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# SOCIAL NETWORK INFLUENCE ON RESIDENTIAL SOLAR PHOTOVOLTAIC ADOPTION IN AN AGENT-BASED ELECTRICITY SYSTEM MODEL

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## ABSTRACT

*As the United States phases out traditional fossil fuels in favor of renewable energy sources, it is important to capitalize on all available avenues to increase renewable penetration. In the last decade, the costs associated with residential solar photovoltaic (PV) installations have decreased significantly, providing more homeowners with the opportunity to generate their own clean electricity. Research has found that the decision to invest in a residential solar PV system is guided by economic, social, and personal factors. Accounting for such complexities, the joint power of agent-based modeling and social network analysis is leveraged in this study to evaluate the effect of social influence on solar PV adoption. Featuring residential consumer agents with data-driven attributes, a logistic regression function to predict solar adoption, and random and small-world social network implementations, this work simulates residential solar PV adoption in New Jersey. Results indicate that including social influence in an agent-based electricity system model leads to increased installed residential solar capacity, but not necessarily higher adoption rates. These findings suggest that, with an understanding of the intricacies of consumer social networks, there are potential opportunities to bolster residential solar installations through low-cost social campaigns that motivate individuals to adopt home solar through their social ties.*

## Introduction

In November and December of 2023, thousands of participants attended the 28th Conference of the Parties to the UN Framework Convention on Climate Change (COP28) in Dubai to assess efforts in climate change mitigation and identify a path to reach climate goals designed to prevent irrevocable damage to the environment. One of the key takeaways from COP28 was

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the global need to phase out fossil fuels and increase the penetration of renewable energy sources [1]. According to a 2011 report on consumer attitudes towards renewable energy, 80% of consumers care about the implementation and usage of renewable energy [2]. In the decade following that study, renewable energy sources have become more prominent in the electricity grid, and the adoption of renewable energy has expanded across the United States [3]. Consumers have gained the ability to financially support the deployment of renewable electricity by participating in renewable energy programs and purchasing renewable energy credits [4]. Consumers can also invest directly in home solar photovoltaic (PV) systems, which lead to the reduction of utility energy consumption and provide opportunities to feed renewable energy back into the grid through net metering. Federal and state governments incentivize these decisions through tax rebates and other financial mechanisms [4, 5]. As such, consumers have the opportunity to increase the supply and usage of renewable sources, making it important to forecast future demand for renewable energy, encourage the adoption of renewable sources, and evaluate the impact of such a shift in electricity grids.

One avenue that could potentially help increase renewable energy penetration is encouraging residential solar PV adoption. For most, the decision to invest in a solar PV system is based not only on cost, but also on moral and social factors [6]. Social influence, described as the ability for one's beliefs or behaviors to be altered by others, can be a powerful motivator for investing in renewable energy. Individuals have the capacity to directly influence other members of their social networks, persuading their connections to invest in solar. With a targeted approach, low-cost social norm campaigns or referral programs could result in increased adoption of solar PV, ultimately accelerating the penetration of renewable energy sources in the grid. Considering the powerful influence of social connections, this study seeks to address the following research question:

> How do consumer social networks influence the diffusion and adoption dynamics of residential solar photovoltaic (PV) systems?

To answer this question, an agent-based electricity system model calibrated to represent consumers and producers in the state of New Jersey [7] was extended to include social networks for evaluating their potential influence on the consumer agents' decision to invest in solar PV. By incorporating social network models in the agent-based model (ABM), the solar PV investment decision was made more realistic as the decision was influenced by each agent's social ties. Understanding and quantifying the potential impact of positive and negative recommendations will provide opportunities to design referral programs or social norm messaging campaigns that motivate increased adoption of solar, decreasing the demand for electricity generated from fossil fuels.

## Background

Data-driven agent-based modeling has been successfully used to forecast solar panel adoption in San Diego County [8]. The model detailed in [8] uses machine learning with multiple household features to predict solar PV adoption, but does not explicitly investigate the influence of social ties on the investment decision. Within social networks, social influence determines the impact factor of a given node [9]. A social network is made up of nodes and edges, in which nodes represent individuals (represented by agents in an ABM) and the edges represent social ties between the agents. Social network modeling enables characterizing a network of distinct nodes by the relationships and interactions between individual nodes [10].

Multiple methods of network modeling exist, serving to establish the connections between these distinct nodes. In a purely random network, each agent has a random probability of tying to another agent [11]. This method can provide a basic network structure, but it does not consider proximity or homophily as input factors. Alternatively, small-world modeling establishes connections between adjacent nodes, with a degree of randomness such that a given node is also tied to non-adjacent nodes. This structure design is intended to demonstrate the close connections held by most nodes, along with the random distant connections that can be found in real-world social networks [12].

Another approach is to construct networks based on spatial or geographical proximity, where agents are more likely to form connections with others in their local neighborhood or community. This captures the tendency for social ties to be stronger among individuals who are physically closer, due to increased opportunities for interaction and shared experiences.

Network models can also incorporate homophily, the principle that connections are more likely to form between similar individuals. Agents may preferentially connect with others who share attributes such as age, income, education level, or other demographic or psychographic characteristics. Incorporating homophily into network models can help capture the segregation and cluster formation often observed in real-world social networks.

These various network types were implemented in prior ABM work by the lead author [7] to introduce social influence to the solar PV adoption decisions. Implementation of social influence in this study follows the method of magnitude and influence rank that has been previously applied to retail applications [13]. This approach models how the adoption decisions of highly influential agents can propagate through the network and impact the decisions of their peers and connections.

By integrating realistic social network models into the agent-based framework, this study provides a powerful tool for investigating the complex interplay between social influence, peer effects, and the diffusion of renewable energy technologies. The insights gained can inform targeted policies and interventions to leverage social dynamics and accelerate the transition towards sustainable energy systems.

## Method

This work extends the prior agent-based model developed in [7] by incorporating social network models to determine the influence of consumer social ties on residential solar photovoltaic (PV) investment decisions. The original model simulated consumer agents making decisions on whether to invest in solar PV, and if so, the system capacity to install. However, it did not account for the potential impact of social influence and peer effects on these adoption choices.

In the extended model, residential consumer agents inherit various attributes including income, savings, a dollar amount they are willing to invest in a solar PV system (WTIS), property suitability for solar panels, monthly electricity consumption, a social influence level, and a social influence orientation. With the exception of the social influence parameters, these attributes are directly assigned to each agent upon initialization using survey responses from actual consumers recorded in [14]. This ensures that the agent population accurately represents the diversity and heterogeneity of real-world residential consumers.

The model is configured to run for 40 years, with time steps of one month. At each time step, agents reassess their electricity consumption and solar PV investment decisions based on their current circumstances and preferences. Crucially, the new social network component introduces an additional layer of complexity, allowing agents to be influenced by the adoption decisions and experiences of their peers within their respective social networks. Throughout the simulation, the solar PV cost to consumers is determined based on the size of the system with a constant price per panel.

Two distinct network topologies are incorporated: random networks and small-world networks. In random networks, each agent has a random probability of forming a connection with any other agent, regardless of proximity or shared characteristics. This provides a baseline network structure for comparison. Small-world networks, on the other hand, are designed to more closely resemble real-world social networks by establishing connections between nearby agents (capturing geographical proximity) while also allowing for random long-distance connections (capturing acquaintances or weak ties).

By integrating these social network models, the solar PV investment decision becomes more realistic, as it is influenced not only by an agent's individual attributes but also by the adoption choices and recommendations of their social connections. Positive experiences and word-of-mouth from satisfied solar adopters can motivate their peers to follow suit, while negative experiences may discourage adoption within a given social circle. This captures the dynamics of social influence and information propagation within consumer networks.

With the addition of the two types of social networks, consumers are assigned a social influence level on a scale of -1 to 1. A consumer's decision to install solar PV is determined using a logistic regression function that was developed when analyzing survey responses from residents of the Northeastern United States [14]. The regression equation (Equation 1) includes terms for willingness to invest in solar PV (WTIS), annual income, political affiliation (PA), efficient behaviors (EB), and average monthly electricity bill.

$$\begin{aligned} f(X) = &-8.21*10^{-5}*WTIS+6.63*10^{-7}*income \\ &-0.78*PA+0.40*EB+3.65*10^{-4}*bill \end{aligned} \quad (1)$$

The probability of the agent investing in solar panels is calculated using Equation 2.

$$p = 1/(1+e^{-f(X)}) \quad (2)$$

In the baseline scenario, if the calculated probability is greater than a pre-specified threshold (e.g., 0.65 to align with the survey responses in [14]) the agent invests. The size of the system is determined based on the agent's WTIS and available savings. If an agent has more money in their savings than their WTIS, they purchase as many solar panels as their properties can hold. If their savings are less than their WTIS, they purchase as many solar panels as their savings can afford while also considering the physical limits of their properties. Social influence from the agents' social ties alters each consumer's probability of investing in solar PV. The more positive influence an agent receives from their social ties, the more likely they are to invest in a system. Furthermore, the evaluation of the regression equation and investment decision only occurs if an agent is determined to have a solar-suitable property.

## Social Network Definitions

Two independent implementations of social networks (i.e., random and small-world social network structures) were incorporated into the baseline model to evaluate their influence on solar investment decisions. Prior to running a simulation, the network to be used was specified. The networks were independent of each other in the model to allow for comparing the effects of different social networks while all other factors were held constant. Upon initialization of the model, all agents were assigned a baseline social influence level on a scale from -1 to 1. The influence orientation distribution was derived from renewable energy survey results within New Jersey [15]. Survey respondents who did not have a viewpoint were considered neutral for our analysis and did not influence other agents. Each agent, regardless of the social network structure, is treated in the same manner for developing viewpoints and willingness to invest. The values for the influence levels and orientation for the initial agent parameters are detailed in Table 1.

**TABLE 1**. Initial agent social network parameters including the distribution of orientations and agent influence levels.

| Agent orientation | Agent influence level |
|---|---|
| 73 % Positive | Random distribution |
| 22 % Negative | min = 0 |
| 5 % Neutral | max = 1 |

Each social network implementation operates in a similar manner with respect to impacting consumer decisions. When an agent is generated, it forms social ties with the residual agents using the specific methods detailed below. With each of these connections, the tied agents' influence orientation and influence level are used to calculate a resultant influence for each agent. This resultant influence is a weighted average with the agent's baseline influence accounting for 50% of the resultant influence and the influence of the social ties each accounting for an even portion of the remaining 50%. The resultant influence is then used to calculate an adjusted WTIS and the probability of investing in solar PV. Each agent's WTIS can increase or decrease by up to 0.05% each time step, and the increase or decrease is defined by the agent's attitude towards solar, defined as their influence orientation. The probability of investing increases or decreases by the difference between the baseline influence and the resultant influence. Each agent's influence impact on its social ties is applied to each connection in the same way. For example, an agent with a 40% favorable view of solar energy would exert that viewpoint on all ties it may have, regardless of the number of connections it has. A schematic representation of social tie influence can be seen in Figure 1.

As the simulation progresses, new agents are added at each time step and the social networks are adjusted accordingly. For each time step, there is a chance for each of the agents to form new ties, dissolve existing ties, or adjust existing ties. After each adjustment cycle, influence-weighted averages are recompiled to determine the adjustments in each agent's probability of investing in solar PV. Research has shown that decision-making, when considered within a social network, is bidirectional, with consumers influencing the same consumers that are influencing them [16]. For computational ease, once an agent's resultant influence is calculated, it does not update again until the next time step, despite changes to the orientation and influence level of its connections.

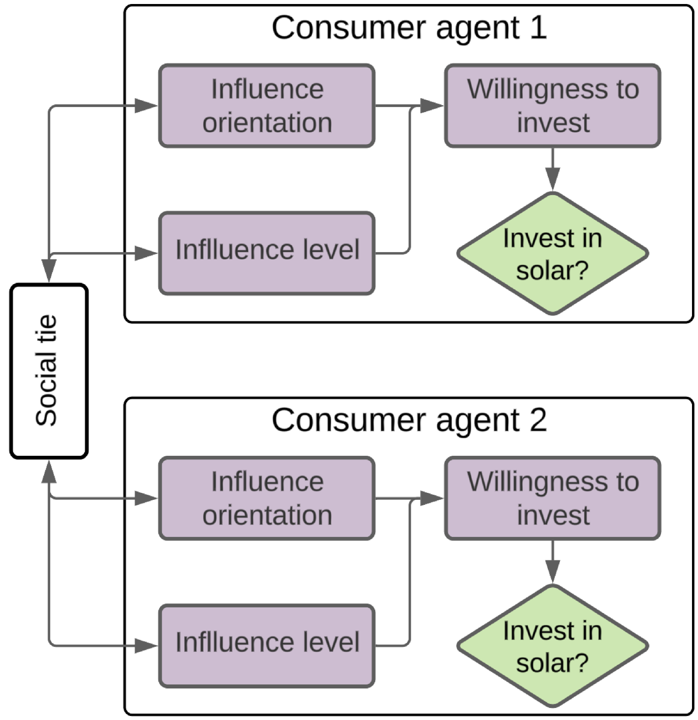


**FIGURE 1**. Influence of social ties on willingness to invest in solar. A resultant influence level and orientation for agent 1 is determined by evaluating the sum product of agent 1's initial influence along with that of all agents tied to them. In this example, the agent has only one influencing social tie, that of agent 2. Influence is bidirectional and agent 1 influences agent 2 in the same manner.

## Random Network

When the random network structure is used, agents are initialized with the baseline network parameters detailed in Table 1 and agent attributes are assigned from New Jersey survey data as described above. After all agents have been initialized, each individual agent has a randomly assigned probability of sharing a social tie with all other agents. Once all agents are evaluated for ties, the agent's influence level and orientation are updated based on those connections. When a new agent is added to the network, this new agent has a random probability of being tied to existing agents in the model. As each tie is bidirectional, both new and existing agents will add each other to their libraries of ties. Random networks are inherently sparse [17], so the network used in this study features a 5% probability of a tie between each pair of nodes.

## Small-World Network

The Watts-Strogatz method was used for the small-world network generation [12]. As each agent is initialized, a small-world generation will occur. The model has a predetermined number of neighboring agents which are used to form social ties in a given agent network. The number of neighbor ties was set to four in this study (i.e. agent 100 initially has four ties to neighbors, those being agents 98-99 and 101-102). After these four initial ties are established, each tie is evaluated for a chance to be rewired to a different random node. Rewiring probability was tuned to 0.2 for this study to allow for some dynamic social ties within the network. When rewiring occurs, the existing tie is removed from each agent and the agent in generation has a random node from the agent pool tied to it. When an additional agent is added to the network, each new agent will follow the same distribution rules, starting with a set of tied neighbors and having random rewiring. Once again, each tie is bidirectional, so newly added agents will have existing agents added to their library of ties and existing agents will gain a tie to the new agent. After creating the initial network generation and following each new agent addition, each agent will have a resultant small-world influence factor calculated using the same weighted average approach as the random network with all tied agents' influence levels and orientations. This factor then feeds into an adjustment to the agents' probability of investing in solar PV using the same process as the random network.

### Comparing Simulation Outputs

Due to the uncertainties included in the model and to make statistical comparisons of the results, the model was simulated 100 times for each of the configurations (baseline, random network, and small-world network). Employing Monte Carlo simulations provides the opportunity to determine significant differences in outputs by conducting t-tests. Amongst the various metrics tracked and recorded during the simulation, the two key outputs monitored in this study were the number of residential households that installed solar panels on their roof or property, and the total installed capacity of residential solar. These values were recorded during each month of the simulation, and a comparison of the values was made at different points to see how the inclusion of social influence alters consumers' decisions to invest in solar PV. The comparison points included in this study were after the 10th, 20th, 30th, and 40th years of the initialization of the simulation.

### Results

With the random and small-world social network structures configured in the agent-based model, simulation results were generated for a baseline case without any social network influence along with each of the different configurations. As mentioned above, this study focuses on identifying changes to the number of residential households that installed solar panels on their roof or property, and the total installed capacity of residential solar PV when social influence is introduced to the solar investment decision. Figure 2 contains a line plot of the total number of residential households that owned solar panels during each month of the simulation period. The solid line for each model configuration represents the average value across 100 Monte Carlo simulations, and the shaded region covers one standard deviation from the mean. Comparing the three scenarios,

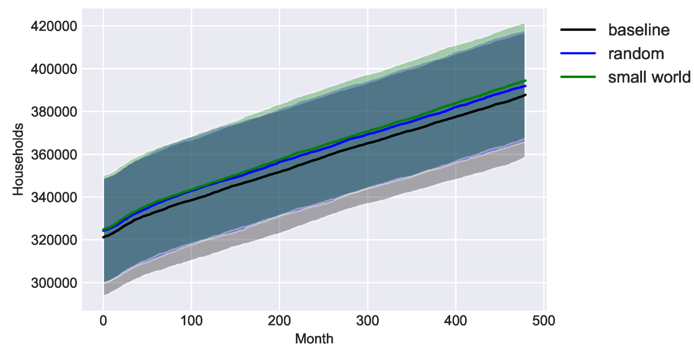


**FIGURE 2**. Total number of residential households that have invested in a solar PV system during each time step.

the baseline and both network structures appear to lead to similar rates of adoption, i.e., a relatively steady and linear increasing adoption trend. The small-world network resulted in the highest participation and the baseline model configuration led to the lowest number of adopters.

The total installed residential solar capacity that resulted from each of the simulation scenarios is included in Figure 3. Similar to 2, the main line for each model configuration represents the average value across 100 Monte Carlo simulations, and the shaded section is one standard deviation from the mean. The

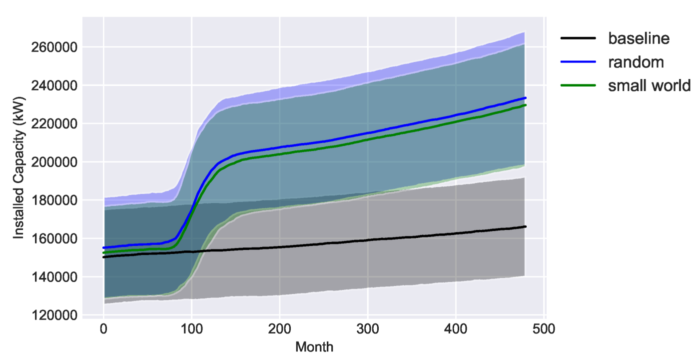


**FIGURE 3**. Total installed residential solar capacity during each time step in kilowatts (kW)

solar installation behavior is more interesting than that of adoption in general. After the first six or so years of the simulation, the random and small-world networks saw a huge increase and rate of increase in installed capacity. The rate of increase levels off around the 10-year mark, and capacity seems to increase at a similar rate for all three configurations. The rapidly increasing installed capacity is a direct result of agents' increased willingness to invest in solar during those years. For the duration of the simulation, the random network configuration resulted in the highest total installed solar capacity and the baseline configuration in the lowest. For a more direct year-to-year comparison, the average number of solar adopters and total installed solar capacities after the 10th, 20th, 30th, and 40th year (120th, 240th, 360th, and 480th months respectively) of the simulation for each of the model configurations are included in Table 2.

To identify statistically significant differences in the decennial results in Table 2, t-tests were conducted comparing each of the social network structures with the baseline as well as between the social network outputs. The results of these t-tests are included in Table 3.

Table 3 indicates significant differences in the installed solar capacity between each of the social network configurations and the baseline model. With p-values less than 0.001 for each 10-year comparison, it is clear that the inclusion of the random and small-world networks alters the total installed solar capacity in the simulation. For both networks, the installed capacity is higher than the baseline scenario, indicating social influence leads to higher residential solar capacity. There was, however, no statistically significant difference in the installed capacity between the random and small-world network model configurations. Interestingly, the social networks did not significantly alter the number of households that adopted solar. Adoption rates were similar between all three methods and there was not enough evidence to suggest social influence played a role in motivating either more or less adopters. In this case, increased capacity without increased adoption rates suggests that social influence led adopters to install larger systems.

## Discussion

Considering the results presented in the previous section, social network influence from random and small-world networks leads to increased total installed residential solar capacity but not increased adoption rates, when incorporated in an ABM as detailed in this study. The surge in solar capacity during years six through ten of the simulation suggests a tipping point in social influence. Adopters, motivated by social connections, maximized their allowable solar PV capacity, indicating a rise in investment willingness. The different social network structures did not result in any significant changes to the simulation outputs when compared to one another, suggesting that the inclusion of social influence was powerful, but network structure was not as important. With the knowledge that social influence can lead to an increased solar capacity in the grid from residential installations, efforts can be made to change social perceptions of household solar PV systems and promote increased penetration in the real world. Increasing the residential solar capacity will lessen the total electricity demand felt by utility providers, while decreasing the demand for electricity specifically from fossil fuels by providing a larger supply of renewable energy sources.

In future work, sensitivity analysis would be useful to explore whether there are significant differences in the adoption rates and installed capacities when changing the network parameters for the different social network configurations. A comparison study considering changes to the distribution of positive, negative, and neutral attitudes towards solar power, the distribution of influence level, the probability of ties between agents in the random network, and the average degree in the small-world network would help uncover the importance of social network parameters when modeling the adoption of solar PV. Identifying the structure and composition of a social network that motivates increased adoption rates and increased installed capacity at the household level will provide the opportunity to implement referral programs or social campaigns to accelerate the transition towards a more sustainable electricity grid.

Other considerations for future studies could include dynamic solar PV costs to consumers as well as scenario analysis with variables to account for disruptive innovations that could arise during the further development of solar panel and battery storage technologies. In this study, the solar PV costs were constant over time to ensure that any changes in adoption rates and installed solar capacity were a direct result of the social influence introduced in the system. In reality, the price of solar panels has been decreasing over time as the technology improves and becomes more accessible to consumers. The introduction of dynamic prices would provide the opportunity to study the interactions between social influence, costs, and the resulting consumer behaviors. It would also allow for the simulation of future scenarios where scientific advancements lead to increased efficiency, affordability, and accessibility of solar PV, changing the market for household solar in the process. Studying these scenarios would provide information on various potential futures for household solar and could uncover more approaches to further the adoption of renewable energy technologies.

## Conclusion

By expanding the agent-based model to include social network considerations, the simulation of complex consumer decision-making in electricity systems can be elevated. The incorporation of social influence allows simulated consumer solar PV investment decisions to be more realistic as many factors influence this decision. By creating a more thorough simulated decision-making process, the model has the potential to uncover

**TABLE 2**. Average number of residential households who have adopted solar PV and the total installed residential solar capacity after years 10, 20, 30, and 40 of the simulation for the baseline, random network, and small-world network model configurations.

| | Solar Adopters | | | Installed Solar Capacity (kW) | | |
|---|---|---|---|---|---|---|
| | Baseline | Random | Small-world | Baseline | Random | Small-world |
| Year 10 | 341,080 | 345,540 | 346,040 | 153,605 | 193,255 | 188,665 |
| Year 20 | 357,280 | 361,240 | 362,680 | 156,815 | 209,855 | 206,315 |
| Year 30 | 372,160 | 376,500 | 378,160 | 161,000 | 220,575 | 216,805 |
| Year 40 | 387,800 | 391,940 | 394,440 | 166,140 | 233,330 | 229,595 |

**TABLE 3**. Results from t-tests comparing the key metrics from the baseline and random network, baseline and small-world network, and random network and small-world network model configurations.

| | Baseline vs Random | | Baseline vs Small-world | | Random vs Small-world | |
|---|---|---|---|---|---|---|
| | Adopters | Installed Capacity | Adopters | Installed Capacity | Adopters | Installed Capacity |
| Year 10 | p = 0.245 | p = 2.11E-18 | p = 0.197 | p = 6.47E-15 | p = 0.89 | p = 0.317 |
| Year 20 | p = 0.303 | p = 3.8E-28 | p = 0.166 | p = 5.69E-28 | p = 0.696 | p = 0.411 |
| Year 30 | p = 0.263 | p = 2.67E-32 | p = 0.131 | p = 2.91E-31 | p = 0.658 | p = 0.398 |
| Year 40 | p = 0.295 | p = 8.69E-35 | p = 0.100 | p = 6.88E-35 | p = 0.509 | p = 0.434 |

insights into the power of social norms and informational campaigns. The social networks presented in this study lay the foundation to simulate social influence on energy decisions or study the spread of information within such networks. With the help of this model, policymakers and businesses will be able to gauge the potential of low-cost methods of encouraging pro-environmental behaviors both with respect to electricity use and in other energy-efficient applications. Encouraging such behaviors can play a role in helping decrease the harmful emissions that result from electricity use. Indeed, while large, systematic changes to the electricity grid will take time to implement, social science can be leveraged to encourage individual behavior changes now.

This modeling framework can be applied to various socio-technical systems and heighten the complex system simulation capabilities in many fields. Not only can the existing model be extended to different sectors, but it can also be expanded to include more energy decisions such as electric vehicle (EV) adoption, investment in battery storage and other advanced generation technologies, and participation in community solar or clean energy programs. Including more energy decisions in such a model will help paint a more complete picture of pro-environmental behavioral intentions and allow for the study of interactions between these decisions. The social networks can also be further improved by tying in demographic considerations. In tandem with the underlying structures of established networks, demographics such as age, race, and gender could influence the likelihood of agents forming social ties, leading to better predictions of future behaviors. All such additions will contribute to further improving the quality of simulation outputs, providing more accurate observations to assist regulators in implementing proper changes in electricity systems.

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