Agent-Based Modeling of Consumer and Producer Behavior in Sustainable Energy Markets

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***Abstract*—As electricity consumption significantly contributes to carbon dioxide emissions in the U.S., increased renewable energy utilization and individual behavior changes could combine to substantially decrease the carbon footprint of the sector. This study proposes an agent-based modelling (ABM) framework of the New Jersey electricity market that features consumer and producer agents, each defined by a unique set of attributes. The consumer agents are capable of making decisions about energy use, opting into a clean energy program, and investing in solar panels, while the producer agents decide when to retire and introduce power plants of each type. The model is used to simulate agent behavior and to thereby explore the resulting system outcomes. The results show how ABM is an effective modeling technique for energy markets, upon which we may introduce more market complexities such as compound and dynamic policy scenarios as well as social network analysis.**

***Index Terms*—Sustainable energy, agent-based modeling, complex systems, consumer behavior**

I. Introduction

Still heavily reliant on fossil fuels, the electricity sector contributes considerably to greenhouse gas emissions (GHG) in the U.S. Individual energy choices such as reducing electricity consumption and investing in renewable energy sources can help reduce GHG emissions and assist in efforts to remain below 1.5 degrees Celsius of global warming, a critical threshold internationally agreed upon in the Paris Agreement and reaffirmed during the 26$^{\text{th}}$ UN Climate Change Conference of the Parties (COP26) [1], [2]. Effectively motivating individuals to make pro-environmental energy decisions could reduce emissions by 123 million metric tons of carbon per year by the tenth year of consistent behaviors [3]. While individuals are not solely responsible for taking action to protect the environment, these numbers indicate the value in determining effective techniques for influencing consumer behavior in energy markets.

Achieving a more efficient and sustainable energy market involves promoting individual behavior changes, integrating renewable energy sources, and understanding the interplay of power systems with regulatory, economic, and social structures. However, current practices of designing energy policies, investing in new energy technologies and assets, understanding consumer behaviors, and quantifying social-environmental-economic impacts are often made at individual stages of an open-loop framework (see Fig. 1, top), while the interaction of these key components has been largely neglected. To realize a more sustainable electric power system, interactions among individual consumers, power producers, and policy makers need to be simultaneously considered in a closed-loop system, see bottom of Fig. 1. One suitable approach to simulating such systems with independent and autonomous decision makers is ABM, an acronym referring to either the agent-based modeling approach or a particular agent-based model [4]. Decades of behavioral research demonstrate that humans often make decisions based on what they feel is the best or the right thing to do and, contrary to expectations, often do not make the most economically rational or logical choices [5]. To this end, characterizing the behavior of consumers can reveal insights into the effects of regulatory policies and decision-making strategies on system-level sustainability, while integrating consumer behavior into a closed-loop multi-agent modeling framework

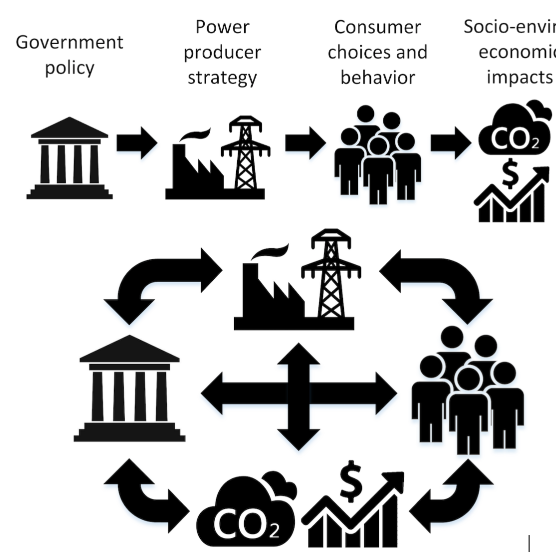

Fig. 1. Key electricity market system stakeholders, interactions, and impacts; top: current open-loop approach to system modeling; bottom: proposed closed-loop multi-agent system modeling approach.

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can provide valuable insights for business and policy decision-makers. An energy market system model that simulates realistic consumer behavior will allow the interactions between consumers, producers, and policies to be studied and analyzed via simulation without the need to implement policy changes in the real world. ABM of energy systems offers a bottom-up approach that can account for complex consumer actions, provide high temporal resolution, and accommodate diverse modeling techniques. In this study, an agent-based energy model was developed to examine energy markets with various user inputs. The proposed model effectively captures individualized behaviors and complex interactions while quantifying sustainability outcomes.

II. Methods

To explore sustainability outcomes of energy market systems, an ABM consisting of residential consumer, commercial consumer, and producer agents was developed. The model extends a previously-developed model [6], and it features more robust consumer decision making and policy levers. When simulated, the model records various economic, social, and environmental metrics that result from changing policies, behavioral strategies, and assumptions.

Fig. 2 provides a schematic representation of the flow of information and decision making within the ABM. The arrows signify interactions between the components, highlighting the values and attributes that influence the major decisions in the model. The model inputs, defined by the user prior to the simulation, include the producer strategy, producer properties, energy policy, and consumer attributes that shape the system behavior. The inputs, calculated values, and agent attributes together guide the decision making in the system, leading to updated calculated values and agent attributes and eventually producing system-level outcomes as the model outputs. The system-level outcomes help quantify market sustainability.

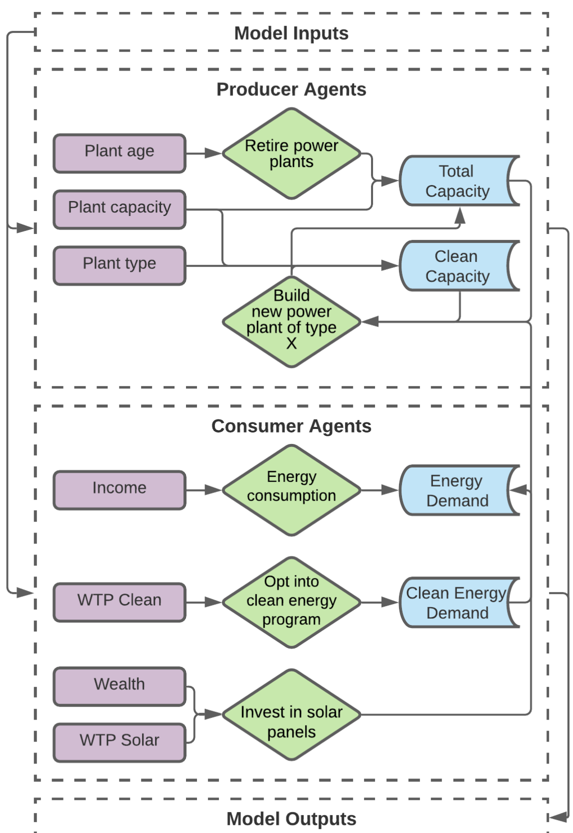

Fig. 2. ABM behavior and information flow during one time step; agent attributes are in purple, decisions in green, and calculations in blue.

A. Consumer Behavior

The model is initialized with a diversified population of residential and commercial consumer agents that represent typical electricity consumers in the state of New Jersey (NJ) as estimated by the U.S. Census Bureau [7] and the Energy Information Administration (EIA) [8]. To speed up the simulation, the agents are scaled down by a user-adjustable factor such that each consumer agent represents 2,000 residential or commercial customers. An additional residential consumer agent is introduced in each time step of the simulation, and a commercial consumer agent is added in every ninth time step. This growth aligns with forecasts from the U.S. Census Bureau [7].

Upon initialization, individual consumer agents are assigned distinct parameters for their wealth, annual income, monthly energy use, willingness to pay (WTP) for clean energy, and willingness to invest (WTI) in solar panels. These parameters were set based on publicly available data or reasonable assumptions when data were unavailable. The distributions used to define the consumer agent parameters are shown in Table I. The parameter distributions were defined using techniques and sources similar to those in [6]. For the residential consumers, the wealth distribution was based on the Federal Reserve's Survey of Consumer Finances [9], the income distribution was based on NJ income data published by the U.S. Census Bureau [7], and the energy consumption distribution was estimated via data from the EIA [10]. The residential consumer WTP distribution was based on a meta-analysis of WTP literature [11], and the solar panel WTI distributions for residential and consumer agents were calculated via historical solar installation data from NJ's Clean Energy Program solar activity reports [12]. The remaining commercial agent parameters were scaled up based on the residential parameters.

TABLE I
INITIAL PARAMETERS FOR CONSUMER AGENTS.

Parameter	Distribution	Residential	Commercial
Wealth	lognormal	$\mu = \$700K$ $\sigma = \$400K$	$\mu = \$3M$ $\sigma = \$1M$
Income, annual	lognormal	$\mu = \$75K$ $\sigma = \$70K$	$\mu = \$300K$ $\sigma = \$150K$
Energy use, monthly	normal	$\mu = 700$ kWh $\sigma = 100$ kWh	$\mu = 6300$ kWh $\sigma = 1000$ kWh
WTP clean	normal	$\mu = \$16$ $\sigma = \$16$	$\mu = \$200$ $\sigma = \$200$
WTI solar	lognormal	$\mu = \$5,850$ $\sigma = \$1,325$	$\mu = \$12,800$ $\sigma = \$4,525$

During each time step, the consumer agents update their parameters and make new decisions about adjusting energy consumption, opting into a clean energy program, and investing in solar panels. These decisions are influenced by the parameters in Table I and the existing policy structure. Since each agent's parameters are randomly drawn from statistical distributions at the beginning of the simulation, the model is stochastic. Upon initialization, no consumers are opted into the clean energy option, but they have the opportunity to do so in each time step based on their WTP. A portion of consumer agents are initialized with solar panels based on the historical data available on installed systems in NJ, and those initialized without solar panels are able to invest in future time steps.

Consumers decide whether to increase or decrease their energy consumption each month by checking if they can afford to use more energy. If they can afford to, they increase consumption; if not, they decrease consumption. The demand for energy is simply calculated by summing the amount of energy used by the consumer agents in each time step. When consumers opt into clean energy programs, they increase the demand for clean energy, and when consumers install solar panels on their homes, the demand for energy from the utility companies decreases. By opting into a clean energy program, consumer agents agree to pay a premium to ensure their electricity comes from renewable sources. A consumer's decision to opt into a clean energy program depends on their WTP in addition to their regular energy costs each month; they will opt in if their WTP exceeds the cost of the program. The final major decision for the consumer agents is whether to invest in solar panels for their home. This decision depends on the agent's WTI in solar panels, their wealth, and the suitability of their roof or property. If consumers cannot accommodate the system, they will not invest, and if their WTI exceeds their wealth, they will purchase a smaller system with the potential to expand in the future as they accumulate wealth. These decisions are revisited in each time step and are not constant, e.g., agents can opt back out of clean energy programs at any point if their WTP decreases below the program cost.

B. Producer Behavior

The producer agents in the ABM are a simplified representation of the generation, transmission, and distribution processes in the electricity market. Each agent represents a single power plant in NJ and is defined by its plant type (nuclear, coal, natural gas, wind, or solar), capacity, and age. The model is initialized with producer agents whose attributes correspond to those of current power plants in NJ [13]–[15]. New producer agents are introduced to the simulation when additional capacity is needed to meet the demands of the consumer agents, and existing producer agents are retired when a power plant reaches the end of its life. The decision to retire a power plant is influenced by the plant's age and the predefined lifetime for that type of power plant, based on EIA estimates [13]. When power plants are retired, the capacity in the system decreases. The total capacity and clean capacity are calculated by summing the capacities of all the producer agents and the capacities of solar and wind producer agents, respectively. The decisions on building a new power plant and choosing the type of plant to build are influenced by the energy demand, clean energy demand, total capacity, total clean capacity of the grid, and the levelized cost of electricity (LCOE) of each source; the producer strategy also plays a role in the type of power plant that is built.

Plant lifetimes, efficiencies, capital costs, operating costs, variable costs, and fuel costs are defined by statistical distributions, adding uncertainty to the simulations. The LCOE for each source estimates the price per kilowatt-hour (kWh) a power plant would need to charge to break even [13] and is updated each time step. A major decision made by the producer agents is whether it is necessary to build a new power plant, and if so, the type of power plant to build. Fig. 2 highlights the system capacity, clean capacity, total demand, and clean demand as factors that are considered when making these decisions. The LCOE for each source and policy levers, such as requiring a minimum percentage of energy from renewable sources, also impact the decision. Considering all of these factors, the producer strategy plays a key role in specifying the type of power plant to build when additional capacity is needed. Prior to simulating the model, one of three producer strategies is selected by the model user:

1) **Cost minimization:** If the clean energy demand and renewable energy minimum are both met, power sources are chosen that correspond with the lowest-cost energy source at that time; otherwise, the lowest-cost renewable energy source at that time is added.
2) **Renewable only:** When energy demand is not met, the lower-cost option between solar and wind is added.
3) **On-demand:** If the clean energy demand and renewable energy minimum are both met, the lowest-cost on-demand source (nuclear, coal, or natural gas) is added to meet the total energy demands.

Changing the producer strategy alters the fundamental structure of the electricity market, directly shaping market behavior.

C. Policy Levers

Energy policy comes in many different forms, from mandates and market-based solutions to incentives and investments. Policies influence consumer and producer behavior and can therefore be effective in motivating individuals and companies to make sustainable decisions with respect to their electricity consumption and investments. As such, different policy levers have been included in the ABM that can be implemented and adjusted to see the impacts they have on the simulation outcomes. The user can implement various policy levers including:

1) **Renewable portfolio standards (RPS):** Require producers to source a minimum percentage of energy from renewable sources.
2) **Carbon taxes:** Charge producers a price per metric ton of carbon dioxide (CO_2) released.
3) **Clean energy incentives:** Subsidize the additional cost to consumers when opting into clean energy programs.

4) **Solar panel tax credits:** Subsidize the total cost of a solar panel system by a certain percentage.

Model users have the ability to set these levers prior to simulation and can therefore compare multiple combinations of policies.

D. Sustainability Outcomes

Due to the stochastic nature of the ABM, 500-run Monte Carlo simulations are used to explore the economic, environmental, and social outcomes over a 40-year time horizon. The following metrics are monitored to provide insights into the market behavior:

1) **CO_2 emissions:** Total CO_2 emitted over the 40-year simulation from electricity generation, in metric tons.
2) **Power mix:** Generation capacity from each of the five power sources (nuclear, coal, natural gas, solar, and wind), in kilowatts (kW).
3) **LCOE by source:** Cost to generate energy from each of the five power sources, in dollars ($) per kWh.
4) **Energy use:** Average energy consumed by residential and commercial consumer agents, in kWh.
5) **Average bill:** Average electric bill for residential and commercial consumers, in $ per month.
6) **Installed Solar:** Total installed solar capacity for residential and commercial agents, in kilowatts.

The system-level outcomes are used to compare the overall sustainability of the simulated energy market configurations. Analyses of the simulation results can help uncover patterns and emergent behaviors that arise when policies are introduced to energy markets, providing a better understanding of how policy influences these markets. It also provides policy makers with the opportunity to identify any relationships between energy prices, electricity consumption behaviors, environmental impacts, and policy design. These insights can contribute to the improved sustainability of energy markets as a whole.

III. Results

The baseline model configuration is comprised of a cost minimization producer strategy, no RPS, carbon tax, nor clean incentive, and 26 percent solar tax credits for both residential and commercial consumers corresponding to current NJ tax credits [16]. The system-level outcomes of the simulation are presented in Fig. 3. For the first half of the simulation, CO_2 emissions rise steadily; however, as the cost to generate renewable energies falls below the LCOE of conventional energy sources, the power mix becomes predominately solar and wind power as coal is phased out. Throughout the 40-year simulation, the average residential and commercial energy use increases linearly; however, as renewable energy becomes more affordable and installed solar capacity increases throughout the simulation, the average electricity bills do not constantly increase with the increased consumption. The solar installation costs are incurred as a one-time investment; therefore, monthly electricity bills decrease as installed capacity increases, reducing the need for electricity from the utility company.

IV. Discussion

The simulation results indicate that over time, renewable energy sources are expected to overtake conventional sources and CO_2 emissions will eventually fall as renewable energy penetration increases. Such outcomes are encouraging and can help reduce the negative impacts of electricity consumption on the environment. However, the speed of this transition is critical to reducing the scale and effects of climate change. Implementing more policy levers and studying the effects of combined policy levers could uncover favorable policy structures that result in improved social, environmental, and economic conditions.

As with any modeling endeavor, some assumptions were made to facilitate this simulation development. Specifically, while the agents are simulated as individual entities that interact with each other and make optimal decisions, they are still defined by aggregated distributions. To more closely represent the behavior of real consumers in energy markets, and to better take advantage of ABM capabilities, future work may consider defining consumer agents using individualized consumer attributes based on real people, allowing for greater diversity among the agents and a better representation of consumer decision making. To that end, all consumption and investment decisions are currently made from an economically rational perspective; the agents lack attributes that account for peoples' inclinations to spend more to protect the environment and conserve electricity when they cannot afford to do so. Accounting for non-financially motivated pro-environmental behaviors would contribute to our understanding of consumer behavior in energy markets.

To improve upon the limitations of the model, a parallel study is underway to determine the effects of incentives, fees, and social norms on individual consumer energy decisions. Survey experiments are capturing the intended behavior, attitudes, beliefs, and WTP expressed by participants in an effort to identify the intervention combinations that result in the most pro-environmental intentions and attitudes. Once these data are collected, individualized residential consumer behaviors revealed in the survey experiments will be incorporated into the energy model, and the system-level outcomes from individualized consumer agents will be compared to the results from this paper, which uses aggregate statistics.

Social network implementation could also further improve the model. Using survey responses and social network analysis, social influence that will shape the consumers' decisions to purchase solar panels and opt into clean energy programs can be introduced. The inclusion of social networks would account for interactions such as referral behaviors and recommendations that exist in peoples' social circles, improving upon the residential consumer agents' portrayal of real consumer behavior. Once the model is sufficiently comprehensive and representative of true electricity markets, it can be turned into a user-friendly tool for policy makers and businesses. The tool could be used to simulate different policy structures and output summary reports and statistics, indicating the expected results

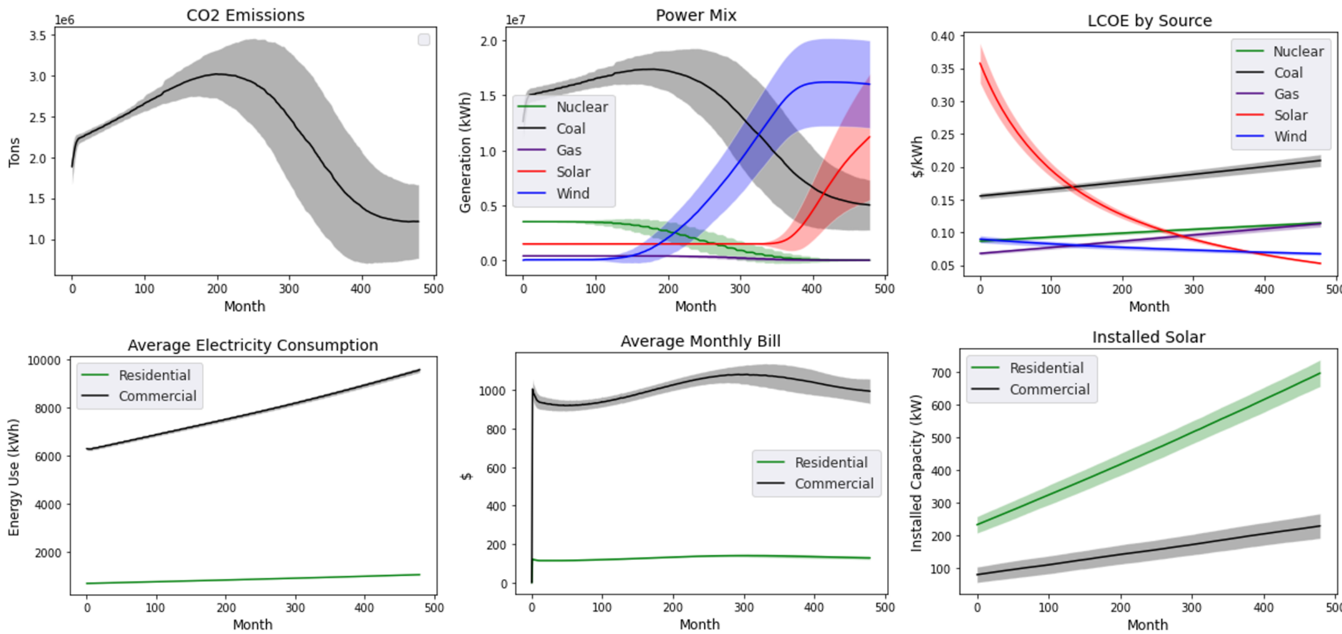

Fig. 3. Average results from 500 simulation runs with error bands of one standard deviation; CO_2 emissions, power mix, LCOE by source, average electricity consumption, average monthly bill, and installed solar using the baseline model structure

of policies and producer strategies.

V. Conclusions

This paper presents an agent-based modeling approach for simulating electricity market systems and exploring the system-level outcomes generated via simulation. The model considers consumer and producer behavior and policy levers, thereby shaping the system-level sustainability outcomes observed. The results suggest that this approach is suitable to study policy influence and trade-offs, providing the opportunity to identify favorable policy structures that result in pro-environmental energy decisions. The approach and results from this study can serve as a reference point to consult as the model is expanded to include technological challenges, individualized consumer agents, and social networks.

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