AGENT-BASED MODELING OF DECISIONS AND DEVELOPER ACTIONS IN WIND FARM LANDOWNER CONTRACT ACCEPTANCE

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ABSTRACT

This paper presents an agent-based model to investigate interactions between wind farm developers and landowners. Wind farms require hundreds of square miles of land for development and developers typically interact with landowners to lease land for construction and operations. Landowners sign land lease contracts without knowing the turbine layout, which affects aesthetics of property as well as value of the lease contract. Having a turbine placed on one’s land is much more lucrative than not, but landowners have to sign over the use of their land without knowing if they will receive this financial benefit or not. The timing of this process, typically referred to as “Landowner Acquisition,” introduces high uncertainty for both stakeholders and represents a major pain point of the industry—a source stated up to 50% of wind projects fail due to landowner acquisition issues. We present an agent-based model that models the land lease contract period with unique decision-making characteristics for a set of landowners and a wind farm developer. Citizen participation is an integral part of community acceptance of wind farms, thus we use principles from past studies to quantify three actions a developer can take to influence landowner decisions: (1) community engagement meetings; (2) preliminary environmental studies; and (3) sharing the wind turbine layout with the landowner. The results show how landowner acceptance rates can potentially change over time based on what actions the developer takes. Overall, developers can use this model to better understand interactions with landowners and determine what actions may help positively influence landowner acceptance rates.

NOMENCLATURE

\( P_j \) Total power landowner \( j \) will generate  
\( u_{i,\text{Local}} \) Local wind speed at turbine \( i \)  
\( N_j \) Number of turbines on landowner \( j \)'s land  
\( u_0 \) Uniform unidirectional wind speed  
\( r_0 \) Offered compensation rate from developer  
\( t_0 \) Initial time step in model  
\( \Delta t \) Duration of community meeting effect  
\( \alpha \) Exponential decay coefficient for community meeting action

1. INTRODUCTION

Wind is an important resource in the US energy portfolio. Wind energy is responsible for approximately 6.3% of total US utility-scale electricity generation and the capacity continues to grow at an exponential rate [1]. Strides in wind technology have resulted in a decrease in levelized cost of energy for wind projects from $71/MW in 2010 [2] to $49/MW in 2016 [3]. However, landowner acquisition, the process of securing adequate land for the wind farm, remains a pain point for development, both in terms of timelines and financial ramifications. At a wind energy short course offered by Iowa State University, wind farm implementers reported approximately 50% of their wind projects fail because of landowner acquisition issues [4]. Wind farms require more land than solar developments or other forms of renewable energy, requiring developers to interface directly with landowners to lease land for construction and operation. Typically, landowners are farmers with large plots of farmland and have varying levels of knowledge of wind energy and different perceptions of wind farms; deciding to lease their land can be an emotional and complicated decision. Additionally, the landowner acquisition process occurs at the start of a development project, a highly uncertain time for both the landowners and developers. Developers can take actions to help alleviate the uncertainty and engage with the landowners to influence their decision to accept...
land lease contracts, however the effects of these actions on landowner acquisition not well-understood. To our knowledge, a gap exists in the literature to represent landowner decisions on a quantitative and time-dependent basis, and to explore the effects of developer actions on landowner decision-making. To fill this gap, we present an agent-based model to represent the landowner acquisition process; we quantify both stakeholder decision-making and the effects of developer actions and use the results from the model to study how a group of landowners’ decision process can be influenced. Researchers often use agent-based models to represent interactions between decision-making agents in a closed system and learn how the interactions affect outcomes. Results from an agent-based model are generative and can offer insight into multiple scenarios based on different inputs. Results from this model are meant to demonstrate the model’s feasibility to capture the effects of developers’ actions, rather than presenting the effects in real life scenarios. Wind developers can use these generative trends to explore how potential actions might influence landowner decision-making and develop strategies for increased success in landowner acquisition.

This paper is organized as follows: Section 2 provides a background of the wind farm landowner acquisition process and a review of previous literature in representing stakeholder decisions in wind farms, agent-based modeling in the design community, and factors that affect community acceptance towards wind. Section 3 describes our methodology for creating the agent-based model. Section 4 presents the results of the model, followed by a discussion of the results and limitations in Section 5. Finally, Section 6 presents the conclusions.

2. BACKGROUND

2.1 Wind Farm Landowner Acquisition Process

To build a wind farm, a developer offers monetary compensation to multiple landowners to construct and operate wind turbines on their land. An industry report titled “Wind Energy Easements and Leases: Compensation Packages” states compensation packages are typically structured in one of three ways: (1) a one-time lump sum payments to the landowner at the time of contract signing, (2) fixed payments at scheduled intervals to the landowner throughout the duration of the wind farm life, or (3) royalty payments to the landowner based on gross revenues throughout the wind farm life [5]. The most common form of compensation is a mixture these payment structures and the actual payout to each landowner depends on if the developer uses their land or not [5]. From interviews with wind and farmland industry professionals, we learned that developers typically enter a community and collect wind data for a few years, then approach the community and its landowners with lease and easement contracts for the land required for the turbines and any other land required for the project. The developer offers each landowner the same contract terms with additional compensation, called “riders,” for individual circumstances such as service roads, electrical lines, and construction laydown areas. The developer can only start the development process (permitting, impact assessments, contracting, financing, etc.) once they secure the land.

Every landowner has the freedom to accept or decline the offer. Leasing land can be an emotional decision that is not simply financial in motivation. Additionally, developers intentionally write land lease contracts in vague language because the development process and wind farm layout are not set by the time they offer land lease contracts, making it challenging for landowners to understand the process. Land lease agreements can last up to 20–40 years, making the initial decision by the landowner a crucial one for the next generation [5]. Industry groups and university researchers have provided many “guides” online for landowners, who have varying knowledge of wind energy, to consider all the different options and implications of signing a contract (i.e. [5–7]); all guides encourage legal advice before making a decision. However even with professional help, navigating the uncertainty of the process can be challenging for both landowners and developers, and often hinders the progress of many wind farms.

2.2 Modeling Stakeholder Decisions in Wind Optimization Models

As cost of energy (COE) is an important measure of farm viability, much of the literature focuses on building models to minimize COE. Building on the work done by [8–10] in wind farm layout optimization using a genetic algorithm, Chen and MacDonald performed extensive work incorporating landowner decisions into a wind farm optimization layout. The optimization model relaxed the assumption that a continuous piece of land is required and incorporated landowner decisions as an input to minimize the COE [11]. The model used a genetic algorithm to solve for the minimized COE for different scenarios based on different numbers of landowners who accept the land lease offer. The model was enhanced by incorporating additional cost parameters [12], noise disturbance modeling and compensation [13], and additional uncertainty parameters and sensitivity analysis [14]. This work was instrumental in creating a model to predict wind farm COE while incorporating landowner decision-making in the optimization process. However, the model did not offer generative results with the landowner as a full decision-making agent. In reality, landowners make decisions to accept or decline a land lease contract based on many factors, including innate characteristics, perception of wind farms, and personal motivations, all of which cannot be represented in a predictive optimization model. Representing the landowner as a decision-making agent can unlock new learnings and offer insight into what might influence their decision process.

2.3 Agent-Based Models in Design Literature

Design researchers have used agent-based models (ABMs) to represent human systems in multiple ways. These models are most useful when representing systems with complex individual behavior and nonlinear decision-making; additionally, ABMs are flexible and thus useful for showing trends of a system for different parameters, agents, and scenarios [15]. Previous literature shows the ABM approach
used to study the product and service design industry [16–18]. For example, Fernandes et al. focused on the early phase of the design process via the ABM approach [16]. Each agent represented a different person in the design process (customer, lead designer, senior designers, junior designers) and the agents worked together to design a jet engine. While the early phases of product design are typically uncertain and hard to predict, the ABM provided the authors with a versatile structure to model not only the dynamics of early-phase design, but also how uncertainty, interactions, and other characteristics influenced the process. Studying the whole development process with an ABM can also offer insights beyond just focusing on one phase of the design process. Le and Panchal take a more holistic approach to studying the product development process by creating an ABM to study the “Mass Collaborative Product Development” (MCPD) approach [17]. The authors used the ABM to understand how different product architectures (mapping functions of a product to a physical component) can influence how a product evolves over time using the MCPD process. In addition to focusing on product design, Mashhadi et al. expanded the use of ABMs to service design by representing a “take-back system” for electronic waste products [18]. These systems generally see low consumer participation; although past literature explored potential factors to increase participation in take-back systems, Mashhadi et al. was the first to quantify the impact of these factors on consumer behavior and decision-making in a generative model. Their ABM provided a framework for modeling the different interactions between stakeholders, something a predictive model may not have been useful for, and used the resulting trends to offer recommendations for designing a better take-back system service.

Researchers have also used ABMs to study market systems and the complex trends associated with these systems. Wang et al. modeled a product design decision-making approach based on agents’ learning schemes under uncertainty instead of the typical game theoretic approach used in past market system analyses [19]. The model allowed the two agents, manufacturers and retailers, to interact, compete (for manufacturers) and use learning schemes to update information (for retailers). Zadbood and Hoffenson used ABM techniques to represent customers, producers, and the policy maker in a simplified automotive market system [20]. They used the model to study the interactions of consumers and producers in a policy-influenced market and found many benefits with using an ABM approach compared to previous modeling approaches. Inchiosa et al. modeled a simplified version of the global product development financial market and studied the interactions between firms, countries, local banks, global banks, and stock traders [21]. In each of these references, [19–21], the authors used ABM techniques to model the design of market systems on a broader scale, while still representing the details of complex stakeholder interactions.

ABMs have many functions other than just product design and market systems. For example, Meluso and Austin-Breneman used an ABM in the context of systems engineering to show the effect of engineers’ bias on parameter estimation and system performance [22]. The authors developed an ABM based on interviews with experienced aerospace engineers to show how biases and heuristic approaches in decision-making can influence system performance. Fay and Hoffenson focused on an educational outlook and developed an ABM to teach students about product design markets and the variables that affect products [23]. The authors focused on creating a model that was easy to understand, transparently displayed underlying methods, and resulted in outputs that students could use.

Finally, researchers have used the ABM approach to represent energy systems. Sinitskaya et al. built an ABM as a tool to understand how photovoltaic (PV) solar instalar decision behavior affects panel design and market penetration [24]. The model represented three agents—manufacturers, installers, and costumers—based on knowledge gained from industry interviews. Studying the complex interactions between these agents provided insight into the impacts of technology decisions and installer decision processes on PV adoption rates. Hoffenson and Wisniowski simulated the electricity market in New Jersey and individual behaviors by consumers using an ABM approach [25]. The model showed how policies and programs affect consumer behavior, as well as the overall sustainability of the electricity market. Zeiler et al. took a similar focus on consumer behavior and used an ABM to represent consumer preference for indoor climate control in buildings. The purpose of the ABM was to represent a control system with user preferences and help integrate user needs into building design [26].

Overall, the references presented in this section show examples of using the ABM approach to represent complex human systems in design, agent interactions, and their influence on design and market outcomes. In each example, ABMs do not output a particular or optimal solution, but rather provide generative trends based on model inputs. The model we present in this paper is a simple, exploratory ABM to understand how to represent the complexities of wind farm developer and landowner interactions and how developer actions influence landowners to accept a land lease contract.

### 2.4 Community Participation and Acceptance in Wind Farm Development

To meaningfully study the interactions between landowners and wind farm developers and to understand how a landowner makes a decision to accept a land lease contract, it is important to understand what factors cause a landowner to accept wind energy. Wüstenhagen et al. introduces a framework with three dimensions of social acceptance for renewable energy acceptance (socio-political, community, and market acceptance) and writes that community acceptance is a key part to the social acceptance of renewable energy innovation [27]. Understanding community acceptance is especially pertinent to the “apparent contradiction between general public support for renewable energy innovation and the difficulty realization of specific projects” [27]. Researchers have qualitatively explored the concept of community acceptance in the literature in attempt
Environmental Impact Assessments (EIAs) are required for the community by showing their environmental commitment to pay for environmental conservation during wind farm projects based on preserving the rural landscape and agricultural lifestyle [33]. Supporting this finding, Álvarez-Farizo and Hanley conducted a study in Spain to quantify public preferences over environmental impacts of wind farms and found that the community exhibited a positive willingness to pay for environmental conservation during wind development [34]. Communities value environmental and landscape preservation, and a developer could gain more acceptance from the community by showing their environmental commitment to a community before developing a wind farm. While formal Environmental Impact Assessments (EIAs) are required for wind farm development at the federal, state, and often local levels [35], the EIA process occurs after the landowner acquisition process and does not give the landowners the chance to participate before accepting a land lease contract. A developer who conducts a preliminary environmental study and shares the information openly with landowners before the contract acceptance period begins may garner trust and potentially convince environmentally-conscious landowners who may be hesitant to accept a land lease offer.

Finally, research suggests proximity to wind farms and increased exposure to wind energy over time can increase community acceptance. Contrary to the typical NIMBY (“Not In My BackYard”) approach to describing public opposition to wind farms, Devine-Wright found multiple studies that suggest those living closer to wind farm developments had a positive perception toward wind farms [31]. The studies detailed in Devine-Wright’s review spanned across different geographies, such as the UK, USA, and Denmark, and suggest that living near a wind farm causes communities to be more familiar with the development and may positively influence community acceptance. However, developers typically do not share their desired layout with landowners during the landowner acquisition process; thus, landowners making a decision to accept or decline a land lease contract do not know if they will be living by a turbine or not. Through interviews, we learned that the developer has the option to share their desired wind farm layout with landowners before starting the acquisition process. Developers cannot guarantee a final version of the turbine layout; however, they can share their desired layout of where they hope to place wind turbines. Developers who take this action offer information to the landowners and may convince landowners who will be living near turbines to accept the contract. Additionally, studies show that a fair and transparent process can lead to higher acceptance; Gross found that based on her study of a wind farm development in Australia, communities who perceive a fair process will lead to increased social acceptance of wind developments [36]. By sharing the desired layout with the landowners, developers can conduct a fair and transparent process to wind development and gain added trust and acceptance from the landowners.

3. METHODOLOGY

In this section, we present an ABM to model the interactions between landowners and a wind developer during the landowner acquisition process. Unlike a traditional optimization model, ABM allows us to study the evolution of landowner and developer decision-making over time. The model outputs the number of landowners who accept the contract over time for different scenarios based on different developer actions. Developers can use this model to better understand the landowner acquisition process and plan future strategies to increase landowner acceptance.

3.1 Problem Formulation

The model incorporates nine landowners and one wind developer as decision-making agents in the landowner
acquisition process. The model builds off of optimization work conducted by Chen & MacDonald, thus the same number of agents were chosen to match their early work [4]. Fig. 1 shows a systems diagram representation of the model. Two classes of agents, the developer and the landowner, interact in the model with their own decision-making objectives. The model begins with the developer offering a contract rate to the landowner, specifically a certain dollar per MW. The model uses the offered contract rate combined with landowner’s expected power generated on his/her land to calculate the total offered compensation for each landowner in dollars. Additionally, each landowner possesses their Personal Indifferent Selling Price (PISP). The PISP is defined in decision analysis literature as the least an owner would be willing to accept to forgo the use of something that he or she has [37, Chapter 3, pp. 44]. In our study, the PISP is the minimum monetary compensation that a landowner will accept the land lease offer, in dollars. The model computes the PISP based on landowner’s expected power generation as well as their innate characteristics, represented by a willingness-to-accept factor. Once the model has computed the PISP and the offered compensation, the landowner agent compares both values. Since the PISP is the minimum amount a landowner would be willing to accept, if the offered compensation is greater or equal to the PISP, the landowner would accept the offer; in the opposite case, the landowner would not accept the offer.

The decision-making process of both the developer and landowners is modeled as an iterative process. Each iteration corresponds to a unit of time. We learned from our interviews that the landowner acquisition process usually lasts one to two months; based on this information, we set the model to run for 28 units of time (to mimic 28 days, one month).

Throughout landowner acquisition process, we model three actions a developer can take to affect community engagement and participation: community meetings, preliminary environmental studies, and desired layout sharing, all represented as purple trapezoids in Fig. 1. Note that these actions are stand-ins for evaluating different ways in which the PISP can be modified. Future users can model actions appropriate to their situation using this approach. We chose to model these three actions based on the literature presented in Section 2.4. In reality, the land lease contract rate is set based on the overall project financial models, making it near impossible for developers to change these rates and sway landowner acceptance. Modeling these actions can help developers understand what effect potential actions may have to influence landowner decision-making. The model incorporates each action into the landowner decision-making process as well as the developer’s overall cost of energy (if applicable). Details of each action are described in Sections 3.4-3.6.

To determine the cost of energy, a wind farm layout optimization model is computed within the ABM. We borrowed many assumptions from Chen and MacDonald’s work in [4] on the wind farm specifications and assumed the wind farm in the model is in Iowa, a state that has high wind potential [38]. We also used their assumptions of GE1.5sle turbines, with a hub height of 80 meters and a rotor diameter of 77 meters. For simplification, we take the wind to be unidirectional uniform wind from the west at 12 meters/second and the surface roughness to be 0.25 millimeters for flat land. Additionally, we use the same plot of land as in Chen and MacDonald, with each turbine separated by two rotor diameters to reduce wake loss. Fig. 2 shows the land representation used in this model:

**FIGURE 1: SYSTEMS DIAGRAM OF AGENT-BASED MODEL**
3.2 Landowner Decision Process

In reality, the decision to accept a land lease contract is complicated and based on many factors, including the contract rate, property value, and emotional values. As described in the previous section, the PISP value (the lowest dollar value an owner would be willing to accept to forgo the use of the land for something else) is used to capture these factors and the landowner’s decision-making is determined by the PISP; because the PISP is a personal value that cannot be quantitatively computed, we use estimation techniques to model this parameter.

During a realistic landowner acquisition process, landowners do not know where the developer will place turbines. Therefore, they are required to make a decision to accept or decline the land lease contract offer from the developer with an uncertainty. To model this uncertainty, we give landowners a “layout perception” or in other words, a guess about the layout the developer will use to place turbines on their land. We assume that each landowner will get compensation for a maximum of one turbine built on their land. We chose this assumption to mimic the lack of information landowners have when considering land lease contracts. We also assume that there is no wind wake loss due to external turbines (i.e. there is no other turbine built nearby).

The model calculates the \( PISP_j \) for landowner \( j \) by multiplying his/her the willingness-to-accept factor, \( WTA_j \), and his/her expected power generated, \( P_j \), as shown in Eq. (1):

\[
PISP_j = WTA_j \times P_j
\]  

We define the willingness-to-accept factor as the minimum compensation a landowner would be willing to accept for unit power. Using the power equation in [4], we define the expected power generated on a landowner’s land to be:

\[
P_j = \sum_{i=1}^{N_j} 0.343 \times u_{3,local}^3
\]  

Where \( N_j \) is the total number of turbines installed on land owned by landowner \( j \) and \( u_{3,local} \) is the local velocity at each turbine \( i \). The probability that the wind speed of 12 m/s occurs, 0.343, is based on the expected value of that wind speed in the state of Iowa [14].

The willingness-to-accept factor is dependent on individual landowner’s characteristics. In reality, some landowners may be more willing to lease their land, while others may be near impossible to convince. Therefore, we categorize landowners into four types to account for their uncertain attitude towards wind project. Each landowner is classified into one of the types based on a simple discrete probability distribution, shown in Table 1. The values and probabilities are hypothetical numbers adapted from Chen & MacDonald’s work in [13]; in practice, developers will estimate these distributions based on their interactions with landowners.

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Within each landowner type, we chose to use a normal distribution to further model the uncertainty. Individual landowners of each type draw their unique \( WTA_j \) from the normal distribution for their type. Table 1 shows the means and standard deviations that characterize each distribution. All dollar quantities are listed in 2002 dollars to be constant with one another and with the previous literature.

3.3 Developer Decision Process (Passive)

At the beginning of the negotiation, the developer makes a compensation offer to the landowners, which comes in the form of a compensation rate per unit power. To estimate this offer, we set the offered rate, \( r_o \), to be $2,757/MW (in 2002 dollars). This number is an average compensation package value based on data from 26 different wind projects across different regions, summarized in [5]; Chen and MacDonald converted these numbers into 2002 dollars and used $2,757 in their analysis as an average compensation package [12]. Subsequently, we compute the offered compensation by the developer to an individual landowner based on the landowner’s layout perception:

\[
Offered\ Compensation = r_o \times P_j
\]  

Each landowner compares its offered compensation to their unique \( PISP_j \) and determines if they accept the offer or not.

3.4 Action 1: Community Engagement Meeting

As described in the Background Section, there is a need for public participation in wind development process. We incorporate a community engagement meeting as an action that a developer can take to affect the \( PISP_j \) of each landowner. Through this meeting, the developer has the chance to educate the community about the wind farm and build trust, especially with the landowners, by offering genuine answers and incorporating community input.

In the model, holding a community meeting lowers \( PISP_j \) for each landowner; this means the landowners will accept the land lease contract for a lower dollar amount if the developer holds a community meeting. For this model, we assume that a community meeting has positive effect on the landowners. We chose to model this positive effect using an exponential decay function, with decay coefficient \( \alpha \), used in many applications such as natural science, public health, and economics.

\[
PISP_{j,t_0+\Delta t} = PISP_{j,t_0} \times e^{-\alpha \Delta t}
\]  

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Eq. (4) shows the effect of community meetings on landowners’ \( PISP_j \) is the greatest directly after the meeting occurs and will gradually decrease as time goes by. Additionally, the earlier the community meeting occurs, we assume it will accumulate a greater effect on the landowner decisions. The community meeting can vary in the time, \( t \), it is introduced and the decay coefficient. We use the exponential decay function as an example; other decaying functions can also be applied as long as it satisfies these constraints.

### 3.5 Action 2: Preliminary Environmental Study

As described in the Background Section, environmental studies can have a positive effect on community acceptance of wind farms. We introduce a preliminary environmental study as a “planning” action that a developer can take to gain valuable environmental information. This preliminary environmental study builds trust between the developer and landowners by showing developer’s commitment to the environment. Since we limit our scope of the environmental study as a planning action, we assume it only occurs before the developer makes an offer to landowners and the result of the study is communicated to landowners at the time of the offer; in the model, this means the action can only be introduced at \( t = 0 \).

Recall from Section 3.1, we defined four types of landowner categorizations based on their attitude toward the wind farm project. Within each landowner type, the model samples the \( WTA_j \) of each landowner from an assumed normal distribution. We model the effects of the preliminary environmental study as a shift in the mean of a landowner’s \( WTA_j \) distribution. We assume that if a developer has performed a preliminary environmental study and shared the results with the landowners at the time of the contract offer, the mean for each distribution decreases, i.e. \( E(WTA_j) \) decreases. This decrease in mean may lead to a lower willingness-to-accept for each landowner when drawn from the distribution, ultimately lowering their \( PISP_j \) value.

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### 3.6 Action 3: Desired Layout Sharing

The final action a developer can take is to share the desired turbine layout with the landowners. As outlined in the Background Section, developers cannot guarantee where turbines will be built, thus typically do not share the potential turbine layout with landowners. However, from our interviews, we learned that the developer has the option to share this potential layout with the landowners to increase the perception of fairness and gain trust with the landowners. Additionally, landowners may be more willing to accept the contract if they know they have a greater chance of a turbine on their land.

Recall from Section 3.1, we chose to mimic the landowner’s lack of information by assuming each landowner will get one turbine on his/her land. The model uses this assumption to calculate the total expected power generated for each landowner, which in turn, is used to estimate landowner \( PISP_j \). To model the developer sharing the desired turbine layout, we update the landowner turbine assumption – instead of assuming one turbine, the landowner now has access to the envisioned layout and the true number of turbines \( N_j' \) that the developer will build on his/her land, and can now calculate the true expected power on his/her land using Eq. (5), an updated version of Eq. (2):

\[
P_j = \sum_{i=1}^{N_j'} 0.343 \times u_{i,local}^3
\]

The developer can introduce this action at any time, \( t \), and the model will calculate the new expected power for each landowner. The \( WTA_j \) for each landowner remains unchanged if this action is introduced. Ultimately, sharing the desired layout leads to a different \( PISP_j \) value for each landowner, based on an accurate turbine count.

### 4. RESULTS

We used the Mesa package in Python to build the ABM and MATLAB optimization toolbox for the optimization model. The optimization model was built based on previous research by Chen and MacDonald [4]. The model uses a genetic algorithm (GA) in the standard MATLAB optimization toolbox to generate the optimized layout. The population size in GA is 1000 with 1000 generations. The generated optimized layouts from MATLAB were fed back into the Python ABM using MATLAB Python API. The outputs show the number of landowners who accept the lease contracts over time. As mentioned in Section 3.2, \( WTA_j \) for landowner \( j \) was randomly drawn from the distributions. To study the effects of different actions, we placed a seed in this sampling process so that landowners are identically initialized each run.

To analyze the effects of community meetings and layout sharing, we examine the landowner acceptance profile over the 28-day contract period. Because the preliminary environmental study is introduced before the contract period begins, we examine the distribution of initial landowners who accept the contract at \( t = 0 \). In the industry, the offered rate and the contract timeline are not negotiable during the landowner acquisition process, thus we keep these terms constant in our model.
FIGURE 3: BASELINE LANDOWNER ACCEPTANCE PROFILE (NO ACTIONS)

FIGURE 4: BASELINE DISTRIBUTION OF INITIAL LANDOWNER ACCEPTANCE (MEDIAN = 4)

FIGURE 5: VARYING DECAY CONSTANT FOR COMMUNITY MEETING ACTION (INTRODUCED AT t = 1)

FIGURE 6: VARYING TIME OF INTRODUCTION FOR COMMUNITY MEETING ACTION (α = 0.1)

FIGURE 7: DISTRIBUTION OF INITIAL LANDOWNER ACCEPTANCE WITH PRELIMINARY ENVIRONMENTAL STUDY (MEDIAN = 6)

FIGURE 8: VARYING TIME OF INTRODUCTION FOR DESIRED LAYOUT SHARING ACTION
To establish a baseline for the landowner acceptance profile over time, Fig. 3 shows the trend remains flat over the contract period if no developer actions are implemented. Landowners do not have any incentive to change their decision-making process, thus the number of landowners who accept the contract from the developer stays the same over time the 28-day decision period. To understand the effects of the community meeting and desired layout sharing actions, we compare the landowner acceptance profile over time with each action to the baseline shown in Fig. 3.

To establish a baseline for the initial landowner acceptance, we ran the model 100,000 times (without a pre-defined seed) to create a histogram of the initial landowners who accept the contract. Fig. 4 shows the baseline distribution with a median 4. Because the preliminary environmental study action can only affect the number of initial landowners who accept the contract, we compare the distribution of initial landowners who accepted after introducing this action with the baseline distribution shown in Fig. 4.

The community meeting action can be varied in two ways to study its effects on landowner acceptance profile: (1) the decay coefficient $\alpha$ and (2) the time of intervention. Fig. 5 shows the acceptance profiles for a community meeting introduced on Day 1 with decay coefficients ranging from $\alpha = 0.01$ to $\alpha = 1$. As $\alpha$ increases, the positive effect of the community meeting is stronger directly after the meeting is introduced and has a stronger lasting effect. A value of $\alpha$ closer to 1 is analogous to a developer’s increased attention to engagement efforts – the higher the engagement level, the greater positive effect the meeting will have. Fig. 6 shows the acceptance profiles for a community meeting introduced at different times in the contract period (Day 1, Day 14, and Day 26) with a constant $\alpha = 0.1$ decay coefficient. The case where the meeting is held on Day 1 shows an initial increase in landowner acceptance directly after the meeting is held as well as later in the contract period (around Day 21). The case where the meeting is held on Day 14 does not show the same level of positive impact. Introducing meeting on Day 26 shows little positive benefit in number of acceptances compared to the other cases.

The preliminary environmental study can only be introduced before the contract period begins and impacts the initial landowners who accept the contract at $t = 0$. To understand the effects of this action, we ran the model 100,000 times (without a pre-defined seed) to create a histogram and compare the median to the baseline distribution. Fig. 7 shows the distribution with the preliminary environmental study action activated on Day 0; compared to Fig. 4, Fig. 7 is skewed to the right and has a median number of initial landowner acceptances of 6, higher than the median of 4 from the baseline distribution.

Finally, the desired layout sharing action can vary in the time the layout is introduced to the landowners. Fig. 8 shows the acceptance profiles for the layout being shared at different times of the contract period (Day 1, Day 14, and Day 26). The transparency has the same, immediate positive impact on landowner acceptance directly after the action is introduced, regardless of the introduction time. Unlike the community meeting action, the layout sharing action does not have a continued positive effect.

5. DISCUSSION

The model demonstrates what positive benefits can potentially occur from the developer actions and how the actions influence landowner acceptance. We built our model to suggest that holding a community meeting not only increases the initial acceptance of landowners, but also continues to have a lingering positive effect as time progresses, due to the decay function in Eq. (4) and depends on the decay coefficient specified. An engaging meeting can create an open forum for community participation and education. Additionally, spending time with community members to discuss wind farm plans brings up potential co-design opportunities, i.e. designing the wind farm with the community instead of for the community. Community members and landowners can have a greater sense of ownership over the development by participating in the design of the wind farm and working with the developer to implement the project in their home community. The time at which the community meeting is also important to the overall acceptance of the project; trends show that a community meeting introduced at the beginning of a contract period introduces additional positive effects over time that may not be realized if the action is introduced later in the period. Future research should be conducted to gain a deeper understanding of the effects of community meetings and understanding the social networks within communities as it relates to wind development.

While this ABM only modeled one type of community meeting with a decay function, we know from literature sources that multiple engagement opportunities, both formal and informal, are key to community acceptance [28]. In future work, the model should be expanded to study the effects of multiple meetings and distinguish between different types of community engagement meetings, i.e. large meetings vs. one-on-one meetings.

Additionally, the assumptions built into our model suggest that conducting an environmental study before offering a land lease contract can positively influence landowner acceptance. Developers should consider environmental preservation strategies when developing land; communities care about conserving their landscape and developers may gain trust by studying the area and making environmentally conscious choices in the design of the wind farm. Creating initial trust with the community before the contract period even begins can also be a strategy for developers to increase landowner acceptance.

Finally, our model was built to suggest that sharing the desired layout can have a positive step change on landowner acceptance directly after the layout is introduced. Additionally, the magnitude of the step change is not dependent on the time at which the action is introduced. When the developer shares the desired layout, landowners can immediately use the more accurate information to compute their compensations; landowners who only assumed they would get one turbine built on their land now may have more turbines to contribute to their
compensation. Developers should use these trends to consider the level of transparency shown to landowners and take into account that the transparency and fairness may prove useful to both stakeholders in the overall wind development process. If the landowners perceive a fair process from the developer from the start of their interactions, future steps in the project may run more smoothly for the developer.

When the layout is introduced at the very end of the contract period (Day 26), the trend shows a slight increase in landowner acceptance; this trend can be interpreted as what we heard in interviews as a “last ditch effort.” If most landowners had agreed to lease their land to the developers and few undecided landowners remain, the developer can benefit from sharing the desired turbine layout as a tool to sway reluctant landowners. It is important to note that while we assume layout sharing has a positive effect on landowner acceptance rates, in reality this may also negatively influence landowners if their land is not included in the proposed turbine layout. Future studies should include this additional aspect of layout sharing.

This ABM is a simple model, designed to model the preliminary effects of developer actions on landowner decision-making; by nature of simplicity, the model contains several limitations. First, this “proof-of-concept” model uses an ABM approach to account for different human decision factors in the landowner acquisition process; human decisions are difficult to accurately represent and the model depends completely on how we chose to represent each agent and the simplified calculations we chose to use (i.e. neglecting wake loss when calculating $P_e$).

Second, while we based of our input parameters on past literature and knowledge of the wind industry, the values are hypothetical and further research should be done to input more accurate values, such as additional literature review, industry and stakeholder interviews, and data mining. Additionally, we chose the developer actions based on past literature and knowledge of the industry, but these actions may also be refined. We focused on providing three approaches to modeling developer actions and in the future, users can update the actions as they see fit and study multiple actions together.

Third, we conducted our simulation with a limited number of landowners. The choice to use nine landowners was based on previous research and available computation power. This limited number may have led to bias in our result, especially when examining trends of landowner acceptance. A small number of landowners did not provide enough granularity when examining total number of landowners accepted; actions that have a strong effect resulted in 100% acceptance, which may not be realistic. Future models should include a more realistic number of landowners to provide more granularity to the trends.

Finally, while our ABM calculated the cost of energy when optimizing the wind farm, it did not explore cost of the developer actions and how the cost influences landowner acceptance. Future work should explore the range of costs for each developer actions and how that cost affects a developer’s decision to incorporate actions into their project.

6. CONCLUSIONS

In this project, we investigated the wind farm landowner acquisition process using an ABM approach. Building off previous work that represented stakeholder decisions in the landowner acquisition process, we created an ABM to represent stakeholder and landowner decision-making. Additionally, we introduced three developer actions chosen based on qualitative literature in community acceptance factors of wind farms—community meeting, preliminary environmental study and sharing the desired wind layout—to show how developer actions influence landowner acceptance. We used the ABM to run a baseline scenario and additional scenarios based on different action and varying parameters. The generative trends display the effects of three actions and their positive effects on landowner participation. While limitations exist, this model provides a proof-of-concept for representing landowner and developer interactions and can inform future developers to build their strategy for their landowner acquisition process and influence landowner acceptance.

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REFERENCES


