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Evaluating Peer-to-Peer Electricity Markets across the U.S. Using an Agent-Based Modeling Approach

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Abstract

The diffusion of distributed energy resources can overcome some challenges associated with the historical centralized model of electric power distribution. Decentralized generation by residential solar photovoltaic cells creates the potential for peer-to-peer (P2P) electricity trading, where households can act as consumers and prosumers to buy and sell renewable electricity. P2P energy markets are emerging at locations across the globe, and market performance is affected by various social, economic, and environmental factors. This research applies an agent-based modeling (ABM) framework to simulate electricity trades between heterogeneous households in a decentralized market. The P2P system is tested for 15 locations in the United States that vary in climate parameters and local economic factors. The results from these simulations are compared to assess how differences in climate, demand pattern, retail rate, and irradiance affect market performance. Simulations demonstrate that market outcomes rely on the ratio of prosumers to consumers, environmental factors, and geographic conditions. Battery energy storage overcomes limitations associated with faulty forecasting and improves the flexibility of household-generated solar resources to increase the proportion of production that is sold in the P2P market. The application of the agent-based modeling framework demonstrates how P2P markets can be expected to perform for various locations and can be applied to assess alternative locations for market performance.

Keywords
Peer-to-peer energy trading; distributed energy resources; battery energy storage; sociotechnical systems; agent-based modeling

1. Introduction

The electric grid is centralized, dispatchable, and large scale, and the majority of energy is generated at fossil fuel fired power plants. Historical designs specify that power flows unidirectionally from large-scale sources to distant end-users. The widespread diffusion of distributed energy resources (DERs), as part of a smart grid, can shift production of electricity from remote generation facilities to commercial buildings and residential households. A smart grid provides a large portion of energy from renewable resources, such as solar photovoltaic (PV) cells and battery storage, and allows bidirectional flow of electric power [1]. The adoption of DERs and their integration within the smart grid provides an opportunity to re-evaluate the traditional centralized system of business in the electric power distribution industry, and peer-to-peer (P2P) electricity markets have emerged as an alternative model for meeting energy demands [2-4]. P2P electricity trading allows consumer households to purchase electricity from peer households acting as prosumers, who both consume and produce energy [5]. A decentralized P2P electricity exchange creates a free market system where solar power producers compete to sell their excess to local buyers. Prosumers can sell their electricity at a higher rate than typical utility buy-back offers, and consumers can purchase electricity below retail rates. Economic analysis has identified the incentives needed to encourage adoption of domestic production units that can be used within P2P markets [6]. P2P energy markets create new value around DERs while simultaneously encouraging conservation of natural resources [7, 8], reducing the price of renewable energy, and increasing the accessibility of renewable energy for large segments of the population [9, 10]. Several pilot-scale P2P markets have been implemented and tested, including Vandebron in The Netherlands [8, 10], sonnenCommunity in Germany [8, 10], Piclo in the UK [8, 10], the Brooklyn Microgrid (US) [4, 8, 10], the Renewable Energy and Water Nexus in Perth, Australia [11, 12], and the White Gum Valley site in Fremantle, Australia [13].

Although P2P energy markets promise to provide economic and environmental benefits, the characteristics of a P2P market can lead to a range of performance in the realized electricity cost and profits for consumer and prosumer households, respectively [8, 9, 14]. Prosumers may have a range of capabilities for solar generation forecasts, battery storage technology, and battery discharging strategies. In a typical P2P market, trades are completed before power is produced, and forecasts of power flow are required for the market to function. The dynamic nature of power flows from solar resources to residential consumers presents a major challenge in forecasting [15, 16]. Errors in forecasting solar power production can lead to overproduction or shortfall of electricity. Overproduction in the decentralized grid leads to loss of revenue for prosumers, who sell excess energy to the utility at the avoided fuel cost rate [17]. Shortfall of electricity also leads to loss of revenue for prosumers, who pay penalties to make up for shortages, likely through purchasing the shortfall quantity from the utility at the retail rate [18]. Battery storage can be used to offset uncertainties in solar generation forecasts and reduce market inefficiencies; however, the timing of charging and discharging batteries can also affect their efficiency in offsetting high demands during nighttime and cloudy days.

Simulation studies have been developed to simulate P2P energy markets within a residential sector to assess market performance. Agent-based modeling (ABM) is an approach to model the actions and interactions of multiple goal-seeking agents within a closed environment to simulate complex systems and assess the emergence of system-level properties [19, 20]. While ABM has been applied to explore a wide range of smart grid applications [21], a smaller set of ABMs have been developed applied to assess outcomes of residential P2P energy markets. ABMs that simulate energy trading among residential consumer and prosumers have focused on outcomes including the price of electricity, consumption of solar energy, weather, and the balance between generation and demand, or penetration of prosumers [14, 22-25]. ABM has also been applied to test market parameters, including centralized and decentralized battery solutions [4]. Previously conducted research focuses on a small set of market parameters in siloed studies but have not considered how the intersection of multiple characteristics affects the performance of a smart grid. This research explores how variations in local conditions and market characteristics contribute to or undermine P2P markets. The local conditions that are explored and simulated in this research go beyond existing studies to include electricity demand profiles, regional economics of energy distribution, forecasting capabilities, battery storage, variations in solar irradiance, and penetration of prosumers. Existing computational frameworks that model P2P solar markets focus on the application to one locale (e.g., [11]), hypothetical applications [26], or large-scale applications [27]. This research, on the other hand, focuses on small scale P2P markets that rely on household participation and decision-making, while comparing performance across locations representing diverse geography and climate conditions in the U.S.

In this research, an ABM framework is applied to simulate the behavior of utility managers and residential single-family households with solar PV and evaluate trades in a decentralized electricity market. This research builds on an ABM framework that was developed to simulate a pilot program, ReNEWS Nexus, located within Perth, Australia [11]. Previous work applied the ABM for observations of trading behaviors in a real system and used modeling rules to represent the market governance that was specified for the ReNEWS Nexus System. The framework was validated for existing trading data, and errors in model simulations were attributed to inconsistencies between the market design as specified by the market rules and market implementation on the ground. In this work, the validated ABM is applied to explore market performance for 15 locations across the U.S. using a range of environmental and market conditions. The ABM framework simulates a low-voltage grid network that connects single-family residential households in a neighborhood. In the framework, models of solar power generation, solar generation forecasting, and battery storage dynamics are coupled with agents that represent prosumer and consumer households. Consumer and prosumer agents bid on buying and selling energy, and prosumers employ alternative forecasting technologies and battery storage. Different trade scenarios are tested by applying the ABM framework for 15 cities in the United States, and sensitivity analysis explores the effects of the proportion of consumers and prosumers in the market. Results are evaluated based on overproduction, shortfall, and seller average electricity price to explore the impact of varying electricity demand profiles, regional economics of energy distribution, solar irradiance profiles, battery energy storage systems and solar forecasting on P2P markets. Results identify locations where simple solar PV systems, such as those that use simple forecasting and no storage, will perform well, and locations where forecasting algorithms and storage will have the most effect on market performance. The research conducted here evaluates the implementation of P2P solar trading at these locations to provide a mechanism to prioritize funding for sustainable economic solutions. This framework can be used to develop economic solutions to incentivize the adoption and implementation of P2P solar PV markets.

2. Agent-Based Modeling for P2P Energy Markets

ABM simulates the behaviors and micro-interactions of a population of autonomous and heterogenous agents to model and study system-level phenomena [19, 20, 28]. Agents represent decentralized entities, such as households or persons, that are situated in a shared environment. Agents interact with the environment and with other agents. Agent behaviors and decision-making processes are simulated using mathematical, logical, and statistical representations to react from stimulus received from the environment and agents. System-level properties describing the state of the environment and the population of agents emerge due to the complexity of agent interactions and behaviors.

ABM has been employed to simulate and test several smart grid concepts, including the diffusion of rooftop solar PV systems [29], storage devices [30], smart meters [21], smart metering platforms [31], and dynamic tariffs [32]. ABM has also been used to simulate the dynamics of competitive wholesale electricity markets [33-35] and has been identified as a key approach in modeling electricity markets [36]. A few studies have applied ABM to simulate decentralized market structures for various natural resources [26, 27, 37, 38]. Gnansounou et al. [26] developed a multi-agent approach for planning activities in decentralized electricity markets, leading to a conceptual market model that included consumers, transmission system operators, distributors, wholesalers, and retailers. Yasir et al. [27] simulated community coordination of local energy distribution using an ABM approach; they modeled decentralized trades between a utility and multiple community micro-grids with wind generation and battery energy storage present. Another set of studies simulated a market that allows households to trade rainwater via a non-potable water infrastructure network [38] and a shared aquifer [37]. Other ABMs have focused specifically on P2P energy markets within a residential sector. Mengelkamp et al. [24] used ABM to simulate a local energy market to evaluate electricity cost, and other studies evaluated the price of electricity, consumption of solar energy, and the balance between generation and demand within P2P markets [14, 23, 25]. Another ABM tested the effect of storage in a P2P market and explored both centralized and decentralized battery solutions [4]. These ABM studies provide valuable insight into possible designs and dynamics of P2P energy markets. Monroe et al. [11] developed an ABM and applied the model for a trading network in Perth, Australia, using real consumption and generation data to run the simulation, and simulation results were validated against observed dynamics. The research presented here uses the framework developed by Monroe et al. [11] to evaluate alternative locations for P2P markets. This study integrates alternative forecasting methods, compares no storage with alternative discharging solutions for batteries, varies the number of prosumers that can participate, and simulates seasons to explore the effect on electricity price, solar energy sold in the P2P market, and overproduction.

3. Agent-Based Modeling Framework

The Overview, Design, and Details protocol [39] is used to describe the model, as follows. A full description of the model framework and its development are provided by Monroe et al. [11].

3.1 Overview: Purpose

An ABM is used in this research to simulate a P2P energy market and represent electricity exchanges and the emergence of price within a residential system.

3.2 Overview: Entities, State Variables, and Scale

Agents represent a market coordinator, an energy utility, a set of prosumer households, and a set of consumer households (Figure 1). The state variables and attributes of the two household agent types are listed in Table 1 and Table 2. Prosumer agents are assigned a storage method from three battery energy storage methods: no storage, automatic discharging, and predefined discharging. The no storage method simulates the behavior of a household without any battery storage capabilities. The predefined storage method constrains the flow of electricity to and from battery banks to daily timelines set by the household; electricity is not allowed to flow into battery units outside of the charging timeline, and electricity is unable to flow from the units outside of the discharging timeline. This method approximates how households may advantageously pinpoint the exchange of their energy resources, such as during peak demand hours. For this method, default charging and discharging timelines are set as 9:00 am-3:00 pm and 5:00 pm-11:00 pm respectively. The automatic storage method simulates households with full flexibility over energy storage resources, allowing battery units to charge when irradiance is present and to discharge when there is available capacity. The perfect forecasting model assumes that the prosumer knows exactly the solar generation for the upcoming trade interval. The simple forecasting model assumes that the solar power generation value in the first minute of trade interval j stays constant throughout the entire 60-minute period.

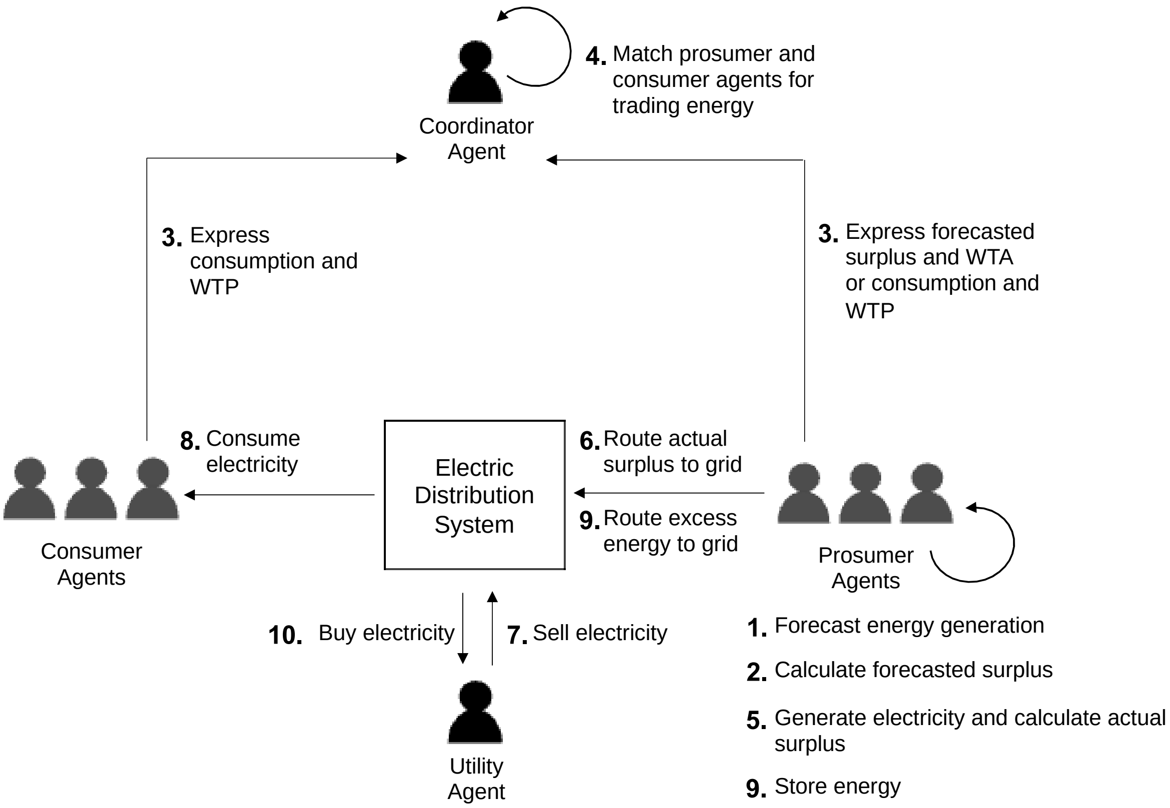

Figure 1 ABM framework simulates a P2P energy market to model electricity exchanges among household agents. Numbers refer to steps, described in Section 3.3.

Table 1 State variables for prosumer and consumer agents, which are updated at each time step *j*.

Prosumer Agent	**Consumer Agent**
Generation of electricity in interval j-G_j	Consumption in interval j – C_j
Generation forecast in interval j-GF_j	
Consumption in interval j-C_j	
Storage available at beginning of interval j-S_j	
Forecasted surplus in interval j-FS_j	
Actual surplus at end of interval j-AS_j	

Table 2 Attributes for prosumer and consumer agents.

Prosumer Agent	**Consumer Agent**
Willingness to pay – *WTP*	Willingness to pay-*WTP*

Willingness to accept-*WTA*
Storage Method-*SM*
Forecasting Method-*FM*

The coordinator agent represents the trading platform, and the electricity retailer is represented as a utility agent; their state remains static, and they only react to information that changes for the household agents. The model is simulated for one month, and each time step *j* is equal to one hour.

3.3 Overview: Process and Scheduling

At each time step, the order of operations in the ABM are executed as follows at each hourly time step.

Step 1. Prosumer agents forecast supply. Each prosumer agent initializes a generation forecast, GF_j, based on their forecasting method.

Step 2. Prosumer agents calculates surplus. The prosumer agent calculates surplus or demand based on the generated forecast:

$$FS_j = GF_j + S_j - C_j \tag{1}$$

Storage is not included in the surplus calculation ($S_j = 0$) for the predefined storage method if outside of discharge hours.

Step 3. Prosumer agents and consumer agents submit bids to coordinator agent. If a prosumer agent reports a forecasted surplus ($FS_j > 0$), then the prosumer agent passes a message to the coordinator agent, expressing forecasted surplus and *WTA*. Otherwise ($FS_j < 0$), the prosumer passes a message expressing consumption (equal to $-FS_j$) and *WTP* to the coordinator agent. Consumer agents communicate their consumption, C_j, and *WTP* to the coordinator agent.

Step 4. Coordinator agent performs market exchanges. Consumer and prosumer agents are aligned in a bilateral exchange market based on their *WTP* and *WTA* values. Trades are successful if the *WTP* value of the consumer is greater than or equal to the *WTA* value of the prosumer; transactions are cleared at the consumer's *WTP* value. Trading is repeated until all demand is exhausted, surplus is completely bought, or the highest *WTP* value of the consumer is smaller than the lowest *WTA* value of the prosumer.

Step 5. Prosumers generate electricity and calculate surplus: The solar irradiance data, taken as direct beam radiation at the surface of the earth, is converted into solar power generation, G_j, for a fixed axis collector face tilted at local latitude [40]. Prosumer agents calculate surplus, AS_j as

$$AS_j = G_j + S_j - C_j \tag{2}$$

Storage is not included in the surplus calculation ($S_j = 0$) for the predefined storage method if outside of discharge hours.

Step 6. Prosumer agents route energy to grid. Prosumer agents route actual surplus energy to the grid to satisfy electricity trade agreements.

Step 7. Utility agent sells electricity. The utility agent sells energy to prosumers at retail rate to make up any consumer shortfalls that remain, based on the difference between the forecasted surplus and actual surplus.

Step 8. Consumers consume electricity. Consumer demands are met through the actual surplus energy that is routed from prosumers.

Step 9. Prosumers fill battery energy storage unit and route excess to grid. Any solar generation remaining after satisfying electricity exchanges in the market is routed into the battery bank. If there is more solar generation remaining than storage capacity available, then the battery bank will be charged to maximum capacity and leftover generation will be routed to the local grid. Battery energy storage will not be charged by remaining solar generation for the predefined storage method if outside of charging hours; in this case, all leftover solar generation will be routed to the local grid.

Step 10. Utility agent buys and sells electricity. The utility agent buys excess energy from the prosumer at the avoided fuel rate if there is any overproduction.

3.4 Design Concepts

3.4.1 Interactions

Prosumer agents and consumer agents communicate bids for selling and buying energy based on their WTP and WTA values and their demand and supply profiles. A bilateral market is used to couple consumers and prosumers, and the efficiency of the trade, based on the price, between a consumer and prosumer is unique due to the differences in demand and supply at each time step that are exerted by agents.

3.4.2 Emergence

The price of electricity emerges from the interactions of the prosumer and consumer agents. The energy that is available at each time step emerges due to storage and solar irradiance, and the price of the electricity emerges based on the forecasted value, the energy purchased from or sold to the utility, and the demand profile of consumers.

3.4.3 Stochasticity

Stochasticity is generated through assigning randomized value for the home footprint.

3.4.4 Heterogeneity

Prosumer and consumer agents are assigned unique values for building footprint that leads to unique consumption profiles and energy generation profiles. See Section 4 for these settings. In addition, each agent is initialized with a randomized value for *WTP* and *WTA*, as applicable.

3.4.5 Prediction

Prosumers predict energy generation at the beginning of each trading interval using a forecasting model. They do not learn, or update predictions based on past performance.

3.4.6 Sensing

Both the prosumer and consumer agents are aware only of their own demand profile and characteristics. They do not sense information about other agents, but they receive information about trades through the coordinator agent.

3.5 Details: Initialization

The ABM framework is initialized with values for number of prosumers as well as charging and discharging timelines for the predefined storage method. For each simulation, a total of 25 households are engaged in the market, and modeling scenarios test varying combinations of prosumer and consumer households. A group of 25 households was selected to represent that residential trading would occur within a neighborhood that is demarcated as a distribution feeder system. The application is based on a realistic distribution feeder system adapted from a model provided by Pacific Gas and Electric Company (PG&E) [41, 42].

Values for WPT and WTA are determined based on a random sampling of numbers from 0.00-1.00. Random numbers are used to place the bid price values between the avoided fuel cost rate and retail rate for a location of interest. Avoided fuel cost, $FC_{avoided,c}$ is determined for each city, *c,* as:

$$FC_{avoided,c} = \sum_{n} \frac{p_{n,c}}{p_{total,c}} \times FC_{n,c} \tag{3}$$

where *n* is the fuel type (coal, natural gas, nuclear, hydro, and other non-hydro renewables), $p_{n,c}$ is city *c*'s energy production for fuel type *n* (MWh), $p_{total,c}$ is the total energy production for city *c* (MWh), and $FC_{n,c}$ is the unit fuel cost for fuel type *n* for city *c*. State-wide electric fuel mix and price data were taken from the Energy Information Administration for the year 2017 [43]. The price used for nuclear fuel comes from a national average of investor-owned electric utilities for the year 2017 [44].

The floor area for each household is randomly chosen from a standard normal distribution with a mean of 1,500 ft^2 and a standard deviation of 200 ft^2. This distribution allows heterogeneous dynamics and behaviors among household agents. Roof area is calculated as 1.12 times the floor space, based on a house with a 6/12 pitched roof [45]. For prosumer agents, 10% of the roof area is simulated as a solar collector. Households are assigned an electricity consumption pattern derived from the Building America B10 Benchmark building simulation framework [46]. Consumption data are normalized per square foot based on the size of the B10 building structure type and multiplied by the assigned household square footage to calculate electricity demand.

Households are assigned battery energy storage units modeled after the Tesla Powerwall 2.0. The storage units hold a maximum charge of 13.5 kWh, and a minimum charge of 4.05 kWh, representing a 70% depth of discharge [47]. The battery energy storage unit is modeled with a 100% round trip efficiency to calculate a best-case scenario for battery functionality.

3.6 Details: Input Data

The input data provided for the ABM framework include the irradiance profile of the modeled city. Real minutely solar irradiance data from the National Renewable Energy Laboratory's

Measurement and Instrumentation Data Center was used to calculate solar power generation for household PV systems [48]. The solar irradiance data, taken as direct beam radiation at the surface of the earth, is converted into solar power generation values for a fixed axis collector face tilted at local latitude [40]. Total radiation on the PV collector's surface is determined by summing the direct beam, diffuse, and reflected radiation on the collector. Actual generation values are determined by multiplying the total radiation on the PV collector by the total area of the surface.

4. Modeling Scenarios

The ABM framework is applied for 15 locations in the United States (Figure 2, Table 2). Locations were chosen based on the availability of solar irradiance data in one-minute and five-minute intervals from the National Renewable Energy Laboratory's Measurement and Instrumentation Data Center [48]. One or five-minute solar irradiance data are used by the ABM framework to calculate solar power generation for household systems. The year of irradiance data was chosen based on the most recent year with a complete set of data. Solar irradiance data is used with PV system tilt and geographic coordinates to calculate direct, diffuse, and reflected irradiance captured by a solar PV system (Table 3). For each of the 15 cities, six modeling scenarios are applied across two forecasting models and three storage methods (Table 4). The two forecasting models, the perfect and simple model, are tested to predict solar generation for each trading interval. The three battery energy storage methods are no storage, automatic discharging, and predefined discharging. To capture data seasonality, each scenario is applied for the months of March, June, September, and December, representing Spring, Summer, Fall, and Winter, respectively.

Table 3 Sites with minutely irradiance data chosen for simulation. Avoided fuel cost and retail rates for utility provided electricity are provided for each city. Retail rates for utility electricity were taken from an online database [49].

Site Name	City	Year of Irradiance Data	Avoided Fuel Cost Rate (¢/kWh)	Retail Rate (¢/kWh)	Source	Latitude (degrees N), Longitude (degrees W)	Local Time Meridian (degrees W)	Total Floor Size (ft^2)	B10 Climate Type
Humboldt State University (SoRMS)	Arcata, CA	2018	1.33	15.59	Andreas and Wilcox 2007 [50]	40.88, 124.08	120	2090	Marine
SOLRMAP Loyola Marymount University (RSR)	Los Angeles, CA	2013	1.33	13.03	Andreas and Wilcox 2012 [51]	33.97, 118.42	120	2000	Hot-Dry
Solar Technology Acceleration Center (SolarTAC)	Denver, CO	2018	1.64	11.05	Andreas and Wilcox 2011 [52]	39.76, 104.62	105	2696	Cold
Xcel Energy Comanche Station (RSR)	Pueblo, CO	2010	1.64	16.27	Andreas 2015 [53]	38.21, 104.57	105	2696	Cold
SOLRMAP Sun Spot Two-Swink (RSR)	Swink, CO	2014	1.64	16.27	Andreas 2011 [54]	38.01, 103.62	105	2000	Mixed-Dry
SOLRMAP Kalaeloa Oahu (RSR)	Kalaeloa, HI	2010	9.32	35.10	Wilcox and Andreas 2010 [55]	21.31, 158.08	150	2023	Hot-Humid
SOLRMAP La Ola Lanai (RSR)	La Ola Lanai, HI	2011	9.32	35.10	Wilcox and Andreas 2009 [56]	20.77, 156.92	150	2023	Hot-Humid

Elizabeth City State University	Elizabeth City, NC	2006	2.06	12.65	Andreas and Stoffel 1985 [57]	36.28, 76.22	75	2546	Mixed-Humid
Oak Ridge National Laboratory (RSR)	Oak Ridge, TN	2018	1.52	10.43	Maxey and Andreas 2007 [58]	35.93, 84.31	75	2546	Mixed-Humid
University of Texas Pan-American Solar Radiation Lab	Edinburg, TX	2017	1.72	10.98	Ramos and Andreas 2011 [59]	26.31, 98.17	90	2023	Hot-Humid
SOLRMAP Tri-State Escalante (RSR)	Prewitt, NM	2012	1.87	12.31	Andreas 2013 [60]	35.42, 108.09	105	2000	Mixed-Dry
SOLRMAP University of Arizona (OASIS)	Tucson, AZ	2016	1.70	10.15	Andreas and Wilcox 2010 [61]	32.23, 110.96	105	2000	Hot-Dry
University of Nevada-Las Vegas	Las Vegas, NV	2018	1.97	12.15	Andreas and Stoffel 2006 [62]	36.11, 115.14	120	2000	Hot-Dry
University of Oregon (SRML)	Eugene, OR	2017	0.56	9.64	Vignola and Andreas 2013 [63]	44.05, 123.07	120	2090	Marine
SOLRMAP Utah Geological Survey-State Energy Program (Milford)	Milford, UT	2012	1.88	10.31	Andreas 2013 [64]	38.41, 113.03	105	2696	Cold

Table 4 Settings for modeling scenarios.

Scenario Name	Forecasting Model	Storage Method
Perfect-No Storage	Perfect Forecasting	No Storage
Perfect-Auto		Automatic Storage
Perfect-Predefined		Predefined Storage
Simple-No Storage	Simple Forecasting	No Storage
Simple-Auto		Automatic Storage
Simple-Predefined		Predefined Storage

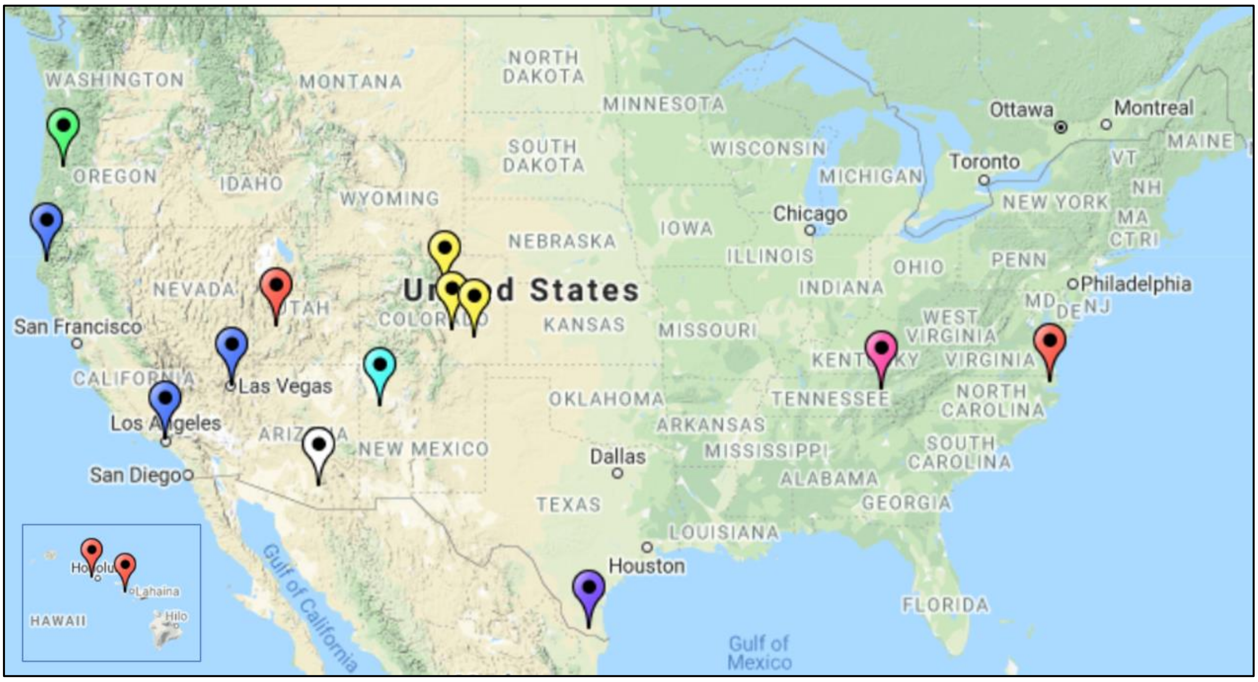

Figure 2 Map of 15 cities in the United States that are used to simulate the P2P electricity market [65].

5. Results

5.1 Monthly Electricity Demand and Solar Energy Production

Monthly electricity demand and solar energy production are shown below for each of the 15 cities (Figure 3). The total monthly solar energy production for each city is much smaller than the associated monthly electricity demand. The largest monthly production value is reported during the month of June in Milford, UT at 4,487 kWh. The lowest monthly production value, 488 kWh, occurred during December in Kalaeloa, HI; although this is one of the sunniest places in the country, areas in Hawaii suffer from partly cloudiness (discussed further in Section 5.4). Energy production shows seasonal variation for all cities [40]. Eight of the 15 cities produce the most solar energy during June, and ten of the cities produce the least during December.

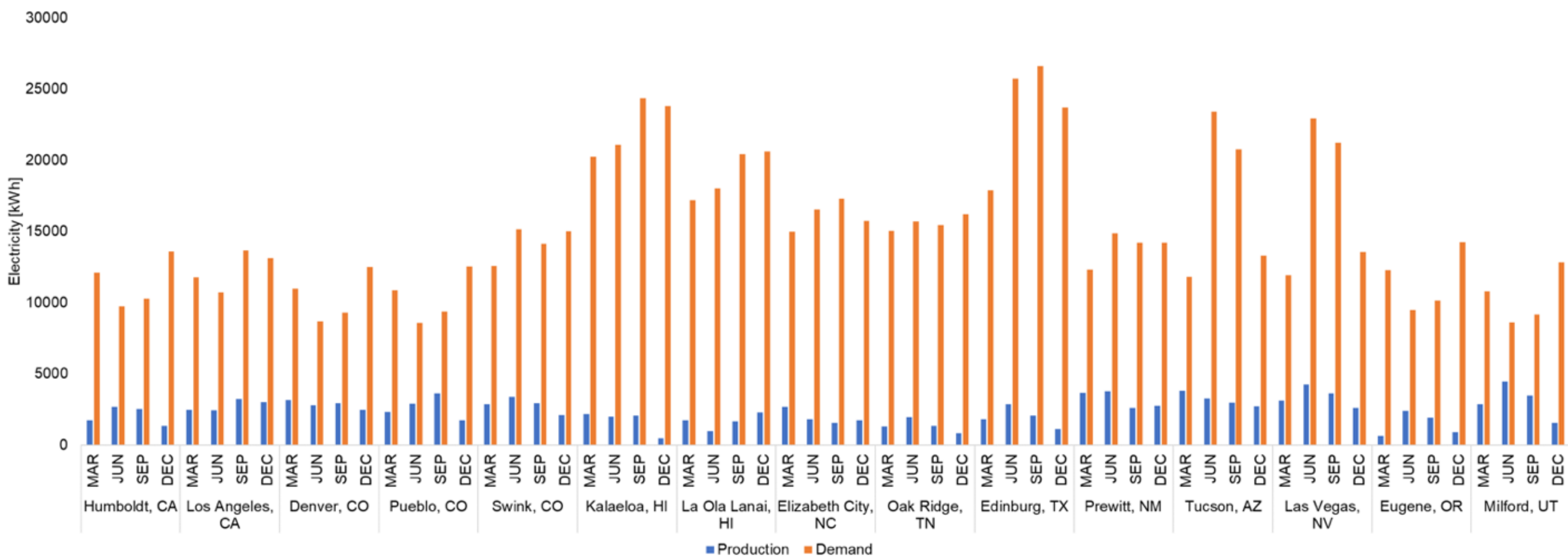

Figure 3 Monthly electricity demand and solar energy production for 15 simulated cities. Values are shown for the months of March, June, September, and December.

Las Vegas, NV, Prewitt, NM, and Tucson, AZ have the largest average production values among the months modeled at 3,404, 3,213, and 3,196 kWh, respectively; these cities are generally closer to the equator and are located in areas that are less cloudy. Electricity demand also varies seasonally and is influenced by latitude. Cities such as Las Vegas, NV, Tucson, AZ, and Edinburg, TX, which lie in lower latitudes, tend to have high electricity demand during the summer and fall (represented by the months of June and September, respectively), due to air conditioning. Cities located in higher latitudes, such as Denver, Pueblo, and Swink, CO; Milford, UT; and Eugene, OR, record higher demand in spring and winter (represented by March and December, respectively), due to heating demands. Edinburg, TX, Kalaeloa, HI, and La Ola Lanai, HI show consistently high demand for electricity, with average values of 23,477, 22,370, and 19,068 kWh respectively. High demands shown in the month of December for these locations may be attributed to energy consumption during the holiday season [66]. Kalaeloa and La Ola Lanai have relatively high electricity demands for an area that is described by others as having modest demand for electricity, needing little for heating and cooling because of its mild tropical climate. High demands reported here are a result of the B10 simulation protocol, however, which simulates a higher electricity demand for air conditioning than what is used in Hawaii. Las Vegas (17,402 kWh) and Tucson (17,321 kWh) also have high average electricity demands, and these cities show extreme seasonal swings in demand; the margin between the highest and lowest demand month is 11,033 kWh for Las Vegas and 11,614 kWh for Tucson.

5.2 Market Performance

Market performance is analyzed according to the seller average price of electricity, and the proportion of excess solar production traded in the market.

5.2.1 Seller Average Price

The seller average price of electricity traded in the P2P market is shown for the month of June across all six scenarios in Figure 4. The average price is calculated and reported in Figure 4 as the average price of energy sold in the market by prosumers over the month of June. The seller price of energy reflects the value that the buyer pays for energy minus the cost of purchasing energy from the utility agent at the retail rate to make up any shortfall quantities. The seller price of energy is low at periods when the seller overproduces energy and sells excess energy to the utility at lower buy-back rates. The full set of results for the months of March, September and December are provided in the Appendix (Figure S1-S3). The seller average price is similar across cities and scenarios, except for Kalaeloa and La Ola Lanai. Cities in Hawaii have the highest prices with an average of approximately 31 cents per kWh among the perfect forecasting scenarios. These high prices are due to Hawaii's high avoided fuel costs (9.31 cents/kWh), which is driven by the heavy use of petroleum fuel oil in power generation. The average irradiance, annual electricity demand, and annual solar production do not show a significant effect on the seller average price.

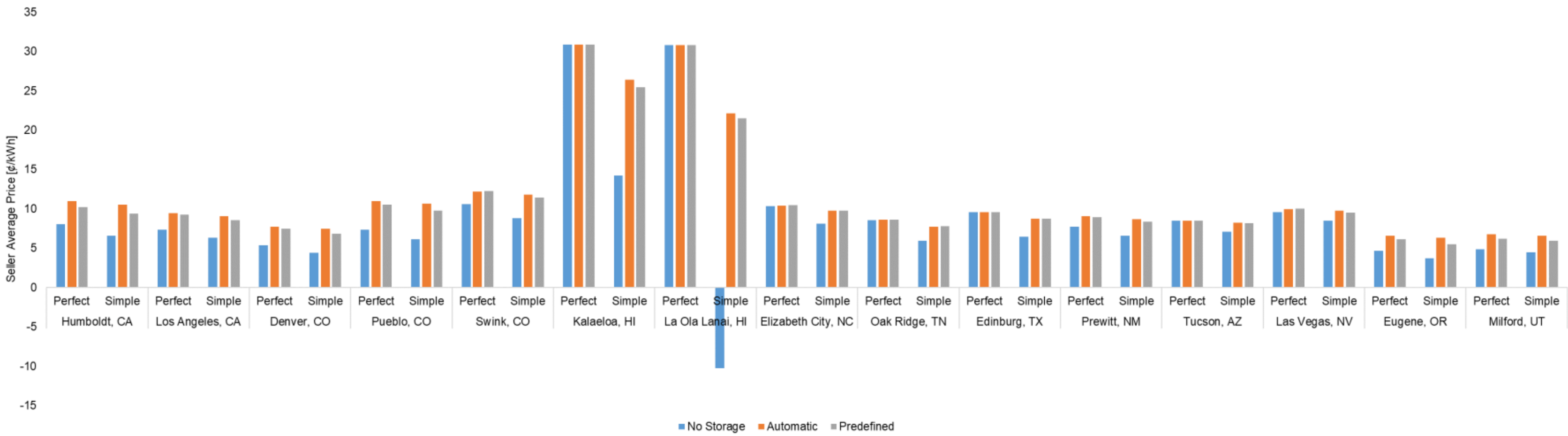

Figure 4 Seller average price of electricity in virtual P2P neighborhood market for 15 simulated cities. Results correspond to alternative forecasting methods (perfect and simple) and battery storage strategies (no storage, automatic, and predefined) and are shown the month of June.

The seller average price exhibits a seasonal variation across all cities, and the range of that variation depends on the city. For example, in the Perfect-No Storage scenario, the range between the minimum and maximum monthly price is highest for Las Vegas, Tucson, and Pueblo at 2.85, 2.83, and 2.62 cents/kWh, respectively; the range is lowest for Oak Ridge, Edinburg, and Denver at 0.90, 1.09, and 1.09 cents per kWh, respectively. Overall, the average price of electricity follows the seasonal variation of neighborhood solar energy supply relative to neighborhood electricity demand (Figure 4); months with a higher supply of excess solar power relative to electricity demand lead the market to lower clearing prices, while those with a lower supply of excess solar power relative to electricity demand lead the market to higher clearing prices.

Battery energy storage increases the average seller price while decreasing its seasonal variability, when compared with no storage, for all cities. The simple forecasting scenarios result in marginally lower seller average prices when compared with perfect forecasting scenarios, except for La Ola Lanai and Kalealoa, which show a substantial decrease for simple forecasting scenarios (Figure 4). La Ola Lanai has a negative price of approximately -10 cents per kWh for the Simple -No Storage scenario due to forecasting errors, which means that sellers must pay to provide electricity to the buyers. The distribution of results among the cities modeled are similar for each month, as shown in the Appendix (S1-S3), though a negative seller average price was discovered only the month of June.

5.2.2 Proportion of Excess to Market

The proportion of excess solar production that is sold in the market is shown in Figure 5 for each of the modeling scenarios. Excess solar production is the energy that is sent to the grid for P2P market exchanges after satisfying the prosumer's household demand, and the proportion of excess solar production to market is the ratio of excess solar production that is sold in the market to the excess solar production that is generated. Cities with low electricity demands sell the lowest proportion of excess solar production sold in the market (Figure 5). Low electricity demands decrease the proportion of excess solar production sold in the virtual market and increase the amount of overproduction that is sold back to the utility. Battery solutions with no storage significantly limit the amount of excess solar energy that is sold (Figures 5a and 5d), while both automatic and predefined discharge storage solutions allow most of the cities to sell nearly all the excess solar production in the virtual market (Figures 5b, 5c, 5e, and 5f). For each city, there is little difference between perfect and simple forecasting for the scenarios that use storage. For example, Figure 5c (Simple-Automatic Storage) and 5f (Perfect-Automatic Storage) show only slight differences. On the other hand, there is large improvement in the amount of excess energy sold when No Storage is combined with Perfect forecasting (Figure 5d), compared with Simple forecasting (Figure 5a). Solar forecasting error associated with the simple forecast decreases the accuracy of electricity exchanges and can leave available excess from sellers untraded. Automatic and predefined discharging, however, show significant differences in some cities. For example, there is an average increase of 5% (with an upper and lower bound of 0% and 10% for Kalaeloa and Milford, respectively) of excess solar sold to the market in the month of March when Automatic storage is used instead of Predefined storage. Automatic storage provides a more efficient algorithm for charging and discharging batteries than predefined schedules, and more excess is sold in most cities. Among the perfect forecasting scenarios, the Automatic storage scenario increases the proportion of excess production sold with an average increase of 16% relative to the No Storage scenario, and the Predefined storage scenario increases by 14% compared to the No Storage scenario across all cities.

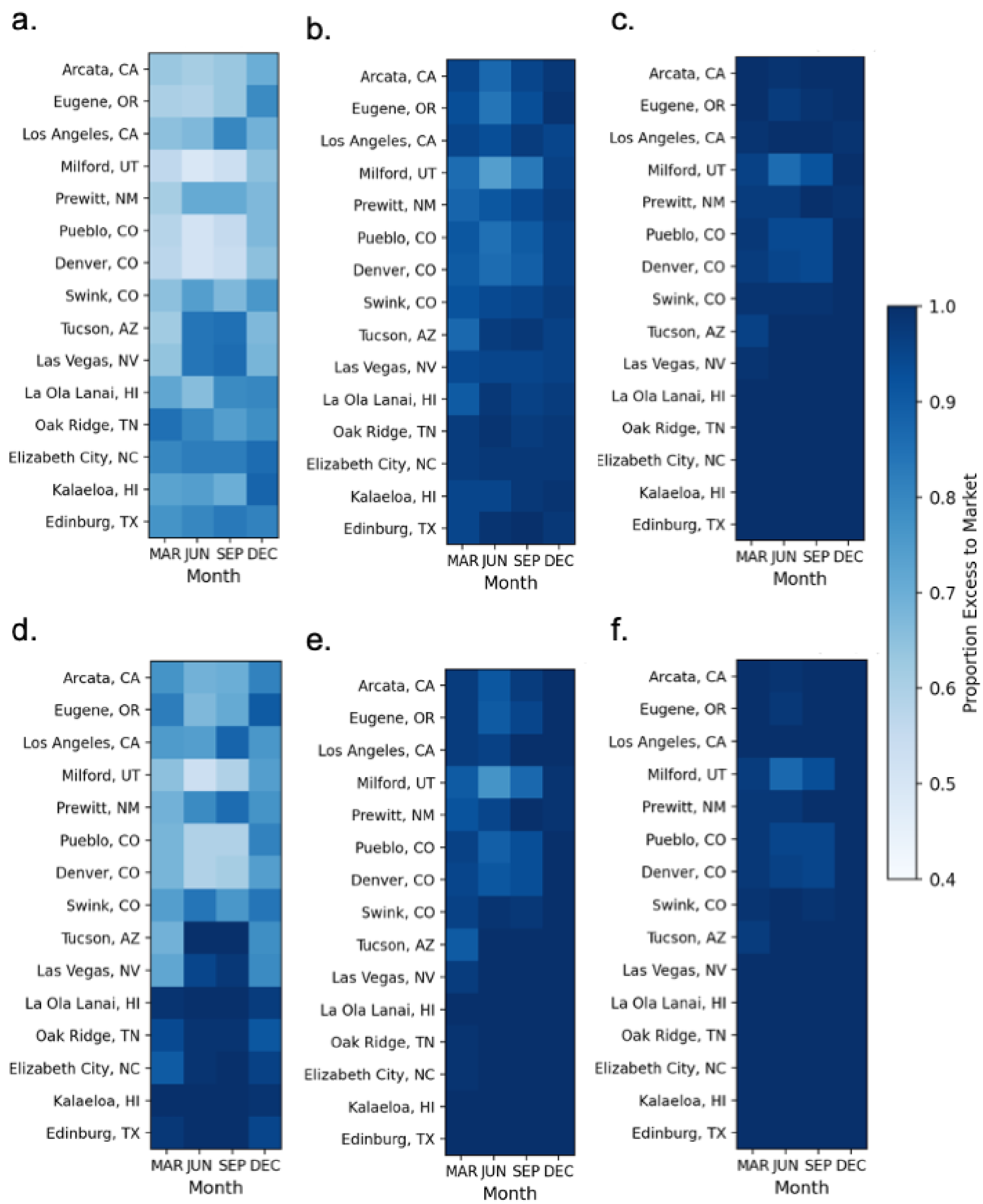

Figure 5 Proportion of excess production sold in each city, sorted by the cities' electricity demand (kWh/year) for a.) Simple-No Storage, b.) Simple-Predefined Storage, c.) Simple-Automatic Storage, d.) Perfect-No Storage, e.) Perfect-Predefined Storage, and f.) Perfect-Automatic Storage scenarios.

In the worst case scenario, with Simple forecasting and No Storage, some cities (Denver, Milford, Pueblo) have an average of 56-58% of excess production sold in the market over the four months (Figure S7 in Appendix). For the same scenario, Prewitt, Eugene, and Humboldt show an average of

64-68% of excess production sold in the market, and the remaining nine cities report an average greater than or equal to 70% of excess production sold on the market over the four simulated months (Figure S7 in Appendix). Perfect forecasting and Automatic storage generate an upper bound on the expected performance, and all cities report at least 95% excess production sold during all seasons, with seven cities reporting 100% excess production sold for all seasons (Figure 5f). These results can be used to guide initial analysis about which cities would be viable locations for incentivizing P2P markets. The results for the months of March, June, September and December are provided in the Appendix (Figure S4-S7).

5.3 Sensitivity Analysis

5.3.1 Number of Prosumers

To test the sensitivity of the ABM to the concentration of prosumers in the network, a set of scenarios were created for Edinburg, TX, Eugene, OR, and La Ola Lanai, HI to test how the market performs with varying numbers of consumers. Simulations are tested for the Perfect-No Storage and Perfect-Automatic Storage scenarios. For each scenario, the total number of households in the market remains at 25, and the number of prosumers varies from one to 12. These scenarios demonstrate the importance of storage as it affects the performance of the P2P market. In Edinburg, the market begins to create overproduction at four, eight, six, and three prosumers for the months of March, June, September, and December respectively (Figure 6a). The smaller numbers for March and December are likely because they are the lowest demand months for Edinburg (Figure 3). December is also a special case both because of its odd demand pattern and because there are lower demands on the days that the production occurs (Figure 6d); this highlights the importance of the hourly dynamics of solar energy production and electricity demand. Storage with automatic discharging increases the market efficiency so that none of the months for Edinburg sell less than 95% of excess solar production for increasing numbers of prosumers (Figure 6d). The monthly trajectories of La Ola Lanai and Edinburg are similar (Figures 6c and 6f). For La Ola Lanai, overproduction is created with four, six, five, and three prosumers for the months of March, June, September, and December, respectively, when no storage is used; storage with automatic discharging enables 12 prosumers to sell more than 95% of excess in the market. In Eugene, the market begins to create overproduction at three, two, three, and four prosumers for the months of March, June, September, and December, respectively, when no storage is used (Figure 6b). Using storage with automatic discharging allows up to five prosumers to sell nearly 100% of their excess production in the market (Figure 6e).

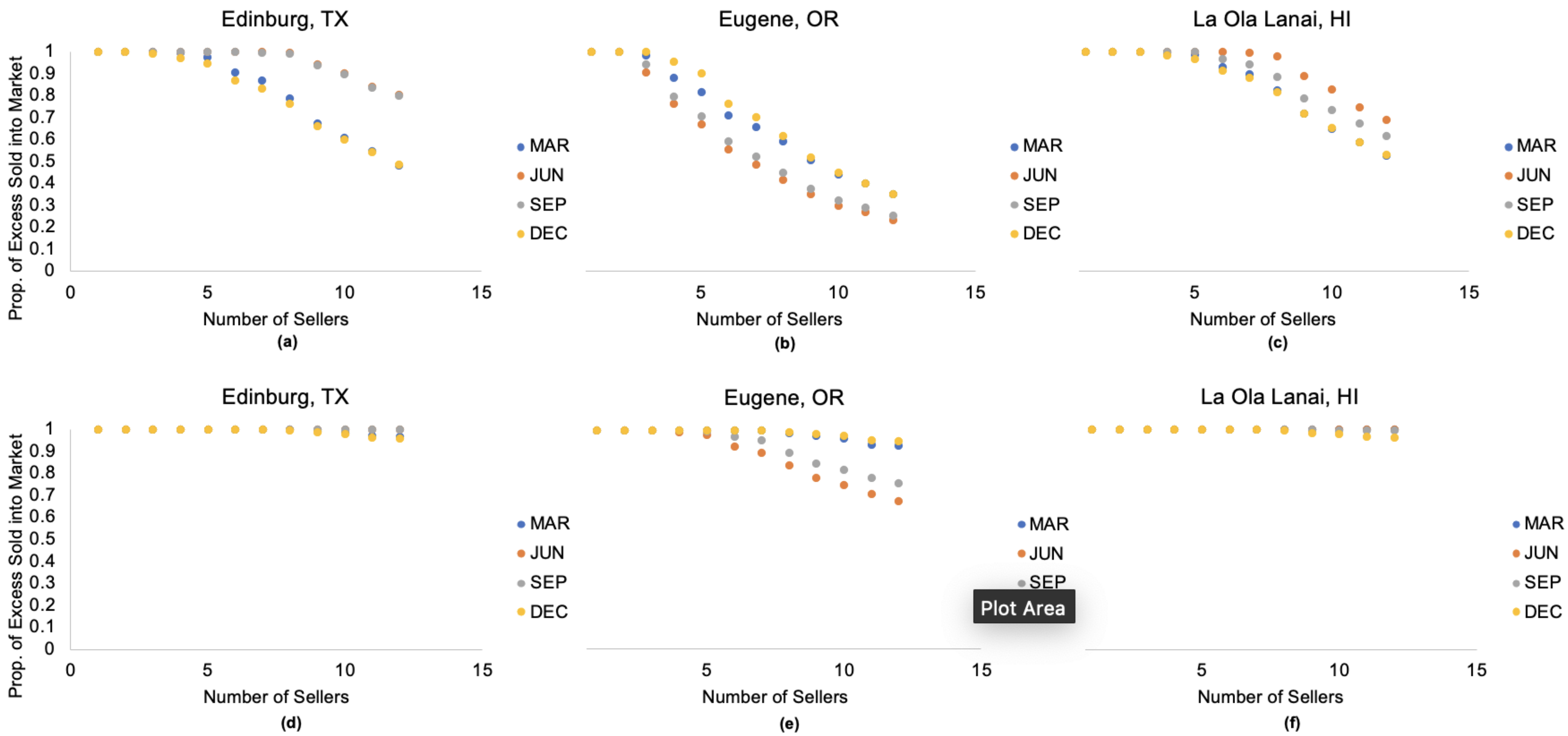

Figure 6 Proportion of excess solar energy production sold into the P2P market versus the number of prosumers in a 25-household neighborhood for three simulated cities. Results are shown for the PF-N scenario for **(a)** Edinburg, TX, **(b)** Eugene, OR, and **(c)** La Ola Lanai, HI. Results are shown for the Perfect-Automatic scenario for **(d)** Edinburg, TX, **(e)** Eugene, OR, and **(f)** La Ola Lanai, HI. Values are shown for the months of March, June, September, and December.

Results of this simulation create new insight around overproduction and the market clearing price of electricity. The analysis here reveals the saturation point for the number of prosumers in a market of excess solar production, where increasing the number of prosumers beyond this point results in overproduction. Twelve prosumers can participate in the market for Edinburg and La Ola Lanai with only marginal generation of overproduction. Simulation results are reported for perfect forecasting, and it is expected that fewer prosumers could be supported without overgeneration with simple forecasting. Results suggest automatic storage capability allows more sellers to participate in the market before overproduction becomes an issue, which leads to lower average market clearing prices.

5.3.2 Dynamics of Electricity Demand and Solar Energy Production

Hourly dynamics of supply and demand are analyzed for three cities to explore drivers for market performance and trading outcomes. Hourly profiles of neighborhood electricity demand and solar energy production for Edinburg, Eugene, and La Ola Lanai are explored for 5-prosumer and 10-prosumer scenarios (Figure 7, Figure 8 and Figure 9). These three cities were chosen to explore further because they represent a range of outcomes in market performance and dynamics in demand and supply.

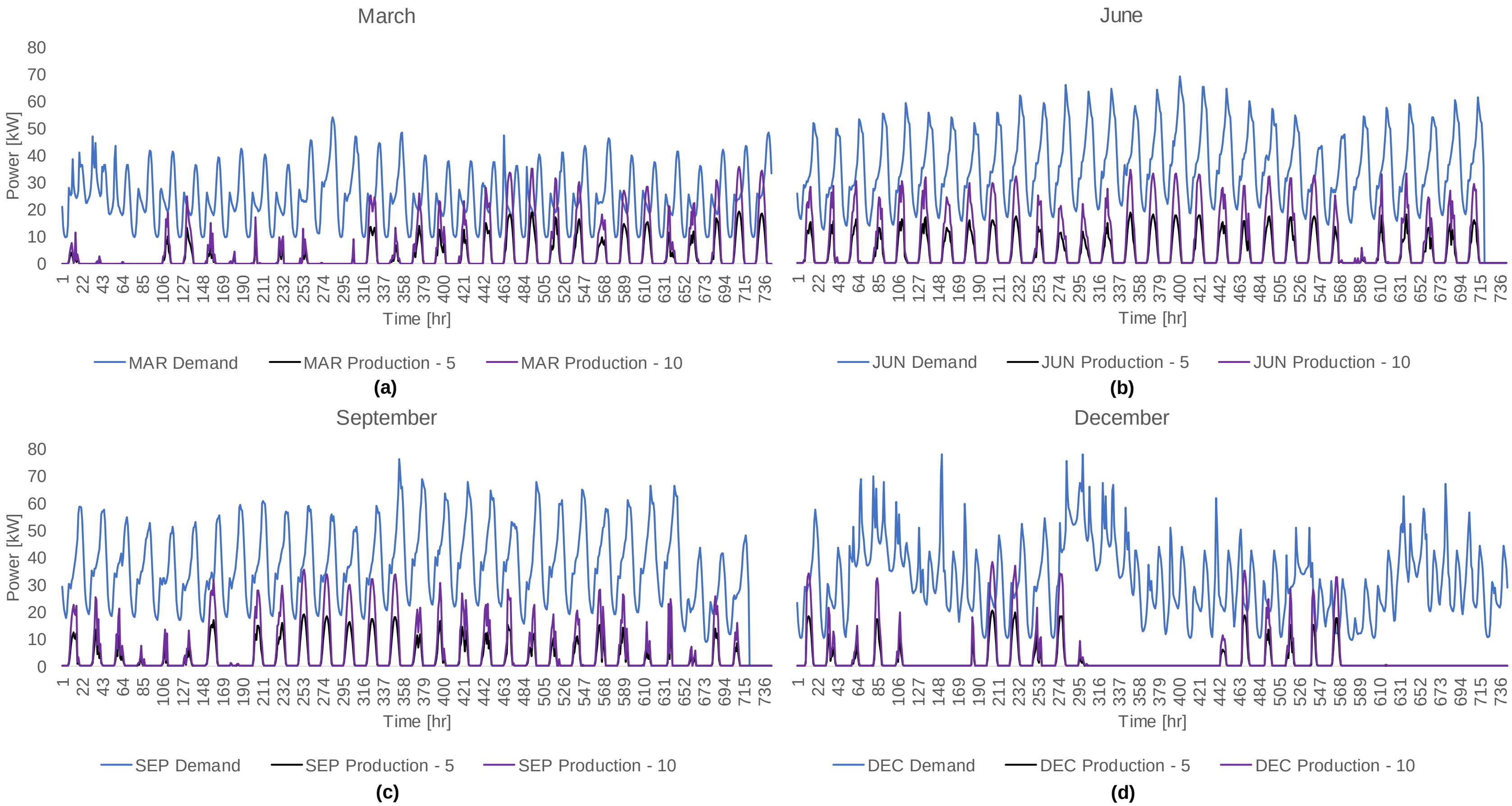

Figure 7 Temporal profile of electricity demand and solar energy production for Edinburg, Texas. Solar energy production is shown for a neighborhood with both five and ten households with solar PV systems. Values are shown for the months of **(a)** March, **(b)** June, **(c)** September, and **(d)** December. The demand and production profile are constant throughout all scenarios.

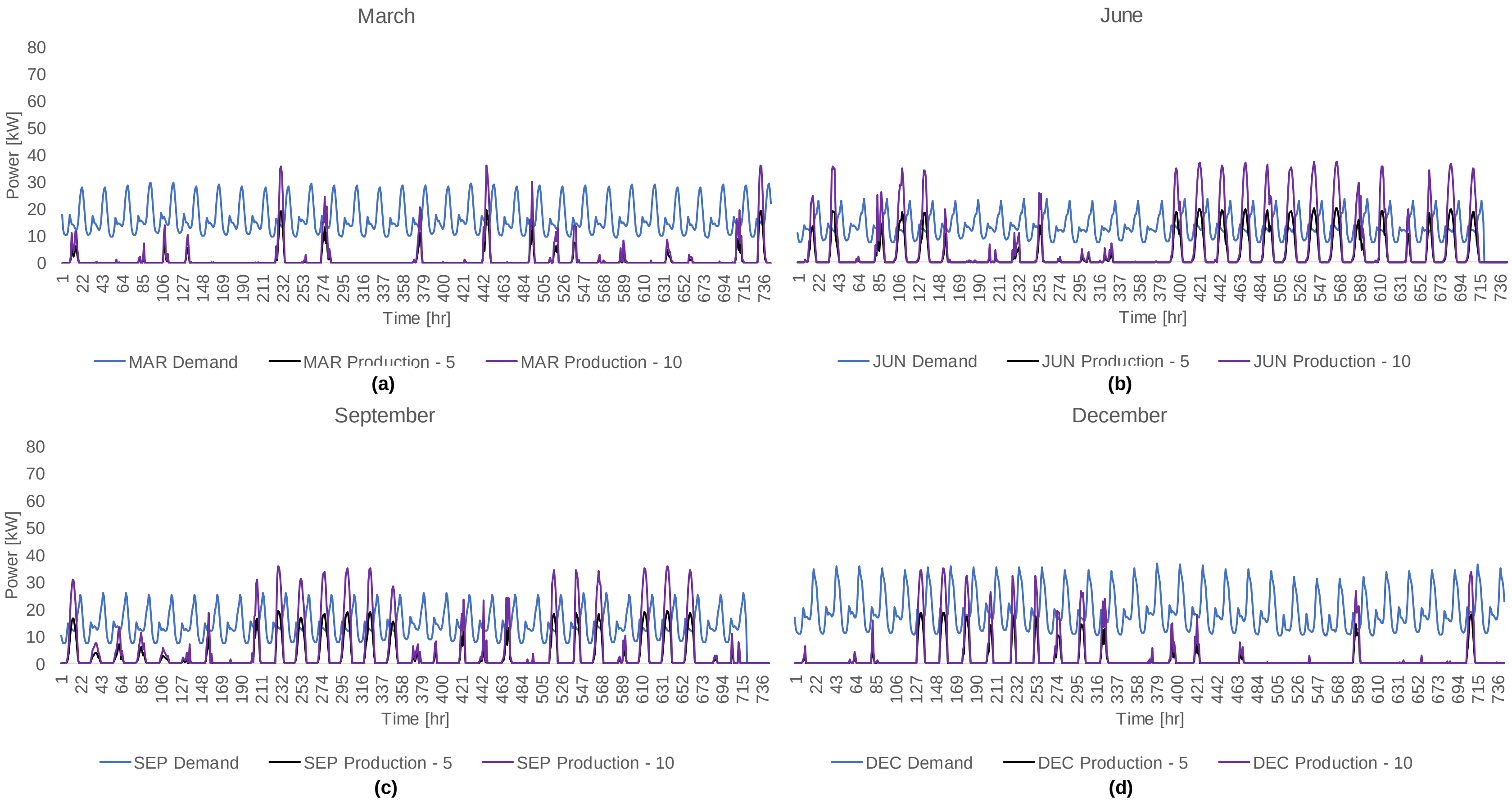

Figure 8 Temporal profile of electricity demand and solar energy production for Eugene, Oregon. Solar energy production is shown for a neighborhood with both five and ten households with solar PV systems. Values are shown for the months of **(a)** March, **(b)** June, **(c)** September, and **(d)** December.

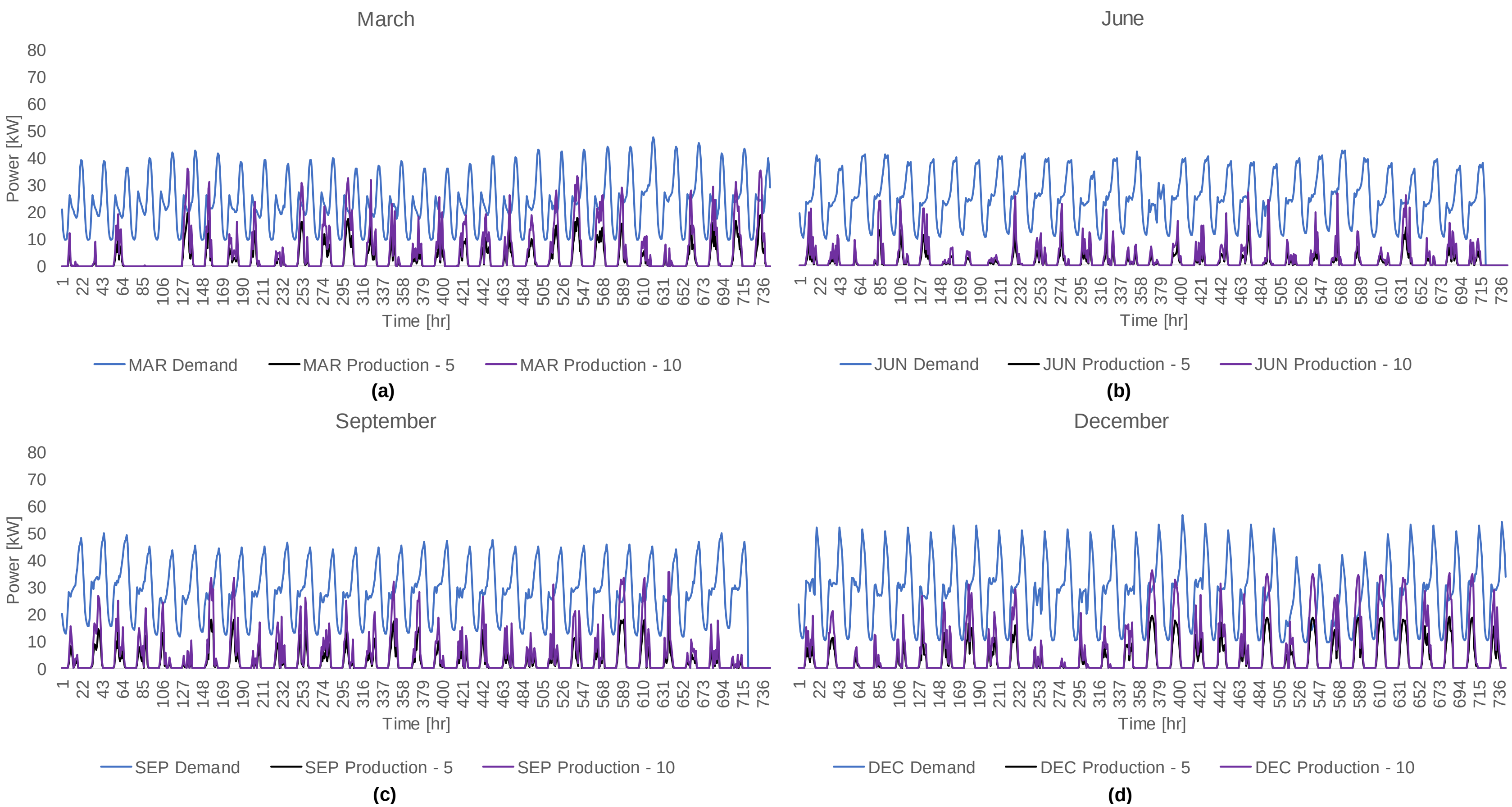

Figure 9 Temporal profile of electricity demand and solar energy production for La Ola Lanai, Hawaii. Solar energy production is shown for a neighborhood with both five and ten households with solar PV systems. Values are shown for the months of **(a)** March, **(b)** June, **(c)** September, and **(d)** December.

Across the three cities, Edinburg has the highest demand and the most variability in demands. The electricity demand for Edinburg shows some inter-daily variation for March, June, and September (Figures 7a, 7b, and 7c) and large variations in December (Figure 7d), attributed to demands associated with holidays. For Eugene, electricity demand follows a standard daily diurnal pattern that is consistent and tight throughout each month with little variation, and peak demands are lower than in Edinburg, in the range of 20-40 kW (Figure 8). La Ola Lanai has peak demands around 40-50 kW, with a larger diurnal variation (Figure 9). For all cities, peak production is offset from peak demand by a few hours. Production profiles for Edinburg are consistent for March, June, and September with a few cloudy days in each month, while production during December is more irregular. Demand exceeds production across the four months for Edinburg. Eugene has fewer days when energy is generated and La Ola Lanai has intermittent electricity production, due to perpetual partly cloudiness, which reduces their total energy production.

5.3.3 Analysis of Predefined Storage Discharge Timeline

While the Predefined storage performed worse than the Automatic storage in most cases, the performance of Predefined storage depends on the timelines that are predetermined for charging and discharging batteries. This analysis tests new discharge timelines to explore if the effectiveness of the strategy can be improved. The proportion of excess solar production sold in the P2P market versus the discharge timeline for the predefined storage case is shown below for the Perfect-Predefined scenarios; results are shown for three cities including Edinburg, Eugene, and La Ola Lanai (Figure 10). A discharge timeline analysis tests the following discharging timelines: 3:00 pm-8:00 pm, 4:00 pm-8:00 pm, 5:00 pm-10:00 pm, and 6:00 pm-11:00 pm. A charging timeline of 9:00 am-3:00 pm remains constant for all scenarios in the discharge timeline analysis. In Eugene, the discharge timeline has a clear impact on the proportion of excess sold into the market for both the five- and ten-prosumer scenarios, because the total supply of excess solar power in the neighborhood is relatively high compared to the demand for electricity (Figure 7), which is the smallest out of the three cities shown here (Figure 3). In Edinburg and La Ola Lanai, nearly 100% of excess solar production is sold into the P2P market for almost all discharge timelines tested with five prosumers, probably because the neighborhood demand for electricity in these two cities is high relative to the total supply of excess solar power (Figure 3).

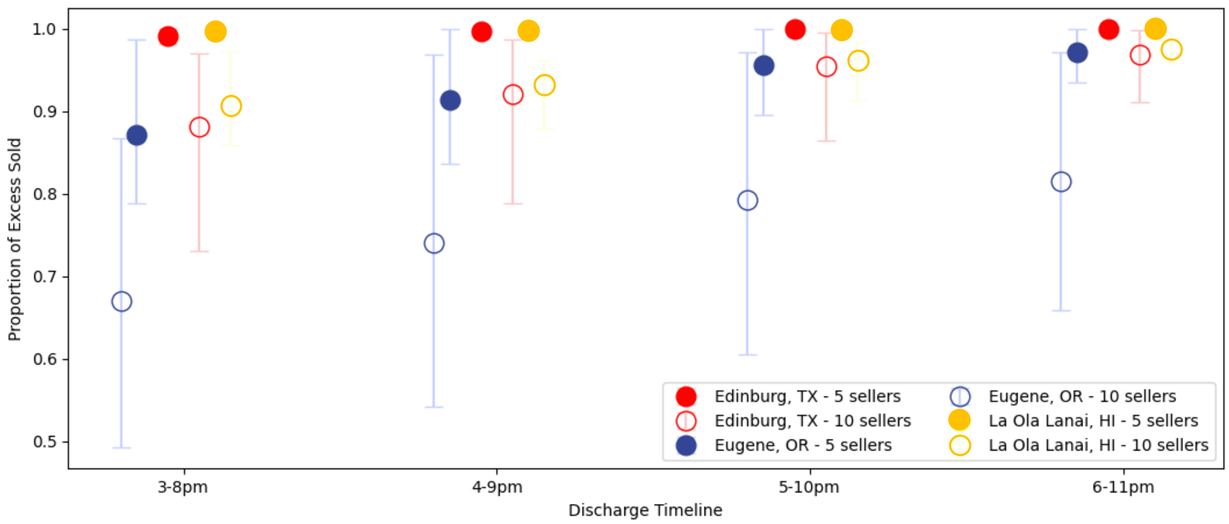

Figure 10 Proportion of excess solar energy production sold into the P2P market for predefined storage discharge timelines in Edinburg, TX, Eugene, OR, and La Ola Lanai, HI. Results are shown for the Perfect-Predefined scenario with 5 and 10 sellers. The circles represent the average proportion of excess sold, and the bars represent the maximum and minimum monthly proportions for each scenario.

Both Eugene scenarios (5- and 10- prosumers) and all 10 seller scenarios improve as the discharge schedule occurs later, with the optimal automatic discharging schedule occurring between 6-11 pm for all three cities. Discharging later in the day leads to a larger proportion of excess sold in the P2P market because the energy is being released closer to the peak daily demand hour; this will lead to a higher seller average price of electricity.

6. Discussion

This research develops an ABM to simulate a P2P market and tests how a market may behave for a range of climate conditions, storage solutions, solar irradiance forecasting models, and market participation. Simulations in this study reveal that market outcomes are heavily influenced by the ratio of sellers to buyers as well as environmental and geographic conditions, such as cloud cover and local latitude. Market price is ultimately determined by local supply and demand for excess solar power, but more importantly it is determined by the timing of supply and demand. Battery energy storage increases both the flexibility of household generated solar power and the proportion of production that is sold in the P2P market. Seller average electricity prices in all scenarios are higher than the avoided fuel cost rate in each modeled city, indicating that prosumers reap financial gains compared to a typical utility buy-back program.

Forecasting penalties propagate heavily in cloudy cities, such as Kalaeloa and La Ola Lanai. Penalties lower the value of excess generated solar power for prosumers specifically, which could be a negative stimulus that perturbs or eliminates their bids in future trading intervals for a real system. P2P markets must plan for geographic issues such as cloud cover by improving short-term solar forecasting. Short-term forecasting may be improved by developing sophisticated algorithms to track local cloud formations through satellite imaging and ground telemetry [67]. Storage solutions can reduce the impact of forecasting on market prices, as stored energy, which is known with certainty, can be placed on the market. Although battery storage provides a promising outlook for increasing the proportion of excess energy that is sold on the market, there are many limitations associated with installing batteries at residences, including maintenance concerns, installation complexities, space limitations, low battery recycling rates and expense [68].

While heterogeneity is modeled in this study through differing electricity demands and solar generation values, other household characteristics may be simulated as heterogenous in further studies. For example, the electricity demand profile is the same for each household and scaled by the floor area, and each prosumer has a similar solar generation profile, which is scaled by the solar coverage area. Energy storage system specifications and functionality are also modeled to be alike for all prosumers in each simulation scenario. The demand profiles of households would realistically be different based on characteristics such as the number of occupants, age groups, daily activities, and preference for indoor climate. Further, the composition of distributed energy resources in a neighborhood would likely be dissimilar as well; from the size and cell efficiency of solar arrays to the presence, capacity, round-trip efficiency, and functionality of battery energy storage systems. Local geographic and environmental differences would be expected to influence the solar generation profiles of households as well, including the presence of trees, unequal distribution of clouds, and even the topology of the neighborhood. The architecture of households could impact generation by influencing the available area for solar coverage as well as the optimal orientation and tilt of solar panels. Intermittent shading and temperature effects from the chosen architecture could control generation during certain times of the day. P2P electricity markets must be simulated with a higher level of heterogeneity to assess the impact of local differences on the dynamics of electricity bids and closing prices. This study applies a simulation-based approach to forecast or project the efficiency of markets in various locations. Other work has applied the agent-based modeling approach for real-world data to validate the model [11], and further research can continue to test and improve the performance of the model for data about the adoption of P2P markets as they emerge.

Agents are modeled in this study as static with respect to electricity demand and placing market bids. Goal-directed households may modify or adapt their behaviors over time to better achieve their set goals; they alter their behavior based on accumulated experiences [69]. Electricity market participants may have price expectations when making bids, the rejection of those bids over multiple trading periods can influence buyers and sellers to adapt their pricing strategy [70]. Additionally, the temporal variation of prices in a real-time electricity market may motivate participants to shift their demand to periods that are consistently low in price [71]. Monitoring of energy consumption in real-time can also prompt behavioral changes to reduce wasteful energy use [72]. New modeling approaches are needed to conduct quantitative analysis of bidding and consumption strategies that considers the interactions between infrastructure and market participants; new approaches will help us better understand the role of human decision-making in the dynamics of decentralized electric distribution systems.

The ABM framework developed here simulates a virtual electricity market where households can exchange excess solar generation to anyone who places a bid in the system. Physical constraints of the electric grid are not represented in this study and should be modeled using power system simulation. Power system modeling may reveal voltage or frequency issues with the low-voltage network that serves the neighborhood participating in the market. Further, inverter constraints on power output from both the solar array and battery storage system are not modeled; these may be more appropriately modeled using a power system model. Power flow constraints imposed by the inverter system may limit the transfer of power from prosumers to the grid, so they must be considered when placing bids in the market. A P2P electricity market could be expanded to allow households in different low-voltage sub-networks to trade excess generation, which could have a negative impact on the main transmission system that feeds them. Reverse power flow through the transformer from the low-voltage to the medium-voltage side of the grid could result in operational issues for the utility maintaining the network. Market rules may be designed to restrict trade based on distance between buyers and sellers to ease any distribution-level interference from reverse power flow. The idea of restricting trade based on distance raises an important question on how to appropriately scale P2P markets. It may be necessary to aggregate households into clusters to better facilitate the flow of excess solar generation across long distances.

The P2P electricity market simulated in this study requires the generated electricity to be verified, including generation time and total amount. Electricity trades would also need to be transparent and auditable so that bills can be calculated accurately [24]. Enabling P2P electricity trading requires an adaptable electricity trading platform that allows both P2P and utility-to-peer trades. Blockchain can be utilized and is being used in existing applications as a trustless ledger to facilitate the accounting needed for P2P trading for infrastructure and natural resources markets [73, 74]. Advanced metering infrastructure must be deployed in the form of smart home energy meters and distribution level network sensors. Appropriate algorithms must be developed that can leverage smart meter data to pair, order, and execute trades among electricity users all while maintaining operational reliability of the grid. All components must be integrated together into an easy to use online platform to digitally facilitate the shared energy resources [13].

Households are modeled here to participate in the P2P market with any excess solar power they have generated; however, some households with energy storage may choose to optimize the price of their generation by maximizing solar self-consumption. In a scenario where all consumers place their WTP values below the retail rate, prosumers maximize the value of their solar power by consuming it all themselves; this is because self-consumed power would be priced at the retail rate since it is offsetting energy purchased from the utility. Rules may be developed to commit prosumers to bid a certain proportion of their excess into the market for consumers to buy. Alternative electricity market structures can be developed and simulated to determine the impact on the dynamics of both the electricity market and distribution infrastructure.

7. Conclusion

Several cities in the United States are modeled using an ABM framework to simulate the emergence of the seller average price of electricity in a residential P2P electricity market. Simulations explore the benefits and disadvantages of decentralized electricity markets. Battery energy storage systems are modeled to determine the impact of storage on both the flexibility of solar generated energy and electricity market prices. Solar forecasting is modeled to assess transaction penalties and to determine the effect on market effectiveness.

The ABM framework is applied for 15 cities to compare how a range of climate conditions, storage solutions, solar irradiance forecasting models, and market participation affect market efficiency. The results of the study can be used to rank locations for incentivizing new P2P markets.

These results show that for simple solar PV systems, such as those with no storage and simple forecasting, Edinburg, Oak Ridge, and Elizabeth City report high values for average excess energy production sold on the market. Forecasting algorithms can greatly improve the performance of systems for cities in Hawaii without the need for battery storage, due to cloudy patterns that affect solar production. Both automatic and predefined discharging for battery storage can greatly improve performance and increase the excess energy sold on the P2P market. Oak Ridge and Edinburg also have low change in performance among seasons, and robust behavior may be another component of selecting locations that are viable for P2P markets. Analysis is also conducted here to assess the number of prosumers that can be supported in a market before overproduction is generated. The flexibility of storage is important to expand the market beyond two to five prosumers in a 25-household neighborhood. Among the cities assessed, storage allows 12 prosumers to participate in the market for Edinburg and La Ola Lanai with only marginal generation of overproduction. These results, however, rely on perfect forecasting, and La Ola Lanai shows inefficiencies with simple forecasting and would support fewer prosumers without perfect forecasts. The framework developed here allows simulation and analysis of complex dynamics that drive market performance to provide guidance for market implementation.

Future work can explore novel methodologies to analyze the impact of adaptive behaviors on demand shifting and placing market bids. ABM frameworks that use empirical data and considers adaptation will bridge social-science and engineering disciplines to provide a flexible framework for simulating evolutionary dynamics of decentralized electricity systems.

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Author Contributions

JM – Conceptualization, Methodology, Software, Validation, Analysis, Writing – Original Draft; ERB – Writing – Review & Editing, Visulization; EZB - Conceptualization, Methodology, Writing – Review & Editing, Supervision.

Competing Interests

The authors have declared that no competing interests exist.

Additional Materials

The following additional materials are uploaded at the page of this paper.

1. Figure S1: Seller average price of electricity in virtual peer-to-peer neighborhood market for 15 simulated cities. Results above are for the month of March. Results are shown for all forecasting and storage scenarios.
2. Figure S2: Seller average price of electricity in virtual peer-to-peer neighborhood market for 15 simulated cities. Results above are for the month of September. Results are shown for all forecasting and storage scenarios.

3. Figure S3: Seller average price of electricity in virtual peer-to-peer neighborhood market for 15 simulated cities. Results above are for the month of December. Results are shown for all forecasting and storage scenarios.
4. Figure S4: Proportion of excess solar production sold in virtual peer-to-peer neighborhood market for 15 simulated cities. Results above are for the month of March. Results are shown for all forecasting and storage scenarios.
5. Figure S5: Proportion of excess solar production sold in virtual peer-to-peer neighborhood market for 15 simulated cities. Results above are for the month of June. Results are shown for all forecasting and storage scenarios.
6. Figure S6: Proportion of excess solar production sold in virtual peer-to-peer neighborhood market for 15 simulated cities. Results above are for the month of September. Results are shown for all forecasting and storage scenarios.
7. Figure S7: Proportion of excess solar production sold in virtual peer-to-peer neighborhood market for 15 simulated cities. Results above are for the month of December. Results are shown for all forecasting and storage scenarios.
8. Figure S8: Average proportion of excess solar production sold in virtual peer-to-peer neighborhood market for 15 simulated cities.
9. Figure S9: Seller average price of electricity for 15 simulated cities.

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