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Curtailing wind turbine operations to reduce avian mortality

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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

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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:

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

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

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

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