▪ The same results were observed, even when we varied how the activity categories were defined.
Regression Trees	▪ Given the constraints of the data set, it was decided to try a brand new technique (for mixed effects models) that can withstand large variance and nonlinear effects in the data. ▪ Regression trees partition the response variable into mutually exclusive groups based on the explanatory variables.	▪ The trees were uninformative for the count data. ▪ Used presence-only data to create trees. ▪ Same results as all previous analyses.

Note: GLMM = Generalized Linear Mixed Model, LACI = *Lasiurus cinereus*

10-Minute Data Models

Following the logic used to analyze the hourly data, researchers modeled the data collected in 10-minute blocks to see if a shorter time scale would provide better agreement between bat activity and weather parameters. The two different methods tried gave results similar to those observed with the nightly and hourly models (Table 3-6), including the weather covariates that were significant.

10-minute data models provided no better prediction of bat activity than the nightly and hourly models.

Table 3-6
Explanation of each inferential statistical model used to analyze 10-minute data

10-Minute Model Type	Why We Tried It	Results
Poisson GLMM	To see if modeling bat activity and weather on a very short time scale would provide better agreement between the predicted and observed values.	As previously seen, the models were poor at predicting bat activity levels.
Zero-inflated GLMM (Poisson and Negative Binomial Distributions)	To better model the large number of zero values (10-minute periods when no bats were recorded).	Models were poor at predicting bat activity levels.

Note: GLMM = Generalized Linear Mixed Model

Although it was impossible to predict bat activity levels using Inferential Statistical Models, the models did predict bat presence/ absence fairly well.

Summary of Inferential Statistical Model Performance

All the inferential statistical models that were tried yielded significant effects of certain covariates, but the effects were small and the predictive power of the models was low. This could mean that important covariates (whatever they may be) were missing, and that these missing covariates would account for most of the variation in the data. Furthermore, the poor predictive power of the models could result from limitations of the data set. Data were collected from only four acoustic detectors—ideally there would be at least 10. Finally, the overall bat activity levels were relatively low during the 2012 monitoring season at BSGF.

Although it was impossible to predict bat activity levels using these models, the models did predict bat presence/absence fairly well. The lack of robust performance from the inferential statistical approaches led to the investigation of a descriptive statistical approach to analyze bat activity in relation to weather.

Descriptive Statistical Analysis Modeling takes a cost–benefit approach. Cost is predicted lost power generation (MWh) and benefit is predicted reduction in bat mortality, assuming bat activity is positively correlated with mortality.

Descriptive Statistical Analysis Modeling

Descriptive statistical analysis began with an exploration of the data to look for trends and patterns of bat activity and ultimately led to a cost–benefit approach. The cost of curtailment is the predicted amount of lost power generation (in megawatt hours), while the benefit of curtailment is the predicted reduction in bat mortality, assuming that activity is positively correlated with mortality. Curtailment is defined as a turbine speed of less than 2 rpm.

Power Generation and Economic Cost

The Vestas V82 turbines have a cut-in speed (the lowest wind speed at which they generate power to the transmission system) of 3.5 m/s. At wind speeds of less than 3.5 m/s it was assumed that no cost was associated with curtailing turbine speed to less than 2 rpm. In practice there is a small cost, but for simplicity sake none was assumed. Above 3.5 m/s, the more hours are curtailed, the more power generation is lost. A standard power curve for the V82 turbines (Figure 3-4) was used to estimate power loss during curtailment. Due to the cubing of wind power relative to wind speed, there was increasing power loss at higher wind speeds. There was no attempt to convert power generation to revenue for the predictive models described below.

The more hours are curtailed above the Vestas V82 cut-in speed, the more power generation is lost.

Conservation Benefit

Activity at the nacelle is a measure of bat exposure to the RSZ. Although the relationship between exposure and fatality is not necessarily one-to-one, a positive correlation between the two variables was assumed. Thus, the predicted reduction in mortality during curtailment was calculated using bat activity at the nacelle as a surrogate for mortality (see Figures 4-9 and 4-10 for validation of this assumption).

There are several benefits to using bat activity data. The precise timing of the activity is known (within seconds), whereas the timing of fatal events is imprecise (within hours). The temporal imprecision of mortality data makes it impossible to associate mortality with weather conditions, since the weather changes throughout the night. With activity data, the exact time of exposure to the rotor and the associated weather conditions at that moment are known with high precision, making relationships easier to discern.

It was assumed that the more active bats were during the curtailment period, the greater the probable reduction in their mortality.

It was assumed that the more active bats were during the curtailment period, the greater the probable reduction in their mortality.

Initially, the relationships between all of the weather variables used in the inferential statistical modeling effort and bat activity were explored. Wind speed had the largest and most consistent impact on conservation (lowering bat fatality rates). Adding other weather variables to wind speed had only a small positive effect on the predicted conservation benefit, while increasing the economic costs. Therefore, the only weather variable used in the final model was wind speed (Table 3-7). The table presents the results of this cost–benefit analysis using 2012 activity and weather data. Each row of the table shows the approximate cost and benefit of a given curtailment model applied to the 2012 season.

For example, consider the first row of the table. If, during the 2012 season, turbines were curtailed in 10-minute intervals whenever the wind speed was less than 3.5 m/s, then they would have been curtailed for 19% of the night hours within the season (less than 1% annual MWh, as power generation does not occur below the cut-in speed). However, 46% of total bat exposure (49% of LACI, 59% of LANO, 27% of LABO) occurred during these same hours, potentially reducing bat mortality substantially. In the third row, if turbines were curtailed whenever the wind speed was less than 4.5 m/s, they would have been curtailed for more hours (31%) and more power generation would have been lost (although still less than 1%). However, because 62% of the bat exposure events occurred during these hours, bat conservation would be greater.

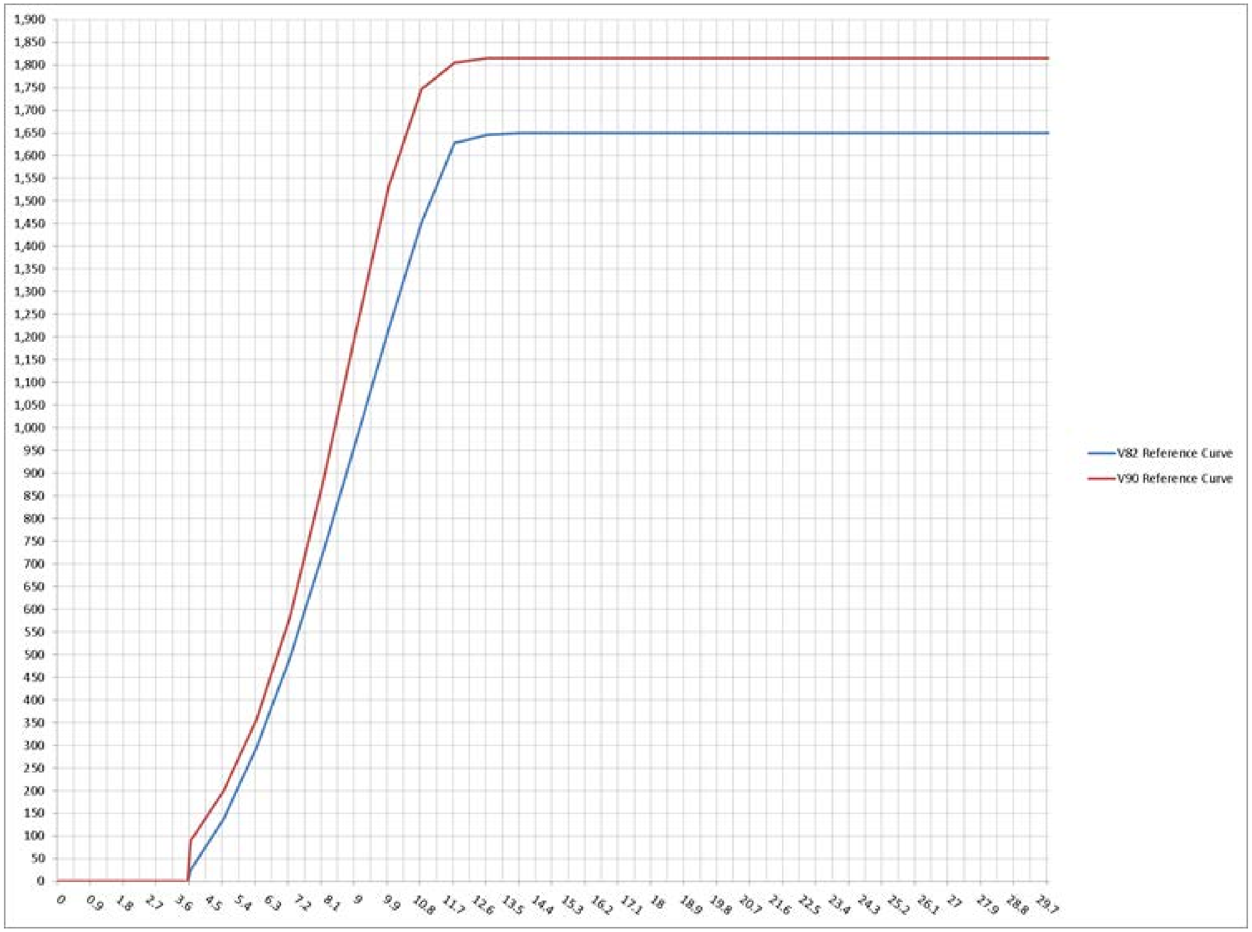


Figure 3-4
Power curves for Vestas V82 turbines (blue line) and Vestas V90 turbines (red line)

Table 3-7
Predicted cost–benefit for various descriptive statistical analysis curtailment models and rules

Model	% Annual MWh	% Night Hours within Season	% Activity				Implementation
			All Species	LACI	LANO	LABO	
Curtail for 10 minutes if…							
WS < 3.5	< 1	19	46	49	59	27	Curtail for 10 minutes if current WS ≤ 3.5 m/s
WS < 4.0	< 1	25	55	58	65	39	Curtail for 10 minutes if current WS ≤ 4.0 m/s
WS < 4.5	< 1	31	62	65	70	47	Curtail for 10 minutes if current WS ≤ 4.5 m/s
WS < 3.5 or WS > 3.5 and 1+ bats	< 1	25	59	63	66	41	Curtail for 10 minutes if current WS ≤ 3.5 m/s or if WS > 3.5 and at least 1 bat has been detected in the last 10 minutes
WS < 3.5 or WS > 3.5 and 2+ bats	< 1	23	56	59	66	38	Curtail for 10 minutes if current WS ≤ 3.5 m/s or if WS > 3.5 and at least 2 bats have been detected in the last 10 minutes

Note: MWh = megawatt hour, m/s = meters per second, WS = wind speed, LACI = *Lasiurus cinereus*, LANO = *Lasionycteris noctivagans*, LABO = *Lasiurus borealis*. Data from 7/3/2012 to 9/30/2012, 6 pm to 6 am.

Final Models: Two Options

This expansive modeling effort developed two different models, either of which could plausibly be used at BSGF in 2015:

- The **inferential statistical presence/absence (P/A) model** developed using a generalized linear mixed model (GLMM) with Bernoulli distributions (Table 3-5); and
- The **descriptive statistical analysis cost–benefit model** (Table 3-7).

This expansive modeling effort developed two different models, either of which could plausibly be used at BSGF in 2015.

Inferential Statistical Presence/Absence Model Using GLMM

The inferential statistical presence/absence (P/A) model developed using hourly bat activity data had the best prediction capability of all the statistical models tested. The advantages of using only presence/absence data are as follows:

- Models are easy to implement in statistical software;
- Computing time is short, which allows for real-time computation and implementation;
- Model selection is relatively simple; and
- Predicted values and 95% confidence intervals are easily obtained.

In spring 2015, the P/A models were finalized for LACI, LABO, and LANO. Given the large differences in temporal activity patterns among these species, different data sets were used for each species as follows:

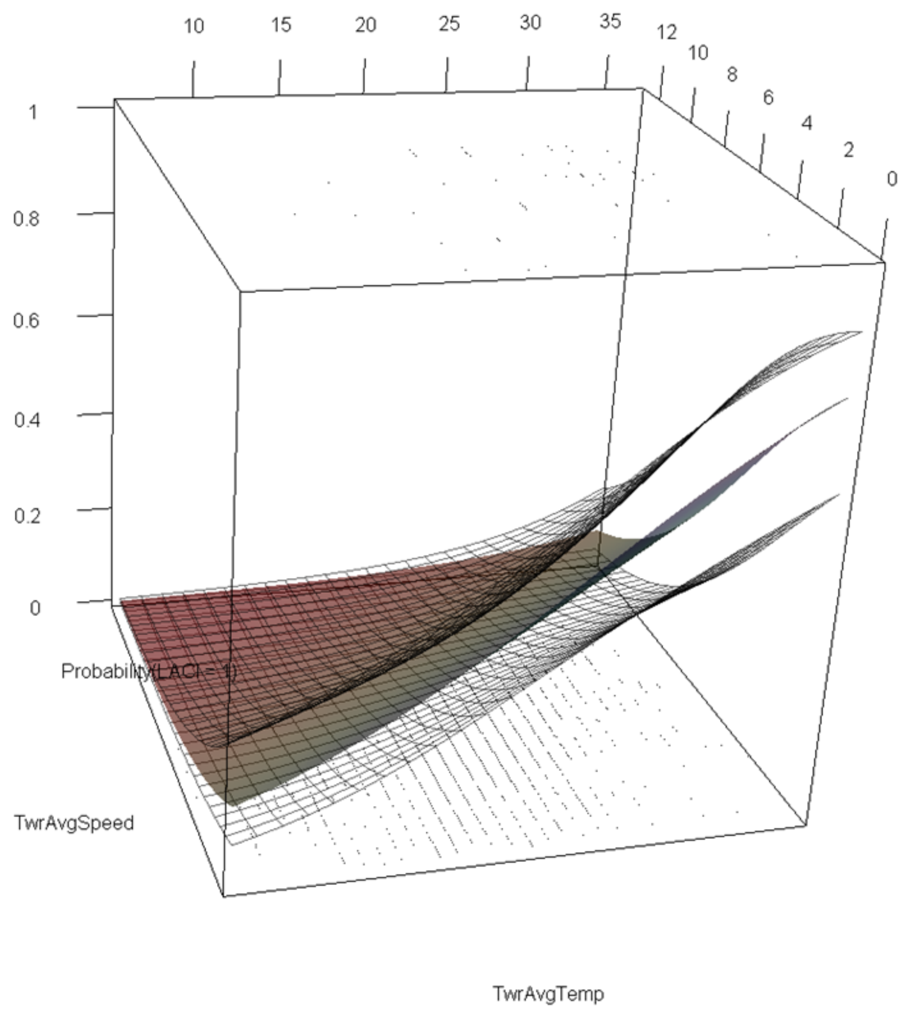
- LACI—Data from the whole season (July 1 to September 30);
- LABO—Data from the first half of the season (July 2 to August 14); and
- LANO—Data from the second half of the season (August 15 to September 30).

Advantages of choosing the inferential statistical presence/absence model using GLMM.

"Turbine" was included as a variable within the models to determine which turbines had the highest likelihood of detecting each species. The final models were chosen for each species, for a single tower. Since wind speed was a categorical variable (north, south, east, west), there were four separate models for each species, representing the four major wind directions. For example, if the wind was from the north, the north models for each species would be implemented. For ease of implementation, the final models for each species included only temperature and wind speed. Therefore, the simplified base model for each species, each wind direction, was:

$$\text{Predicted bat activity} \approx \text{turbine} + \text{temperature} + \text{wind speed}$$

Real-time temperature and wind speed values could be added to the equation to obtain a result between 0 and 1, which is the probability that a given species will be present (Figure 3-5).



Drawbacks of choosing the inferential statistical presence/absence model.

Figure 3-5
Predicted probability of LACI presence (solid band, ± credible intervals) for varying temperature and wind speed values when the wind direction is from the east

A potential drawback of the inferential statistical presence/absence (P/A) approach is that a single year of data (2012) was used to build the models. For example, if the weather is much hotter in a given year than in 2012, the model may predict bats when they are not present. Conversely, if it is colder than in 2012, the model may predict no bats when in fact bats are present.

The other main drawback of these models is the complexity of trying to predict presence on a species-specific level. Since there are separate models for each species, multiple models must be run to check the risk level for each species. Alternatively, turbine curtailment decisions could be based solely on the model for the species that had the highest probability of being detected (LACI).

Descriptive Statistical Analysis Cost–Benefit Model

Advantages and drawbacks of choosing the descriptive statistical analysis cost–benefit model.

The descriptive statistical approach is simple to understand and resembles the standard curtailment strategy known to be effective in reducing migratory tree bat fatalities (see Section 1, Turbine Operating Conditions). It is also simple to implement in real time, because all species use the same approach and minimal computation is required. However, since this approach was developed without the use of complex statistics, it lacks measureable uncertainty intervals around the predictions.

Final Model Chosen

We Energies opted to test the descriptive statistical analysis cost–benefit model at BSGF in 2015, using a 30-minute curtailment period to minimize turbine impacts from frequent operating changes.

Both the inferential and descriptive statistical models were presented to We Energies, who opted to test the descriptive statistical analysis cost–benefit model at BSGF in 2015. Personnel from We Energies and Vestas requested that the curtailment period be extended from 10 minutes to 30 minutes to minimize potential impacts to the turbines from frequent operating changes (see Section 7, Potential Impacts on Turbine Operation and Maintenance). Extending the minimum curtailment period to 30 minutes increased the total amount of curtailment time (Table 3-8); zero conservation benefit is expected from some or all of this extended curtailment time. Conversely, the total predicted conservation benefit increased, because the length of curtailment increased. Even with the 30-minute rule, the cost is still predicted to be less than 1% of the annual MWh.

It was predicted that implementation of this model would result in a 76% reduction in bat mortality, with turbines curtailed for less than 1% of the annual MWh.

Based on the bat activity levels and weather patterns at BSGF in 2012—and assuming that there is a strong relationship between bat activity and mortality—it was predicted that implementation of this model would result in an estimated 76% reduction in bat mortality. It was estimated that the turbines would be curtailed for less than 1% of the annual MWh.

Table 3-8
Predicted final cost–benefit for various descriptive statistical analysis curtailment models or rules

Model	% Annual MWh	% Night Hours within Season	% Activity				Implementation
			All Species	LACI	LANO	LABO	
Curtail for at least 30 minutes if....							
WS < 3.5	< 1	25	54	57	64	35	Curtail for at least 30 minutes if current WS ≤ 3.5 m/s
WS < 4.0	< 1	32	64	67	69	51	Curtail for at least 30 minutes if current WS ≤ 4.0 m/s
WS < 4.5	< 1	38	71	74	74	60	Curtail for at least 30 minutes if current WS ≤ 4.5 m/s
WS < 3.5 or WS > 3.5 and 1+ bats	< 1	36	72	75	75	63	Curtail for at least 30 minutes if current WS ≤ 3.5 m/s or if WS > 3.5 and at least 1 bat has been detected in the last 10 minutes
WS < 3.5 or WS > 3.5 and 2+ bats	< 1	33	69	72	76	56	Curtail for at least 30 minutes if current WS ≤ 3.5 m/s or if WS > 3.5 and at least 2 bats have been detected in the last 10 minutes

Note: MWh = megawatt hour, m/s = meters per second, WS = wind speed. Data from 7/3/2012 to 9/30/2012, 6 pm to 6 am

Section 4: The BSGF Study—Test and Validate Predictive Model, Test Shutdown System

Introduction

In 2015, the 30-minute interval, descriptive analytical cost–benefit model was tested at BSGF during the fall migratory season (July 15 to October 31). Twenty turbines were randomly selected from the 30 turbines used during the 2008–2009 fatality monitoring study. Ten turbines were randomly selected to operate under the model.

Model Tested

In 2015, the 30-minute interval, descriptive analytical cost–benefit model was tested at BSGF during the fall migratory season (July 15 to October 31). Ten turbines operated normally and ten turbines operated under the model.

The rules for the 2015 season (July 15 to October 31) were, as follows:

- If wind speed is < 3.5 m/s and TIMR is not on red alert status, turbines blades are pitched out (rotor at ≤ 2 rpm).
- If wind speed is ≥ 3.5 m/s and > 1 bat call in the previous 10 minutes, turbines are curtailed (rotor at ≤ 2 rpm). This rule was modified on July 16 to set wind speed upper limits of ≥ 3.5 m/s and < 8.0 m/s. Above 8.0 m/s, the turbines would not be curtailed regardless of the level of bat activity.

While a threshold of 1 bat call seems low, less than 5% (4 of 88 turbines) of the facility is equipped with acoustic monitoring equipment. Thus, each acoustic monitor represents 25% of the facility (or 17.6 turbines). If bat activity is evenly distributed across the facility, then 1 call represents about 22 exposure events.

The data inputs to implement this model were as follows:

- Real-time activity data from the nacelles of four turbines equipped with acoustic monitors; and
- Real-time wind speed data from the nacelle of a single turbine.

The possible outputs from this model were communicated to the SCADA every 10 minutes as a high or low risk of fatality.

Operationally, if the risk of fatality is high, then the turbines curtail for 30 minutes. If the risk continues to be high, then the curtailment is extended in

10-minute blocks. If the risk of fatality is low, then turbines continue to operate normally.

Data Inputs to Model

Bat Activity Data

Model input—real-time bat activity data from the nacelles of four turbines equipped with acoustic monitors.

The model required real-time (or near real-time) data feed of bat activity at the nacelle, which was provided by the four ReBAT systems on Turbines A22, A9, B4, B22 at BSGF (see Figure 2-1). One was on a model-operated turbine, two were on normally operated turbines, and one was on a turbine that was not part of this study.

The sound signal data were processed through two filtering programs: SCAN'R© (Binary Acoustic Technology LLC) and a Normandeau-developed program to remove noise files. These filtering programs removed most of the noise files, but did not remove any files containing bat calls. Retaining some noise files (thus inflating activity levels) was determined to be a better strategy than removing some bat-call files (thus potentially under-reporting bat activity).

Model input—real-time wind speed data from the nacelle of a single turbine.

The overall bat activity was summed within 10-minute intervals to match the weather data collection intervals.

The model was based on overall bat activity. Thus, the files containing bat calls (n = 14,785) were not analyzed further before serving as input to the model.

Weather Data

The model also required weather data, specifically wind speed, from the nacelle of a turbine. This information was provided by the BSGF operations center in 10-minute increments for Turbine B16.

Bat Fatality Data to Validate Model

Model validation—bat carcass counts for each day from July 1 to October 31, 2015.

Carcass searches were conducted each day from June 1 to October 31, 2015, at all 20 study turbines, except when severe weather prevented completion of the daily searches. In Figure 4-1, green indicates the number of TIMR turbines searched each day during the shorter data analysis period from July 15 to September 30, 2015.

For each fatality, carcass condition was recorded, along with sex, age, and species, as condition allowed. Carcass condition helped indicate which night the fatality occurred—important information for the success of the model. Fatalities were assigned to the previous night if eyes were round and fluid-filled or slightly dehydrated; there was no decomposition; the body was flexible, and tail and wing membranes were supple; no infestations other than flies and eggs were found; and the fur was clean, glossy and silky (unless it had rained overnight).

Descriptive statistics and mean fatalities with 95% confidence intervals were used to determine whether the fatality rates at the model-operated turbines were different from those at the normally operated turbines (free-wheeled below 3.5 m/s, rpm more than 2 even when no generation occurred). Mean fatalities and 95% confidence intervals are presented separately for all bats and for the little brown bat, MYLU. Because the count data were not normally distributed, confidence intervals were calculated by bootstrapping over 10,000 samples. Bootstrapping is a method for calculating confidence (*e.g.*, confidence intervals) in a statistical result. It involves resampling from a data set multiple times (in this case, more than 10,000 times) to calculate the degree of variation among the answers and, therefore, the accuracy of the final result.

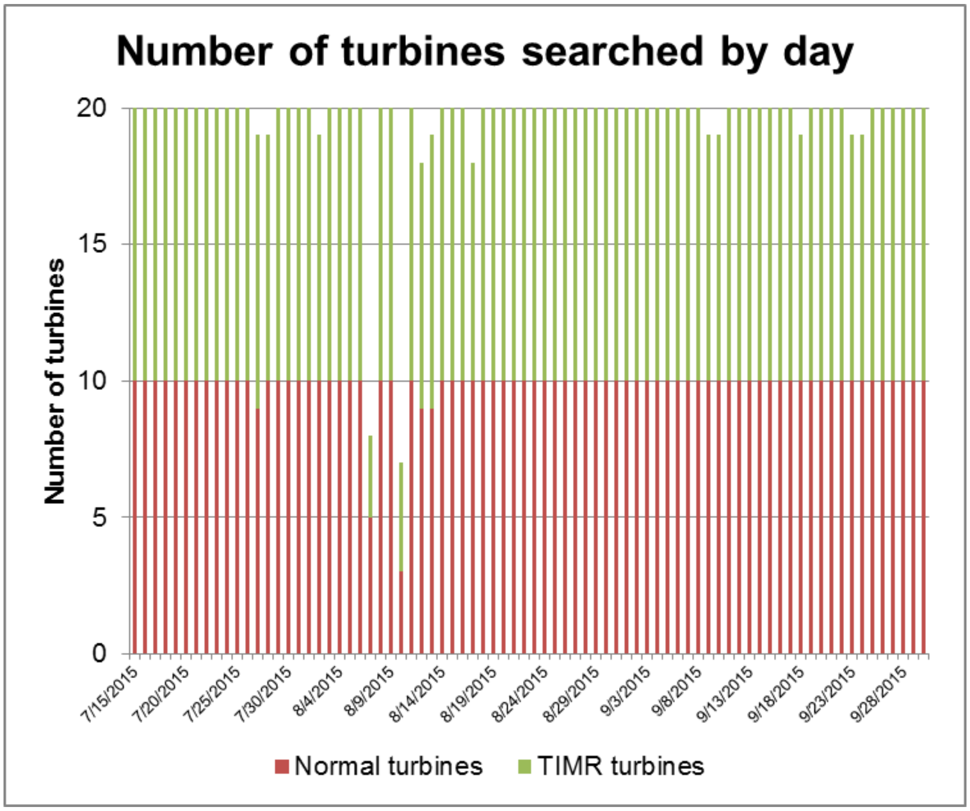


Figure 4-1
Number of turbines searched for carcasses each day of the study

Results

Results are presented for the period from July 15 through September 30, since only 4 bat fatalities occurred in October.

Although the study period was July 15 to October 31, 2015, bat mortality (n = 4) and activity were very low during October; in future years, curtailment may not to be applied during October unless required by permit. Thus, only results through September 30, 2015, are presented here. The fatality data are the raw, uncorrected numbers of carcasses recovered from each turbine.

Bat Mortality

There was an 83% reduction in fatalities for all bats and a 90% reduction in fatalities for little brown bats (*Myotis lucifugus*) at model-operated turbines, compared with normally operated turbines. The reductions are statistically significant at α = 0.05.

Fatality reductions were consistent across all model-operated turbines and all species.

A total of 213 carcasses (Table 4-1) of 6 species (Table 4-2) were recovered during the daily searches of the 20 turbines: 182 were from the normally operated turbines and 31 were from the model-operated turbines (Figures 4-2 and 4-3). For all bat species, mean number of fatalities was 18.2 (95% CI: 15.5–20.8) for the normally operated turbines and 3.1 (95% CI: 2.1–4.1) for the model-operated turbines. Thirty-three little brown bat (MYLU) fatalities were recorded: 30 at normally operated turbines and 3 at model-operated turbines (see Figure 4-2, Figure 4-4). There was a mean of 3.0 (95% CI: 1.7–4.3) MYLU fatalities found under the normally operated turbines and a mean of 0.3 (95% CI: 0.02–0.58) MYLU fatalities found under the model-operated turbines. For all bats, as well as for MYLU, 95% confidence intervals were non-overlapping, indicating statistical significance at α = 0.05.

There was an 83% reduction in fatalities for all bats and a 90% reduction in fatalities for MYLU at model-operated turbines, compared with normally operated turbines. The fatality reductions were consistent across all model-operated turbines and all species (Figures 4-3 through 4-8).

Table 4-1
Bat carcass count and percentages by treatment type

Turbine	# Carcasses		% Carcasses		Treatment
	All	MYLU	All	MYLU	
All turbines	213	33	100.0	100.0	–
Normally operated turbines	182	30	85.4	90.9	Normal
Model-operated turbines	31	3	14.6	9.1	Model
A10	17	6	8.0	18.2	Normal
A20	22	4	10.3	12.1	Normal
A26	15	3	7.0	9.1	Normal
A42	20	5	9.4	15.2	Normal
A44	23	0	10.8	0.0	Normal
B4	20	2	9.4	6.1	Normal
B19	20	4	9.4	12.1	Normal
B23	23	5	10.8	15.2	Normal
B31	10	0	4.7	0.0	Normal
D43	12	1	5.6	3.0	Normal
A7	2	1	0.9	3.0	Model
A11	2	0	0.9	0.0	Model
A27	3	0	1.4	0.0	Model
A41	3	0	1.4	0.0	Model
A43	2	0	0.9	0.0	Model
B12	1	1	0.5	3.0	Model
B20	3	0	1.4	0.0	Model
B22	6	0	2.8	0.0	Model
B26	3	0	1.4	0.0	Model
D30	6	1	2.8	3.0	Model

Note: MYLU = little brown bat

Table 4-2
Fatalities by bat species

Species	Carcasses Total	Carcasses Normal	Carcasses Model
Hoary bat (LACI)	59	48	11
Silver-haired bat (LANO)	46	42	4
Eastern red bat (LABO)	43	37	6
Big brown bat (EPFU)	32	25	7
Little brown bat (MYLU)	33	30	3
Tri-colored bat	1	0	1
Grand Total	**213**	**182**	**31**

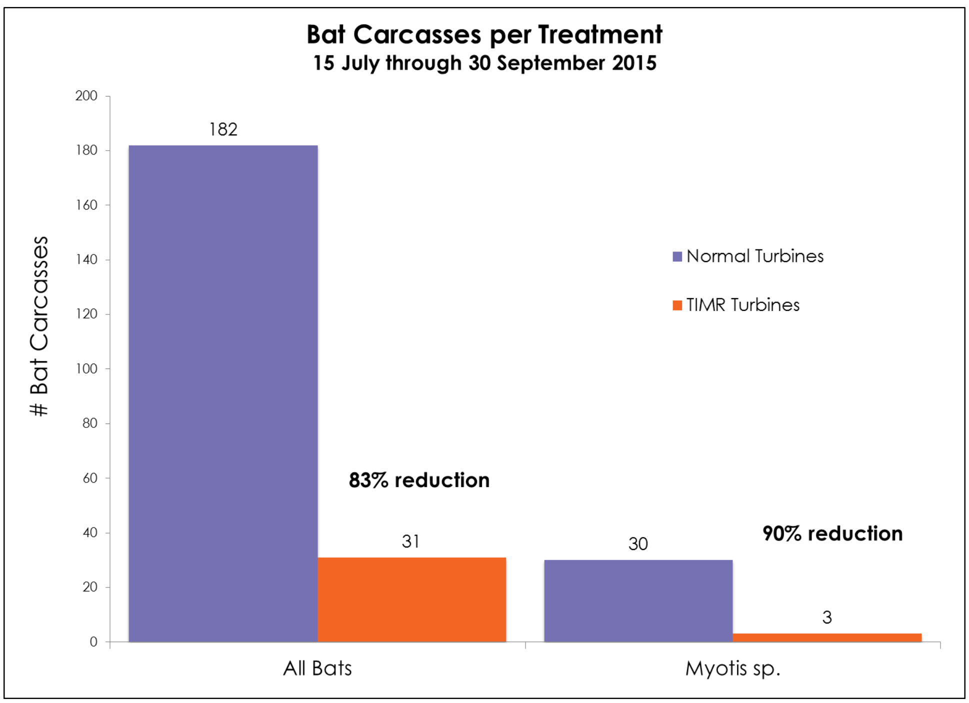


Figure 4-2
Comparison of bat fatalities between normally operated and model-operated turbines for all bats and for little brown bats (Myotis lucifugus). The reductions are statistically significant (α = 0.05).

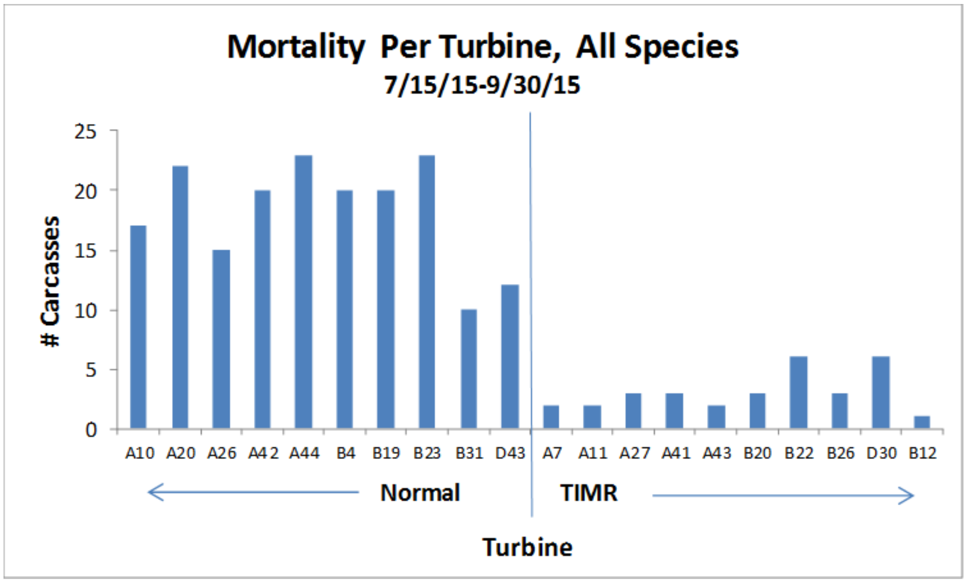


Figure 4-3
Mortality rates by turbine for all bat species

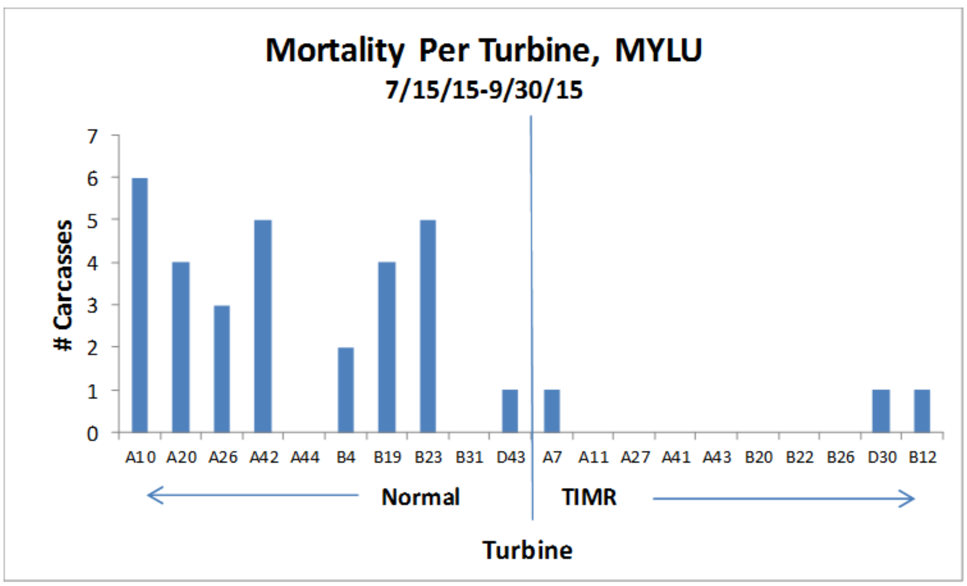


Figure 4-4
Mortality rates by turbine for little brown bat (MYLU)

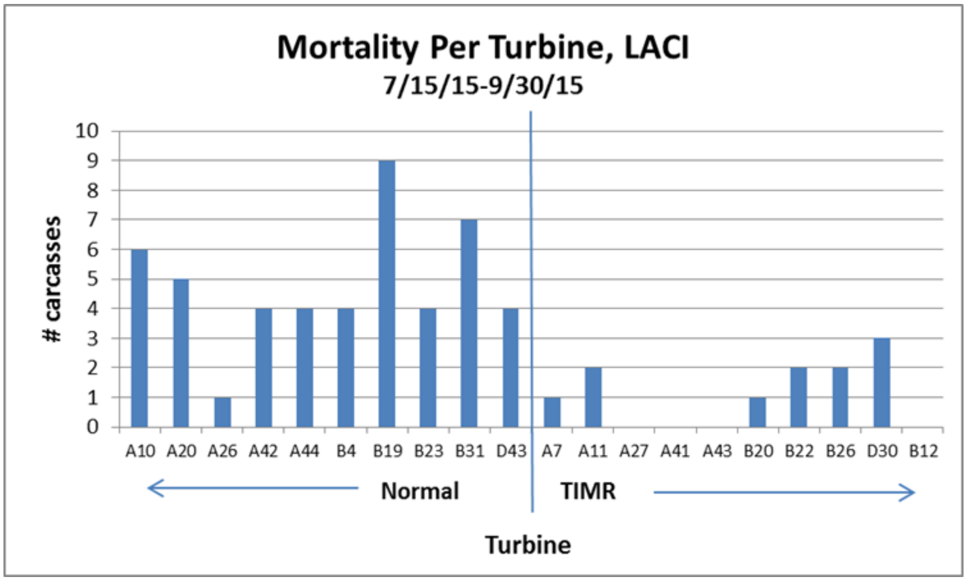


Figure 4-5
Mortality rates by turbine for hoary bat (LACI)

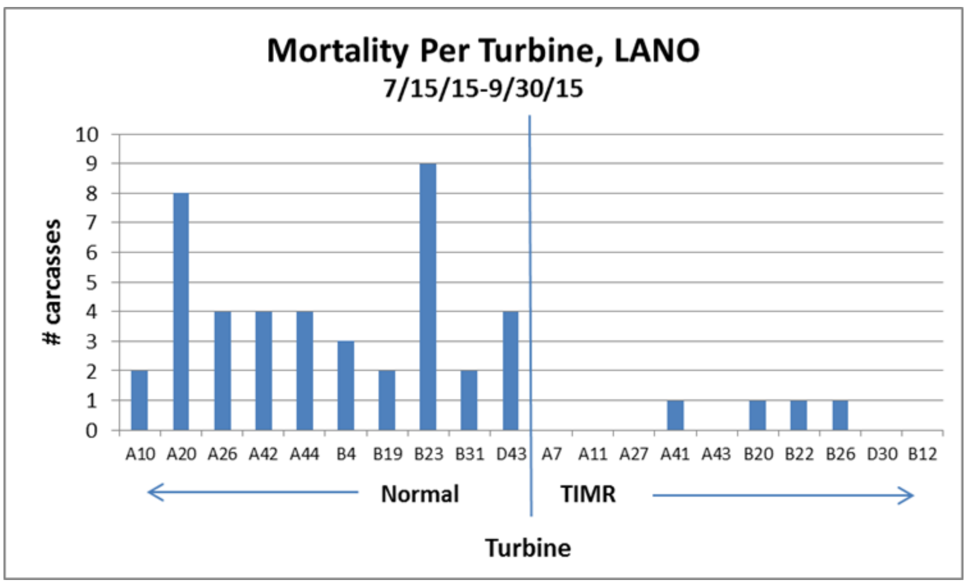


Figure 4-6
Mortality rates by turbine for silver-haired bat (LANO)

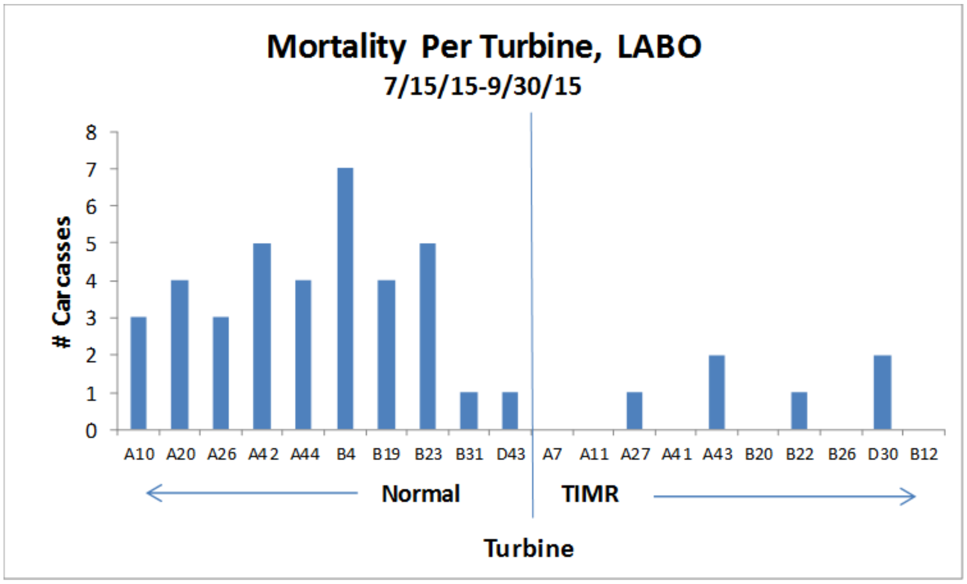


Figure 4-7
Mortality rates by turbine for eastern red bat (LABO)

Bat exposure in the rotor swept zone was a strong indicator of fatality risk.

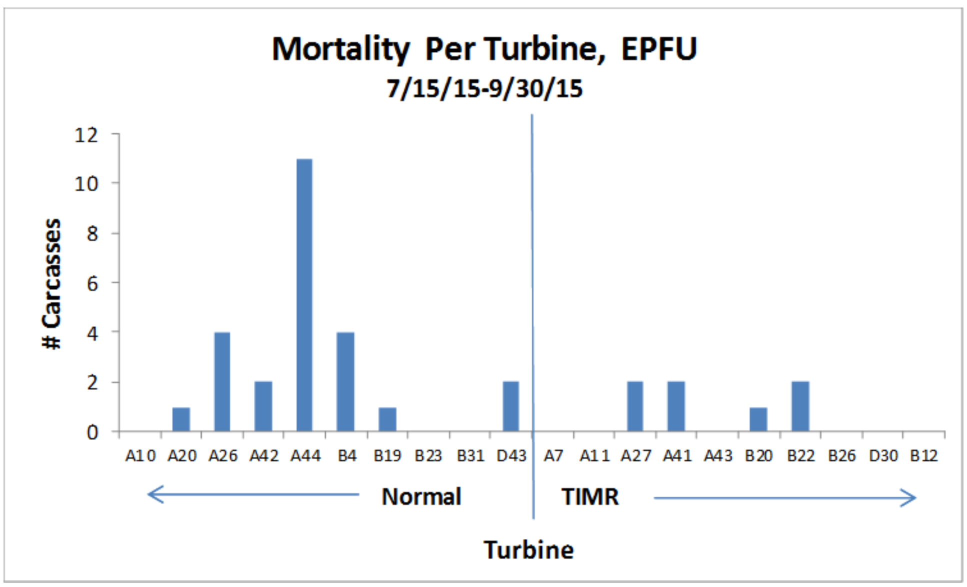


Figure 4-8
Mortality rates by turbine for big brown bat (EPFU)

Bat Activity as an Indicator of Fatality Risk

Bat exposure in the rotor swept zone was a strong indicator of fatality risk (Figures 4-9 and 4-10). Exposure was indicated by the number of bat calls in and around the nacelle at the four acoustically monitored turbines. Fatalities were the number of carcasses at the 10 normally operated turbines. Mortality data from the model-operated turbines are excluded because they were curtailed when bats were present. To fairly compare bat mortality to bat activity, the bat activity has been rpm-adjusted to account for times when the turbine rpm is low (due to low wind speed or maintenance) and very unlikely to cause bat mortality.

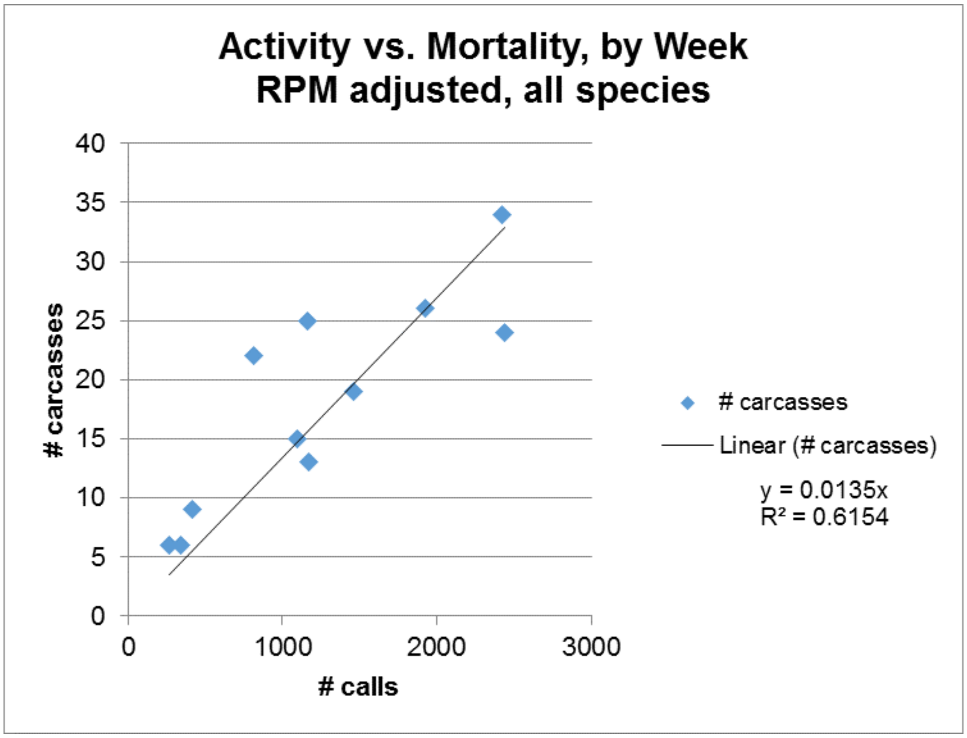


Figure 4-9
"By week" activity alone explains more than 60% of bat mortality

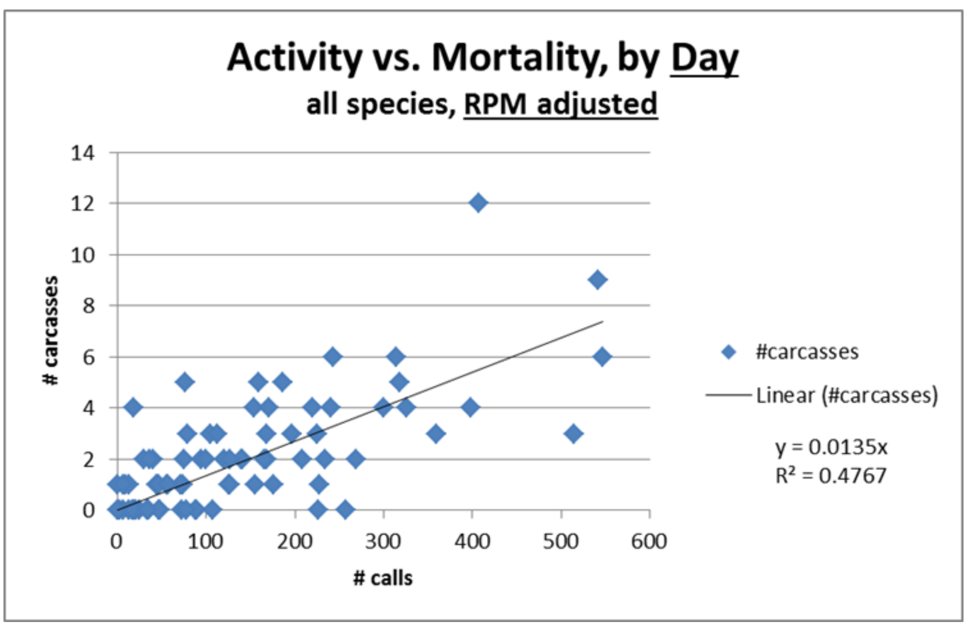


Figure 4-10
"By day" activity alone explains 47% of bat mortality

The rpm-adjusted nightly bat activity was calculated by multiplying the nightly bat activity by the average nightly rpm divided by 14. The turbines generally operate at about 14 rpm; thus the average nightly rpm is usually about 14. However, when wind speeds are less than 3.5 m/s, turbine rpm will decrease to about 0 rpm; thus the average nightly rpm will be less than 14. If the turbines were fully operational during the night (average nightly rpm = 14), then no adjustment was made to the bat activity. If the turbines were not operational during part of the night, the average nightly rpm was less than 14 and the rpm-adjusted bat activity was less than the actual bat activity.

Exposure to risk due to activity explained 47% of the daily bat mortality and 61% of the weekly mortality.

Exposure due to activity explained 47% of the daily bat mortality and 61% of the weekly mortality. The relationship between activity and mortality was stronger on a weekly basis than on a daily basis. This is likely due to the greater difficulty in accurately assigning a day of death to each carcass (Table 4-3), as compared to assigning a week of death.

Table 4-3
Number of carcasses that could not be assigned to a day, week, or month

Time Period	# Carcasses Assigned	# Carcasses Could Not Be Assigned	% Not Assigned
All season	213	0	0.0
Month	210	3	1.4
Week	199	14	6.5
Day	161	52	24.4

The maximum number of fatalities reported on any day was 12 (Figure 4-11); on most days (54 of 77), fewer than 3 fatalities were recorded. Thus, the miss-assignment of just 1 or 2 bats to the wrong day could strongly influence the modeled daily relationship between activity and mortality. A similar rate of miss-assignment per week would have proportionately less influence on the relationship because of the greater number of weekly fatalities (Figure 4-12).

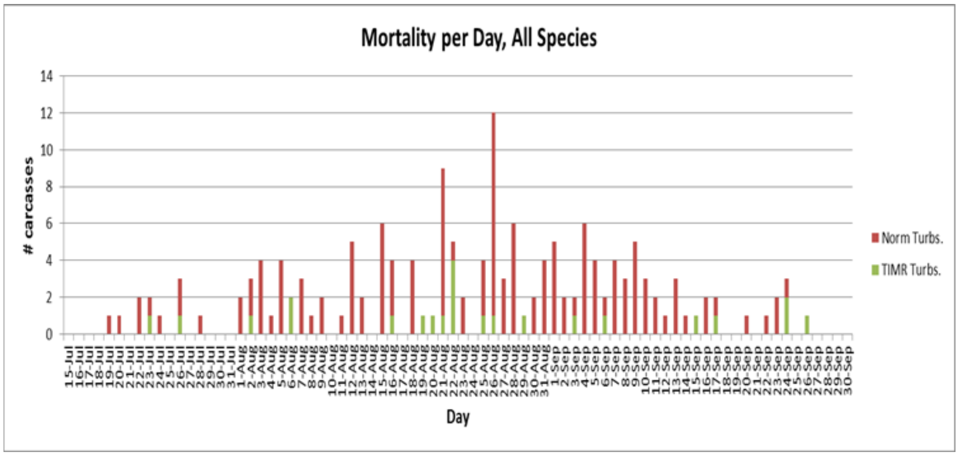


Figure 4-11
Daily bat mortality

When bat activity is relatively constant, fatalities are continuously avoided for the entire 30-minute curtailment period. When bat activity is variable, the conservation benefit is lower.

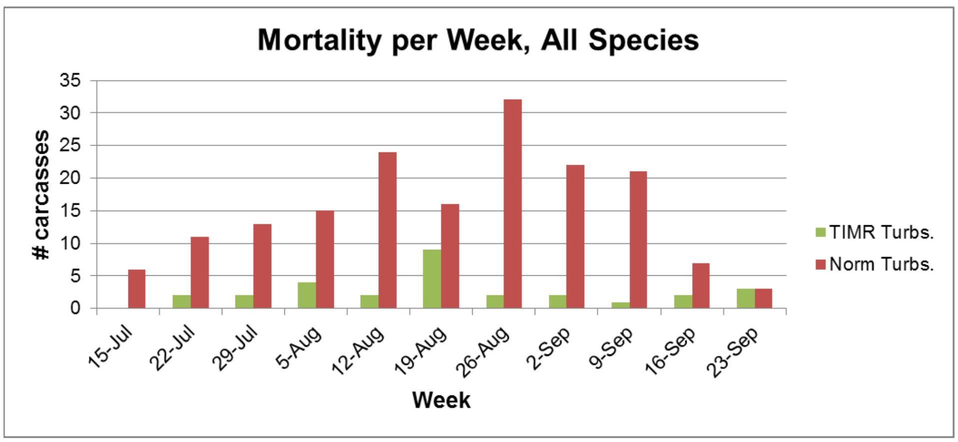


Figure 4-12
Weekly bat mortality

Limitations of Approach

Although the initial curtailment acts on current information (bats currently are exposed and wind speed currently is between 3.5 and 8 m/s), the 30-minute minimum curtailment period may extend well beyond the period of risk. When bat activity is relatively constant, then a continuous (or near-continuous) conservation benefit (avoided bat fatalities) is generated for the entire 30 minutes. But when bat activity is variable, the conservation benefit is lower.

Examination showed that for 77% of the time, current bat activity predicted bat activity for the next 10 minutes (Table 4-4). That is, a continued conservation benefit occurs 77% of the time, but 23% of the time curtailment is extended without a continued conservation benefit.

Next, intervals containing zero bat activity or some bat activity were examined (Table 4-5). Current absence of activity indicates absence of activity in the next

10 minutes about half the time (53%), while current activity indicates activity in the next 10 minutes 21% per of the time. During the remaining 26% of the time, current conditions were not a good predictor of future conditions; when activity is sporadic the model is poor at predicting activity. However, performance might be improved by acoustically monitoring a higher percentage of the turbines (currently less than 5% are acoustically monitored) or by refining the model based on lessons learned in 2015.

Despite these limitations, the model-operated turbines killed 83% fewer bats of all species studied and 90% fewer little brown bats (*Myotis)* than normally operated turbines.

When bat activity is sporadic, the model is poor at predicting activity.

Table 4-4
Bat activity calls

2015	# Calls	% Calls	Note
# Bat calls, total	17,558	100	–
# Bats calls, previous interval bats = 0	3,992	23	Previous does NOT predict current
# Bats calls, previous interval bats > 0	13,566	77	Previous predicts current

Table 4-5
Bat activity intervals

2015	# Intervals	% Intervals	Note
# Intervals, total	5,538	100	–
# Intervals, current bats = 0, previous bats = 0	2,936	53	Previous predicts current
# Intervals, current bats > 0, previous bats > 0	1,156	21	Previous predicts current
# Intervals, current bats > 0, previous bats = 0	720	13	Previous does NOT predict current
# Intervals, current bats = 0, previous bats > 0	726	13	Previous does NOT predict current

The model was good at curtailing the turbines at the right time—when bats were present.

Curtailing at the Right Time

From July 15 to September 30, 2015, a total of 17,325 bat calls were recorded (Table 4-6): 12,529 bat calls (72% of total) occurred when the model-operated turbines were at less than 2 rpm. This indicated that the model was good at curtailing the turbines at the right time—when bats were present. In comparison, the normally operated turbines were at less than 2 rpm (times of low wind speed) when only 1,072 bats (9% of total) were present.

Table 4-6
Bat activity and turbine rpm

2015	# Calls	% Calls	# Hours	% Hours
Total	17,325	100	936	100.0
Curtailed turbines < 2 rpm	12,529	72	373	40.0
Non-curtailed turbines < 2 rpm	1,072	9	92	1.6

Discussion

As hypothesized, there was a strong correlation between bat exposure due to activity (as measured by rpm-adjusted acoustic activity) and bat mortality at the 10 turbines operating normally (without TIMR). This relationship was strongest when comparing bat activity with weekly carcass numbers, where bat activity alone explained more than 60% of weekly bat mortality.

The results of TIMR Smart Curtailment and similar European systems suggest that combining bat activity monitoring, weather parameters, and temporal trends to reduce bat mortality while maintaining adequate levels of turbine operation can be applied across geographic regions and adapted to site-specific requirements.

In their review of the relationship between bat activity and mortality, Hein *et al.* (2013) argue that using post-construction activity to predict fatality has produced highly variable results in past studies and may not be possible for all species. However, several of these previous studies had very small sample sizes, and—perhaps most importantly—the activity measurements were often taken from ground level and not from within the RSZ (Jain 2005, Fiedler 2004, Johnson *et al.* 2004). Accurate characterization of bat migratory activity at wind energy facilities requires that detectors be placed well above ground level (Reynolds 2006, Kunz *et al.* 2007). Indeed, other studies found a positive relationship between post-construction activity and mortality when acoustic activity data were collected by detectors placed at least 30 meters above ground level (Korner-Nievergelt *et al.* 2013, Baerwald and Barclay 2009).

The positive correlation of bat activity with fatality documented in the present study meant that curtailment could be optimized based on real-time bat activity levels within the RSZ. Optimized curtailment resulted in a significant decrease in mortality of all bat species. These findings support the prediction of Weller and Baldwin (2012) that installing detectors on nacelles to monitor bat activity levels could provide significant improvements in tailored curtailment over detectors using only weather parameters. These findings also corroborate the results of similar systems that have been tested in Europe (Behr *et al.* 2014, Korner-Nievergelt *et al.* 2013, Lagrange *et al.* 2013). Thus, the results of TIMR and similar European systems suggest that the method of combining activity monitoring, weather parameters, and temporal trends to effectively reduce bat mortality while maintaining turbine operation at sufficient levels can be applied across geographic regions. Moreover, the TIMR Smart Curtailment system is immune to inter-annual temporal shifts in bat exposure that may occur due to changes in the timing of migration.

The current approach assumed that the presence of one bat in the RSZ was sufficient to trigger curtailment action. Although this seems like a low threshold, This is the first study to demonstrate a reduction in mortality for any *Myotis* species.

The overwhelming success of the TIMR Smart Curtailment system has implications for the future of bat conservation at wind energy facilities.

each of the four acoustic monitoring units represented 25% of the facility (or 17.6 turbines). If bat activity is evenly distributed across the facility, then that 1 call represents about 22 exposure events. The same approach could be adapted to site-specific conditions present at other facilities, for example, by using a higher threshold of calls or calls per unit of time. BSGF has a relatively high rate of bat activity. In more than 3,696 hours (77 nights × 12 hours/night × 4 ReBATs = 3,696 hours) of monitoring, 17,325 calls or 4.7 calls per hour were recorded. Thus, when a small percentage (5–10%) of a site is instrumented with acoustic monitors, a low exposure threshold may be warranted. Also, other sites could adopt a minimum curtailment period shorter than 30 minutes (*e.g.*, 10 or 20 minutes) that would likely increase curtailment efficiency.

Management Implications

Controlling turbine operation with a model that combines real-time bat exposure data and real-time information about weather conditions can greatly reduce the number of curtailment hours needed to effectively control bat fatalities at operating wind energy facilities. This mitigation is effective for all species tested, including the three species of migratory tree bat that constitute the majority (more than 75%) of fatalities, as well as the little brown bat (*Myotis*). This is the first study to demonstrate a reduction in mortality for any *Myotis* species. The overwhelming success of the TIMR Smart Curtailment system indicates a significant advance in the study of wind and wildlife interactions, and has implications for the future of bat conservation at wind energy facilities.

Section 5: TIMR Hardware and Software

Overview of TIMR with SCADA Interface

Turbine-Integrated Mortality Reduction (TIMR^{SM}) is a hardware and software system that runs real-time bat activity and weather data in models to generate bat mortality risk levels (alert statuses).

Turbine-Integrated Mortality Reduction (TIMR^{SM}) is a hardware and software system that receives real-time bat activity and weather data and uses the data in models to predict when events exposing bats to high mortality risk are occurring or will occur. It provides bat mortality risk levels to the SCADA system, indicating when the turbines should be shut down to reduce mortality and when it is safe to restart the turbines.

TIMR communicates each alert status (green, red, or yellow) to the SCADA system, which automatically shuts down the turbines to reduce bat mortality or restarts them when bats are no longer in danger.

TIMR provides a central server (TIMR server) that receives data from multiple ReBAT systems located at the same wind energy facility. Normandeau's ReBAT system is a separate, full-spectrum acoustic bat detection and monitoring system that is often used on its own. ReBAT is suitable for long-term deployments of many months to a few years with minimal hands-on maintenance and high reliability. It includes full-spectrum ultrasonic receivers that detect bat calls. Each monitoring station typically has two receivers at different heights, including one in the RSZ for wind turbines. In ReBAT, a Linux-based computer collects the bat acoustic data and transmits it to a central server, typically using cellular modems. The TIMR server is an enhanced version of the ReBAT data collection and analysis server. With TIMR, the data are transmitted in near real-time from the ReBAT systems to the TIMR server, which automatically runs the data through custom filters that remove noise files so that only files containing bat calls remain.

Operators monitor alert statuses and turbine responses on a computer screen in the SCADA Operations Center. They have override control, if needed.

The TIMR receives weather data from the Vestas Online Business (VOB) server, which is the central server for the wind energy facility providing turbine park overview and control, advanced reporting facilities, client remote access, and alarm and status messages by email and short message service (*e.g.*, text message). For this study, the weather data were collected at Turbine B16 (see Figure 2-1). Vestas turbines incorporate weather sensors that are monitored electronically through the VOB server and the SCADA system. These data were made available to the TIMR system.

The TIMR server runs the bat activity and weather data in models (see Section 3) to generate bat mortality risk levels (*i.e.*, alert statuses). It communicates each alert status to the SCADA system, which automatically responds (Table 5-1). In addition, the alert status is displayed on a computer screen in the operations center via a Human Machine Interface (HMI) interface

(Figure 5-1), allowing the operators to monitor alert statuses and turbine responses.

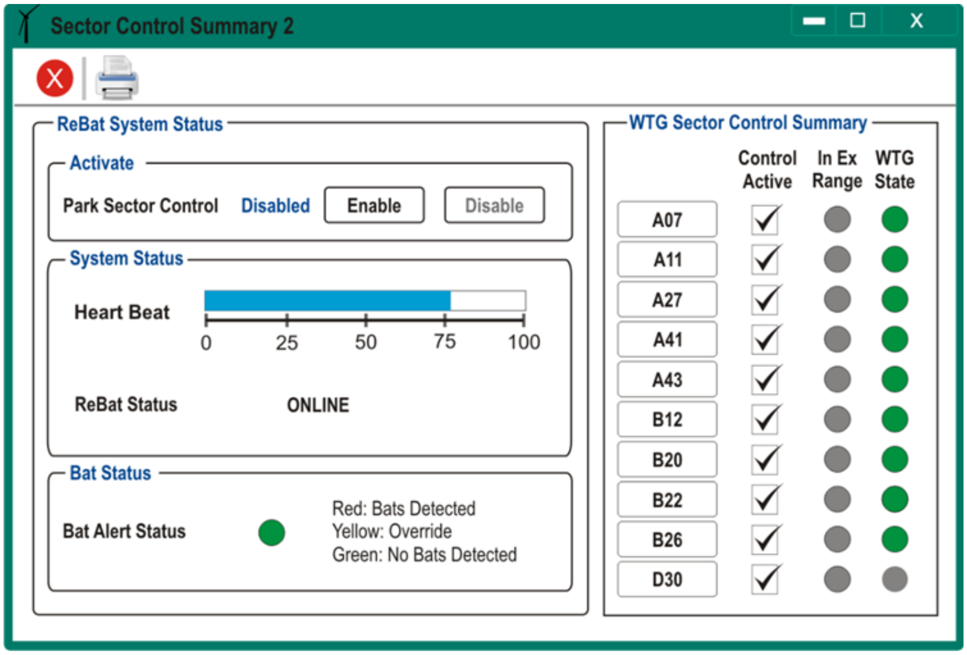


Figure 5-1
SCADA Human Machine Interface display for TIMR

Table 5-1
TIMR status changes based on risk values and current conditions

Alert Status		Current Alert Status			
		1 Green No Bats Detected or Predicted	**2 Yellow Override (Wind ≥ 8 m/s)**	**3 Red Bats Detected**	**4 Red Bats Predicted by Model**
Alert Status During the Previous 10-Minute Interval	1 Green: No bats detected or predicted and wind speed < 8 m/s	Action—None. The alert status stays Green, and turbines continue to operate normally.	Action—Changes alert status to Yellow. Turbines continue to operate normally.	Action—Initiates curtailment. Changes alert status to Red.	Action—Initiates curtailment. Changes alert status to Red.
	2 Yellow: Override (wind ≥ 8 m/s)	Action—Changes alert status to Green. Turbines continue to operate normally.	Action—None. The alert status stays Yellow. Turbines continue to operate normally.	Action—Initiates curtailment. Changes alert status to Red.	Action—Initiates curtailment. Changes alert status to Red.
	3 Red: Bats detected and wind speed < 8 m/s	Action—Ends curtailment. Changes alert status to Green.	Action—Ends curtailment. Changes alert status to Yellow.	Action—Turbines curtailed. Alert status stays Red. If within the last 10 minutes of curtailment, then extends curtailment 10 minutes. If outside the last 10 minutes of curtailment, then no action.	Action—Turbines curtailed. All turbines curtailed. Alert status stays Red. If within the last 10 minutes of curtailment, then extends curtailment 10 minutes. If outside the last 10 minutes of curtailment, then no action.
	4 Red: Bats predicted by model	Action—Ends curtailment. Changes alert status to Green.	Action—Ends curtailment. Changes alert status to Yellow.	Action—Turbines curtailed. All turbines curtailed. Alert status stays Red. If within the last 10 minutes of curtailment, then extends curtailment 10 minutes. If outside the last 10 minutes of curtailment, then no action.	Action—Turbines curtailed. All turbines curtailed. Alert status stays Red. If within the last 10 minutes of curtailment, then extends curtailment 10 minutes. If outside the last 10 minutes of curtailment, then no action.

System Configuration

C1000 Datalogger and Distributed Network Protocol

The TIMR server and VOB server communicate via a CR1000 datalogger (Campbell Scientific, Logan, Utah; Figure 5-2). The VOB server directly controls the turbines, based on risk level. TIMR software uses the Distributed Network Protocol (DNP3) to update an array of analog values (*i.e.*, bat activity and weather data) in the CR1000 datalogger. DNP3 is a set of communications protocols used between components in process automation systems. It is an alternative to the Modbus protocol and provides equivalent functionality plus significant enhancements. DNP3 is used mainly by electric and water utilities. It plays a crucial role in SCADA systems, where it is used by SCADA Master Stations (*i.e.*, Control Centers), Remote Terminal Units (RTUs), and Intelligent Electronic Devices (IEDs). It is primarily used for communications between a Master Station and RTUs or IEDs.

TIMR software uses the Distributed Network Protocol (DNP3) to update an array of analog values (bat activity and weather data) in a CR1000 datalogger.

Figure 5-2
Campbell Scientific CR1000 datalogger with NL-116 (NL-120 was used) Ethernet option (cover removed)

Only one CR1000 datalogger is required. Typically, it is installed at the SCADA Operations Center, but for this application the CR1000 is installed at the same location as the TIMR server. The TIMR server must be able to access the CR1000 over the network. The TIMR server is configured as DNP3 (Master) device 1, and the VOB server is configured as DNP3 (Master) device 3. They both update the CR1000, which is configured as a DNP (Slave) outstation device. The TIMR server updates the system status (red, yellow, or green), including which species of endangered bat has been detected, how many bats are detected over what time period, *etc.* The VOB server updates various weather data. Both sets of data are used in the TIMR models to determine the risk level. The system status can be monitored on an HMI display at the SCADA Operations Center (see Figure 5-1).

Network Traffic

The ReBAT systems and the TIMR server communicate data over an encrypted Secured Socket Shell (SSH)—a secure command line interface to access a remote computer—that consists of audio (WAV) files (*i.e.*, bat calls) and management data (*e.g.*, system voltage, hard drive usage, temperature, signal strength, and transducer status). An encrypted SSH was also used to manage the TIMR server.

The CR1000 DNP3 and the TIMR server communicate data indicating system status (red, green, or yellow) as integer values. The TIMR server does not send the status data directly to the Vestas VOB server; instead, it sends it to the CR1000, and the VOB server obtains it from the CR1000.

Encrypted data are communicated over a secure command line interface used to access remote devices.

The VOB server provides three index locations (ambient temperature, wind speed, and nacelle direction) to the CR1000, and the TIMR server obtains that information from the CR1000.

System Status and Other Analog Values

For TIMR, the CR1000 includes an array of analog values used for storing real-time information (Table 5-2). The array is zero index-based, meaning that the first value is at index offset 0, the second value is at 1, *etc.* Once data have been written into the array, the values remain the same until an index location is rewritten with a different value. All index values are 16-bit, DNP3 Object types 30, 40, and 41 (analog input and output).

The CR1000 includes an array of analog values used for storing real-time information. For TIMR, these are bat activity values and weather values.

The TIMR server writes bat activity values into index locations marked with a "W." The Vestas VOB server writes weather values into index locations marked with an "R," which the TIMR server reads (see Table 5-1). Other options include the following:

- The VOB server could provide weather and other data directly to the TIMR server; or
- The TIMR server could maintain its own weather data using simple instrumentation, or could receive it from National Oceanic and Atmospheric Administration (NOAA) weather stations.

Table 5-2
DNP3 array of analog values for TIMR

Index	Index Description	Values	Values Description	W/R*
0	System status, ReBAT or TIMR	0–3	0 = Off-line (all ReBAT® systems are off-line, no bats are being detected); if at least one ReBAT system is sending data, this will not be 0. 1 = On-line (some ReBAT systems are off-line) 2 = On-line (all ReBAT systems are on-line) 3 = Off-line (TIMR system is in maintenance mode)	W
1	Combined bat alert status	1–4	1: Green = No bats detected or predicted (wind < 8 m/s) 2: Yellow = Override (wind ≥ 8 m/s, no curtailment) 3: Red = Bats detected, curtailment (wind < 8 m/s) 4: Red = Bats predicted by model, curtailment (wind < 3.5 m/s)	W
2	Species 1 bat alert status			
3	Species 2 bat alert status			
4	Species 3 bat alert status			
5	Species 4 bat alert status			
6	System health register	0–100	Shows system activity once per second. After 100, it rolls over to 0.	W
7	CR1000 voltage			–
8	CR1000 temperature, Celsius			–
9–20	Unused	–	–	–
21	Ambient temperature, Celsius	0–110	From Turbine B16	R
22	Wind speed, meters per second	0–150	From Turbine B16	R
23	Nacelle direction, wind	0–360	Wind direction; 90 = from the east; 180 = from the south; 270 = from the west, 0 = from the north; from Turbine B16	R

*W = written by TIMR server; R = Written by VOB server and read by TIMR server

Curtailment Timer and Override

When no bats are detected by ReBAT or predicted by the TIMR model, the alert status is green (No Bat: no bats detected or predicted; see Table 5-1). When a bat is detected, the alert status changes to red (Alert: bats detected and wind speed < 8 m/s) and curtailment starts on a 30-minute timer. If another bat is detected in the first 20 minutes of the timed interval, the curtailment time is not extended. If one or more bats are detected during the last 10 minutes of the timed interval, the curtailment timer extends for another 10 minutes. The curtailment timer will continue to extend each time one or more bats are detected in the remaining 10 minutes of the timed interval.

Alert status is green when no bats are detected or predicted; red when bats are detected and wind speed < 8 m/s; and yellow when wind speed is ≥ 8 m/s, all other conditions are ignored, and override turns off curtailment.

An override condition (yellow alert status) occurs when the wind speed is ≥ 8 m/s (see Section 7, SCADA System Modifications and Curtailment Override). In yellow alert status, all other conditions are ignored and any curtailment ceases to be in effect. Override occurs automatically as part of TIMR's operating parameters.

An example of status changes and curtailment timer operation is provided in Table 5-3. In this example, if 2 bats are detected at minute 21 in the timed interval—which is within the remaining 10 minutes of timer operation—the timed interval will be extended 10 minutes to curtail for 40 minutes total. If another bat is detected at minute 29—which is outside the remaining 10 minutes of the extended 40-minute timer operation—the timer will still run for 40 minutes total. If another bat is detected at minute 33—which is within the remaining 10 minutes of the extended 40-minute timer operation—the extended timer will now run for 50 minutes total. When no bats are detected in the last 10 minutes of the timed interval or the extended timer operation, the status will change to green.

If the risk of fatalities is too high, turbines are curtailed for a minimum of 30 minutes. If risk continues to be elevated, curtailment can be extended in 10-minute increments.

Table 5-3
Example of status changes and curtailment timer operation

Report Time and Bats Detected	Status	Curtailment Timer
0090 no bats	green	
0100 bat detected	red	30-minute timer begins
0110 no bats	red	30-minute timer continues (status locked)
0120 no bats	red	30-minute timer continues (status locked)
0130 bats detected at 0121	red	Timer extends for 10 minutes (40 minutes total)
0140 no bats	green	Extended 40-minute timer expires
0150 bat detected	red	30 minute timer begins
0200 no bats	red	30-minute timer continues (status locked)
0210 bat detected	red	30-minute timer continues (status locked)
0220 bat detected	red	Timer extends for 10 minutes (40 minutes total)
0230 bat detected	red	Timer extends for 10 minutes (50 minutes total)
0240 bat detected at 0233	red	Timer extends for 10 minutes (60 minutes total)
0250 no bats	green	Extended 60-minute timer expires

Section 6: Economic Analysis

Introduction

Economic impact studies of turbine curtailment to protect wildlife estimate a loss of 1–5% of annual revenue at a given wind energy facility.

Only a few studies have documented the economic impacts of turbine curtailment to protect bats (Baerwald *et al.* 2009, Arnett *et al.* 2011, Martin 2015). These studies reported a loss of 1–5.3% of annual revenue at a given wind energy facility.

Methods

To understand the impact of turbine curtailment on the generation and revenue of a specific facility, knowledge of the turbine specifications (make and model) and of the wind speed regime at the location are critical. This information is used to determine the capacity factor (or load factor) for the facility.

Turbine specifications and local wind speed are used to calculate the capacity factor for a facility. Capacity factor, in turn, is used to estimate the average generation and revenue of turbines for the lifespan of the facility—and whether or not the facility is cost-effective to operate.

The capacity factor is used to estimate the average generation and revenue of the turbines for the lifespan of the facility. The capacity factor, among other factors, is used in the economic assessment of a facility to determine whether or not the levelized cost of energy (LCOE) makes that facility cost-effective and economically feasible to operate.

The factors determining estimated changes in generation and revenue are (a) the time at which curtailment occurs (month and time of night), and (b) the wind speed during each curtailment—which potentially can reduce the capacity factor and LCOE for a wind energy facility. A negative impact on the LCOE could influence existing contracts and power purchase agreements for wind energy facilities, especially if curtailment was not part of the original operating plan.

Turbine Specifications

Vestas V82 turbines begin generating 0.25 MW at a cut-in speed of 3.5 m/s. Peak production occurs at 13.5 m/s, providing 1.65 MW of generation.

The V82 turbines begin generating 0.25 MW at the cut-in speed of 3.5 m/s. Generation output steadily increases between the cut-in speed and the rated speed of 13.4 m/s, at which maximum production begins (see Figure 3-4). Peak production occurs at 13.5 m/s, providing 1.65 MW of generation. The turbines have a rated cut-out speed of 24.1 m/s.

The Vestas V82 turbines are designed to freewheel (Table 6-1). At 3.5 m/s wind speed, the turbine generator can engage and produce energy. Turbines using the TIMR system were allowed to operate normally—the only time these turbines were pitched to pause was when the model indicated that bats were present or were predicted. Under those conditions, the SCADA system issued an alarm status directing the turbines to go into curtailment (pitch-to-pause mode).

Table 6-1
Vestas V82 turbine configuration and operation

Operating Mode	Turbine Configuration			Turbine Operation	
	Blade Orientation	**Nacelle Movement**	**Brakes**	**Rotor Speed**	**Generating?**
Pitch to stop	Pitched to avoid/ minimize wind capture	Does NOT turn to capture wind	On	0 rpm	No
Curtailment (pitch-to-pause: feathered or feathered out of the wind)	Pitched to avoid/ minimize wind capture; wind speed is sufficient for generation	Turns to capture wind	Off	< 1 rpm	No
Pitch to run	Pitched to capture maximum wind	Turns to capture wind	Off	3.5 m/s to 24.1 m/s maximum of 14.4 rpm	Yes
Freewheeling or idling	Pitched to capture maximum wind	Turns to capture wind	Off	< 3.5 m/s maximum of 14.4 rpm	No

rpm = revolutions per minute, m/s = meters per second, "feathered" = rotating turbine blades at a 90-degree angle

Wind Speed

Average annual wind speeds vary from approximately 4 m/s to more than 10 m/s across the United States (Figure 6–1), making the location of a wind energy facility a key factor in determining the impact of curtailment on generation and revenue. BSGF has an average annual wind speed of 6.3 m/s, which is relatively low when compared with other parts of the United States. A significant portion of generation at this facility occurs between 3.5 m/s and 8.5 m/s. Thus, curtailment at low wind speeds can have a greater impact on overall revenue for BSGF, compared with facilities in other areas of the United States that have higher average wind speeds.

BSGF has an average annual wind speed of 6.3 m/s, which is relatively low when compared with other parts of the United States.

Average wind speed also varies by month, and in the summer months is generally greater at night than during the day. Wind speed—and thus generation—at BSGF is typically at its lowest point in July and August, after which it starts to increase in September and October (Figure 6-2).

Wind speed—and thus generation—at BSGF is typically at its lowest point in July and August.

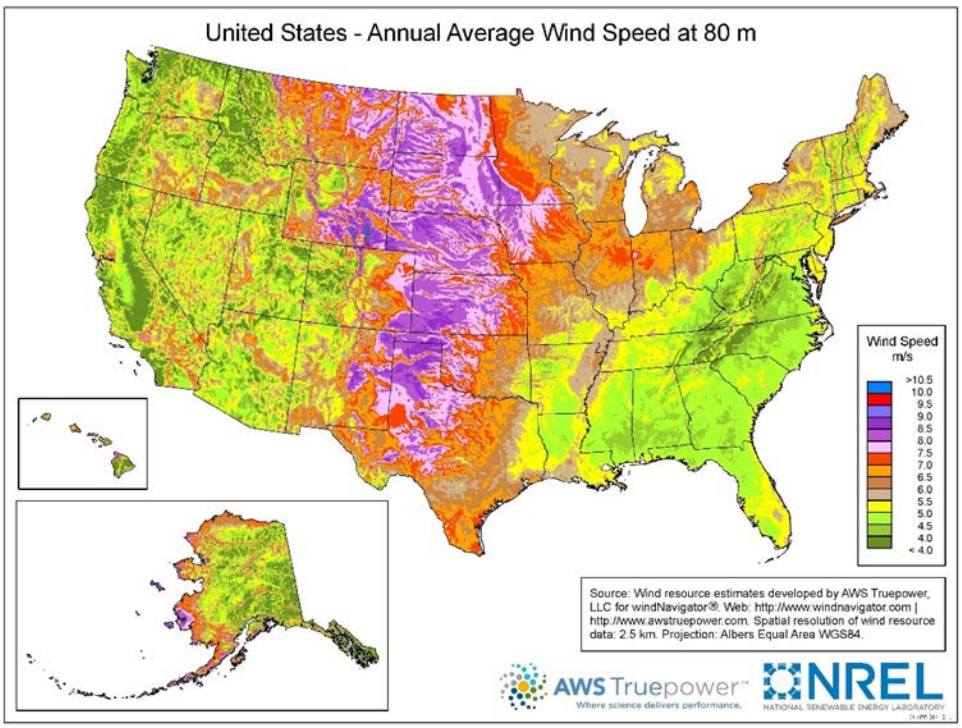


Figure 6-1
Average wind speeds across the United States[1]

[1] http://www.nrel.gov/gis/images/80m_wind/USwind300dpe4-11.jpg

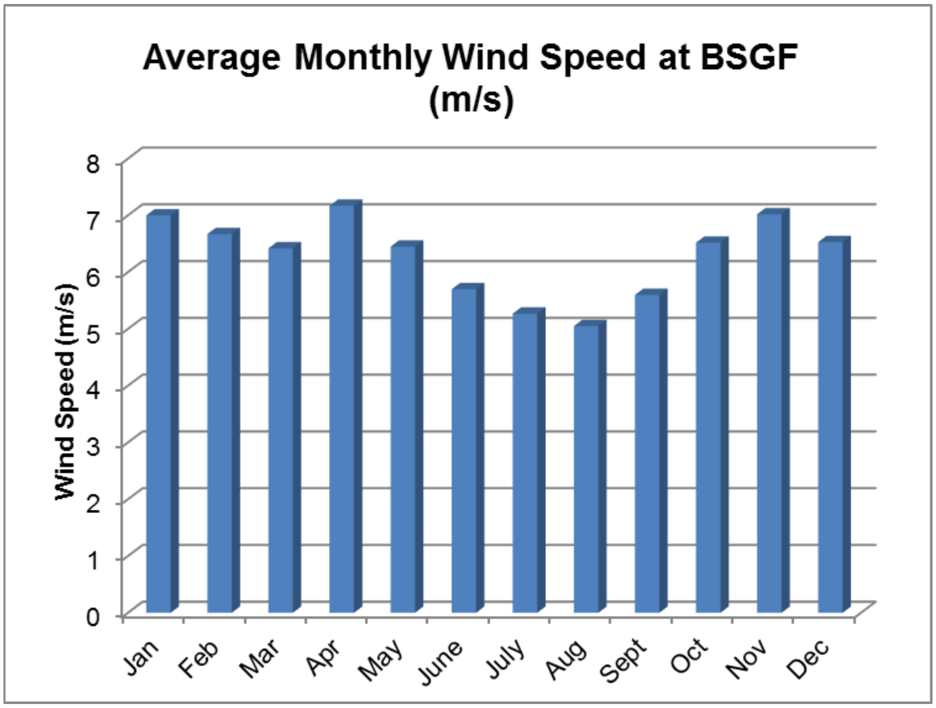


Figure 6-2
Average monthly wind speed at BSGF

The capacity factor for BSGF is 26.9%, compared with capacity factors of 26–50.6% at other U.S. wind energy facilities

Capacity Factor

The capacity factor of a power plant is the ratio of average power generated over a period of time divided by the rated peak power generation (or nameplate capacity) of the plant. The rated peak power generation and power curve for each turbine make and model is unique, and is based on the structural design of the turbine. Operating wind energy facilities in the United States currently have capacity factors ranging from 26–50.6%, with a current median of 38%. The capacity factor for BSGF is 26.9%.

Generation change (in MWh) was estimated based on wind speed at the time of curtailment. Revenue change was calculated at $40/MWh of market revenue.

Generation and Revenue Analysis

To calculate how generation changed for turbines using the TIMR Smart Curtailment approach, output from the SCADA system was used to determine the curtailment period of each turbine (in hours.minutes, which expresses time in decimal format: for example, 4 hours and 15 minutes is 4.25). Generation change (in MWh) was estimated based on wind speed at the time of curtailment and the total period of curtailment (during which all study turbines were in pitch-to-pause mode).

The following assumptions were used to calculate the difference in revenue corresponding to a change in generation: a locational marginal price (LMP, overnight hours) of $15/MWh, a production tax credit (PTC) of $20/MWh, and a renewable energy credit (REC) of $5/MWh. This calculation results in an estimated $40/MWh of market revenue.

However, calculations using these assumptions and estimates do not take into account issues such as curtailment to meet grid restrictions or curtailment to honor agreements with municipalities to mitigate shadow or sound, for example.

Finally, calculations for BSGF assumed that bats in the upper Midwest region migrate during the period from July 1 through October 31, which is the period of turbine curtailment recommended by the U.S. Fish and Wildlife Service (USFWS). This migratory period may vary in other parts of the United States. Therefore, the actual generation reduction and estimated difference in revenue will vary by site.

Between July 15 and September 30, the estimated difference between normally operated turbines and model-operated turbines was 89.8 MWh per turbine.

Results

Estimated Lost Generation

Between July 1 and October 31, the 10 normally operated turbines each generated an average of 1,105.2 MWh and the 10 model-operated turbines each generated an average of 990.8 MWh, resulting in an estimated production difference of 114.4 MWh per turbine (Table 6-2).

However, curtailment during July 1–14 and October 1–31 was likely superfluous due to limited bat mortality; in October, only 4 carcasses were recovered. Therefore, if the TIMR Smart Curtailment approach had been used only from July 15 to September 30—when implementation actually helped reduce bat fatalities—the 10 normally operated turbines each would have generated an average of 606.3 MWh and the 10 model-operated turbines each would have generated an average of 516.5 MWh, resulting in an estimated production difference of 89.8 MWh per turbine (Table 6-3).

Details of estimated lost generation calculations based on data collected for each turbine are shown in Tables A-1 through A-4 in Appendix A.

Between July 15 and September 30, the estimated difference between normally operated turbines and model-operated turbines represents an average revenue loss of $3,591.80 per turbine—or $316,082 for all 88 turbines at BSGF.

Estimated Lost Revenue

Assuming a market revenue value of $40/MWh, the estimated revenue generation between July 1 and October 31 was $44,208 for each of the normally operated turbines and $39,632 for each of the model-operated turbines. The difference between these two estimates represents an average revenue loss of $4,578.60 per turbine. If all 88 turbines had operated under the TIMR Smart Curtailment scheme, estimated total revenue loss would be $402,916 (Table 6-2).

However, if only the period when TIMR Smart Curtailment was actually needed to reduce bat fatalities is considered, the revenue losses are a bit smaller. The estimated revenue generation between July 15 and September 30 was $24,253.80 for each of the normally operated turbines and $20,662.00 for each of the model-operated turbines. The difference between these two estimates represents an average revenue loss of $3,591.80 per turbine. If all 88 turbines had operated under the TIMR Smart Curtailment scheme, estimated total revenue loss would be $316,082 (Table 6-4).

Table 6-2
Comparison of estimated generation and revenue between July 1 and October 31, 2015

	Generation			Revenue		
Operation Method	**All 10 Study Turbines (MW)**	**Average for a Single Turbine (MW)**	**Theoretical for all 88 Turbines (MW)**	**All 10 Study Turbines**	**Average for a Single Turbine**	**Theoretical Revenue for all 88 Turbines**
Normal	11,052.44	1,105.2	97,261.47	$442,097	$44,209.70	$3,890,458
Model	9,907.79	990.8	87,188.55	$396,311	$39,631.10	$3,487,542
Difference	1,144.65	114.4	10,072.92	$45,786	$4,578.60	$402,916 (10.35% of the season)

MW = megawatt

Table 6-3
Comparison of estimated generation and revenue between July 15 and September 30, 2015

	Generation			Revenue		
Operation Method	**All 10 Study Turbines (MW)**	**Average for a single turbine (MW)**	**Theoretical for all 88 Turbines (MW)**	**All 10 Study Turbines**	**Average for a Single Turbine**	**Theoretical Revenue for all 88 Turbines**
Normal	6,063.45	606.3	53,358.36	$242,538	$24,253.80	$2,134,334
Model	5,165.49	516.5	45,456.31	$206,620	$20,662.00	$1,818,252
Difference	897.96	89.8	7,902.05	$35,918	$3,519.80	$316,082 (14.8% of the season)

MW = megawatt

Section 7: Other Factors Relevant to Facility Operations

Introduction

This section discusses topics that facility operators may find useful when implementing TIMR, including:

- Regulatory requirements;
- Potential impacts on turbine operation and maintenance; and
- SCADA system modifications and curtailment override.

This study found that wildlife regulatory requirements were not an obstacle to TIMR implementation, but operation may require proactive planning with federal and state agencies responsible for wildlife protection and power system reliability.

Regulatory Requirements

This study found that wildlife regulatory requirements were not an obstacle to TIMR implementation at the time of the study, but TIMR operation may require proactive planning with the Regional Transmission Organizations (RTOs) and the North American Electric Reliability Corporation (NERC).

Wildlife Regulations and Permits

The threatened northern long-eared bat (*Myotis septentrionalis*) is the only federally listed bat species known to live in Wisconsin. Although the USFWS did not require a permit for the present study, if a northern long-eared bat were to become a fatality during TIMR operation, the USFWS would require immediate notification, triggering a Section 7 Consultation process. No fatalities of federally listed bat species were found during this study.

The Wisconsin Department of Natural Resources lists four cave bat species as state threatened, but does not require a permit for wind energy facility operation.

State and federal permits were required for the collection of bat carcasses during this study.

North American Electric Reliability Corporation

NERC[2] is the regulatory authority that assures reliability of the bulk power system throughout North America. NERC develops and enforces mandatory reliability standards and is subject to oversight by the Federal Energy Regulatory Commission (FERC) in the United States and governmental authorities in Canada. NERC regulates users, owners, and operators of the bulk power system.

RTOs are nonprofit organizations that administer the wholesale electricity market with the intention of providing reliable and cost-effective systems. The RTO for BSGF is the Midcontinent Independent System Operator (MISO).[3] Each power producer operates under a tariff approved by FERC for its RTO. That tariff requires the power producer to register its generation resources by type (*e.g.*, wind, natural gas, coal, *etc.*) and MW capacity, and to forecast the amount of electrical energy output that each power plant will produce on an hourly basis. Any changes to this production forecast, or information regarding planned or forced outages, must be communicated to the RTO. A permanent change in turbine operation may result in a necessary contract change with the RTO.

Any proposed change to turbine operation aimed at reducing bat fatalities will require proactive planning with a power producer's Regional Transmission Organization and the North American Electric Reliability Corporation to ensure that curtailment operations will not trigger an Order of Noncompliance.

Daily communication between RTOs and power producers is critical and provides each RTO with accurate daily data on the type and amount of energy that will be loaded onto the grid. The RTO uses these daily data to ensure that all customers receive the energy that they require.

Maintenance activities that require shutting down a power plant are typically scheduled months in advance. Power producers schedule planned outages with their RTOs. This allows each RTO to coordinate regional energy production to ensure a sufficient supply for customers at all times.

Unplanned outages can occur for various reasons, such as animal interference at a substation, a vehicular accident that damages a transformer, or a lightning strike at a facility. NERC defines an outage as an occasion when one protective relay (*i.e.*, breaker) goes out (MISO 2016). When a NERC-defined outage occurs, the power producer has 15 minutes to contact its RTO and report the outage. This allows the RTO to immediately increase energy load onto the grid to compensate for the lost load.

To ensure that they maintain compliance with NERC and avoid the possibility of significant NERC fines, some power companies have internal reporting procedures and operating requirements that are more restrictive than those defined by NERC.

Under the Energy Policy Act of 2005, NERC has the authority to issue Orders of Noncompliance, which can result in issuance of fines up to $1 million per day

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[2] http://www.nerc.com/Pages/default.aspx

[3] https://www.misoenergy.org/Pages/Home.aspx

of occurrence (FERC 2010). Any proposed change to turbine operation aimed at reducing bat fatalities will require proactive planning with a power producer's RTO and NERC to ensure that curtailment operations will not trigger an Order of Noncompliance.

Potential Impacts on Turbine Operation and Maintenance

The present, relatively short (4-month) study was not long enough to detect cumulative impacts on turbine electrical and mechanical systems that may arise from implementing Smart Curtailment. However, one potential operating issue and one apparent maintenance benefit came to our attention.

To reduce the possibility of rapid changes in operating mode leading to temporary loss of turbine operation, the curtailment period was extended from 10 to 30 minutes at the BSGF site.

Temporary Loss of Operation

TIMR can signal curtailment on the order of every 10 minutes. To reduce the possibility of rapid changes in operating mode leading to temporary loss of turbine operation, the curtailment period was extended from 10 to 30 minutes at the BSGF site. There were no other noticeable mechanical or electrical system issues associated with operation of TIMR.

Operation of the TIMR system was discussed during the spring and early summer of 2015. Using a 10-minute curtailment period would have caused turbines to cut in and out of operation on a rapid basis. For example, when wind speed is not consistently maintained at 3.5 m/s, the system will cause a turbine generator to start up and shut down many times over a short period. The Vestas V82 turbines have hydraulic pitch control, which allows for multiple, rapid changes in operation via hydraulic pumps. With rapid changes in operating mode, these hydraulic cycling breakers may error and fault, causing temporary loss of turbine operation. Other turbine makes and models that use electronic pitch controls would have similar issues.

Operation of TIMR appears to have saved maintenance costs related to the main bearing assemblies on two of the wind turbines.

Such rapid change in operating mode leading to loss of turbine operation was minimized with use of the TIMR system, which locked the bat activity signal for at least 30 minutes. Once the SCADA system received a red alert status signal and curtailed the turbines (pitch-to-pause mode), the duration of curtailment continued for a minimum of 30 minutes. This eliminated the possibility of rapid changes in operating mode.

Maintenance Cost Savings

Operation of TIMR appears to have saved maintenance costs related to the main bearing assemblies on two of the wind turbines.

Before the study began, two model-operated turbines had been experiencing poor performance of the main bearing assembly in the nacelle. We Energies decided to delay replacement of these bearing assemblies, because replacement would have removed the turbines from study participation for up to 2 weeks. This decision worked in favor of We Energies, as both turbines continued to operate throughout the study and replacement work was delayed by 5 months. It is possible that reduced operation of these two turbines under the curtailment scheme briefly extended the lifespan of the main bearing assemblies—saving maintenance costs and allowing time to coordinate their replacement after the study.

SCADA System Modifications and Curtailment Override

The SCADA system is designed with open alarm codes that do not identify a specific turbine operation. One of these open alarm codes was chosen as the destination for alert status signals from the TIMR system.

The TIMR system can send a signal to a selected computer/phone for manual operation of the turbines, or it can send a signal directly to the turbines. The turbines at BSGF use the Vestas SCADA system for remote operating system control. The TIMR system curtails turbines by sending a signal directly to the SCADA system. Establishing this control pathway required several modifications to the SCADA system, including allowing TIMR access through the We Energies computer system firewall.

An open (available) alarm code was used to integrate the TIMR alert status signal into the Vestas SCADA system. The SCADA system is designed with open alarm codes that do not identify a specific turbine operation. One of these open alarm codes was chosen as the destination for alert status signals from the TIMR system (see Section 5 for a description of the red, yellow, and green alert status signals).

When the TIMR system triggered a red alert status (curtailment), rotation of the hub and blades reached near zero within one minute of receiving the signal.

In early testing during periods of high wind speed (more than 8.0 m/s), the TIMR system predicted bat activity and issued a red alert triggering curtailment. This curtailment caused a significant generation loss, as well as a report to MISO (the facility's RTO) to describe the nature of the unexpected outage. A discussion with Normandeau staff resulted in a decision to allow the turbines to operate during high winds. This decision preserved significant generation with few to no bat fatalities, since bats are most active during periods of low wind speed.

A yellow alert status (override) was included to avoid unexpected outages by overriding curtailment.

Thus, a yellow alert status (override) was included in the study design. This yellow alert status avoids unexpected outages by overriding curtailment. For example, during a red alert status, if wind speeds increase beyond 8 m/s, the TIMR system generates a yellow alert status to override the red alert, and turbines return to normal operation.

Vestas provide 24-hour surveillance for wind turbine operations. Thus, the other open alarm codes in the SCADA system are used for various turbine operations that require round-the-clock monitoring. If a turbine is experiencing problems, an alarm is sent to the Vestas surveillance system. The SCADA system flags the distressed turbine on a monitor at BSGF headquarters, allowing facility personnel to give immediate attention to the problem. A specific numerical code identifies each individual turbine operation and any potential problem that may occur.

Site personnel are notified when problems persist at a turbine so they can maintain TIMR system performance and modify turbine operation, if necessary

When a single turbine sends an alarm, the surveillance alarm concentrator determines whether the alarm can be reset by remote control or requires notification of on-site personnel. When an alarm cannot be reset remotely, or when it is not reset within 30 minutes by site personnel, all site technicians and the site supervisor receive a notice identifying the turbine and describing the alarm code. This notification allows oversight of TIMR system performance and the opportunity to modify turbine operation, if necessary.

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Appendix A: Details of Estimated Lost Generation Calculations

Tables A-1 through A-4 present details of estimated lost generation calculations based on data collected for each of the 10 turbines operating under normal conditions and each of the 10 turbines operating under model conditions. Data were collected from July 1 to October 31 and, for a shorter time period, from July 15 to September 30, 2015. Observations of bat fatalities at the test facility showed that implementation of TIMR Smart Curtailment would be most effective in protecting bats during the July 15–September 30 time period.

Table A-1
Estimated lost generation for normally operated turbines between July 1 and October 31, 2015

Normally Operated Turbines—July 1 to October 31, 2015								
Turbine Number[1]	Average Wind Speed (m/s)	Generation (MW)	Total Hours of Turbine Generation[2]	Percentage of Turbine Generation Time (%)	Actual Curtailment Occurrences (hours.minutes)[3]	Percentage of Time Turbines Were Curtailed (%)	Calculated Lost Generation (MW)[4]	Availability (%)[5]
A10	5.6	1,092,873	1,198.67	81	–	–	–	98.82
A20	6.5	1,337,443	1,236.83	84	–	–	–	99.54
A26	6.1	1,148,699	1,220.00	83	–	–	–	99.77
A42	6.0	1,219,136	1,201.00	81	–	–	–	98.82
A44	5.8	1,091,246	1,186.83	80	–	–	–	99.63
B4	5.8	1,111,513	1,192.17	81	–	–	–	99.25
B19	6.1	977,560	1,214.33	82	–	–	–	98.45
B23	5.8	910,144	1,170.33	79	–	–	–	99.05
B31	5.9	1,009,418	1,191.67	81	–	–	–	99.90
D43	6.0	1,154,407	1,240.33	84	–	–	–	97.82
Total	–	**11,052,439**	**12,052.16**	–	–	–	–	–
Average	**6.0**	**1,105,244**	**1,205.22**	**82**	–	–	–	**99.11**

[1] All data in the table are from the study period
[2] Total hours available for any one turbine: 1,476 hours
[3] Curtailment may occur at any wind speed less than 8 m/s
[4] Calculated lost generation due to curtailment
[5] Availability is the percentage of time the turbine is available to function
m/s = meters per second
MW = megawatt

Table A-2
Estimated lost generation for model-operated turbines between July 1 and October 31, 2015

Model-Operated Turbines—July 1 to October 31, 2015								
Turbine Number [1]	**Average Wind Speed (m/s)**	**Generation (MW)**	**Total Hours of Turbine Generation[2]**	**Percentage of Turbine Generation Time (%)**	**Actual Curtailment Occurrences (hours.minutes)[3]**	**Percentage of Time Turbines Were Curtailed (%)**	**Calculated Lost Generatio n (MW)[4]**	**Availability (%)[5]**
A7	5.6	983.34	924.83	63	494.30	33.49	70.59	99.67
A11	6.3	1049.10	953.17	65	483.43	32.75	82.69	98.89
A27	5.7	1,030.43	924.33	63	494.40	33.50	70.86	98.37
A41	6.1	1,138.82	964.33	65	497.48	33.70	89.83	99.88
A43	6.1	1,136.69	942.83	64	499.26	33.83	91.00	98.60
B12	5.7	925.93	861.00	58	453.20	30.70	68.05	94.50
B20	5.5	984.57	931.17	63	485.57	32.90	61.90	97.78
B22	5.7	876.94	945.17	64	500.48	33.91	59.47	99.30
B26	5.9	928.30	937.17	63	493.36	33.43	57.34	99.21
D30	5.7	853.70	914.00	62	484.59	32.83	54.15	98.80
Total	**-**	**9,907.79**	**9,298.00**	–	**4,888.20**	–	**705.88**	**985.00**
Average	**5.83**	**990.78**	**929.80**	**63**	**488.82**	**33.12**	**70.73**	**98.50**

[1] All data in the table are from the study period
[2] Total hours available for any one turbine: 1,476 hours
[3] Curtailment may occur at any wind speed less than 8 m/s
[4] Calculated lost generation due to curtailment
[5] Availability is the percentage of time the turbine is available to function
m/s = meters per second
MW = megawatt

Table A-3
Estimated lost generation for normally operated turbines between July 15 and September 30, 2015

Normally Operated Turbines—July 15 to September 30, 2015								
Turbine Number[1]	Average Wind Speed (m/s)	Generation (MW)	Total Hours of Turbine Generation[2]	Percentage of Turbine Generation Time (%)	Actual Curtailment Occurrences (hours.minutes)[3]	Percentage of Time Turbines Were Curtailed (%)	Calculated Lost Generation (MW)[4]	Availability (%)[5]
A10	5.4	604,450	752.50	81	–	–	–	99.57
A20	6.3	745,161	774.83	84	–	–	–	99.33
A26	5.8	625,915	757.50	82	–	–	–	100.00
A42	5.9	692,932	748.17	81	–	–	–	98.72
A44	5.6	602,814	739.50	80	–	–	–	99.96
B4	5.6	616,241	752.33	81	–	–	–	98.81
B19	5.8	525,106	757.67	82	–	–	–	97.99
B23	5.6	481,477	734.33	79	–	–	–	98.63
B31	5.7	546,065	744.00	81	–	–	–	99.97
D43	5.8	623,288	767.67	83	–	–	–	96.56
Total	–	**6,063,449**	**7,528.50**	–	–	–	–	–
Average	**5.8**	**606,345**	**752.85**	**81**	–	–	–	**98.95**

[1] All data in the table are from the study period
[2] Total hours available for any one turbine: 1,476 hours
[3] Curtailment may occur at any wind speed less than 8 m/s
[4] Calculated lost generation due to curtailment
[5] Availability is the percentage of time the turbine is available to function
m/s = meters per second
MW = megawatt

Table A-4
Estimated lost generation for model-operated turbines between July 15 and September 30, 2015

Model-Operated Turbines—July 15 to September 30, 2015								
Turbine Number[1]	**Average Wind Speed (m/s)**	**Generation (MW)**	**Total Hours of Turbine Generation[2]**	**Percentage of Turbine Generation Time (%)**	**Actual Curtailment Occurrences (hours.minutes)[3]**	**Percentage of Time Turbines Were Curtailed (%)**	**Calculated Lost Generation (MW)[4]**	**Availability (%)[5]**
A7	5.4	522.47	539.17	58	383.00	40.92	55.59	99.99
A11	6.0	555.73	551.50	59	372.00	39.74	65.82	98.75
A27	5.4	536.15	526.83	56	384.00	41.03	55.75	98.52
A41	5.9	609.96	554.67	59	385.00	41.13	72.08	99.80
A43	5.9	612.62	540.00	58	387.00	41.35	72.24	98.37
B12	5.3	449.68	466.83	50	356.00	38.03	54.27	90.65
B20	5.3	510.90	526.83	56	374.00	39.96	48.17	96.48
B22	5.4	449.35	544.50	58	388.00	41.45	45.87	98.87
B26	5.6	478.08	543.00	58	383.00	40.92	44.03	99.19
D30	5.4	440.56	532.67	57	381.00	40.71	42.31	98.96
Total	**-**	**5,165.49**	**5,326.00**	**-**	**3,793.00**	**-**	**556.10**	**979.58**
Average	**5.6**	**516.55**	**532.60**	**57**	**379.30**	**40.52**	**55.61**	**97.96**

[1] All data in the table are from the study period
[2] Total hours available for any one turbine: 1,476 hours
[3] Curtailment may occur at any wind speed less than 8 m/s
[4] Calculated lost generation due to curtailment
[5] Availability is the percentage of time the turbine is available to function
m/s = meters per second
MW = megawatt

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