# Agent-Based Modeling of Decisions and Developer Actions in Wind Farm Landowner Contract Acceptance

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*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 alternative land uses, but landowners must sign over the use of their land without knowing whether they will receive this financial benefit or not. This process, typically referred to as "Landowner Acquisition," is highly uncertain for both stakeholders—a source stated up to 50% of wind projects fail due to landowner acquisition issues. We present an agent-based model to study the landowner acquisition period with unique decision-making characteristics for nine landowners and a developer. Citizen participation is crucial to the acceptance of wind farms; thus, we use past studies to quantify three actions a developer can take to influence landowners: (1) community engagement meetings, (2) preliminary environmental studies, and (3) sharing the wind turbine layout with the landowner. Results show how landowner acceptance rates can change over time based on what actions the developer takes. While still in the "proof of concept" stage, this model provides a framework for quantifying wind stakeholder interactions and potential developer actions. Suggestions for how to validate the framework in the future are included in the discussion.* [DOI: 10.1115/1.4047153]

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## 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 [1]. Strides in wind technology resulted in a decrease in cost of energy (COE) for wind projects from $71/Megawatt (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, in terms of both 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 as well as 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 are 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 (ABM) to represent the landowner acquisition process. Researchers often use ABMs to represent interactions between decision-making agents in a closed system and learn how the interactions affect outcomes. Rather than predicting one optimal solution, ABMs provide generative results that offer multiple solutions based on different scenarios, inputs, and assumptions. We use this approach to quantify stakeholder decision-making and the effects of developer actions over a defined period of time to study how landowner acceptance rates change based on different developer actions. Additionally, we offer preliminary results on how costs of the actions affect the overall COE of the project. The results from the model show acceptance trends for different scenarios and offer insight into how actions can affect acceptance; the cost analysis shows that the overall influence of an action on landowner acceptance may be more important to project finances than the upfront cost of the action itself. The model is still at the "proof of concept" level, and the actions are based on data from the literature and interviews, not on regional-specific data; thus, the resulting trends provide insight, but are not experimentally validated and cannot be translated to the current wind industry. However, with further development and data acquisition, the model can be a useful framework for wind developers to explore how potential actions might influence their communities and help develop strategies for increased success in landowner acquisition.

In Sec. 2, we give an overview of the wind farm landowner acquisition process and present past literature on ABMs and community acceptance of wind projects. Section 3 provides a description of the model we built and used for the analysis. Section 4 presents the

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results of the model, followed by a discussion and limitations in Sec. 5. Finally, Sec. 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 payment 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 of these payment structures. The actual payout to each landowner depends on whether the developer installs a turbine on the landowner's land or not [5]; if a landowner signs a contract with the developer and has turbines placed on their land, the outcome is financially lucrative for the landowner (compared with other land uses, such as farming). 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; thus, the decision by the current landowner has implications for the next generation [5]. Industry groups and university researchers have provided many "guides" online for landowners to consider the different options and implications of signing a contract (i.e., Refs. [5–7]); all guides encourage legal advice before making a decision. 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 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 Refs. [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.** Many disciplines have used ABMs to study systems and the complex human interactions within the system. ABMs consist of autonomous agents that can make decisions while incorporating interactions, evolution of behavior, and learning over time. The modeler defines the decision characteristics for each agent and the environment in which the agents interact, then the model steps through time to let the interactions play out. The results of an ABM simulation show a series of trends based on defined scenarios, instead of one optimized solution. Given this generative (versus predictive) approach, ABMs are most useful when representing systems with complex human behavior and decision-making under uncertainty; additionally, ABMs are flexible and thus useful for showing trends of a system for different parameters, agents, and scenarios [15].

Design researchers have utilized these powerful features of ABMs in multiple ways; many examples in the literature guided our choice to use an ABM for this study and informed our model design. Researchers in the product design space have used ABMs to study the uncertainty of early phase design and the effects on the final design of a product [16], as well as how the entire design process can influence a final product [17]. Mashhadi et al. expanded the use of ABMs to service design and quantified the impact of consumer behavior and decision-making for a "take-back system" of electronic waste products [18]. The flexibility to model different scenarios and the ability to incorporate agent interactions over time has given designers a way to study how product and service design processes from different perspectives can be influenced.

Researchers have also used ABMs to study the design of market systems, incorporating a macro-view analysis of how agent interactions influence these systems, in contrast to the micro-view of how a specific product process is influenced. They investigated different scales of influences, including individual agent's learning schemes [19], as well as broader external forces, such as policy [20]. Additionally, financial considerations have also been considered when studying market influences [21]. These examples display a broader view of how ABMs can be used on large systems, while still studying the details of complex stakeholder interactions.

Designers have used ABMs in additional contexts, such as quantifying engineers' bias in system engineering [22] and using the ABM itself as an educational tool to teach about product design markets [23]. To directly inform our model design, we were particularly interested to understand how designers have used the ABM approach to represent energy systems. Sinitskaya et al. built an ABM to understand how photovoltaic (PV) solar installer decision behavior affects panel design and market penetration [24]. The model represented three agents—manufacturers, installers, and customers—based on the 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]. Their 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 how the design community uses ABMs to represent complex human systems, agent interactions, and their influence on design and market outcomes. We draw from these examples to present an ABM in this paper that explores the complexities of wind farm developer–landowner interactions and how developer actions may 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. Community acceptance is a key part to the social acceptance of renewable energy innovation, especially when understanding 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 to explain this "social gap" or the divide that exists between the general public support for renewable energy and the slow uptake in technology [28]. While literature on the topic of community acceptance of wind energy does not distinguish landowners as a different category of citizens, we use the findings from this literature to understand landowner decision-making factors and inform our choice of developer actions.

Citizen participation activities are important components to project acceptance for any developer and operator. Specifically for wind farm projects, studies have found "participation plays a crucial role in the acceptance of wind energy projects by citizens," [29] and that community participation could help increase environmental literacy, thus increasing the likelihood of the public accepting a wind farm project [30]. Authors in both Refs. [29] and [30] cite community meetings as an effective way for wind energy developers and operators to offer participation opportunities. Based on our interview with a Midwestern farmland manager, developers are usually required to hold at least one public meeting for a wind project; however, Devine-Wright states the quality of their interactions with the public is typically poor [31] because the meetings are often not publicized or the community does not feel like they have any control over the decisions. The quality of the public engagement is crucial; Dwyer and Bidwell describe a positive example of high-quality public engagement in Ref. [28] for the development of the first offshore wind farm in the United States. A series of community meetings and engagement interactions were held throughout the development process, leading to increased acceptance and trust between the developer and the community. A wind developer who conducts one or multiple community meetings can gain trust with the landowners and foster participation during the development process, potentially leading to higher acceptance rates for the project.

Environmental studies also have the potential to garner acceptance from a community. Wind farms can cause harm to the environment, including birds, bats, crop damage, as well as light and noise emissions [32], which can lead many people to reject wind farm projects. Residents of rural communities, often the potential landowners targeted by wind developers, care about their landscape and agricultural lifestyle [33]; one study even quantified a community's 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 before starting the development process. 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 "Not In My BackYard" (NIMBY) 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]. 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 while developers cannot guarantee a final version of the turbine layout, they have the option to share their desired wind farm layout with landowners before starting the acquisition process. Developers can take this action to be more transparent about their plans and potentially convince landowners who will get turbines on their land. A study found that communities who perceive a fair and transparent 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 Model Description

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 framework 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 and MacDonald, thus the same number of agents were chosen to match their earlier work [4]. Two classes of agents, the developer and the landowner, interact in the model with their own decision-making objectives. The model begins by using a fixed contract rate ($/MW) 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) to determine if they will take the offered compensation from the developer. 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 they already possess [37]. In our study, the PISP is the minimum monetary compensation that a landowner is willing to accept for 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 (WTA) 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 developer then uses the resulting landowner acceptance rate to calculate the COE of the total project. The decision-making processes of both the developer and landowners are modeled as an iterative process, with each iteration corresponding to one 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 represent 28 days, one month). Figure 1 shows a systems diagram representation of the model for one time unit.

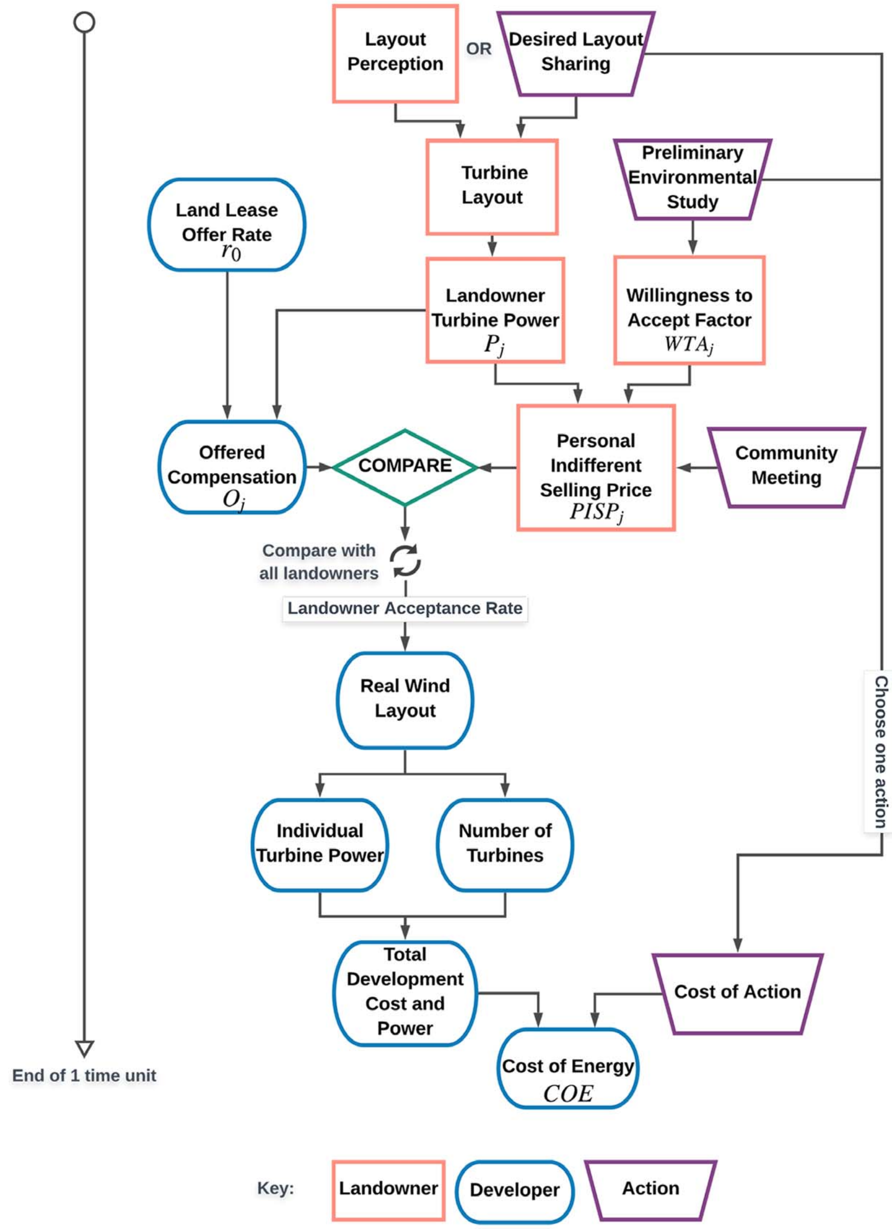


**Fig. 1 Systems diagram of one time-step in the model. The diagram is organized from top to bottom in a chronological order.**

Throughout the 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. These actions are based on the literature presented in Sec. 2.4. Each action represents a different way to modify the landowner's decision-making process and influences the resulting landowner acceptance rate; future users can model actions appropriate to their situation using this approach. 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 additional actions may have to influence landowner's decision-making. In our model, the developer can choose one action to perform, which will (1) affect the landowner acceptance rate in a unique way and (2) add the cost of that action to the overall COE, calculated by the developer agent. We estimate the cost of each action for this analysis (see Secs. 3.4–3.6 for more details), but in the future, specific dollar amounts for each action should be determined by the developer. Note that all dollar quantities in the following section are listed in 2002 dollars to be constant with one another and with the previous literature.

To determine the COE, a wind farm layout optimization model is computed within the ABM. We borrowed many assumptions from Chen and MacDonald's work in Ref. [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 m and a rotor diameter of 77 m. For simplification, we take the wind to be unidirectional uniform wind from the west at 12 m/s and the surface roughness to be 0.25 mm 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. Figure 2 shows the land representation used in this model.

**3.2 Landowner Decision Process.** In reality, the decision to accept a land lease contract is complicated and based on many

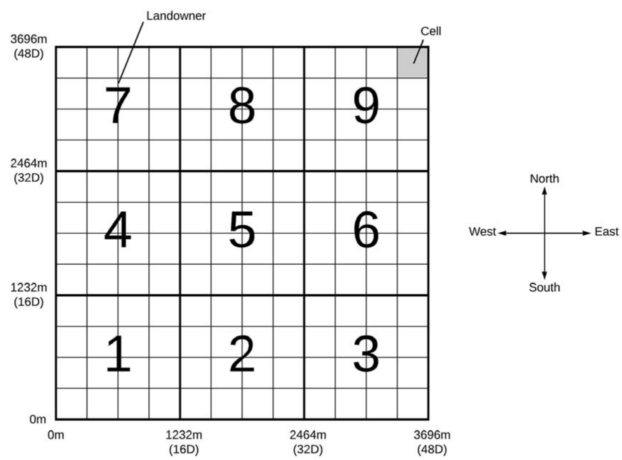


**Fig. 2 Land representation from Ref. [4]**

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) captures these factors and determines the landowner's decision-making; 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 this uncertainty. To model the uncertainty, we give landowners a "layout perception," or 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 $\mathrm{PISP}_j$ (\$) for landowner $j$ by using the individual WTA, $\mathrm{WTA}_j$ (\$/MW), and expected power generated, $P_j$ (MW), as shown in Eq. (1)

$$\mathrm{PISP}_j = \mathrm{WTA}_j \times P_j \tag{1}$$

As discussed in Refs. [8] and [4], power from an individual turbine is directly related to the local wind speed $u_{i,local}$ with the following relationship:

$$P_i = \begin{cases} 0, & \text{for } u_i \in [0,\ 2) \\ 0.3 \times u_i^3, & \text{for } u_i \in [2,\ 12.8) \\ 629.1, & \text{for } u_i \in (12.8,\ +\infty) \end{cases} \tag{2}$$

Since we assumed our external wind to be unidirectional at 12 m/s, considering the wake loss along the wind's passage [4], $u_{i,local}$ is always less than or equal to 12 m/s. Therefore, it is clear that only the second case in Eq. (2) applies and we can define the expected power generated on a landowner's land to be

$$P_j = \sum_{i=1}^{N_j} 0.3 \times u_{i,local}^3 \tag{3}$$

where $N_j$ is the total number of turbines installed on land owned by landowner $j$ and $u_{i,local}$ is the local velocity (m/s) at each turbine $i$.

WTA is dependent on the 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 define WTA as the minimum \$/MW a landowner would be willing to accept and categorize landowners into four types to account for their uncertain attitude toward wind projects. Each landowner is classified into one of the types based on a discrete probability distribution, shown in Table 1. The values and probabilities are hypothetical numbers adapted from Chen and MacDonald's work [13]; in practice, developers should estimate these distributions based on their interactions with landowners.

**Table 1 WTA distributions for different landowner types**

| Type | A | B | C | D |
|---|---|---|---|---|
| Discrete probability distribution | 0.35 | 0.4 | 0.2 | 0.05 |
| Mean $\mathrm{WTA}_j$ | \$2500/MW | \$3150/MW | \$5000/MW | \$12,000/MW |
| Standard deviation | \$500/MW | \$1000/MW | \$2000/MW | \$4000/MW |

Within each landowner type, we choose to use a normal distribution to further model the uncertainty. Individual landowners draw their unique $\mathrm{WTA}_j$ from the normal distribution for their type. Table 1 shows the mean WTA values and standard deviations that characterize each landowner-type distribution.

**3.3 Developer Decision Process (Passive).** At the beginning of each time unit, the developer makes a compensation offer $O_j$ (\$), to each landowner. To calculate this offer, we set the offered compensation rate, $r_o$, to be \$2757/MW; while compensation rates are generally proprietary within the industry, our assumed value is based on the average compensation package value calculated using data from 26 different wind projects across different regions of the United States [5] and converted into 2002 dollars [12]. Subsequently, we use $r_o$ and $P_j$ (defined above) to compute $O_j$

$$O_j = r_o \times P_j \tag{4}$$

Each landowner agent compares their $O_j$ to their unique $PISP_j$ and determines if they accept the offer or not.

At the end of each time unit, the developer calculates the COE. We define COE (in \$/MWh) based on the simplified model used by Chen and MacDonald in Ref. [12]

$$\mathrm{COE} = \frac{C_{tot}}{\mathrm{AEP}} \tag{5}$$

where $C_{tot}$ is the total cost (in \$), AEP is the farm's total energy (in MWh). The total cost includes the annual operating expenses, the initial capital costs for the farm, and the cost of the actions.

**3.4 Action 1: Community Engagement Meeting.** As described in Sec. 2.4, there is a need for public participation in the wind development process. We incorporate a community engagement meeting as an action that a developer can take to affect the $\mathrm{PISP}_j$ 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 holding genuine dialogue and incorporating community input into the project plans.

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. 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 $\alpha$, and time of introduction, $t$ (in days), as shown in Eq. (4)

$$\mathrm{PISP}_{j,t_0+\Delta t} = \mathrm{PISP}_{j,t_0} \times e^{-\alpha \Delta t} \tag{6}$$

where $t_0$ is the initial time-step in the model and $\Delta t$ is the duration of the community meeting effect (both in days). The effect of community meetings on landowners' $\mathrm{PISP}_j$ 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's influence on landowner acceptance can vary based on $t$ and $\alpha$. We use the exponential decay function as an example for this effect, as decay functions are used in many applications such as natural science, public health, and economics; other decaying functions can also be applied as long as it satisfies the problem constraints.

The cost of a community meeting can vary, depending on the project and region. Developers can conduct the engagement themselves or hire an external consultant; either way, engaging the community requires manpower, careful execution, and dedicated follow up. Based on an interview, fees for engagement consultants can be approximated around \$200/h. For a project that is assumed to take 50 h, we estimate the total project costs to be \$10,000.

**3.5 Action 2: Preliminary Environmental Study.** As described in Sec. 2.4, 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 about the proposed project site to share with the community. We assume a preliminary environmental study builds trust between the developer and landowners by showing developer's commitment to the environment and openness to share information. 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 initial offer; in the model, the action can only be introduced at $t = 0$.

Recall from Sec. 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 $\mathrm{WTA}_j$ 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 $\mathrm{WTA}_j$ 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., $E(\mathrm{WTA}_j)$ decreases. This decrease in mean may lead to a lower WTA for each landowner when drawn from the distribution, ultimately lowering their $\mathrm{PISP}_j$ value (see Table 2).

The cost of an environmental study depends on the scope and requirements of the study. If the National Environmental Policy Act (NEPA) study guidelines are used, environmental assessments have been reported to range from \$3000 to \$1.2 million, with a median cost of \$65,000 [39]. We use this median cost in our analysis. Depending on the size of the wind farm project, this cost may not affect the overall budget (for larger-scale projects) or it may be cost-prohibitive (for smaller-scale projects). Most developers hire contractors to conduct these studies, as they do not have these skills in-house. A full environmental assessment can also require additional time in the development process, around one year if the assessment is compliant with NEPA [39]. A developer must consider the costs and benefits before conducting a preliminary assessment ahead of the landowner acquisition process.

**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 Sec. 2.4, developers cannot guarantee where turbines will be built, thus typically do not share their desired turbine layout with landowners. From our interviews, however, 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 land lease contract if they know they have a greater chance of a turbine on their land.

Recall from Sec. 3.1, we choose 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 $\mathrm{PISP}_j$. 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 desired layout and the true number of turbines $N_j^*$ that the developer will build on their land. The landowner agent can now calculate the true expected power on their land using Eq. (5), an updated version of Eq. (2):

$$P_j = \sum_{i=1}^{N_j^*} 0.3 \times u_{i,local}^3 \tag{7}$$

The developer can introduce this action at any time. The $\mathrm{WTA}_j$ for each landowner remains unchanged if this action is introduced. Ultimately, sharing the desired layout leads to a different $\mathrm{PISP}_j$ values for each landowner, based on an accurate turbine count. Additionally, taking this action does not have any upfront cost to the developer; however, the developer must consider the tradeoff that comes with the loss of confidentiality that comes with this action and how that might affect the other landowners.

## 4 Results

We used the Mesa package in PYTHON to build the ABM and the MATLAB optimization toolbox for the optimization model. The optimization model was built based on the 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 Sec. 3.2, $\mathrm{WTA}_j$ for landowner $j$ was randomly drawn from the distributions. To study the effects of different actions, we placed a seed in the 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. Additionally, we incorporate a preliminary study of how the cost of actions influences the overall COE.

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 the 28-day decision period. To understand the effects of the community meeting and desired layout-sharing actions, we

**Table 2 Mean shift of WTA distributions for landowner types**

| Type | A | B | C | D |
|---|---|---|---|---|
| Mean WTA without preliminary environmental study | \$2500/MW | \$3150/MW | \$5000/MW | \$12,000/MW |
| Mean WTA with preliminary environmental study | \$2000/MW | \$2500/MW | \$3000/MW | \$9000/MW |
| Standard deviation | \$500/MW | \$1000/MW | \$2000/MW | \$4000/MW |

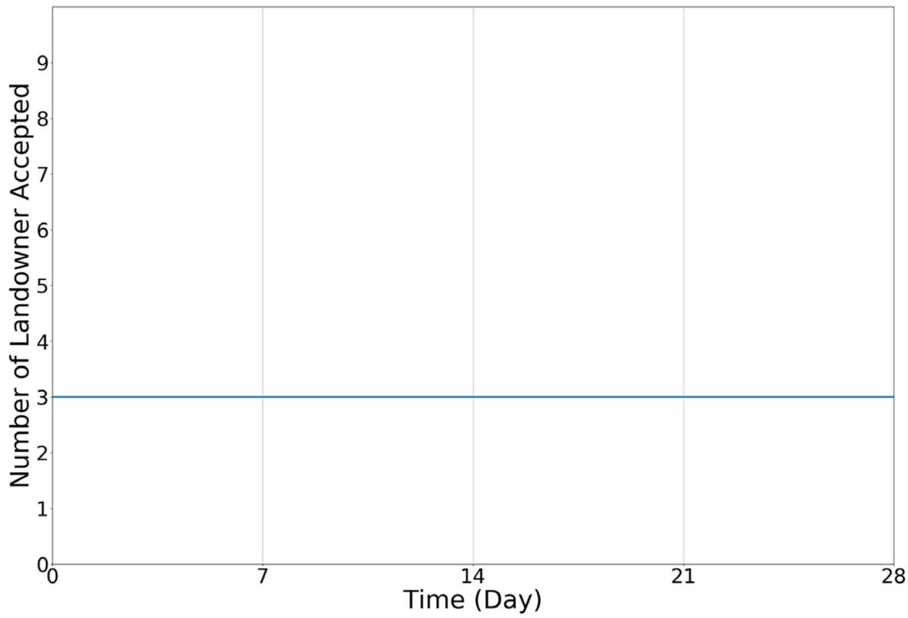


**Fig. 3 Baseline landowner acceptance profile (no actions)**

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 rates, we ran the model 100,000 times (without a pre-defined seed) to create a histogram of the initial landowners who accept the contract. Figure 4 shows the baseline distribution with a median of four landowners accepting at $t=0$. 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. Figure 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. Figure 6 shows the acceptance profiles for a community meeting introduced at different times of 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 the number of acceptances compared to the other cases.

To study the effects of the preliminary environmental study, we ran the model with this action activated on Day 0 in the same

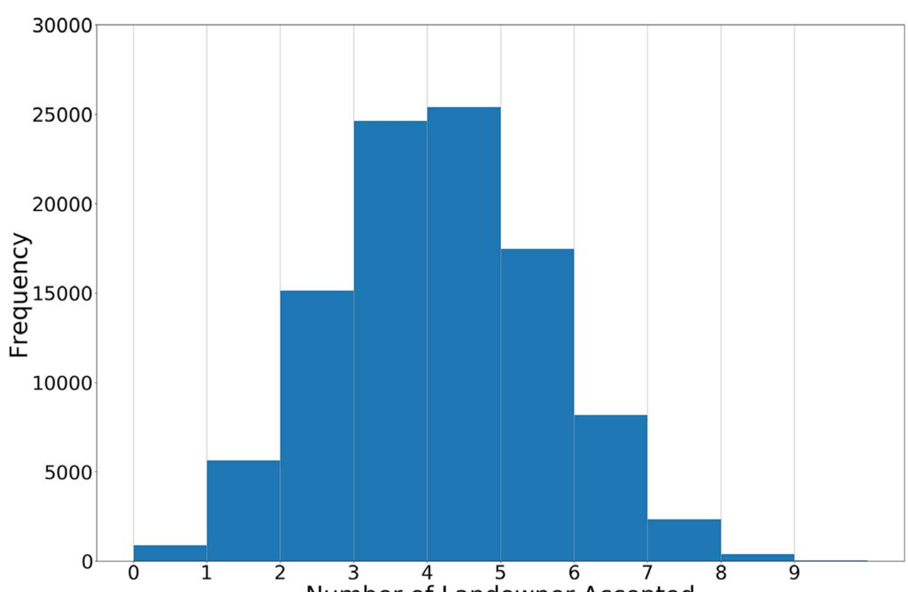


**Fig. 4 Baseline distribution of initial landowner acceptance (median = 4)**

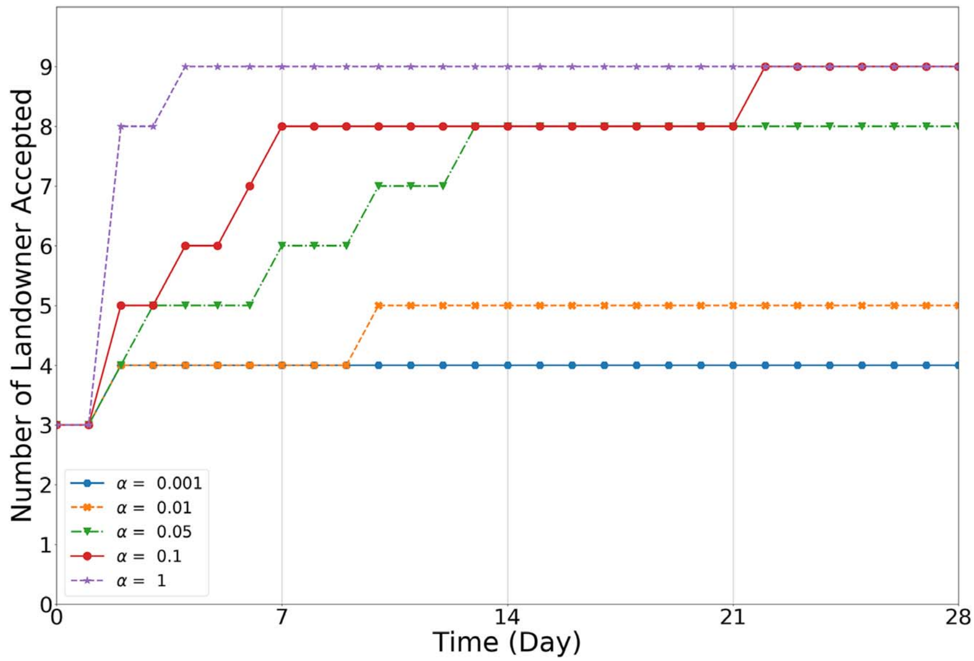


**Fig. 5 Varying decay constant for community meeting action (introduced at $t = 1$)**

manner as the baseline distribution in Fig 4. Figure 7 shows the resulting distribution with the action; 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. Figure 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.

While participation rates appear to increase as per the results, implementing these actions does not come without cost to the developer. We incorporate the cost of each action into a basic analysis of the project COE to study this tradeoff and determine what actions may be worth the effort. Using Eq. 5, we add the cost of the action to the total costs using values defined in Secs 3.4–3.6. We assume the desired layout-sharing action does not cause the developer to incur additional costs, and we assume the community meeting and preliminary environmental assessment does add to the COE. However, we find that the cost of the actions is small compared to the rest of the project costs and thus regardless of the action implemented, the COE mainly depends on the number of landowners that have accepted to participate. If less than six landowners

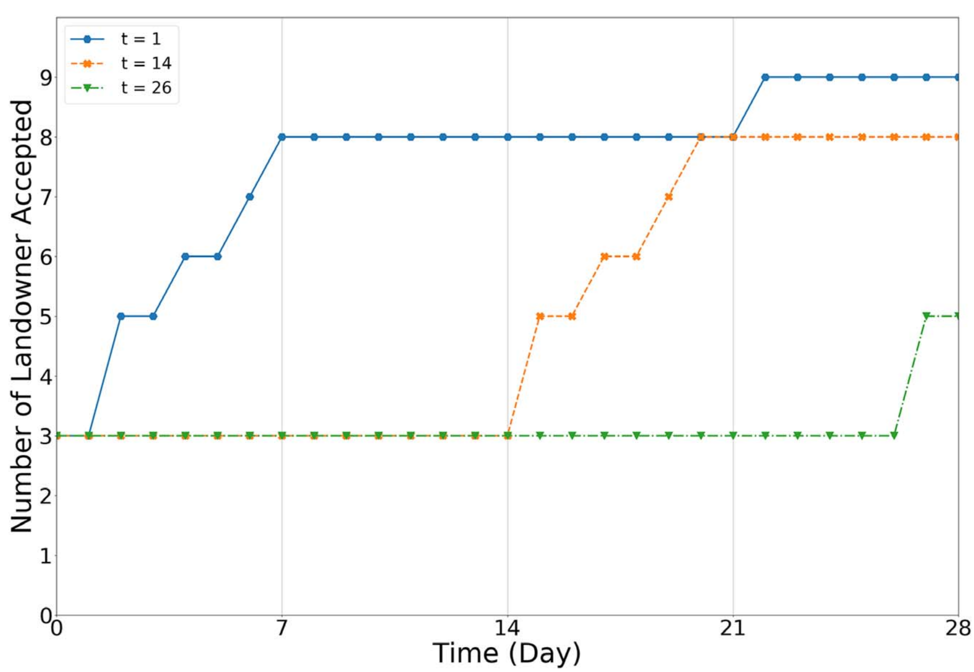


**Fig. 6 Varying time of introduction for community meeting action ($\alpha = 1$)**

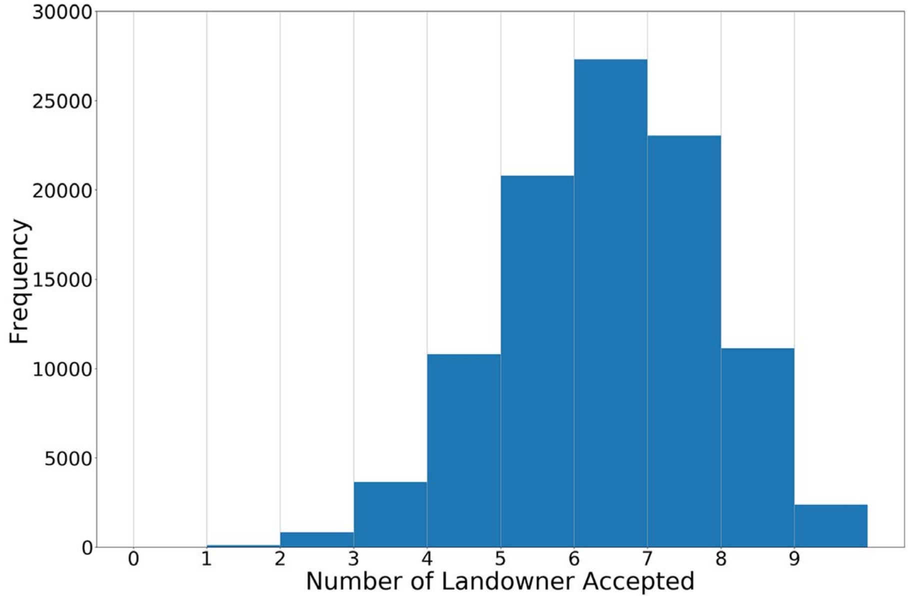


**Fig. 7 Distribution of initial landowner acceptance with preliminary environmental study (median = 6)**

accept the contract, the developer is limited on where turbines can be placed and therefore cannot find an optimized layout with a competitive COE. If greater than or equal to six landowners accept the contract, the developer has enough options for land plots and can place the turbines such that the layout is fully optimized, and the COE is minimized. Figure 9 shows COE results for the scenarios with and without actions; note that we have reported the average COE value when the actions are activated.

We find that the COE for the scenario where no action is activated and all landowners accept is \$50.9/MWh. This value falls in the range of COE values reported by industry, see [40] for more information on the cost of wind energy values. Additionally, the results show that if a community meeting or environmental assessment is performed by the developer, the COE depends significantly on how many landowners accept as a result of those actions: \$244.4/MWh if less than six landowners accept and \$51.35/MWh if greater than or equal to six landowners accept.

## 5 Discussion

The model demonstrates what positive benefits can potentially occur from the developer actions and how the actions influence landowner acceptance. We build 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 given in Eq. (4) and depends on the decay coefficient specified. An engaging

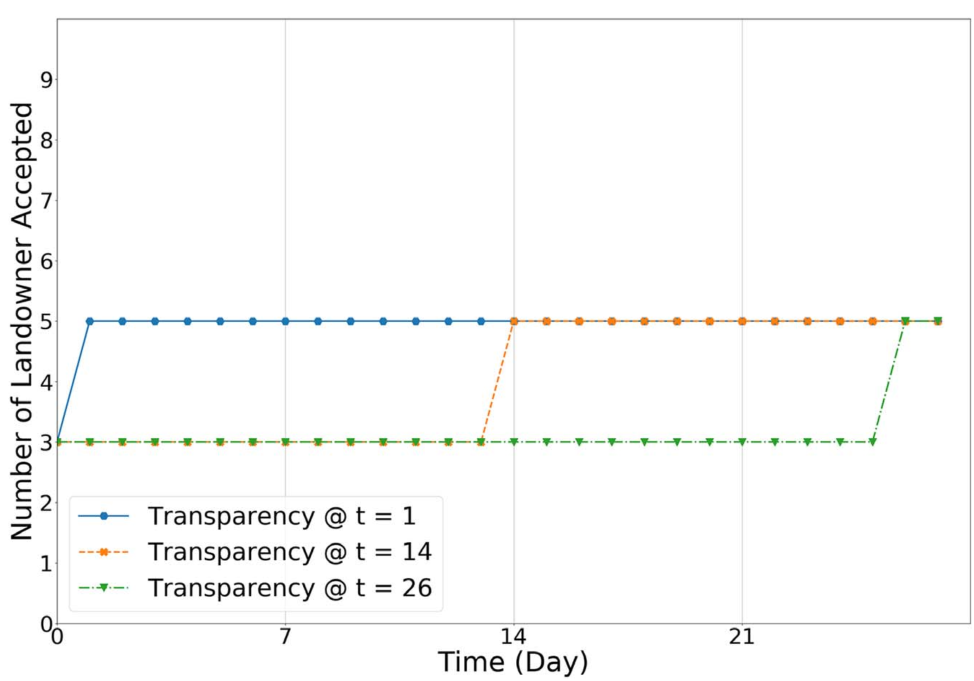


**Fig. 8 Varying time of introduction for desired layout sharing action**

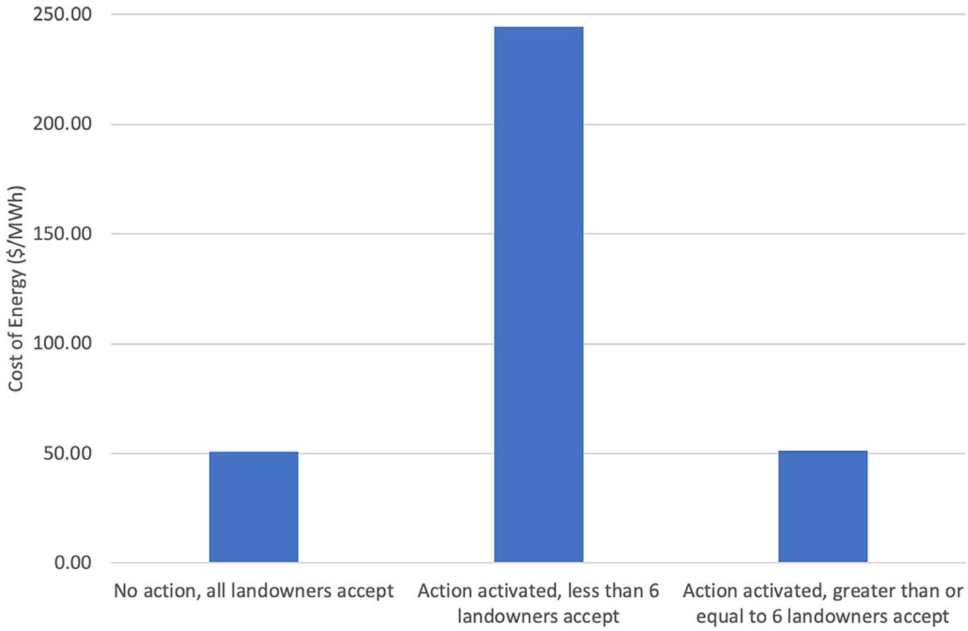


**Fig. 9 COE values for multiple developer action scenarios**

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 occurs 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 versus 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 the 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 be a positive strategy for the developers to increase the landowner acceptance.

Finally, our model was built to show 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 development process 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 have 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.

In addition to the influence of actions on landowner acceptance, we also observed the preliminary effects of the cost of actions on the overall COE. Based on the model architecture and the cost of actions that were available in the current literature, we find that taking an action may be an upfront cost the developer, the overall project COE is mainly influenced by the number of landowners who accept the land lease contract. This brings in an interesting perspective to the tradeoffs developers face with performing additional actions—while the upfront costs are a consideration, the overall benefit of taking action to increase landowner acceptance may be beneficial to the developer for the overall project finances. The estimated costs of community meetings and basic environmental assessments are small compared to the turbine hardware costs; thus, if the action is effective in increasing landowner acceptance rates, it may be worth the developer’s time to incur that action’s cost. If the action does not help increase landowner acceptance rates, it may not be worth it to the developer. While the scenarios in this model are hypothetical, the results suggest that developers may want to consider the potential positive effects of an action before counting it out due to upfront costs.

This ABM is designed to provide a framework for modeling the preliminary effects of wind developer actions on landowner acceptance rates; by nature of simplicity, the model contains several limitations. First, as mentioned in the introduction, this model is in the “proof of concept” stage and is built based on past literature and interviews with simplified calculations, instead of real-world data.

Additionally, the input values, cost values, and developer actions are based on past literature and knowledge of the wind industry; thus, our results represent hypothetical situations. Therefore, we cannot claim the trends presented in this paper are representative of reality. Additionally, human decisions are difficult to accurately represent and our model depends entirely on how we chose to represent each agent and the equations we defined. For this analysis, we focused on quantifying stakeholder decision-making during the landowner acquisition process and providing three approaches for modeling developer actions with a preliminary cost analysis; the work presented in this paper can offer developers a starting framework to consider these complex interactions.

Validation is a crucial step to use this model in future real-world applications and can be conducted in several ways. Though the model utilized the most accurate parameters found in existing literature, more realistic parameters used in the industry should be compared to ensure the parameter accuracy; this effort may include gathering behavior data from specific communities through surveys and interviews, as well as mining regional data to find more accurate values and costs, such as permitting processes. These data could be used further to test the model in extreme cases and determine if input sensitivities are reasonable. Another way to empirically validate the model is to compare the model predictions of landowner and developer decisions using real-world scenarios and then compare these predictions with real-world outcomes. Finally, gathering feedback from experts can be useful to validate this model as well as to develop model credibility; this effort can build a sense of shared understanding for those who will ultimately be using the model.

A second limitation is the small number of landowners considered in our simulation. 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. A more refined version of this model should include a more realistic number of landowners to provide more granularity to the trends.

Finally, while our ABM calculated the COE when optimizing the wind farm and provided preliminary insights to cost tradeoffs, our model has potential for the improvement of future cost analyses. We did not explore the time or preparation an action might take outside of the landowner acquisition process, as our model timeline was focused in scope. The actions presented in this paper may take significant time and have additional costs that we did not consider. Additionally, we did not take into account any unexpected events that may cause major delays and increase developer costs, such as community backlash or unexpected environmental issues. These issues come up in wind industry as major barriers to development, and we suggest future work should incorporate these costs in a probabilistic manner to provide a more realistic cost analysis.

## 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 quantify 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 a developer can influence landowner acceptance and how the cost of the project may be affected. We used the ABM to run a baseline scenario and additional scenarios based on different action and varying parameters. The trends display the effects of three actions and their positive effects on landowner participation. While limitations exist, this early-stage model provides a useful framework that can help developers start to explore these complex interactions during wind farm development. In the future, the model can also be further developed and validated using additional data, real-world comparisons, and expert advice to represent the realistic situations that developers may face in the industry and help build positive strategies for landowner acquisition.


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## Nomenclature

$r_o$ = offered compensation rate from the developer ($/MW)
$t_0$ = initial time-step in the model
$u_0$ = uniform unidirectional wind speed (*m/s*)
$u_{i,local}$ = local wind speed at turbine $i$ (*m/s*)
$C_{tot}$ = total wind farm cost ($)
$N_j$ = number of turbines on landowner $j$'s land
$O_j$ = offered compensation from the developer to landowner $j$
$P_j$ = total power landowner $j$ will generate (MW)
$AEP$ = total wind farm energy (MWh)
$PISP_j$ = personal indifferent selling price for landowner $j$ ($)
$WTA_j$ = Landowner $j$'s unique willingness to accept the land lease contract ($/MW)
$\Delta t$ = duration of community meeting effect (days)
$\alpha$ = exponential decay coefficient for community meeting action

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