Renewable Energy 78 (2015) 351–356

Contents lists available at ScienceDirect

Renewable Energy

journal homepage: www.elsevier.com/locate/renene

Curtailing wind turbine operations to reduce avian mortality

Karamvir Singh*, Erin D. Baker, Matthew A. Lackner

Department of Mechanical & Industrial Engineering, University of Massachusetts, Amherst, USA

ARTICLE INFO

Article history:
Received 26 March 2014
Accepted 29 December 2014
Available online 28 January 2015

Keywords:
Wind energy
Bird mortality
Environmental concerns
Optimization model

ABSTRACT

While wind power is a promising source of renewable energy, there have been persistent questions about the safety of migrating birds in the presence of wind farms. In this paper we develop a framework that allows us to consider the costs and benefits of a very simple strategy: curtailing (turning off) the turbines during high-risk periods for endangered species. We develop a model that allows us to find the lowest financial cost strategy (where cost is represented in dollars) for the curtailing operation, given a specific goal for bird mortality reduction. We apply the model to a specific case study: the proposed Cape Wind project and the vulnerability of the common loon (*Gavia immer*), during one month of the migratory season. We calculate probability distributions over energy produced, price, and revenue to the wind farm, as well as over the numbers of loon mortality, and perform an uncertainty analysis. As an example, we find that with the goal of reducing 10% of the expected bird deaths during the month of March, the cost per bird averages $170, using the most cost effective curtailment strategy.

1. Introduction

Wind power is quickly becoming an attractive renewable energy source across the globe. Wind power is not, however, without environmental impact. One of the major environmental concerns relates to the death of birds, and other flying species, that can fatally collide with turbine towers, blades, and power lines, an issue termed “bird mortality”.

One possible strategy for reducing bird mortality, is curtailing (turning off) turbine operation during certain periods. While there is an economic cost to such a strategy, it may be necessary for continued wind energy development. In this paper we present a framework for balancing the costs and benefits of curtailing wind operations in times of high bird mortality risk. Specifically, we develop an optimization model that identifies the most cost-effective strategy for curtailing turbine operations to meet a given goal for reduction in bird mortality. Our primary goal is to present a methodology for developing these tradeoffs. We illustrate the methodology via a case study, using hourly data on bird observations, wind speeds, and electricity price for a single month in the Cape Cod area. Very limited data were found on bird observations and mortalities and we have made a number of assumptions to account for data insufficiency.

The bird mortality caused by wind turbines has been quantified at various installations, through counting carcasses and adjusting for scavenger removal rates [2,7–9,16,18], including the effect of new repowered turbines on bird mortality [17], and comparing modern larger rotor turbine bird mortality with old smaller turbines [13]. Another method used to quantify bird mortality is using simple collision risk models [19], [1], including avoidance rate in collision models [3,21], and accounting for angle of bird approach [10]. Bird mortality in offshore locations has been quantified by compiling bird observation results from methods including radar, thermal imaging, visual and acoustic observations and using those in collision models [5]. Bird mortality at offshore locations has also been quantified using the Thermal Animal Detection System (TADS), an infrared-based technology developed as a means of gathering highly specific information about actual collision rates, and also for parameterizing predictive collision models [4]. Overall, factors that lead toward collision risk include flight altitude, flight maneuverability, weather conditions, visibility, percentage of time flying, nocturnal flight activity, disturbance by wind farm structures, tower height, ship and helicopter traffic, habitat specialization, angle between bird approach and rotor plane.

Various strategies have been tested and documented to reduce bird mortalities in a wind farm. These include spacing the wind turbines at an optimal level [11], using tubular towers instead of

* Corresponding author. Present address: Apt A29, 1260 Westford Street, Lowell, MA-01851, USA. Tel.: +1 617 758 9574.

E-mail address: kkaramvir.iitd@gmail.com (K. Singh).

http://dx.doi.org/10.1016/j.renene.2014.12.064
0960-1481/

lattice towers to reduce perching, replacing old-generation wind turbines with new ones [17], painting turbine blades to make them more visible, and enlarging the region near the center of rotor hub [19]. However, no previous work has considered the trade-off between expected bird mortality and expected revenue generated.

The rest of the paper is organized as follows. In Section 2, we present our mathematical model. In Section 3, we populate our model with data, using Cape Wind as a case study. We start by estimating the probability mass functions of energy produced, electricity price, and bird mortality on an hourly basis for the month of March. We then estimate the probability distribution over revenue by combining the probability distributions over energy and price. It should be emphasized that the optimization model is a general framework that may be applied to any site or data set. The analysis of Cape Wind as a case study is performed in order to highlight the application of the model. In Section 4, we provide results on the cost of the optimal strategy to reduce expected bird mortalities.

2. Mathematical model

In this section, we develop a mathematical model aimed at finding the most cost-effective strategy for curtailing turbines in order to reach a given reduction in bird mortality. The strategy is defined by the fraction of turbines that are curtailed at different hours of the day. We formulate a linear program as:

$$Max \sum_{i=1}^{31} \sum_{j=1}^{24} x_{ij} E\left[R_{ij}\right] * N \tag{1}$$

$$subject\ to : p \sum_{i=1}^{31} \sum_{j=1}^{24} x_{ij} O_{ij} \leq \in \tag{2}$$

$$0 \leq x_{ij} \leq 1$$

where x_{ij} is the fraction of turbines turned on in the jth hour of the ith day, R_{ij} is the per-turbine revenue for the jth hour of the ith day, $E[.]$ is the expectation operator, and O_{ij} is the number of birds observed on the jth hour of the ith day. $\in$ denotes the constraint on the expected number of bird mortalities over the period of time the model is considering, in this case per the month of March; p is the probability of bird collision and resulting mortality, and N is the number of turbines in the wind farm. The objective function in (1) represents the expected revenue for the wind farm over the month. The left hand side of the constraint in (2) represents the expected number of bird deaths.

We have made a simplifying assumption that the probability of mortality is the same at every hour of the day. This assumption allows us to simplify the formulation even further. In fact, it allows us to avoid using the parameter p at all. We divide both sides of constraint (2) by the number of expected bird deaths in the absence of a curtailment strategy and rearrange terms to obtain a reformulated constraint:

$$1 - \frac{\sum_{i=1}^{31}\sum_{j=1}^{24} x_{ij} O_{ij}}{\sum_{i=1}^{31}\sum_{j=1}^{24} O_{ij}} \geq 1 - \frac{\in}{p\sum_{i=1}^{31}\sum_{j=1}^{24} O_{ij}} \equiv \pi \tag{3}$$

where π measures expected bird mortalities mitigated *with* curtailment, as a proportion of expected bird mortalities in the absence of curtailment. For example, if $\pi = 10\%$, it means that the curtailment strategy specified by a wind turbine operator or a regulator is required to reduce at least 10% of expected bird deaths that would have occurred without any strategy. Note that p, the probability of bird mortality, has dropped out of the reformulated constraint, once we define π. This is useful, since we do not have very good information on the probability of a bird collision. Constraints (2) and (3) are equivalent to each other.

The decision variables x_{ij} are continuous. We interpret values of x_{ij} that are not multiples of 1/N to imply that one turbine is turned off for part of an hour. This formulation also assumes that the per-turbine revenue is constant; thus we are ignoring wake losses in estimating the total energy output and hourly revenue.

Fig. 1 provides a flow chart of data that are input to the optimization model given in equations (1) and (3). Section 3 provides details on the data processing for the optimization model.

We use data on wind speed and a turbine power curve (section 3.1.1) to determine the energy produced per turbine per hour. We use hourly electricity price data (section 3.1.2) with hourly energy to determine the revenue per turbine per hour (section 3.1.3). We use data on bird observations per day to estimate the bird mortalities per hour (section 3.2). The revenue per turbine per hour and the bird mortalities per hour are used as inputs to the optimization model given in equations (1) and (3). The optimization model returns the optimal curtailment strategy.

3. Methods and data analysis

In this section we estimate a probability distribution for hourly revenue R_{ij} based on data of hourly wind speeds and hourly electricity prices, and estimate bird observations for the proposed Cape Wind project in Nantucket Sound.

3.1. Revenue per turbine

The revenue per turbine (in $) for any hour is given by

$$R_{ij} = Pr_{ij} * En_{ij} \tag{4}$$

where Pr_{ij} is the electricity price in the jth hour of the ith day, En_{ij} is the average energy per-turbine in the jth hour of the ith day.

We find the probability distribution of revenue by combining the probability distributions of energy (Section 3.1.1) and electricity price (Section 3.1.2) using a Monte Carlo Sampling Method.

3.1.1. Energy distributions

We use wind speed data from a buoy in Boston harbor [15]. The anemometer, used to measure wind speed, is at a height of 5 m above sea level. For our analysis, we assume that this is a reasonable approximation of the wind speed in the Cape Wind project area, with the caveat that wind shear and other topographical effects would impact the specific values at Cape Wind. The data contains the average wind speed for each hour for 20 years (1984–2003). About 5% of data points are missing due to unavoidable reasons (icing, broken sensors etc.). For simplicity, we assume that the distribution of wind speed is the same for each day of the month of March.

We use a wind turbine power curve to translate data on wind speed into energy. We use the power curve of a land based 1.5 MW GE turbine in the form of tabular data [6]. We scale it up by a factor of 2.4, so the rated power is 3.6 MW, which is representative of an offshore turbine. Fig. 2 depicts the resulting power curve.

We first translate wind speed data for each hour of the day into energy by using the power curve. Then, we estimate the probability mass function of energy produced by plotting the histogram of energy produced for each hour of the day. Each bar in the histogram represents the probability that energy production will lie within a

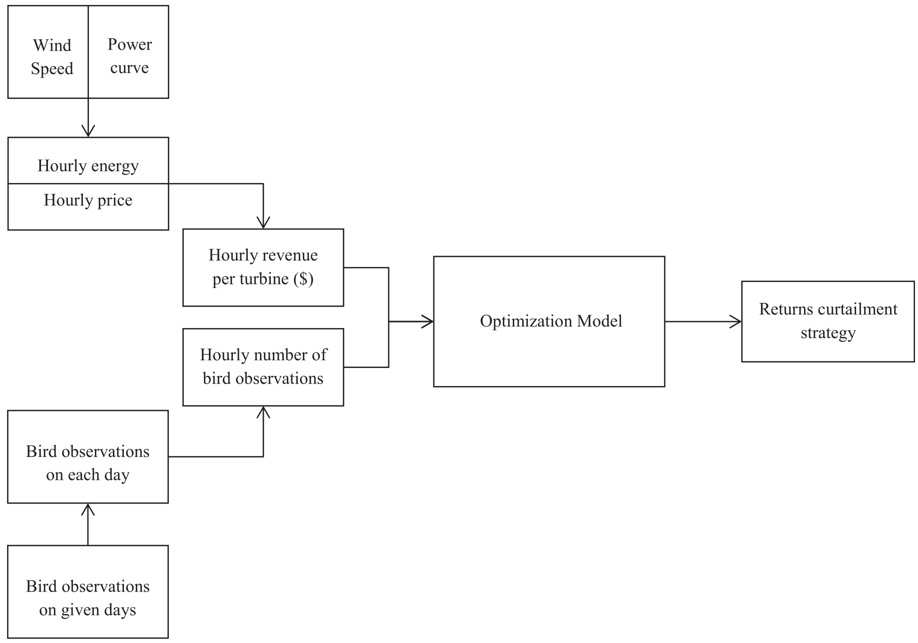

Fig. 1. Data flow diagram.

particular range, for that particular hour of the day. As an example, the histogram in Fig. 3 shows the average energy produced between 8:00 PM and 9:00 PM on any day in the month of March. All 24 histograms, each corresponding to an hour of the day, are found to be bi-modal (2 peaks), with peaks at 0 KWh and 3600 KWh. This is a result of the power curve: when the wind speed is low (0–3 m/s) or very high (>25 m/s), the corresponding energy production is zero and when the wind speed is between the rated and cut-out values (15 and 25 m/s), the corresponding energy production is at a maximum value of 3600 KWh.

3.1.2. *Electricity price data collection and analysis*

We use the price of electricity over the last 7 years in the Southeastern Massachusetts zone, known as the SEMASS zone [12]. The electricity price in this zone is a good approximation for the price at the Cape Wind project site.

We make a simplifying assumption that prices do not vary systematically on different days of March. Specifically, we have assumed that the price does not show much variation between weekdays and weekend (or on other holidays). The histograms of electricity price are determined for each hour of the day to estimate the probability mass function. Two examples are shown in Fig. 4.

The price histograms are unimodal, but not smooth, and some are widely spread at the tail.

3.1.3. *Sampling and revenue distributions*

We find the probability distribution of revenue for each hour of the day by combining the probability distributions of electricity price and energy using a Monte Carlo Sampling Method. We take random draws from both the price and energy distributions and multiply the results to get a single draw for revenue. We run the Monte Carlo sampling one million times for each hour of the day. Two examples of the resulting histograms are shown in Fig. 5. All days for the month of March have the same set of 24 revenue histograms.

The probability of zero revenue is significant in all histograms, since the probability of zero energy is high.

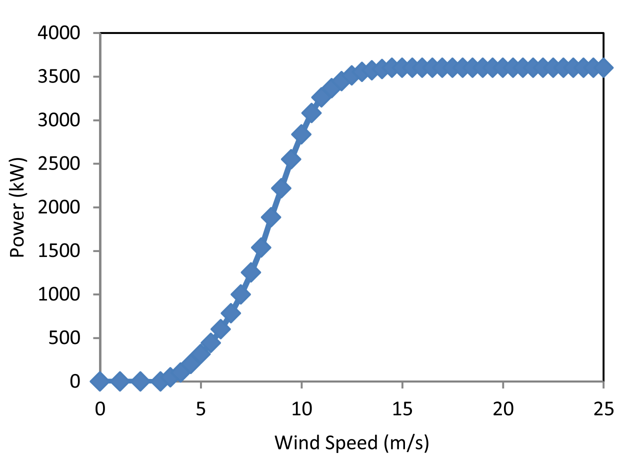

Fig. 2. Power curve of an offshore turbine.

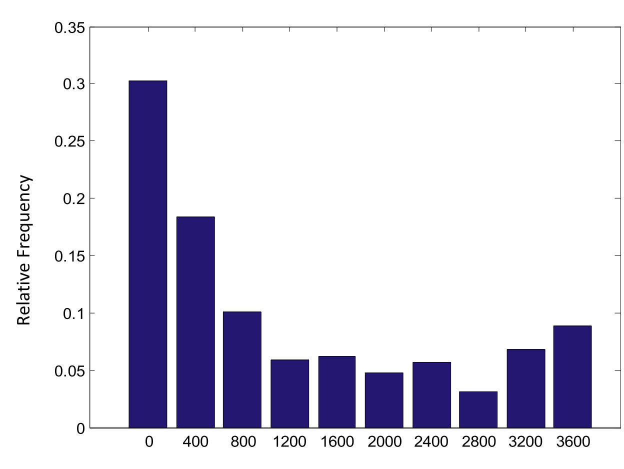

Fig. 3. Histogram of average energy between 8:00 PM and 9:00 PM.

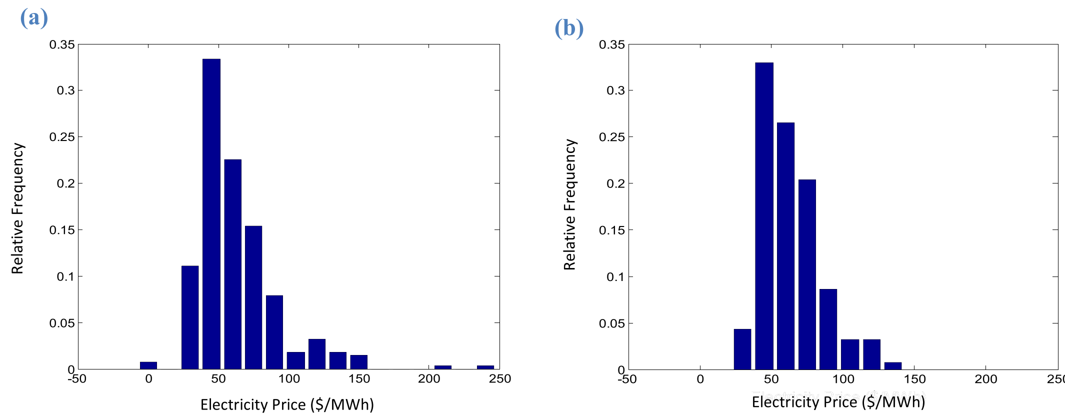

Fig. 4. Histogram of electricity price. (a) 7:00 AM–8:00 AM, (b) 8:00 PM–9:00 PM.

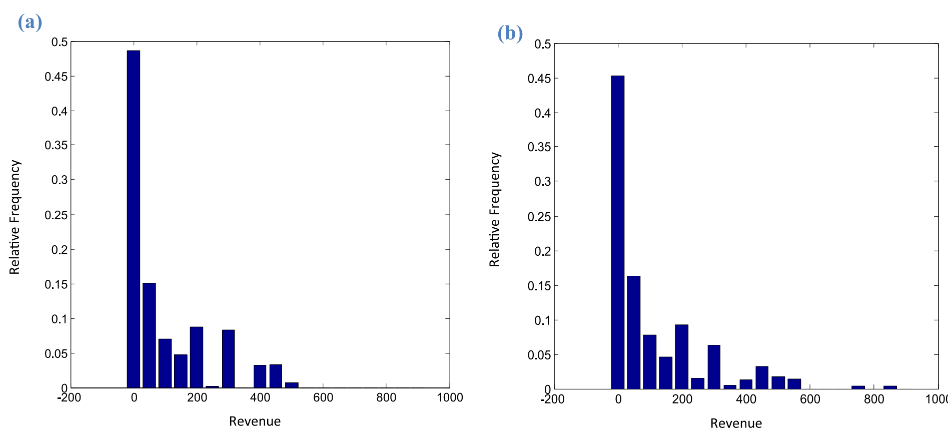

Fig. 5. Histogram of revenue generated for a single turbine. (a) 7:00 AM–8:00 AM, (b) 8:00 PM–9:00 PM.

3.1.4. Expected values and trends

Using the estimated probability mass functions of energy, price and revenue from Sections 3.1.1, 3.1.2 and 3.1.3, we calculate the hourly expected values for each as shown below (Figs. 6–8).

Observing the figures, we note that the expected value of operating a turbine is comparatively low during late-night, early morning and late afternoon.

3.2. Bird mortality data collection and analysis

We collect data on bird observations from the Environmental Impact Statement (EIS) of the Cape Wind Project released by the US Army Corps of Engineers in November 2004. We focus on one endangered bird, the Common Loon (*Gavia immer*), protected by State and Federal law as a migratory non-game bird. As the EIS provides bird data only on certain dates, we do a piecewise linear interpolation to calculate the number of common loons observed on each day. The following bar chart (Fig. 9) shows our estimates of the number of common loons present on different dates in the month of March, with the actual observations highlighted in black. Note that besides the four highlighted observations, we also have one observation each from the month of February and April. We note that the steep increase in the number of birds observed towards the end of month corresponds to the beginning of the migratory period.

Since we do not have good data on patterns of bird migration, we make assumptions about how the number of birds observed is distributed over the course of a day, with our baseline assumption being that they are uniformly distributed during the day. We then

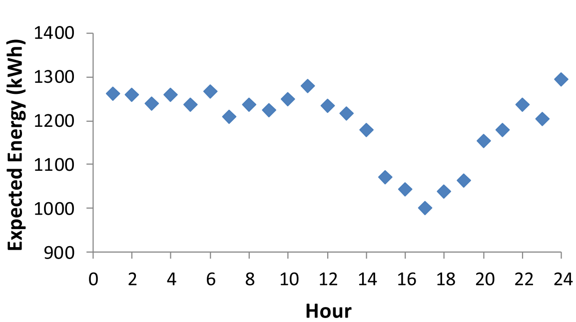

Fig. 6. Trend of expected energy over a day.

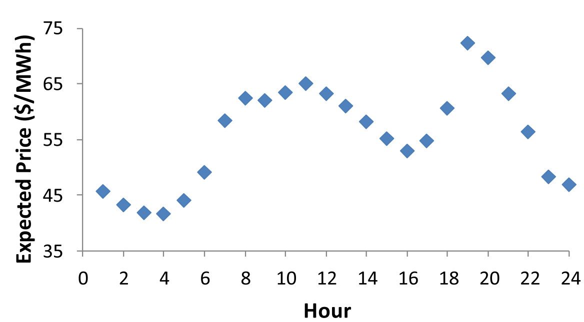

Fig. 7. Trend of expected price over a day.

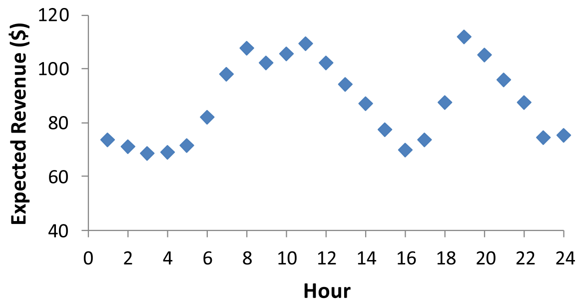

Fig. 8. Trend of expected revenue over a day.

conduct a sensitivity analysis over the distribution of bird observations. Results are provided in Section 4.

4. Results and discussion

We solve the optimization model defined by Equations (1) and (3), applied to the data described in Section 3, as a standard linear program. Fig. 10 illustrates the optimal strategy if the goal is a reduction in bird mortalities of 10%.

The results indicate that the turbines should be curtailed for certain hours on only the last two days of the month of March; all other days have no curtailment. We note a 0–1 solution for all hours except one. That is, the solution dictates curtailing all turbines between the hours of 1:00–5:00 AM, 4:00–5:00 PM on both days, as well as between 1:00–6:00 AM, 2:00–5:00 PM, and 10:00–12:00 PM on March 31; only between 6:00–7:00 PM on March 31st are a fraction of turbines curtailed (20%). The partial curtailment of turbines can be achieved in two ways – either curtail 20% of all turbines in the wind farm for a full 1 h period or curtail all turbines for 12 min during the hour.

The optimal strategy is driven by various factors. First, the number of birds observed increases towards the end of the month (see Fig. 9), and therefore, the most deaths can be avoided by curtailing on these days. Second, since we assume that the number of birds is uniformly observed during the day, the specific hours of the day for which the turbine should be curtailed are governed by the corresponding expected revenue generation. We can see that the hours for which the turbines are curtailed correspond to the lowest points in the expected revenue graph.

We iterate for different values of reduction in bird mortality and solve for the cost-minimizing curtailment strategy. We find that the relation between total costs vs. reduction in bird mortality is slightly convex in nature, as shown by Fig. 11. As we increase the goal, it becomes necessary to curtail on earlier days in the month, where fewer birds are observed, and therefore more hours of curtailment are necessary.

In order to calculate the cost per bird saved, we need to make assumptions about the probability of collision, p. Since we do not have a good estimation for p, we perform a sensitivity analysis. Fig. 12 shows how the average cost per bird changes with the goal, for three different values of p. The lower the chance of collision, the more expensive curtailment becomes on a per bird basis.

Additionally, we conduct a sensitivity analysis over the distributions of bird observations. We split the 24 h day into two parts – day time (6:00 AM to 7:00 PM) and night time (7:00 PM to 6:00 AM). We assume that the number of birds observed per hour at night is a multiple of the number of birds observed per hour during the day, holding the total number of birds constant. For example, if we assume that the number of birds at night is ¼ the number of birds during the day, then on March 31, there will be 18 birds per hour at night and 72 per hour during the day; under the uniform assumption there are 47 birds per hour night and day. We re-calculate the optimal plan under four assumptions for the night

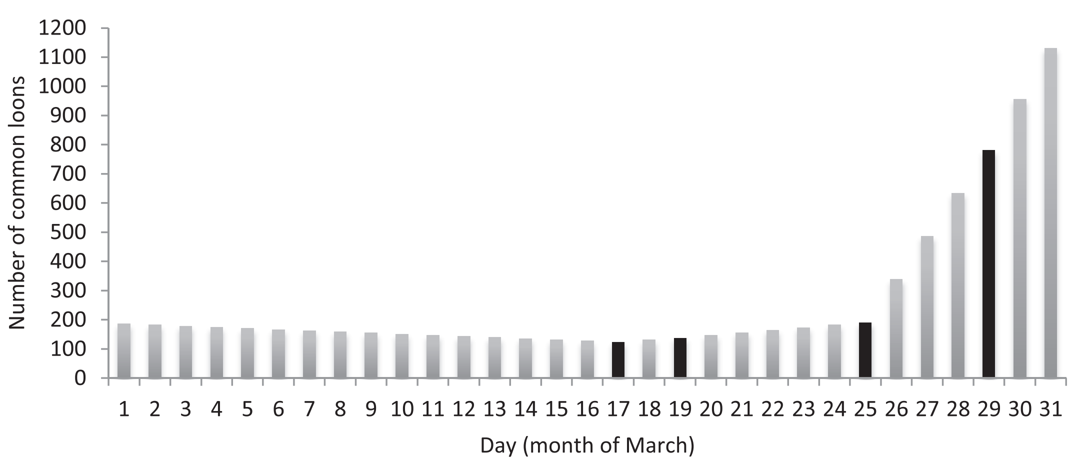

Fig. 9. Number of common loons observed on each day of the month of March.

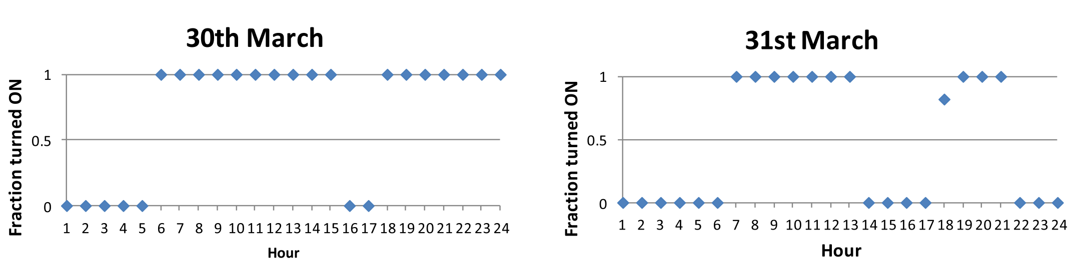

Fig. 10. Optimal curtailment strategy for avoiding 10% of expected bird deaths in March.

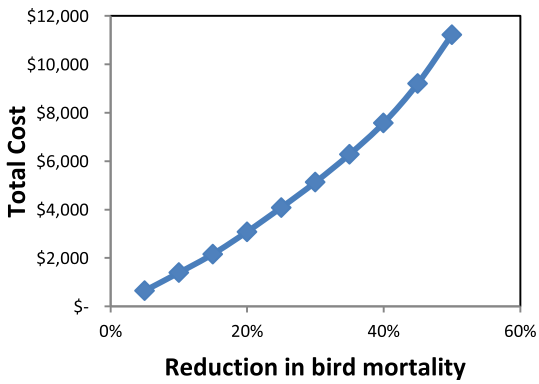

Fig. 11. Overall cost vs. Reduction in bird mortality.

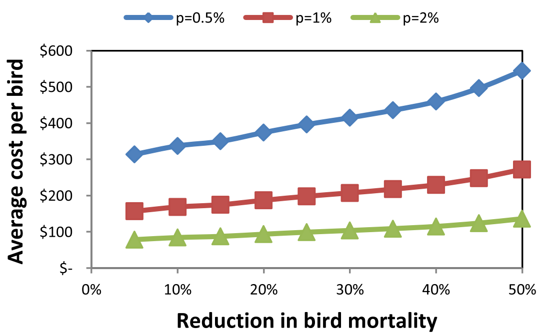

Fig. 12. Sensitivity analysis over *p* with cost per bird.

multiplier: ¼, ½, 2, 3. Table 1 presents the optimal cost for a 10% reduction in expected bird mortality when the probability of collision is 1%.

The costs are non-monotonic in the relative number of birds observed at night, with the highest cost under our base assumption of a uniform distribution. This is because as the distribution becomes more uneven between day and night, some hours end up with a large number of birds. Thus, we can avoid the same number of deaths with fewer hours of curtailment in the whole month; only 12 h when the multiplier is ¼ or 13 h when the multiplier is 3, compared to 20 h under a uniform distribution. It is slightly less costly to have more birds at night versus more birds during the day, since there are more low-revenue hours at night than during the day (See Fig. 5).

With even more precise information, the estimated cost becomes even lower. For example, it is believed that Common Loons typically have peak migration between early morning and noon. We find that if 90% of the Common Loons are observed in the peak 6 h period between 6:00 AM to noon, the total cost for a 10% reduction in bird mortality is only $516, with a per bird cost of $61. Thus, more precise information on migratory patterns brings the cost down considerably.

Table 1
Sensitivity Analysis over distribution of bird observations.

Multiplier for birds at night	Total cost	Average cost per bird
1/4	$981	$116
1/2	$1258	$144
1	$1390	$165
2	$1026	$123
3	$939	$109

5. Conclusions

We have demonstrated a framework for balancing the costs and benefits of curtailment as a strategy for reducing bird mortality. This type of analysis can be used to evaluate curtailment strategies at currently sited wind farms, and also as a tool for evaluating potential sites.

We have found in our simple example, considering only one species and one month of the year that, in the absence of good information about migratory timing, a curtailment strategy may be expensive. However, with more accurate information, it may be a viable strategy in some cases. A recent valuation study [14] estimates a Total Economic Value of $42 per bird, which is one-fourth of the cost per bird under an assumption of uniformity, but is near the cost under the assumption of a peak 6 h migration. Moreover, this cost will decline once we consider the entire year and multiple species, to the point where it may be a reasonable strategy, particularly for highly-endangered birds.

Future work may relax some of our assumptions. A key piece of data needed to populate this model is further detailed data on bird observations and estimates of mortalities corresponding to time of day. Additionally, considering the effect of weather on bird mortalities may be important. Previous studies have suggested that more birds are killed by collision with turbines in overcast conditions [20].

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