Modeling Noise and Lease Soft Costs Improves Wind Farm Design and Cost-of-Energy Predictions

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Abstract

The Department of Energy uses the metric Cost-of-Energy to assess the financial viability of wind farms. Non-hardware costs, termed soft costs, make up approximately 21% of total cost for a land-based farm, yet are only represented with general assumptions in models of Cost-of-Energy. This work replaces these assumptions with a probabilistic model of the costs of land lease and noise disturbance compensation, which is incorporated into a wind-farm-layout-optimization-under-uncertainty model. These realistic representations are applied to an Iowa land area with real land boundaries and house locations to accentuate the challenges of accommodating landowners. The paper also investigates and removes a common but unnecessary term that overestimates cost-savings from installing multiple turbines. These three contributions combine to produce COE estimates in-line with industry data, replacing "soft" assumptions with specific parameters, identify noise and risk concerns prohibitive to the development of profitable wind farm. The model predicts COEs remarkably close to real-world costs. Wind energy policy-makers can use this model to promote new areas of soft-cost-focused research.

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25 **Keywords:** Wind Farm Layout Optimization; Cost-of-Energy; Soft Costs; Optimization
26 under Uncertainty; Land Lease Cost; Noise Disturbance Compensation

27 **1 Introduction**

28 The Department of Energy (DOE) promotes research and policies that investigate
29 alternative renewable energy technologies to alleviate U.S. dependency on coal, oil, and
30 natural gas (Office of Energy Efficiency and Renewable Energy, 2015a). Cost-Of-Energy
31 (COE), or MWH of annualized cost divided by energy output per year, offers a universal
32 metric to compare the competitiveness of different power-generation approaches (U.S.
33 Energy Information Administration, 2014). By far, the majority of research in renewable
34 energy technology focuses on decreasing COE to a level comparable with traditional fuel
35 sources, via improvements in technology and/or hardware-related costs. COE is used as a
36 metric in a variety of modeling studies, including hybrid energy systems, for example see
37 (Lambert et al, 2006; Katsigiannis et al., 2012). Recently, the DOE has initiated programs
38 that aim to reduce the soft costs of renewable energy. For example, the SunShot Initiative
39 (Office of Energy Efficient and Renewable Energy, 2015b), which aims to make solar energy
40 cost-competitive with other forms of energy by the end of the decade, collaborates with
41 industry and research institutes to reduce soft costs for residential solar power installation.
42 In just four years, this program has funded more than 350 projects to make the solar energy
43 resources more affordable and accessible for Americans.

The first contribution of this paper is a nuanced modeling approach to wind energy soft costs which, even though they amount to approximately 21% of a wind farm's annualized costs, have received much less research attention. This 21% calculation comes from the application of the enhanced cost model developed by the authors (Chen and MacDonald, 2014) which is based on the Wind Turbine Design Cost and Scaling Model (Fingersh et al., 2006) by National Renewable Energy Laboratory (NREL) and the Turbine System Cost Report from Lawrence Berkeley National Laboratory (Bolinger and Wise, 2011). This paper enhances this existing work with a detailed investigation and probabilistic modeling of two major soft costs in wind farm projects: the costs of landowner acquisition (land lease costs) as discussed in the authors' previous work (Chen, 2013; Chen and MacDonald, 2015, 2013), and noise disturbance compensation—an important contribution of this work, explained in detail in Section 2.4. Noise not only annoys landowners, but may also induce health issues (Dai et al., 2015), which makes the consideration of noise disturbance compensation a necessity. The second contribution of this paper is the application of this work to a real plot of land in Story County, Iowa. The cleaning and coding of the GIS parcel data is explained in Section 2.1, and weblink is provided to the cleaned parcel data so that other researchers can use it in their modeling as well. The third contribution of this paper is the investigation and subsequent removal of the economies-of-scale term used in previous research to model the reduction in turbine costs when more than one is installed, detailed in Section 2.3. In the early-development stages of commercial wind projects, developers approach landowners for permission to build turbines on their land in exchange for monetary compensation. In a large-scale farmland project, developers can approach over 100 individual landowners. Developers must make

important and expensive decisions, such as placing equipment orders or obtaining funding from potential project backers, with limited and uncertain information of these factors. Much of this uncertainty stems from unknown landowner participation. At the same time, landowners must decide whether or not to participate in the project without knowing the turbine locations and the potential impacts. Both stakeholders, developers and landowners, face high levels of risk.

It is customary for developers to offer all landowners in a project the same compensation structure. However, they make no profit guarantees to landowners. The contract offers a certain dollar compensation per MW per year if developers install turbines, but they may not install any. In this situation, the land is still under contract with the developer, so landowners cannot work with another developer or install their own turbines. Thus, landowners sign away the rights to their land without knowing if they will receive compensation from wind energy produced. This is a large risk. Developers offer particular riders for other disturbances, such as dollar per decibel-level-range noise disturbance and dollar per unit of road built, but do not specify the level of noise or amount of road construction. The agreement also does not specify turbine location on land parcels, or number of turbines. Therefore, it is difficult for landowners to assess compensation packages. Clearly, both stakeholders would benefit from increased information in early-stage farm development. This could decrease both development time, via more-transparent negotiations, and COE, via addressing uncertainty in planning.

This paper uses an optimization-under-uncertainty framework developed previously by the authors (Chen, 2013; Chen and MacDonald, 2015, 2013), to specifically address two major soft-cost challenges: (a) determine land lease terms for all participating

landowners and (b) determine noise disturbance compensation. The robust design optimization problem has two objectives for the farm's COE: minimize the normalized mean value and standard deviation. The authors use probability theory to model the uncertain parameters, Latin Hypercube Sampling to propagate the uncertainty throughout the COE system model, and compromise programming to solve the multi-objective optimization problem. The system model provided in this paper can help developers identify plots of land that are worth the extra investment, and provide a robust wind farm design that is not only profitable but also has minimal noise disturbance for landowners. It can also give landowners an idea of where turbines are likely to be placed on their land, and the likely auditory impacts.

2 Methods

2.1 Test case with real farmland and house locations

In previous related publications, we have used simulated land plots. However, to explore real noise issues and lease concerns, it was necessary to use real land with real home locations, shown in Figure 1, which also shows potential turbine locations, discussed later in Section 2.5.2. A portion of the Story County Wind Farm (Wikipedia, 2013) in central Iowa was selected as a realistic test case. The farm is operated by NextEra Energy (Takle and Lundquist, 2011). The land parcels within the 2-by-2 mile test area are owned by 22 landowners, and most own multiple land parcels. Figure 1 shows the test area; black lines outline the individual land parcels, each parcel is labeled by landowner id (1 to 22), followed by a parcel counter. For example, 9-1 indicates the first parcel owned by landowner 9, 9-2 the second parcel owned by landowner 9, etc. Note that all parcels owned

by the same landowner will have same acceptance profiles for compensation offers and noise disturbance. Note also that not all parcels owned by the same landowner are adjacent to each other, for example see the parcels of landowners 13 and 14.

Figure 1 Test area with parcels labels, home locations, and potential locations of turbines.

Note, in Figure 1, the house in the top-right area: it is surrounded by land owned by someone else. Such an intricacy would not be imagined in a hypothetical layout-scenario, but is a reality when land is bought, sold, and passed down through inheritances. There are also several cases where parcels with the same owner are not adjacent, i.e. they are surrounded by non-owned parcels, as shown in Figure 1. The complexity of the spatial arrangement of parcels and their ownership is a complicating, yet important factor in capturing the complexities of modeling real world conditions. This is especially important when adding a noise model, as noise preferences will be discontinuously (or discretely) identical for some non-adjacent plots of land.

A Geographic Information System (GIS) was used to convert public land information obtained from the Iowa Story County Assessor's office into the geospatial data required to run the model. ArcGIS 10 Desktop (ArcMap) was used to perform a spatial selection of those parcel boundary polygons within the test area from the much larger Story county data set. Coordinates were converted from the feet-based Iowa State plane system used by the county, into a local, UTM (meter) based system as required by the modeling software. The GIS was also used to set up the 10 x 10 and 24 x 24 patterns of potential turbine locations. Satellite imagery (Digital Globe) was used to visually identify and digitize the coordinates of the main house within each homestead (which is assumed to be the location where owners live and experience the noise levels modeled). Extracting and anonymizing the names of the parcel owners into a number system while still retaining the spatial relationships required additional custom programming with the ArcGIS Python API. Maps, combining the parcels, locations of houses and of potential wind turbine locations (Figures 4, 6, and 8) were also designed in ArcMap. To facilitate communication within the team and with other project participants, a public online map was created in ArcMap Online: arcg.is/1gSC75q. This can be used by other researchers.

2.2 System model overview

Figure 2 represents the overview of the COE system model used in this work. Five models are used to calculate the COE: a noise propagation model (introduced in detail in Section 2.4.4), an enhanced cost model developed based on the Wind Turbine Design Cost and Scaling Model (Fingersh et al., 2006) by NREL and the Turbine System Cost Report from Lawrence Berkeley National Laboratory (Bolinger and Wise, 2011), a wind shear model (Ray et al., 2006), Jensen's (1983) wake loss model, and a power model for a GE 1.5sle

turbine (Archer and Jacobson, 2007). The authors' previous work (Chen, 2013; Chen and MacDonald, 2015, 2013) discusses the latter four models. The NREL model includes all costs associated with the construction of a wind farm, including the costs of cabling, roads, and transportation, although these costs do not change based on the locations of the turbines. The assumed land lease costs within the NREL model are removed and replaced by the work here. The cost model here has the additional constraint of equal compensation structures for all participating landowners and eliminates the unnecessary economies-of-scale cost reduction coefficient, as explained later in this section.

The model includes four sources of uncertainty, indicated in gray in Figure 2. Wind condition is modeled as aleatory uncertainty using a wind rose, shown in detail in section 2.5.2. Three epistemic sources of uncertainty are modeled in this paper: wind shear, same as in previous work (Chen, 2013; Chen and MacDonald, 2015, 2013); landowner participation, with more detail given in previous work (Chen, 2013; Chen and MacDonald, 2015, 2013) and Section 2.4.3; and monetary compensation required for a given noise disturbance, as represented by a Willingness-to-Accept-Noise utility model, explained below. There are multiple sources of uncertainty within the noise propagation model, but they are self-contained and not detailed here.

Figure 2 Overview of the COE model with a noise model.

While this is useful for the conclusions drawn in previous work, it is not realistic enough for a detailed soft costs model. In reality, instead of individual negotiations, which would increase the project timeline and cost, developers prefer to offer all landowners the same compensation structure, namely a certain dollar per MWh with riders to cover additional damage. Landowners with good wind resource but more expensive compensation demands may increase compensation for all, as developers work to ensure their participation. However, there is a breaking point at which even wind-wealthy landowners are too expensive for the overall cost of the farm. To realistically model this behavior, the model uses an equality constraint of compensation per MWh per year for all landowners that participate. For each Latin Hypercube draw of WTA_P , the highest WTA_P among all participating landowners determines the final, shared compensation structure

offered to each. The associated costs and wind resource benefits are captured in the calculated COE, ensuring that only optimally cost-effective landowners are included in the final design.

2.3 Economies-of-scale term determined unnecessary

Another improvement of the model in this paper is the elimination of the economies-of-scale turbine cost reduction coefficient. This coefficient is included in many layout optimization studies (DuPont and Cagan, 2012; Grady et al., 2005; Marmidis, et al., 2008; Mosetti et al., 1994), but underestimates costs. The optimal COE in the authors' previous work (Chen, 2013; Chen and MacDonald, 2015, 2013) ranged from USD 42 - 48 per MWh, about 10 USD lower than the real industry data. To investigate the impact of the cost reduction coefficient on optimal COE, the authors conducted an optimization analysis for a portion of the Story County Wind Farm (Wikipedia, 2013), varying the number of turbines and the inclusion of the cost reduction coefficient, as shown in Figure 3. The line indicates COE without the term, and the "X"s mark two examples of the COE with the term. The authors conducted phone interviews with developers with farms in the area to establish COEs, reported as ranging from USD 51-57 per MWh, and shown as a grey area in Figure 3. There is no published reference for these numbers, they were collected via phone interview specifically for this investigation. COEs are difficult to secure on-the-record from developers, as they are competitive information. The result shows optimal COEs are closer to the real industry data without the cost reduction term. In addition, when the number of turbines increases, the advantage of removing cost reduction is more obvious. Therefore, the authors removed the cost reduction formulation in the system model proposed in this paper.

Figure 3 Relationship between the optimal COE and the number of turbines.

2.4 Probabilistically modeling acceptance of noise

When placing wind turbines near residential locations, noise impact becomes a primary concern for landowners. The noise at a residential home depends on the distance between the home and the surrounding turbines. A qualitative analysis conducted by Groth and Vogt (2014) shows noise disturbance is one of the most commonly-stated negative perceptions of wind energy development. People do not like to hear wind turbines, and different people have different perceptions of it (Pedersen and Waye, 2007). Developers receive complaints and lawsuits about excessive noise and its associated adverse health impacts (Ambrose and Rand, 2013). For example, an Oregon landowner claimed he was suffering “emotional distress, deteriorating physical and emotional health, dizziness, inability to sleep, drowsiness, fatigue, headaches, difficulty thinking, irritation and lethargy” due to the wind turbine noise (The Associated Press, 2013) and recently filed a related \$5 million lawsuit. In practice, if the noise disturbance is above a certain decibel (dB) level, homeowners receive an annual compensation amount of up to \$1500 in total from

developers (Mosman, 2015; Muschell, 2015). Landowners argue for safer guidelines in the siting of wind turbines, as they are uncertain of the associated health risks of noise disturbance (Songsore and Buzzelli, 2014).

If developers can guarantee the noise below a certain limit or give landowners an idea of the likely auditory impact, the landowners are more likely to accept the contract. Therefore, it is important to carefully model noise impact in the wind farm layout optimization problem. Current wind farm layout optimization research sets noise disturbance as a constraint or an objective function (Fagerfjäll, 2010; Kwong et al., 2012). No existing research models monetary compensation for noise disturbance. This section addresses this limitation by modeling the landowners' acceptance of noise probabilistically, in combination with a constraint on maximum noise disturbance. The model is built from existing research. Sections 2.4.1 and 0 detail documentation on community reactions to noise that we used to create landowner acceptance profiles. The full Willingness-to-Accept-Noise model is developed in Section 2.4.3, while Section 2.4.4 provides the Noise Propagation Model used in this paper.

2.4.1 Community reaction to different noise levels

Ambrose and Rand (2013) summarized a variety of studies on the community reaction to different noise levels. The results of these studies were plotted in a single chart to identify noise level ranges for different community reactions, as show in Table 1. The chart indicates that people will not react adversely to a noise level below 29 dB, but will strongly oppose a noise level above 43 dB (about as loud as a refrigerator). Therefore, our optimization formulation sets 43 dB as a hard constraint, i.e. the program guarantees that

noise levels for all residential locations are less than 43 dB. The model proposes: (1) if the noise level is below 29 dB, landowners will not receive any compensation; and (2) if the noise level is between 29 dB and 43 dB, landowners will receive compensation of up to \$1500 per year—a typical amount offered by developers as compensation for noise disturbance (Mosman, 2015; Muschell, 2015). Note again that solution will not include noise levels above 43 dB.

Table 1 Community Reaction for Different Noise Levels (Ambrose and Rand, 2013)

Community Reaction	Noise Level (dB)
No Reaction	(0, 29]
Sporadic Complaints	(29, 33.5]
Widespread Complaints	(33.5, 43]
Strong Appeals to Stop Noise	(43, 49.5]
Vigorous Community Action	(49.5, +∞]

2.4.2 Landowner noise perception types

To be able to model uncertainty, landowners are divided into three theoretically possible types depending on their perception of the 43 dB turbine noise: (1) Type-1 landowners: do not notice the turbine noise of 43 dB and thus are not annoyed (10%); (2) Type-2 landowners: notice the turbine noise of 43 dB, but do not feel annoyed (75%); and (3) Type-3 landowners: notice the turbine noise of 43 dB and do feel annoyed (15%). The model's representation of perception of noise at levels lower than 43 dB is explained in Section 2.4.3. Note that the landowner types for noise perception are distinct from the landowner land lease acceptance profiles, as discussed in the authors' previous work (Chen, 2013; Chen and MacDonald, 2015, 2013) and later in Section 2.4.3. Each landowner will have a different profile for noise and lease acceptance.

The percentage of each type is based on a cross-sectional study conducted by Pedersen and Wayne (2007), which evaluated the perception and annoyance of wind turbine noise among people living near the turbines. 754 subjects completed a postal questionnaire regarding living conditions, including response to wind turbine noise. The outdoor noise level for each respondent was calculated separately. Pedersen and Wayne discovered that when turbine noise is around 40 dB, 90% of respondents can notice the noise and 15% of respondents feel annoyed. Therefore, 75% of respondents can notice the noise but do not feel annoyed. This result is in line with Ambrose and R. Rand's study (2013), which asserts that there are only complaints, not strong appeals, when the turbine noise is less than 43 dB. As most of the landowners are not annoyed by turbine noise around 40 dB, they do not make strong appeals to stop the noise. When the turbine noise is above 43 dB, more landowners feel annoyed. Community action might be initiated at this time. More landowners get together to discuss the adverse impacts of turbine noise, which could influence the landowners who do not feel annoyed, which results in wider appeals to reduce the noise.

2.4.3 Willingness-to-Accept-Noise utility model

In order for the landowners to be willing to accept noise compensation, the utility of hearing noise plus the associated compensation must be greater than or equal to the utility of not hearing noise and not receiving compensation. We define $WTA_{n,43}$ as the minimum annual payment that a landowner is willing to accept to compensate for the noise level of 43 dB:

$$U(m_0 + WTA_{n,43}, 1) \geq U(m_0, 0), \quad (1)$$

where U is a landowner's utility function, m_0 is the landowner's initial wealth, $WTA_{n,43}$ is the landowner's minimum WTA dollar amount for a 43 dB noise, "1" represents the presence of a 43 dB turbine noise at the landowner's house, and "0" represents the absence of turbine noise at the landowner's house.

In this paper, $WTA_{n,43}$ is modeled as an epistemic uncertainty. The reasonable range of $WTA_{n,43}$ is set to be between \$0 and \$1500 per year, which is the typical compensation range offered by developers (Mosman, 2015; Muschell, 2015). Landowners are classified into three types, each with their own uncertain $WTA_{n,43}$, as shown in Table 2. (1) Type-1 landowners, as discussed above, cannot notice the turbine noise of 43 dB. Therefore, the $WTA_{n,43}$ per year is most likely to be between \$0 and \$500 (probability = 0.7) and between \$500 and \$1000 (probability = 0.3); (2) Type-2 landowners can notice the turbine noise of 43 dB, but do not feel annoyed. Therefore, the $WTA_{n,43}$ per year is equally likely to be between \$0 and \$500 (probability = 0.5) and between \$500 and \$1000 (probability = 0.5); (3) Type-3 landowners feel annoyed at turbine noise of 43 dB. Therefore, the $WTA_{n,43}$ per year is most likely to be between \$1000 and \$1500 (probability = 0.7) and \$500 and \$1000 (probability = 0.3). These probabilities and other characteristics of the landowner profiles are determined by the authors from literature, but in practice can be replaced with any numbers that developers or researchers see fit.

300 Table 2 Intervals and probabilities, assumed for the $WTA_{n,43}$.

$WTA_{n,43}$ for Type-1 Landowners (\$/yr)			
Intervals	[0,500]	[500,1000]	[1000, 1500]
Probabilities	0.7	0.3	0
$WTA_{n,43}$ for Type-2 Landowners (\$/yr)			
Intervals	[0,500]	[500,1000]	[1000, 1500]
Probabilities	0.5	0.5	0
$WTA_{n,43}$ for Type-3 Landowners (\$/yr)			
Intervals	[0,500]	[500,1000]	[1000, 1500]
Probabilities	0	0.3	0.7

301 Given the $WTA_{n,43}$ amount (\$/yr) of a landowner, the authors assume that the
 302 landowner's minimum WTA amount for a noise level of L_{AT} follows a linear relationship:

$$WTA_n(L_{AT}) = \begin{cases} 0 & L_{AT} \leq 29 \text{ dB} \\ \frac{(L_{AT} - 29) \times WTA_{n,43}}{43 - 29} & 29 \text{ dB} < L_{AT} < 43 \text{ dB} \\ WTA_{n,43} & L_{AT} = 43 \text{ dB} \\ \text{inf} & L_{AT} > 43 \text{ dB} \end{cases} . \quad (2)$$

303 Where $WTA_n(L_{AT})$ is the landowner's minimum WTA amount in \$/yr for a noise
 304 level of L_{AT} ; L_{AT} is real receiver noise level in dB at the landowner's house, calculated
 305 using the Noise Propagation Model described in Section 2.4.4; $WTA_{n,43}$ is the given WTA
 306 amount (\$/yr) of the landowner for a 43 dB noise.

307 As discussed above, when the noise level is below 29 dB, landowners will have no
 308 reaction according to Ambrose and Rand (2013). Therefore, $WTA_n(L_{AT})$ is set to be 0 when
 309 L_{AT} is below 29 dB, indicating landowners are willing to accept a noise level below 29 dB

without compensation. However, when the noise level is above 43 dB, landowners will have strong appeals to stop noise (Ambrose and Rand, 2013). Therefore, $WTA_n(L_{AT})$ is set to be infinite when L_{AT} is above 43 dB, indicating landowners are not willing to accept a noise level above 43 dB no matter how much compensation they receive from developers.

Similar to the equal land lease compensation constraint, the model has an equal compensation constraint for noise disturbance. After the optimization algorithm draws the noise acceptance profiles for all landowners, it sets the WTA_n for a 43 dB noise for all the landowners to the value associated with the least-accepting (most costly) landowner that has been chosen to participate in the iteration's design layout. For all landowners, the algorithm replaces the $WTA_{n,43}$ in Equation (2) with this most-costly WTA, and calculates the final noise compensation for each landowner based on the noise heard at their home.

2.4.4 Noise propagation model

The noise propagation model used here is based on ISO 9613-2 (1996):

$$L_{AT} = 10 \lg \left\{ \sum_{i=1}^n \left[\sum_{j=1}^8 10^{0.1[L_{fT}(ij) + A_f(j)]} \right] \right\}, \quad (3)$$

where L_{AT} is the A-weighted downwind sound power level at a receiver location (landowner's house), n is the number of noise sources (number of turbines), i is an index representing the noise sources, j is an index representing the eight standard octave-band midband frequencies, $A_f(j)$ is the standard A-weighting (IEC 651 or IEC 61672), and $L_{fT}(ij)$ is sound pressure level at a receiver location for noise source i and octave-band j :

$$L_{fT}(ij) = L_w + D_c + A. \quad (4)$$

Here L_w represents the octave-band sound power level for the noise source (turbine), D_c is the directivity correction, which is neglected in this work, and the octave-band attenuation A is defined as the sum:

$$A = A_{div} + A_{atm} + A_{gr} + A_{bar} + A_{misc}, \quad (5)$$

where A_{div} is the attenuation due to geometrical divergence (spreading of sound waves in 3D space), defined as

$$A_{div} = [20 \lg(d/d_0) + 11] \text{ dB}, \quad (6)$$

where d is the distance from the source to receiver and d_0 is the reference distance (1m).

The attenuation due to atmospheric absorption (A_{atm}) is calculated as:

$$A_{atm} = a_c d / 1000, \quad (7)$$

where a_c is the atmospheric attenuation coefficient. The yearly average temperature and relative humidity for Ames in 2011 are 9.2 deg C and 77% according to the real data obtained from the Iowa Environmental Mesonet (2013b). Therefore, the value of a_c for a temperature of 10 °C and relative humidity of 70% is used for all computations in this research.

The attenuation due to the ground effect (A_{gr}) is defined as

$$A_{gr} = A_s + A_r + A_m. \quad (8)$$

The detailed method for calculating attenuations with regard to source region (A_s), receiver region (A_r), and middle region (A_m) is described in ISO 9613-2 (1996). The authors

assume that the ground is porous for source region, middle region, and receiver region ($G=1$). The model assumes that entire noise radiation from a turbine can be approximated to be emanating from a single point located at the turbine hub height. The turbine hub height is taken to be 80 m, and the receiver height to be 2 m.

The model ignores attenuation due to screening obstacles (A_{bar}) and from other miscellaneous barriers (A_{misc}); a reasonable approach for wind farms in Iowa, which are typically installed in farming land with very few buildings or swaths of trees.

2.5 Problem Formulation

2.5.1 Distribution of landowner types for lease acceptance and noise perception

In the authors' previous work (Chen, 2013; Chen and MacDonald, 2013), the authors summarized wind project easement and lease data from published sources (Windustry, 2009), and found out the compensation per MW installed per year for landowners typically ranged from \$1000 to \$5000 with a mean value of \$2757. To model the uncertainty associated with land lease compensation, the authors took into account an uncertain WTA_p in previous work (Chen, 2013; Chen and MacDonald, 2015, 2013). The range of WTA_p was assumed to be from \$1000 to \$50000 per MW installed per year. The upper limit of WTA_p (\$50000) approximates the entire property value, assuming there are multiple turbines on the land. The higher the WTA_p , the more reluctant the landowner, i.e. the reluctant landowner will only participate in the project when the compensation is very high. In extreme situation, the most reluctant landowner will only participate when the compensation is equal to the value of his/her property.

365 Table 3 Intervals and probabilities, assumed for the WTA_p .

WTA_p for Type-A Landowners (\$/yr per MW installed)			
Intervals	[1000,2500)	[2500,5000)	[5000, 50000]
Probabilities	0.5	0.5	0
WTA_p for Type-B Landowners (\$/yr per MW installed)			
Intervals	[1000,2500)	[2500,5000)	[5000, 50000]
Probabilities	0.3	0.7	0
WTA_p for Type-C Landowners (\$/yr per MW installed)			
Intervals	[1000,2500)	[2500,5000)	[5000, 50000]
Probabilities	0	0.5	0.5
WTA_p for Type-D Landowners (\$/yr per MW installed)			
Intervals	[1000,2500)	[2500,5000)	[5000, 50000]
Probabilities	0	0.3	0.7

366 Table 4 Landowner type for lease acceptance, assumed for 22 landowners.

Landowner type for lease acceptance	Landowner ID
Type-A	Landowners 4, 5, 12,15, 18, and 19
Type-B	Landowners 1, 3, 6, 9, 11, 14, 16, and 22
Type-C	Landowners 2, 7, 13, 17, and 21
Type-D	Landowners 8, 10, and 20

367 The range of WTA_p was split into three intervals: (1) interval [1000, 2500)
368 indicates a low WTA_p ; (2) interval [2500, 5000) indicates a moderate WTA_p ; and (3)
369 interval [5000, 50000) indicates a high WTA_p . Four types of landowners are modeled with
370 different land lease acceptance profiles, each with their own uncertain WTA_p . Table 3
371 provides the assumed WTA_p for each landowner type: (1) Type-A landowners will accept
372 low compensation. The WTA_p is equally likely to be between \$1000 and \$2500
373 (probability = 0.5) and between \$2500 and \$5000 (probability = 0.5); (2) Type-B
374 landowners will accept moderate compensation. The WTA_p is more likely to be between
375 \$2500 and \$5000 (probability = 0.7); (3) Type-C landowners will accept high or moderate
376 compensation. The WTA_p is equally likely to be between \$2500 and \$5000 (probability =
377 0.5) and between \$5000 and \$50000 (probability = 0.5); and (4) Type-D landowners will

only accept high compensation. The WTA_p is more likely to be between \$5000 and \$50000 (probability = 0.7). Here, the probabilities hypothetical. In practice, developers will estimate probabilities and assign types based on interactions with landowners. All landowners were randomly assigned a type, as shown in Table 4 and Figure 4, as in the authors' previous work (Chen, 2013; Chen and MacDonald, 2015, 2013).

Figure 4 shows the location of the twelve houses, owned by 9 landowners, used as the noise receivers in this paper. In Figure 4, the central location of each house is marked with a small house symbol. Homeowners/landowners are modeled with three noise perception profiles, i.e. uncertain $WTA_{n,43}$ values range from \$0 to \$1500 per year, shown previously in Table 2. Based on the study conducted by Pedersen and Waye (2007), as discussed in Section 2.4.2, the percentages for Type-1, Type-2, and Type-3 landowners are 10%, 75%, and 15% respectively. Therefore, the formulation assumes one type-1 landowner, seven type-2 landowners, and one type-3 landowner. These types are assigned randomly, and the houses are shaded by type in Figure 4.

Figure 4 Three noise perception types and four lease acceptance types are assigned randomly in the test area.

2.5.2 Wind Condition and Potential Turbine Areas

The system model presented in this section allows for 100 potential locations for turbines, as indicated by the white circles in Figure 1. The distance between any two potential locations is set to be more than four rotor diameters to reduce wake interactions, a typical setting in wind farm layout optimization literature (Ozturk and Norman, 2004;

Kusiak and Song, 2010). The appendix modifies the formulation with more potential locations to investigate a higher-resolution solution space.

Wind condition of the test area. The authors used the actual one-year wind data of 2011 from the Iowa Environmental Mesonet (2013a) website to model the wind condition of the test area. Figure 5 shows the wind rose plot downloaded from the Iowa Environmental Mesonet (2013b). 10-meter-high anemometers were used to collect the data, which range from 3 knots to 38 knots with a mean value of 9 knots.

Figure 5 Wind rose generated from the Iowa Environmental Mesonet website (Iowa Environmental Mesonet, 2013b).

The work used Weibull distribution to model the wind data shown in Figure 5. More complicated wind models are available in the literature. For example, Erdem and Shi (2011) proposed and compared seven bivariate wind distribution models. Zhang et al. (2011) used Kernel Density Estimation to construct a multivariate and multimodal wind model. Researchers, such as Morgan et al. (2011) and Carta et al. (2009) conducted thorough reviews on a variety of wind models, and found out Weibull distribution was able to fit most wind data well. The authors also proved in previous work (Chen, 2013; Chen and MacDonald, 2015, 2013) that Weibull distribution can fit the wind data of Iowa well. Equation(9) provides the Probability Density Function (PDF) of Weibull Distribution (Lackner and Elkinton, 2007), which defines wind speed v as a function depending on the shape factor k and the scale factor λ . More details of this wind model can be found in the authors' previous work (Chen, 2013; Chen and MacDonald, 2015, 2013).

$$PDF(v) = \frac{k}{\lambda} \left(\frac{v}{\lambda} \right)^{k-1} e^{-\left(\frac{v}{\lambda} \right)^k} . \quad (9)$$

2.5.3 Objective function

The objective for the deterministic system model is to minimize the COE given the environmental parameters P and a fixed number of turbines (16 turbines for the selected piece of land), defined as:

Minimize:

$$COE(X, P) = \frac{C(X, P)}{AEP_{tot}(X, P)}, \quad (10)$$

subject to:

$$h(X) = N(X) = 16, \quad (11)$$

where $COE(X, P)$ is the levelized cost of energy of the wind farm in \$/MWh, as detailed in the authors' previous work (Chen, 2013; Chen and MacDonald, 2015, 2014, 2013), $C(X, P)$ is the levelized cost per year of a wind farm in dollars, $AEP_{tot}(X, P)$ is the farm's total annual energy in MWh, $h(X)$ is the equality constraint, and $N(X)$ is the total number of turbines in the farm. X is a 100-bit binary string design variable representing the potential turbine locations shown in Figure 1. The equality constraint $h(X)$ indicates that the total number of turbines selected by the optimization program will be fixed at 16. This number is selected based on the actual number of turbines within the test area. In practice, it is straightforward to modify this number to meet the developers' needs.

3 Results and discussion

3.1 Results

GAlib, a library of genetic algorithms (GAs) developed by Wall (1999), was used to solve the optimization problem in C++. GA is a widely-used heuristic probabilistic search algorithm (Grady et al., 2005), which does not require a differentiable objective function and are less likely to get trapped in a local optimum (Houck et al., 1995; Davis, 1991). GAs are also commonly used as a stochastic heuristic algorithm to optimize wind farm layout (Sorkhabi et al., 2016). The authors decided to use GA as: (1) the design variable in this work is a binary string; (2) the objective function is non-differentiable; and (3) it is likely to have more than one optimal layout (multi-modal).

The design variable was a binary vector of the turbine locations (=1 with a turbine placed and 0 without). This paper used a penalty function for constraint violation, similar

as in previous work (Chen, 2013; Chen and MacDonald, 2015, 2014, 2013, 2012), to address the equality constraint of Equation (11). The optimization program ran in three different scenarios: (1) minimize the mean value of COE (μ_{COE}); (2) minimize the standard deviation of COE (σ_{COE}); and (3) compromise programming with two minimization objectives: the normalized mean value of COE ($\frac{\mu_{COE}}{\mu_{COE}^*}$) and standard deviation of COE ($\frac{\sigma_{COE}}{\sigma_{COE}^*}$), where μ_{COE}^* and σ_{COE}^* are the individually-optimized mean value and standard deviation of COE.

For each scenario, the program ran over ten times with 10,000 iterations each time, at which point it would terminate. Each of the ten runs took four hours to complete. The GA uses a multitude of initial locations of the turbines in order to aid in convergence to the global optimum. The best results of these ten runs are shown in Table 5. The noise levels for the houses ranged from 34 dB to almost 43 dB, as shown in Figure 6.

Table 5 Results summarized from the optimization program for 16 turbines with 100 potential turbine locations.

Scenario	1	2	3
Objectives	Minimize μ_{COE} Individually	Minimize σ_{COE} Individually	Minimize $\left[\frac{\mu_{COE}}{\mu_{COE}^*}, \frac{\sigma_{COE}}{\sigma_{COE}^*} \right]$
μ_{COE} (\$/MWh)	52.44	52.51	52.44
σ_{COE} (\$/MWh)	5.08	5.08	5.08
μ Energy Output (MWh/yr)	73838	73707	73838
μ Cost Output (\$k/yr)	3831	3829	3831

As shown in Table 5, all three scenarios have very similar COEs (around 52.5 \$/MWh) with the same standard deviation (5.08 \$/MWh). The Pareto frontier of COE varies

only by cents, thus it is not included as a figure. A similar finding is discussed in the authors' previous work (Chen and MacDonald, 2015) indicating that the variance of COE is mainly the result of changing the number of turbines in the problem set-up. Minimizing μ_{COE} (Scenario 1) and μ_{COE} & σ_{COE} (Scenario 3) share very similar mean energy outputs and costs. This is because σ_{COE} does not vary when the number of turbines is fixed. Because the results are similar, we only discuss further the results of minimizing μ_{COE} and σ_{COE} (Scenario 3), as shown in Figure 6, with $\odot$ representing an optimized turbine location.

Figure 6 Scenario 3 (minimizing μ_{COE} & σ_{COE}) has a COE of 52.44 \$/MWh.

In the results of Scenario 3 (Figure 6), houses α and β both receive the highest noise level, 43 dB, while house γ receives the lowest. As shown in Figure 6, house β is owned by a Type-1 landowner, who does not hear the turbine noise of 43 dB. The noise level for this house is one of the highest because the associated payment to the landowner is low. On the contrary, house α is owned by a Type-3 landowner, who will feel annoyed at turbine noise of 43 dB. To reduce compensation cost for noise disturbance, the noise level of house α should be minimized. However, house α is located at the boundary of the entire land plot, which is favored by the optimization program to minimize wake losses (Barthelmie, 2006). Therefore, the optimization program does not avoid placing turbines around house α , as the turbine location benefits outweigh the required extra compensation for noise disturbance. On the other hand, house γ , which is also located at the boundary of the entire land plot, receives the lowest noise level. This is because house γ is surrounded by a Type-D landowner (shaded by yellow), who has the highest remittance requirement for participating in the project (see Section 2.5.1 above). If turbines are placed on the land of a Type-D landowner, all the other landowners would have to receive the same high remittance fees package. Therefore, to save on the overall remittance fees for participation, no turbines are placed around house γ , which results in the lowest noise level of house γ . Similarly, none of the three scenarios placed any turbines on the land of other type-D landowners (parcels shaded by yellow), in order to keep overall remittance fees down.

3.2 Implementation Discussion

Implementation of the proposed model framework can initiate from a number of perspectives. For researchers, large-scale developers, and governmental policy-makers, the

coding and parameters are straight-forward to implement. Wind resource and GIS data are readily available. The parameters in the NREL-based portions of the model will require careful review, as there are a number of assumptions that will change with time, such as the cost and power curves of readily-available turbines. Although the authors used C++, MATLAB is another platform that can run the optimizations at a slower speed, which will be manageable with total turbine counts of 20 or less. Developers that we have spoken to approach land owner negotiations carefully, and have much experience gauging their responsiveness from limited conversations, such as town dinners or door-to-door conversations. Such interactions would be best to define the parameters related to landowner acceptances of noise and risk. Note that zoning regulations and road construction regulations are not included in this model. These additional constraints are necessary past the initial planning stages, and can be added to the model.

For landowners, the best path to implementation would be to work with an engineering consultant who can implement the code and collect the required data. It could also be possible to create an online assessment tool—NREL already has similar tools available—and it is possible that this could give landowners significantly more power in negotiations.

In summary, a step-by-step path to implementation would be as follows: (1) Identify parameters within the model and update as necessary to apply to the specific situation, confirm availability of wind and GIS data; (2) Conduct discussions with landowners and other stakeholders to populate the probabilistic acceptance parameters; (3) Code the model, check behavior with test scenarios; (4) Optimize with a step-up/step-down count of turbines, such as 14-16-18; (5) With results, try moving turbine locations slightly

north/west/east/south to determine sensitivity of results to exact turbine positioning; (6)
Share results with all stakeholders, update model constraints as necessary.

4 Conclusion and policy implications

This paper successfully improved the real-world validity and nuanced modeling of landowner concerns in WFLO. New contributions in this work included: (a) the use of real-world land parcels and home locations, which lead to interesting findings on which land parcels guided the cost of acquiring participation from landowners; (b) the determination that the economy-of-scale cost reduction coefficient used in previous work underestimated the cost of energy (and thus was not included in the optimization) and (c) the incorporation of a noise model and probabilistic compensation response of landowners, derived from a collection of real-world data sources. The new system model was tested with different scenarios using realistic data from a 2 by 2 mile plot of an Iowa windfarm containing 22 landowners and 12 noise receivers (houses). Initially using 100 potential turbine locations, the optimal mean COE value created by the model ranges from \$52 to \$53 per MWh (Table 5), which matches the observed COE industry data (\$51 to \$57 per MWh).

Unlike the Wind Turbine Design Cost and Scaling Model developed by NREL (Fingersh et al., 2006), that use a single number to represent land lease cost, the model presented here predicts a realistic COE through the incorporation of landowners' decisions, concerns, and probabilistic models of associated soft costs. The NREL model estimates a cost of 1.08 \$/MWh for land lease costs, and our model offers a similar cost of 1.19 \$/MWh for the farm with 16 turbines. This suggests that our model is a viable replacement for the single-number approach from NREL. It offers flexibility in design with respect to land

availability and noise concerns. It captures the important concept that if landowners find the potential noise generated by the farm unacceptable, or are not adequately compensated for hearing it, then the farm cannot be built as the landowners will decline to participate. This important concept is not captured in NREL's approach, with its single \$/MWh value and lack of noise impact valuation. The realistic COE predicted by this model could help the DOE make better energy policy decisions that are inclusive of all stakeholders' concerns. In general, the work demonstrates the potential impact of more research on landowner-related issues and the associated soft costs in wind projects, similar to the work that has been funded by the DOE's SunShot Initiative that targets reductions in solar energy soft costs (Office of Energy Efficient and Renewable Energy, 2015b).

While the model presented here offers reasonable compensation values and provides useful design suggestions to landowners and developers during early-stage farm negotiations, it does have a few limitations that will require further input for it to be useful in the field. In this paper, the estimations of uncertain parameters are all based on assumptions rather than on measured values, for example, the dollar compensation values in the landowner noise-acceptance profiles. For implementation, it would be best to conduct interviews with developers and landowners to fine-tune these parameters. Additionally, different types and sources of uncertainty could be added, such as those associated with turbine failure. The noise propagation model used in the work (ISO 9613-2, 1996) is the industry standard, however it is fairly rudimentary. Higher-fidelity noise models, such as CONCAWE, could be included in the future to further validate the results. Similarly, a higher-fidelity wake loss model could also be used.

The noise output and the optimal layout shown in Figure 6 indicates that the importance of landowners to the outcome of the project depends on the wind resource their parcels provide, their lease-acceptance profile, and their noise-acceptance profile. Of these factors, lease acceptance (which has an uncertain range from \$1000 to \$50000 per MW installed per year as shown in Table 3) plays a particularly important role - as can be seen in Figure 6, all optimal layouts avoid placing turbines on parcels owned by the landowners that demand the most compensation, type-D and type-C landowners. Noise acceptance plays a less important role in determining crucial landowners, because the compensation for noise annoyance has a much smaller impact on overall farm COE. For example, Figure 6 shows that the noise level of house α is at the highest level (43 dB), although it is owned by a landowner with a high noise compensation request, indicating that the location benefit of house α outweighs the required additional noise compensation.

The results indicate that minimizing μ_{COE} individually provides almost identical COE when compared to minimizing μ_{COE} and σ_{COE} combined, as σ_{COE} is largely dependent on the number of turbines, which is fixed in this model. This finding can be beneficial for developers; if the number of turbines for a farm is predetermined, running only the scenario to minimize the mean value of COE may be sufficient to obtain a robust optimal farm layout. This saves considerable time and computing when planning a wind farm project. Additionally, a higher-resolution solution space with 576 potential turbine locations, instead of 100 locations, is investigated in the Appendix. The optimal μ_{COE} for 576 potential turbine locations is only 0.7% better than that for 100 potential turbine locations while requiring substantially more computing resources, suggesting it may serve a

591 better role in fine turning locations later in the project when geological concerns are
592 included.

593 The implementation of the work is straightforward and extendable beyond the case
594 study by combining existing data sources for wind, land, turbine, and cost parameters.
595 Landowner acceptance probabilistic ranges and corresponding compensation values can be
596 estimated with industry expertise and/or landowner participation. Thus, the approach
597 here, with limitations noted above, emphasizes that not only are soft costs an important and
598 deciding factor in wind-farm development, but also that these costs are not as "soft" as
599 some models suggest—it is possible to put "hard" numbers behind them, with the aid of
600 uncertainty.

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606

607 **NOMENCLATURE**

608	a_c	Atmospheric attenuation coefficient
609	A	Octave-band attenuation
610	A_{atm}	Attenuation due to atmospheric absorption
611	A_{bar}	Attenuation due to screening obstacles
612	A_{div}	Attenuation due to geometrical divergence

613	$A_f(j)$	Standard A-weighting
614	A_m	Attenuation for the middle region
615	A_{misc}	Attenuation from other miscellaneous effects during propagation through
616		foliage or buildings
617	A_r	Attenuation for the receiver region
618	A_s	Attenuation for the source region
619	$AE_{P_{tot}}(X, P)$	Farm's total annual energy in MWh
620	$C(X, P)$	Levelized cost per year of a wind farm in dollars
621	$COE(X, P)$	Cost of Energy of the farm in \$/MWh
622	COE	Cost of Energy
623	d	Distance from the source to receiver
624	d_0	The reference distance (1m)
625	D_C	Directivity correction
626	DOE	Department of Energy
627	$h(X)$	Equality constraint
628	i	An index representing the noise sources
629	j	An index representing the eight standard octave-band midband frequencies
630	L_{AT}	A-weighted downwind sound power level at a receiver location
631	k	Shaper factor for Weibull distribution
632	$L_{fT}(ij)$	Sound pressure level at a receiver location for source i and octave-band j

633	L_w	Octave-band sound power level for the noise source
634	m_0	Landowner's initial wealth
635	n	Number of noise sources (number of turbines)
636	$N(X)$	Total number of turbines in the farm
637	$PDF(v)$	Probability density function for Weibull distribution
638	U	Landowner's utility function
639	WTA_p	Willingness-to-Accept for participation
640	$WTA_{n,43}$	Willingness-to-Accept for a landowner at noise level of 43 dB
641	X	100-bit binary string design variable
642	μ_{COE}	Mean value of Cost of Energy
643	μ_{COE}^*	Optimal mean value if optimize μ_{COE} individually
644	σ_{COE}	Standard deviation of Cost of Energy
645	σ_{COE}^*	Optimal standard deviation if optimize σ_{COE} individually
646	α	House label
647	β	House label
648	γ	House label
649	ε	Previous turbine location shown in Figure 8
650	ε'	New turbine location shown in Figure 8
651	λ	Scale factor for Weibull distribution
652		

APPENDIX

Improved results with higher resolution solution space

This appendix details our reinvestigation of Scenario 1, minimizing the mean COE, using a higher-resolution solution space with 576 (24 by 24) potential turbine locations (Figure 7). The algorithm used the optimal turbine locations found in Section 3.1 as the initial points for the GA. The improved optimal results are summarized in Table 6 and Figure 8. Note that the optimal μ_{COE} and energy output for 576 potential turbine locations are only 0.7% and 0.8% better than those for 100 potential turbine locations (52.08 \$/MWh compared to 52.44 \$/MWh and 74407 MWh/yr compared to 73838 MWh/yr), resulting in a total energy output difference of 17070 MWh over the lifetime of the farm (assumed to be 30 years). However, the computation time for 576 potential turbine locations is almost five times longer than that for 100 potential turbine locations.

Table 6 Results summarized from the optimization program for 16 turbines with 576 potential turbine locations.

Scenarios	1
Objectives	Minimize μ_{COE} individually
μ_{COE} (\$/MWh)	52.08
σ_{COE} (\$/MWh)	5.02
μ Energy Output (MWh/yr)	74407
μ Cost Output (\$k/yr)	3835

Figure 7 Test area with 576 instead of 100 potential turbine locations.

The optimal layout in Figure 8 (Scenario 1 with 576 potential turbine locations) is different from that in Figure 6 (Scenario 3 with 100 potential turbine locations). One major noticeable change is the shift of turbine from location ε to ε' , as shown in Figure 8. Note that the new turbine location ε' is located on plot 15-1 (the purple plot with black borders), and plot 15-1 only has 3 potential turbine locations for the lower-resolution solution space, as shown in Figure 1. However, in this section, plot 15-1 has 12 potential turbine locations, as shown in Figure 7. The higher-resolution solution space increases the possibility of the optimization algorithm to select small land plots with favorable wind resource and less acquiring cost, such as plot 15-1.

Figure 8 Scenario 1 (minimizing μ_{COE}) with 576 potential turbine locations and Scenario 3 (minimizing μ_{COE} & σ_{COE}) with 100 potential turbine locations have different optimal layouts.

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