Decentralizing DERs: Comparing Economic Efficiency between Bilateral Exchange Mechanism and Automated Market Makers for Peer-to-Peer Energy Markets

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https://github.com/nalinbhatt/p2p_solar_abm.git

1 Introduction

Historically, the electricity market has been viewed as unidirectional, where power flows from centralized power plants to households and businesses. However, with the implementation of smart grid technology, there has been renewed interest in Decentralized Energy Resources (DERs) that allow for bidirectional electricity flow and a decentralized grid. DERs consist of households and businesses with renewable energy installations, the most common being solar panels, that both produce and consume electricity (Monroe et al., 2023) .

Currently, excess electricity produced by DERs is sold to utility companies and dispersed to the grid at avoided fuel cost rates. These rates are lower than what the utility companies charge general consumers for electricity. This creates an economic opportunity to facilitate trade between consumers who are willing to pay below utility rates and prosumers[1] willing to sell at prices higher than avoided fuel cost rates. To facilitate this exchange, there has been increased interest in Peer-to-Peer (P2P) energy markets, where consumers and prosumers can trade excess energy production (Capper et al., 2022; Sousa et al., 2019).

If implemented, P2P markets can incentivize more households to adopt solar panels, thereby reducing the carbon footprint from electricity generation. Additionally, in case of centralized power resource failures, P2P markets can reduce the risk of system-wide blackouts.

[1]prosumers is a common term in the literature used to refer to households or businesses that both produce and consume electricity, often using solar panels.

1.1 Problem

Although DERs and P2P markets showcase the benefits of decentralized power generation, most proposed designs have chosen centralized orderbook mechanisms to facilitate the trading of electricity (Mengelkamp et al., 2017; Monroe et al., 2023). Bilateral exchanges and double/single auctions are popular examples of centralized exchange implementations suggested for P2P energy trading (Capper et al., 2022). However, these centralized exchanges, despite being efficient at finding equilibrium prices, pose a threat to decentralized electricity trading if subjected to cyber-attacks or technical failures.

1.2 Proposed Solution

We propose introducing blockchains to facilitate energy trading. In a blockchain system, even if one node is attacked, the overall network of nodes required to reach consensus remains functional, mitigating the risk associated with centralizing the financial trading of electricity. However, centralized orderbooks don't mesh well with blockchains because they require high throughput, complex smart contract code, and are subject to front-running attacks (*AMM vs. Order Book*, 2023; Orderly Network, 2023). On the other hand, Automated Market Makers (AMMs), such as Uniswap on the Ethereum blockchain, have been used to solve this issue. Buyers trade against the liquidity pool/protocol using a simple algorithm instead of directly with sellers. AMMs ensure constant liquidity with relatively simple smart contract code (Xu et al., 2023, pp. 1–2).

1.3 Research Question

This research project explores whether AMMs can achieve the same economic efficiency as traditional orderbooks, specifically bilateral exchange mechanisms. We introduce an AMM as an additional treatment to the bilateral exchange P2P model proposed by Monroe et al. (2023) in "*Evaluating Peer-to-Peer Electricity Markets across the U.S. Using an Agent-Based Modeling Approach*" (Monroe et al., 2023). Like Monroe et al. (2023), we operationalize efficiency as the exchange that maximizes the proportion of excess solar sold on the market and seller average price. If decentralized mechanisms of trade, such as AMMs, perform on par with the bilateral exchange mechanism, it can make a case for further decentralization of energy trading.

2 Model Overview (ODD +D)

2.1 Description

Our model is based on the Monroe et al. (2023) paper "**Evaluating Peer-to-Peer Electricity Markets across the U.S. Using an Agent-Based Modeling Approach**" (Monroe et al., 2023). In the paper, the authors simulate trade between consumers and prosumers using a bilateral exchange mechanism and measure average seller price across different battery storage methods, forecasting techniques, and city environments.

This paper simulates a subset of their model, constrained to the city of La Ola Lanai, Hawaii, for the month of September. Additionally, we restrict our research to the *No-Storage* case, where prosumer households don't have battery storage options available, disallowing agents to store electricity if favorable prices aren't available in the exchange.

The exchange works like a futures market (Capper et al., 2022, p. 4). Prosumers and consumers agree to contracts on traded energy amounts at the beginning of the hour. At the end of the hour, prosumers deliver all energy amounts promised at the beginning of the hour using energy produced by solar panels during the hour or by buying any shortfall amount from the utility provider.

2.2 Time Steps

Like the Monroe et al. (2023) model, our simulation follows a sequential hourly time step j and is simulated for 30 days or 720 hourly time steps. All relevant interactions between agents occur within the hourly time step of the simulation.

2.3 Entities

The model is comprised of *Household* agents and the *Market* agent. The *Market* agent includes both the bilateral exchange and the automated Market Maker. However, only one of the above market mechanisms is active during a given simulation run.

During each time step, *households* submit bids and asks to the *market* to commit to energy trades that will be fulfilled in the next period. At the end of the period, agents fulfill contracts using actual energy production or by buying additional electricity from the utility provider.

The utility provider is not explicitly modeled as a separate agent. However, any profit or losses from excess or shortfall are automatically applied to *households* by the *market agent* at the end of the time step.

2.3.1 Market

Within our model, the *market* agent acts as the de facto model class. It initializes households with their solar consumption and production profiles using *Consumption Data* and *Solar Production Data* and runs the exchange at each hourly time step.

2.3.2 Households

Households are either *prosumer* or *consumer* types. *Prosumer* households are the only ones capable of generating solar energy within the model. *Prosumers* rely on either *simple* or *perfect forecasts* to estimate how much energy they will produce at the end of the current hour. These estimates dictate the futures contracts that the *prosumers* enter into at the beginning of the hour. Each *household* is randomly assigned a *floor area* at the beginning of the simulation, normally distributed around 1500 square feet. The *roof area* is calculated using the *floor area*, which determines the amount of solar PV installation a household will have, thus determining the amount of solar production a *prosumer* is capable of.[2]

The *Market* class initializes *households* with their respective solar *production profiles* and hourly *consumption profiles*. The solar production profiles are generated using minutely solar data from the National Renewable Energy Laboratory's Measurement and Instrumentation Data Center (National Renewable Energy Laboratory, n.d.). The consumption profiles are derived from the *Building America B10 Benchmark building simulation framework* (Wilson et al., 2014).

Table 1: Household Attributes

Attribute	**Units**	**Description**
Index	integer	Agent ID
Has PV	boolean	True for *prosumer*, False for *consumers*
Perfect Forecasting	boolean	*True* implies prosumers have perfect foresight of next hour's solar irradiance, *False* implies prosumers use the current hour solar irradiance as an estimate for the next
Floor Area	sqft	Floor area of the household
Roof Area	sqft	1.12* Floor Area
PV Installation Area	sqft	10% of Roof Area
Willingness to Pay (*WTP*)	$/kWh	Reservation price for buying
Willingness to Accept (*WTA)*	$/kWh	Reservation price for selling

[2]For a detailed explanation of the conversion formulae, please refer to model_design.ipynb notebook in the github repo.

2.4 Overview and Scheduling

During each time step:

1. Prosumer households generate a forecast GF_j about their estimated electricity generation at the end of the current period using *perfect forecast* or a *simple forecast* method.

2. Prosumer households then use this forecast to determine their excess electricity generated $FS_j = GF_j - C_j$.

3. Consumer households determine how much electricity they need in the next hour or time step using C_j.

4. Prosumers and consumers are randomly activated to submit bids and asks for the quantity desired based on their WTA and WTP values to the exchange mechanism.

5. Exchange Mechanisms determine the final redistribution of assets (refer to specific exchange mechanisms for more information).

6. At the end of the period, prosumers realize the actual surplus they generated $AS_j = G_j - C_j$.

   (a) If AS_j is negative (shortfall), sellers buy any additional units of electricity from the utility provider at the retail rate.

   (b) If AS_j is positive (overproduction), sellers sell additional units of electricity to the utility provider at the avoided fuel cost rate.

7. If the total number of time steps is not equal to 720, repeat steps 1-6; otherwise, end the simulation.

Table 2: Household state variables and calculations at time step j

Household Type	Symbol	Units	Description
Consumer	C_j	kW	*Consumption at interval j*
	WTP	\$/kWh	*Willingness to Pay*
	GF_j	kW	*Generation forecast for the estimated energy production in time stepj*
	FS_j	kW	*Forecasted Surplus based on* GF_j
Prosumer	AS_j	kW	*Actual Surplus realized at the end of the time step*
	C_j	kW	*Consumption at interval j*
	WTP	\$/kWh	*Willingness to Pay*
	WTA	\$/kWh	*Willingness to Accept*

2.4.1 Bilateral Exchange Market

1. The Bilateral exchange mechanism facilitates trades between individual buyers and sellers.
   (a) Buyers are sorted in descending order of their WTP values, and sellers are sorted in ascending order of their WTA values.
   (b) Buyers and sellers are bilaterally matched across lists, meaning the highest WTP buyer is matched with the lowest WTA seller, then the second highest and second lowest, and so on.
   (c) Trading stops if and only if:
      i. There is no more demand (no more buyers).
      ii. No excess supply (no more sellers).
      iii. The highest WTP is lower than the lowest WTA, making no trade possible.
   (d) Otherwise, steps a-c are repeated until any of the above exit conditions are met.

2.4.2 Automated Market Makers (AMMs)

1. The Automated Market Maker implemented is a constant product market maker similar to Uniswap V2 AMM (Zinsmeister et al., 2020). Instead of negotiating individual trade agreements, agents trade directly with a liquidity pool, which acts as the counterparty. The liquidity pool's size, often denoted by the variable k (the product of token reserves), reflects

the pool's depth. A larger k value means more stable prices within the AMM, providing greater price stability for trades.[3]

(a) The protocol uses household demand and excess energy supply to determine the *equilibrium price*. It then uses the *equilibrium price* and the k parameter (supplied in the config file for the simulation) to determine the reserves of tokens to initialize the AMM with and initializes an AMM specifically for the current time step or hour.

(b) Agents are randomly activated to sequentially submit bids and asks to the AMM until all trades are made. Consumer agents submit limit orders to buy energy with the maximum price they are willing to pay equal to their WTP value. Similarly, prosumer agents submit limit orders to sell energy for money, with the minimum acceptable price set to their WTA value. At the end of each trade, agents update their states.

(c) Once a single round of random sequential activation takes place, all trading is halted.

3 Simulation Parameters

The model employed within this project is the Python translation of the MASON[4] Java model proposed within the Monroe et. al (2023) paper. As a result, the first task is to replicate the results of the original Java model.[5] We do this in the next section.

3.1 State/Model Parameters

The table below provides a description of all the state/model variables and model attributes used within the model and their purpose within the model. The following values were provided as part of the *java model* and might not be representative of the latest data, specifically, *Retail Electricity Rate*, *Avoided Fuel Cost Rate*, and the *Electricity Consumption Data* (for a 2023 sqft house) for La Ola Lanai, Hawaii.

[3]For a detailed explanation of the mathematical principles behind the AMM, please refer to the `model_design.ipynb` notebook.

[4]Multi-Agent Simulator Of Neighborhoods (MASON) is a JAVA-based agent-based modeling software.

[5]The original MASON ABM model was kindly provided by Dr. Emily Berglund of NC State and can be found here.

Table 3: Table of Geographic Model Parameters

Purpose	State/Model Parameters	Value
	City	La Ola Lanai, Hawaii
	Month	September
Utility Provider Parameters	Retail Electricity Rate (U_{rate})	0.351 $/kWh
	Avoided Fuel Cost Rate (F_{rate})	0.0932 $/kWh
	Latitude	20.77
Solar Production Calculation	Longitude	156.92
	Local Time Meridian	150
	Daylight Savings	False

3.2 Household Parameters

Like the Monroe et al. (2023) model, we use constant profiles for households for all simulations. These profiles are extracted from the Excel file provided as a part of the *java model*. As the number of prosumers increases within the simulation, the household profiles stay the same; however, different households become eligible to be prosumers. The household profiles can be found in the *Appendix*.

Table 4: Table of Household Parameters

Parameters	Units	Values	Comment
hasPV	boolean	True/False	*True for prosumers*
Willingness to Pay (WTP)	$/kWh	$\sim \mathcal{U}(0.0932, 0.351)$	$\mathcal{U}(F_{rate}, U_{rate})$
Willingness to Accept (WTA)	$/kWh	$\sim \mathcal{U}(0.0932, 0.351)$	$\mathcal{U}(F_{rate}, U_{rate})$
Floor Area	sqft	$\sim \mathcal{N}(1500, 200^2)$	

As a part of the model, we were provided hourly consumption data (720 vals) for a 2023 sqft house. This array is used to create consumption profiles for different households within our model dependent on their respective *Floor Area*.

Similarly, we receive kWh/sqft data for solar irradiance, which is converted to estimated solar production for a household dependent on their *PV Installation Area* which is a function of *Roof Area*.

Table 5: Household Parameters: Hourly Consumption and Production

Data	Units	Comment
Consumption Data[6]	$/kWh	For a 2023 sqft house in La Ola Lanai
Production Data[7]	kWh	Minutely solar irradiance data

3.3 Modeling Scenarios/Sensitivity Analysis

We vary the following parameters for our simulation runs, and see the effect on the outcome variables, namely *Proportion of Excess Sold to Market* and *Average Seller Price*. Note, if *perfect forecasting* is set to false in the simulation, then we are effectively doing *simple forecasting* for households.

Table 6: Modeling Scenarios

Parameters	Values	Comment
Prosumers	{1,2,3,4,5,6,7,8,9,10,11,12}	
Forecasting	*simple forecasting, perfect forecasting*	
Exchange	*Bilateral, AMM*	
AMM Liquidity ***(k)***	{50, 100, 200, 500}	Only applies when the Exchange is AMM
Number of Runs	10	Number of times a parameter combination is run

[6] Hourly data was provided by the authors along with the model
[7] Minutely data was provided by the authors along with the model

3.4 Replicating Monroe et. al (2023)

The baseline results below are a replication of the Monroe et. al (2023) paper to establish the validity of our python model. The following simulations employ a bilateral exchange and 5 prosumers within the model.

3.4.1 Total System Demand and Production

The first bar charts confirm that both simulations have about 20,000 kw/h total energy demand within the system and around 2,000 kw/h total energy production using solar panels. Note, not all the production is traded within the market, and most is used to satisfy personal prosumer demand.

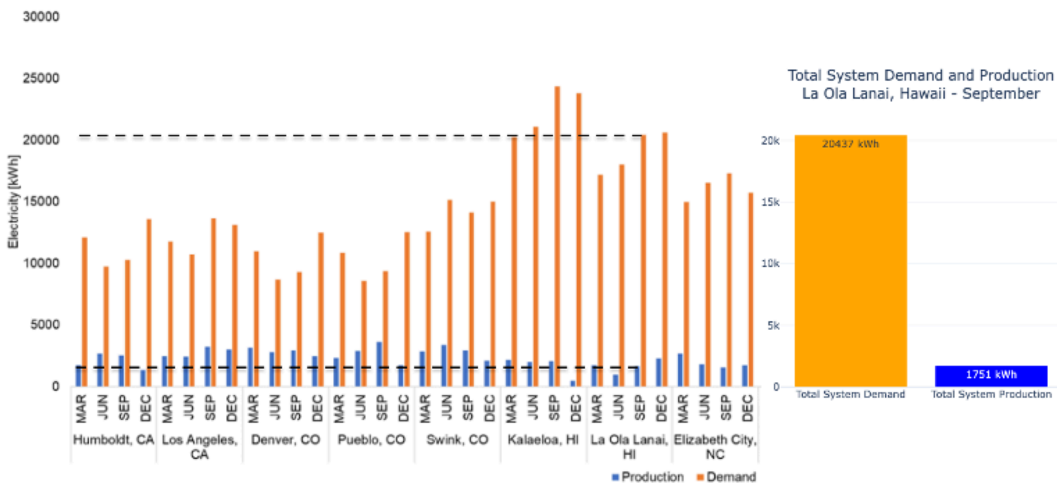

Figure 1: Replicating Total System Demand and Production in La Ola Lanai, Hawaii - September for a bilateral exchange with 5 prosumers. Left graph is Figure 3 from Monroe et. al (2023) paper. Right graph is produced by the python model.

3.4.2 Proportion of Excess Sold

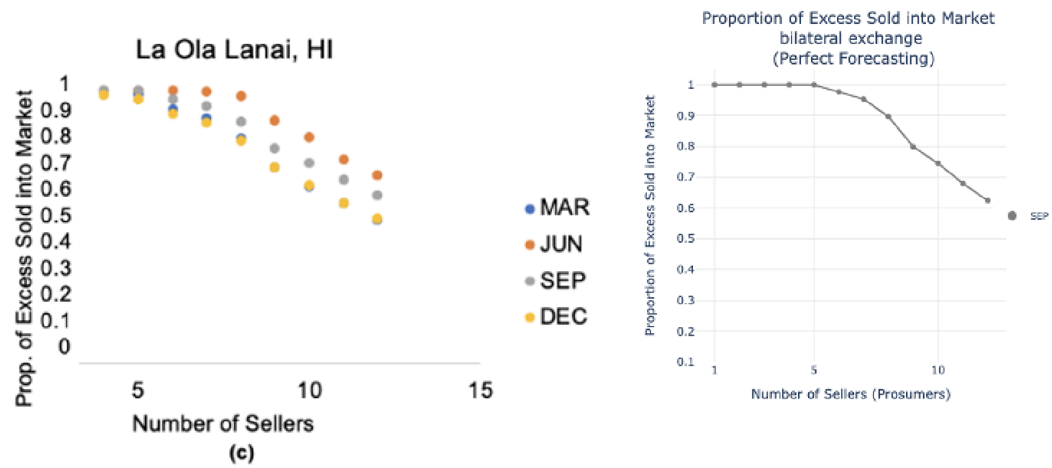

Figure 2: Replicating proportion of excess sold in La Ola Lanai, Hawaii - September for a bilateral exchange with 5 prosumers. Left graph is Figure 6 (c) from Monroe et. al (2023) paper

The *Proportion of Excess* sold for the two graphs (grey lines) follows a sufficiently similar pattern, where it is 100% till the first 4 prosumers and then drops for each additional one.

4 Results

4.1 Average Seller Price

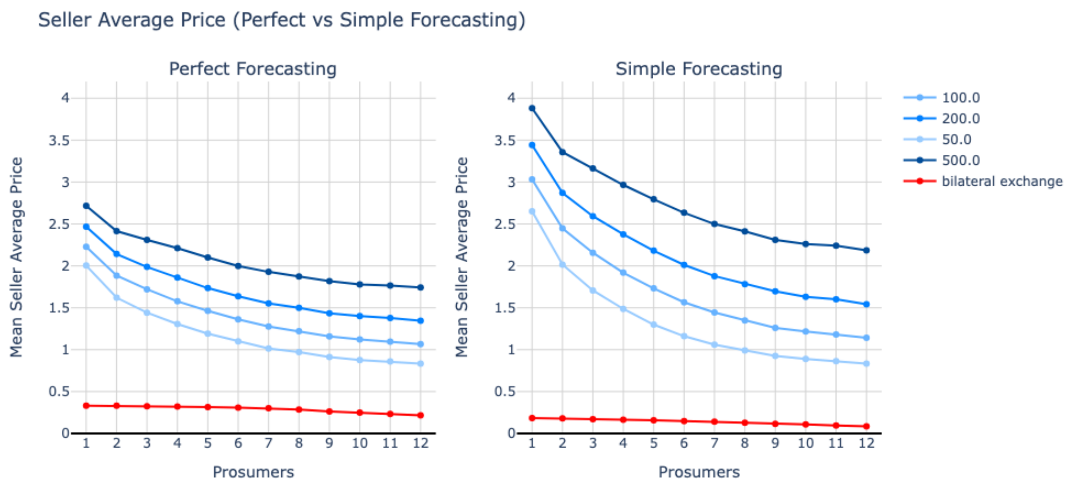

Figure 3: Comparison of seller average price between *AMM* with k = 50,100,200,500 and *bilateral exchange*

The average seller price is calculated by dividing total net seller revenue (total revenue minus total shortfall) by total excess production for all prosumers. It represents the mean price sellers can get during any hourly time step for their excess unit of energy. As we can see, higher liquidity, represented by higher values of k, results in consistently higher average seller prices. This makes economic sense since AMM price movement is dependent on the liquidity/k or the number of tokens within the protocol. A higher liquidity AMM is less prone to price movements, resulting in more sellers trading their electricity at near-equilibrium per unit price for their excess unit of electricity. On the contrary, lower liquidity AMMs are more prone to price movements, so it makes sense that small quantities traded can have a large impact. However, it is important to note that regardless of the AMM size, they consistently produce a higher seller average price than the bilateral trade mechanism proposed by the authors.

Additionally, it makes economic sense that the average seller price decreases as more prosumers enter the market. It is interesting to see the differing slopes and starting values between the two forecasting methods employed by prosumers. Perfect forecasting has a lower y-intercept but a smaller slope for increasing values of prosumers, meaning that prosumers encounter no shortfall, which doesn't reduce their net revenue since they have perfect production foresight.

On the other hand, simple forecasts have a higher y-intercept for high liquidity values. However, their slope is more negative than the perfect storage simulation, because simple forecasts have a higher tendency to lead to erroneous next-hour forecasts, causing shortfalls, as evidenced by Figure 4. Despite higher liquidity's tendency to ensure high seller prices and ensure minimal price movement, nevertheless, for simple forecasting, it can tend to exacerbate the resulting shortfall from futures contracts entered using faulty forecasts. We can see that the *Simple Forecast* has much higher shortfall for higher liquidity AMMs and in those scenarios, a bilateral exchange might be preferred.

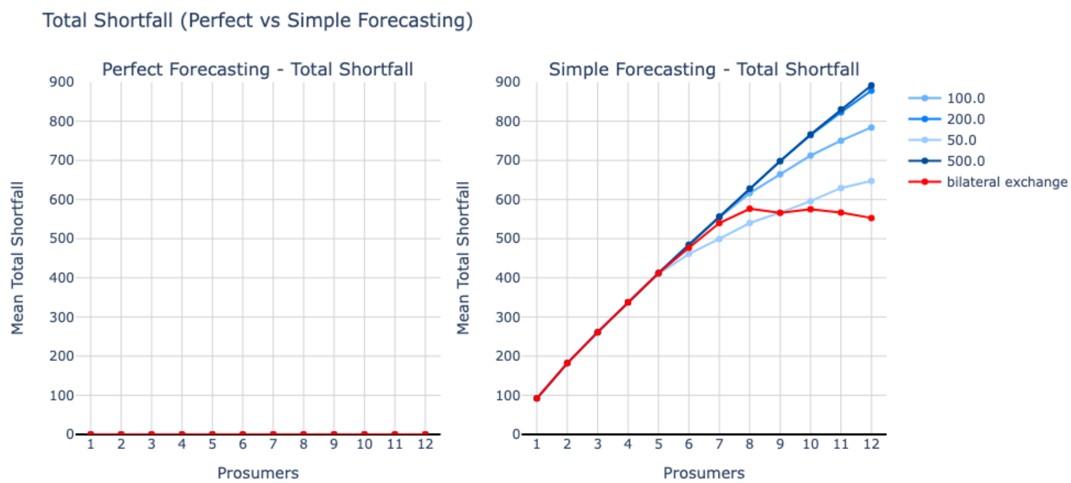

Figure 4: Comparison of shortfall between *AMM* with k = 50,100,200,500 and *bilateral exchange*

4.2 Proportion of Excess Sold in Market

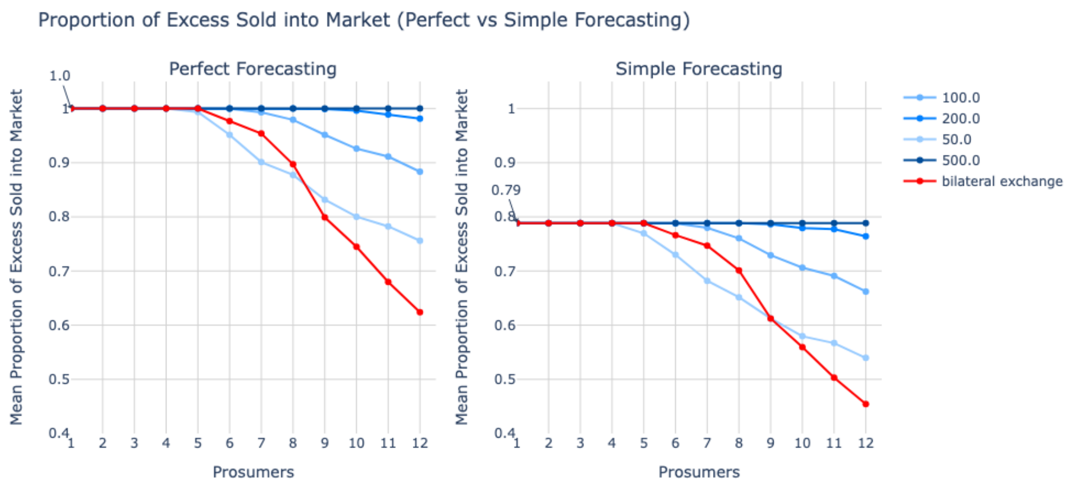

Figure 5: Comparison of *proportion of excess* sold between *AMM* with k = 50,100,200,500 and *bilateral exchange*

Based on the above scatter plot, we can determine that higher liquidity also ensures that a higher proportion of excess solar electricity is sold on the market. We also see that higher liquidity/k, for instance, $k = 500$, can ensure that the proportion stays near 1 for all amounts of prosumers. This makes sense since higher liquidity within the pool implies that more individuals can sell without receiving unfavorable prices. It is important to note that all exchanges perform well up to 4 prosumers. After that, an increasing number of prosumers leads to a drop in the proportion of excess across all exchanges. This is likely because as the volume of trades increases in the market, some agents may be unable to sell their excess electricity within the AMM. Additionally, it is interesting that the slopes across the different energy storage scenarios are similar overall. However, there is a difference between the maximum proportion of excess sold between the two market designs. Specifically, perfect forecasting has a maximum of 1, while simple forecasting has a maximum of roughly 0.8.

5 Conclusion and Further Research

Our research sought to understand the effect of liquidity/k on the economic efficiency of AMMs, and from preliminary analysis, we can determine there is a positive effect. However, it is important to note that we have largely ignored the incentives of individuals who would provide this liquidity within these markets. Further research needs to be done to understand which values of liquidity rationally make sense.

Additionally, like the Monroe et al. paper, the analysis needs to be extended to data from other cities as well, to see how well our preliminary findings hold.

6 Appendix

6.1 Household Profile Table

Table 7: Attributes of Households

Index	Floor Area (sqft)	hasPV	WTA ($/kWh)	WTP ($/kWh)
1	1794.06	true	0.1935	0.3272
2	1276.19	false	0.3166	0.2251
3	1312.77	false	0.3381	0.2312
4	1267.05	false	0.3093	0.3308
5	1204.91	false	0.3069	0.2903
6	1265.34	false	0.2423	0.3258
7	1440.41	false	0.1761	0.3338
8	1269.12	false	0.3285	0.2684
9	1329.31	false	0.3037	0.1728
10	1370.46	false	0.2933	0.3132
11	1594.23	false	0.3283	0.3079
12	1378.00	false	0.2798	0.3074
13	2077.61	true	0.2246	0.3229
14	1619.03	false	0.2090	0.3003
15	1259.74	false	0.3173	0.1968
16	1546.88	false	0.2296	0.2737
17	1354.79	false	0.2355	0.2645
18	1730.28	true	0.2673	0.2850
19	2040.53	true	0.2519	0.3152
20	1385.96	false	0.2683	0.3187
21	1685.14	true	0.2323	0.1944
22	1635.75	false	0.2806	0.2550
23	1626.93	false	0.2560	0.2142
24	1364.47	false	0.2852	0.2810
25	1188.25	false	0.3245	0.1894

References

Capper, T., Gorbatcheva, A., Mustafa, M. A., Bahloul, M., Schwidtal, J. M., Chitchyan, R., Andoni, M., Robu, V., Montakhabi, M., Scott, I. J., Francis, C., Mbavarira, T., Espana, J. M., & Kiesling, L. (2022). Peer-to-peer, community self-consumption, and transactive energy: A systematic literature review of local energy market models. *Renewable and Sustainable Energy Reviews*, *162*, 112403. https://doi.org/10.1016/j.rser.2022.112403

Mengelkamp, E., Staudt, P., Garttner, J., & Weinhardt, C. (2017). Trading on local energy markets: A comparison of market designs and bidding strategies. *2017 14th International Conference on the European Energy Market (EEM)*, 1–6. https://doi.org/10.1109/EEM.2017.7981938

Monroe, J., Bolton, E. R., & Berglund, E. Z. (2023). Evaluating peer-to-peer electricity markets across the u.s. using an agent-based modeling approach. *Advances in Environmental and Engineering Research*, *4*(1), Article 1. https://doi.org/10.21926/aeer.2301017

National Renewable Energy Laboratory. (n.d.). Nrel: Measurement and instrumentation data center (midc) home page [Accessed: 2023-12-08]. https://midcdmz.nrel.gov/

Sousa, T., Soares, T., Pinson, P., Moret, F., Baroche, T., & Sorin, E. (2019). Peer-to-peer and community-based markets: A comprehensive review. *Renewable and Sustainable Energy Reviews*, *104*, 367–378. https://doi.org/10.1016/j.rser.2019.01.036

Wilson, E., Metzger, C. E., Horowitz, S., & Hendron, R. (2014). 2014 building america house simulation protocols.

Xu, J., Paruch, K., Cousaert, S., & Feng, Y. (2023). Sok: Decentralized exchanges (dex) with automated market maker (amm) protocols. *ACM Computing Surveys*, *55*(11), 1–50. https://doi.org/10.1145/3570639

Zinsmeister, N., Robinson, D., & Adams, H. (2020). Uniswap v2 core [Technical paper available online].