Distributed Energy Sharing within Community: A Game-Theoretic Double Auction Approach

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***Abstract*—This paper proposes a double auction-based mechanism that captures the interaction within a community consisting of distributed solar power prosumers and consumers. All agents are assumed to have battery energy storage systems, and can use battery for time-of-use arbitrage. Sellers and buyers can optimize the charging/discharging schedules of their battery systems for community sharing to reduce electricity costs. To determine the market clearing price, a non-cooperative game is formulated among all participants involved in the community sharing. To solve the game, an iterative algorithm is first designed to determine the clearing price and energy trading amount during each round of auction. Then, an adaptive pricing strategy is designed to assist agents better understand the market. A case study with 10 agents is provided to demonstrate the effectiveness of the proposed community sharing market.**

***Index Terms*—Community sharing, distributed solar, energy storage, arbitrage, non-cooperative game, double auction.**

I. Introduction

As the penetration of distributed energy resources such as rooftop photovoltaic (PV) increases, during certain hours of the day, power supplied by distributed generators is anticipated to exceed local consumption needs. This creates the potential to send power flows in the "reverse direction", which may create technical challenges for the grid. Market operators have recently began to explore transactive energy [1] for a changing environment with an increasing number of distributed resources and intelligent devices. Transactive energy utilizes the flexibility of various generation/load resources to maintain a dynamic balance of supply and demand, which features real-time, autonomous, and decentralized decision making.

In a traditional market, the electricity price is set by energy suppliers, and consumers only act as passive price-takers. With the fast development in microgrids and transactive energy, customers in power systems are undergoing a fundamental transition, from traditional passive "consumers" to active "prosumers". It is expected that distributed solar owners are able to sell their excess generation, and consumers can also adjust their energy consumption in response to time-of-use (ToU) prices. However, a critical feature of distributed solar power is that its supply is, by nature, highly variable and uncertain. With the ever-increasing deployment of PV panels, it is challenging to balance the energy supply and demand while fully utilizing their capacities.

One innovative way to deal with this challenge is via a community sharing market [2], [3], which is formed among a group of agents being willing to share their excess resources. The list of buyers and sellers varies at different times of a day, which highly depends on the agents' netload and sharing prices, thereby making this market dynamic. The utility grid also plays a critical role in this transactive market, who generally offers a predetermined ToU rate. In the community sharing market, a sharing price that is "worse" than the utility price is not acceptable, and agents can leave the sharing market spontaneously and trade with the utility grid.

While the uncertain and variable nature of distributed solar creates challenges for PV sharing, energy storage provides new opportunities in energy planning and load management due to its flexibility by acting as back-up for renewable energy resources in power systems [4]. Energy storage is able to assist energy management in a distribution network, aiming to reduce customers' electricity costs through opportunistic demand response (e.g., arbitrage [5]) and improve the efficiency of energy usage. For example, peak solar generation occurs in the early afternoon while peak demand always occurs several hours later. Energy storage can help mitigate the grid pressure by buffering excess resources for future usage. This research is to examine how community sharing of distributed solar and energy storage might disrupt traditional electricity markets. Specifically, we model an environment in which owners of distributed solar and energy storage, are allowed to sell their excess generation to their neighbors through virtual community exchange.

The remainder of this paper is organized as follows: Section II describes the overall framework of double auction energy sharing. The developed two-stage decision process is discussed in Section III, followed by the adaptive pricing strategy in Section IV. Section V shows a case study with 10 agents to evaluate the effectiveness of the proposed community sharing market. Section VI concludes the paper and also discusses the future work.

II. Double Auction-based Sharing

In a double auction scheme, all agents submit their written desired prices in sealed envelops without knowing the strategies of others', which enables multiple agents to decide simultaneously and independently whether to participate in the auction through specific decision-making rules. It is important to note that all agents are equipotent participants in the auction market, and no agent has access to others' private information,

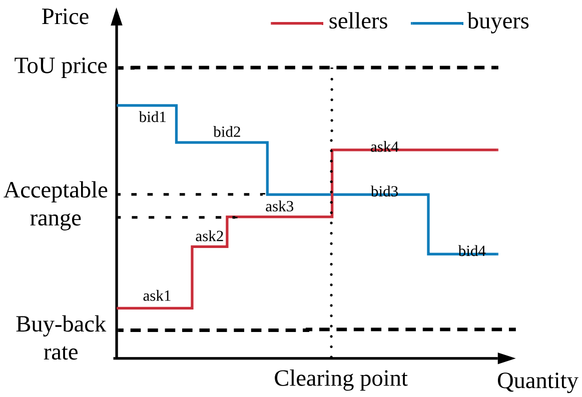

Fig. 1. Aggregation of the bids and asks.

such as bidding prices and the desired amount to sell or buy. Thus the double auction sharing market is privacy-protecting.

At each trading period (e.g., 1h), the buyers announce the amount to be purchased and their desired bids, and the sellers announce their available power to sell with their corresponding asks. Non-iterative bidding is allowed in the market, which means only one-time prices are collected at each round of auction. The determination rules [6] of the proposed scheme are executed via the following steps:

i) The M buyers submit their bids $bid_i, \forall i$ and the amount they want to buy b_i, then we sort bids in a descending order:

$$bid_1 > bid_2 > ... > bid_M$$

ii) Similarly, the N sellers submit their asks $ask_j, \forall j$ and the amount they want to sell s_j, then we sort asks in an ascending order:

$$ask_1 < ask_2 < ... < ask_N$$

iii) Once the sharing market operator receives all the information from all the agents, the aggregated supply and demand curves are generated as illustrated in Fig. 1.

iv) The sharing market operator determines the numbers of participating buyers and sellers based on the aggregated supply and demand curves. Suppose the two curves are intersected by bid_K and ask_L, buyers with index $i \leq K$ and sellers with index $j \leq L$ will participate in the sharing market (e.g. $K = 3$, $L = 3$ in Fig. 1). The market clearing price can locate at any point within $[bid_K, ask_L]$), which is acceptable for all involved agents. Building upon [6], to enable the clearing price be beneficial to all the participants, we propose a scheme for determining the clearing price p_* based on the auction prices, supply, and demand in the market.

$$p_* = ask_L + \frac{\sum_{i=1}^{K} b_i}{\sum_{i=1}^{K} b_i + \sum_{j=1}^{L} s_j}(bid_K - ask_L) \quad (1)$$

where $\sum_{i=1}^{K} b_i$ and $\sum_{j=1}^{L} s_j$ denote the total amount of buying and selling power involved in the market. When the total supply is more than demand, the clearing price gets closer to ask_L, which benefits buyers more, and the marginal seller is only able to sell part of its energy. Similarly, the clearing price will benefit sellers more when the total demand is more than supply, and the marginal buyer needs to purchase the shortfall from the utility grid.

III. Decision-Making Process

In the community sharing market, the optimization goal is to find an equilibrium that enables all the agents to trade excess resources with each other. Considering the capabilities of energy storage in compensating for PV and arbitrage from the ToU price, a two-stage decision-making process is proposed, as shown in Fig. 2.

A. Stage One: Look-ahead Market

Day-ahead (DA) or several-hour-ahead arbitrage takes place before power delivery. It determines power arbitrage schedules based on future generation and consumption for cost reduction [5]. Since the state of charge (SoC) of the battery storage is time dependent, it is reasonable to determine the energy storage scheduling by look-ahead optimization [7]. The main objective of stage one is to determine arbitrage schedules aiming at reducing the customers' look-ahead cost by charging the battery at a lower rate and then discharging at a higher price. The objective function of each agent is formulated as:

$$\begin{aligned} min\ L_i^{h \sim H} = \sum_{t=h}^{H} \big[& p_s^t \cdot \max\left(nl_i^t + x_i^t, 0\right) \\ & - p_b^t \cdot \min\left(nl_i^t + x_i^t, 0\right)\big] \end{aligned} \quad (2)$$

Subject to:

$$-SoC_i^{h-1} \cdot Cap_i \leq \sum_{t=h}^{H} x_i^t \leq (1 - SoC_i^{h-1}) \cdot Cap_i \quad (3)$$

$$-x_{max} \leq x_i^t \leq x_{max} \quad (4)$$

where $h \sim H$ is the optimization horizon, and H is selected to be 24h; $L_i^{h \sim H}$ is the look-ahead electricity cost of agent i from time h to H; nl_i^t denotes the netload (i.e., load minus PV generation in this paper, positive values for buyers or negative values for sellers) at time t. On the first day, all agents start with an assumption of the utility price, so p_s^t is the selling price (i.e., ToU), and the buyers will purchase their shortage from the utility grid at this rate; p_b^t is the buy-back rate, and the seller will sell its excess energy to the utility grid at this rate. The battery charging/discharging schedule x_i^t should meet the constraints of the current SoC_i^{h-1} and the total capacity Cap_i. A positive value denotes charging and a negative value denotes discharging. Besides, the charging/discharging rate of the battery must satisfy certain constraints such as the

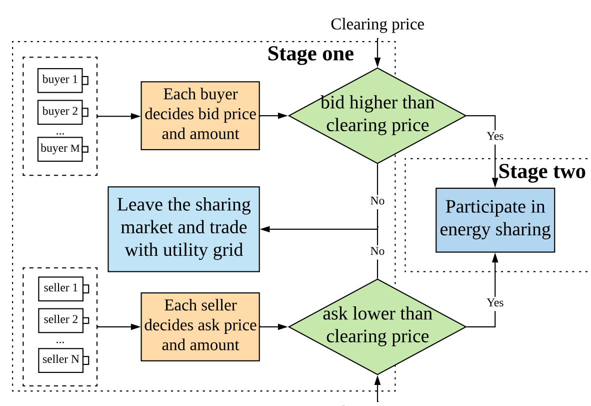

Fig. 2. The proposed community energy sharing scheme.

maximum speed and converter capacity, which is denoted as x_{max}. The energy loss in charging and discharging is not considered in this paper.

B. Stage Two: Real-time Market

We define stage two as a real-time market clearing process. For those agents who submit reasonable bids/asks and get involved in the sharing market, they need to execute the market-clearing. As for those agents who are not involved, they only need to complete look-ahead optimization and follow the charging/discharging schedules determined in stage one.

In the dynamic sharing market, the real-time supply and demand vary over time, thus the auction equilibrium price can't be pre-determined. The market power [8] of an agent reflects its ability to influence the overall outcome of the auction. Imaging an extreme scenario, for example, there is only one seller who dominates the market, and all other agents are passive buyers, then the clearing price is totally determined by the only seller. However, when the auction involves a large number of agents, an individual agent's action cannot exert a great deal of influence on the outcome.

In real-time decision-making, the clearing price and amount of energy to share turn into decision variables, as introduced in (1). After being informed to engage in the sharing market, the agents will update their trading strategies. For example, if an agent is satisfied with the current clearing price, it might choose to trade more energy than scheduled to earn more profit rather than following the schedule determined in stage one. However, this deviation might prejudice the interests of others, resulting in changes in the clearing price, then other agents will also update their trading strategies according to the new clearing price. In such a case, we design an iterative auction approach which allows the buyer or seller to approximate its market power to a stable state, and no agent has the incentive to cheat in the auction.

To define the benefits that agent i can earn in the real-time sharing market by trading more energy Δx_i, we have modeled a utility function by following [4], [6]. The sharing benefits of buyers and sellers at time t are modeled as:

$$max\ U(\Delta x_i^t) = (p_i^t - p_*^t)(nl_i^t + x_i^t + \Delta x_i^t) - \alpha_i {\Delta x_i^t}^2 \quad (5)$$

where p_i^t and p_*^t denotes agent i's price (bids for buyers or asks for sellers) and the clearing price at the current time t, respectively. Since we assume that all agents take stage one's schedules x_i^t as initial strategies, the amount of battery capacity agent i puts into the real-time sharing market is $(x_i^t + \Delta x_i^t)$, which also should satisfy the constraints (3)-(4). The second term $\alpha_i \Delta x_i^2$ stands for the reluctance of agent i using his battery in advance. A higher value of α_i means the agent is more reluctant to use the battery space reserved for future.

C. Equilibrium Analysis

In the market clearing process, the only information that one agent can obtain is the current clearing price. One popular solution to this kind of problem is non-cooperative game theory. The equilibrium solution, also called Nash Equilibrium, is a state in which no player has the incentive to deviate from its strategy unilaterally. To prove the existence and uniqueness of the Nash Equilibrium, first, we notice that the bidding strategy set of the participants is non-empty and the bidding prices are continuous within an acceptable range. Hence, there will always exist a non-empty solution. Second, for any price within the range $[ask_L, bid_K]$, there exists a unique best strategy Δx_i^* for the i^{th} participant which can be chosen from the i^{th} participant's strategies set for maximizing its utility. After collecting an agent's updated strategy in the market, there only exists a unique clearing price within the acceptable range. This iterative process continues until convergence. In general, the best response strategies have been proven to converge to an equilibrium for many classes of non-cooperative games [6]. Thus the designed iterative algorithm is guaranteed to reach the Nash Equilibrium, as shown in **Algorithm 1**.

Algorithm 1 Two-stage community sharing market

1: **for** t=1:H **do**
2:   *Stage one*: Agents initialize strategies according to (2), then submit prices and amounts.
3:   Market operator collects all asks, bids, and amount.
4:   **while** *Stage two* happens **do**
5:     Operator clears the market by double auction and publishes the clearing price p.
6:     **for** each involved agent i **do**
7:       Each agent i updates its Δx_i:

$$\Delta x_i^* = \arg\max\ U(\Delta x_i) \quad (6)$$

8:     **end for**
9:     The market operator updates the clearing price p' according to (1).
10:     **if** $||p' - p|| \leq \zeta$ **then**
11:       Operator clears the market with the price $p_* = p'$.
12:     **else**
13:       $p = p'$, restart from step 6.
14:     **end if**
15:   **end while**
16: **end for**

IV. Adaptive Pricing Strategies

Generally, a conventional auction mechanism is developed by assuming that the market is static, which means the bids and asks are constant in each trading day. However, in this paper, decentralized battery storage systems are used to offer additional flexibility to agents in response to the volatile distributed solar sharing market. Thus, in addition to the iterative auction mechanism, we also propose a dynamic adaptive pricing strategy in the energy sharing market, which is inspired by [9]. The adaptive pricing strategy is essential for all agents as they can predict/forecast the state of the sharing market and then submit better bids or asks in the next round.

A. Prediction in the Auction Process

Once one round of transaction completes, the clearing price and trading amount are recorded. Agents will leverage this recorded information to predict the market behavior in the following hours as well as the same trading period in upcoming days. The hypothesis is that when a player's strategy is successful, the player is more likely to adopt a same or similar strategy again; and if the bidding strategy is unsuccessful, the player will be less likely to use it. The adaptive pricing strategy consists of short-term and long-term estimation mechanisms [9], aiming at providing better bids and asks in response to previous equilibrium price and trading volume.

1) Short-Term Estimation: In the short-term learning, agents aim to adapt their prices to their *desired* equilibrium price by following other agents' successful strategies. In a simple approach introduced in [2], agent i can track the equilibrium price using:

$$\hat{p_{s.i}}^{t+1} = p_i^t + \beta_i (p_*^t - p_i^t) \tag{7}$$

where $\hat{p_{s.i}}^{t+1}$ is the short-term estimated price, p_*^t is the desired price that the agent wants to follow, and β_i is the short-term estimation rate.

2) Long-Term Estimation: Besides short-term estimation, agents should also consider future PV generation and load demand to have a better estimate of the future market. This long-term estimation rule for agents is defined as:

$$\hat{p_{l.i}}^{t+1} = \begin{cases} \hat{p_{s.i}}^{t+1} + (p_s^t - \hat{p_{s.i}}^{t+1}) e^{\frac{-1}{\lambda_i^{t+1}}}, & \lambda_i^{t+1} > 1 \\ \hat{p_{s.i}}^{t+1}, & \lambda_i^{t+1} = 1 \\ p_b^t + (\hat{p_{s.i}}^{t+1} - p_b^t) e^{\frac{-1}{\lambda_i^{t+1}}}, & \lambda_i^{t+1} < 1 \end{cases} \tag{8}$$

where $\hat{p_{l.i}}^{t+1}$ is the long-term estimation, p_s^t and p_b^t denote the lower and upper bounds of the clearing price, respectively. λ_i^{t+1} denotes the predicted future ratio of the total demand to the total supply in the sharing market. Agents will predict a price hike for an upcoming over-demand market and a price drop for an over-supply market. For example, if there is only one seller to dominate the market ($\lambda_i^{t+1} \to \infty$), it will set a price close to the ToU price to earn more profit. Thus, predicting the supply-demand ratio is essential for all agents to submit better bids or asks. However, in the sharing market, each agent only has limited information regarding others, and the following approach is proposed to help predict the future market behavior.

$$\lambda_i^{t+1} = \frac{\sum_{i=1}^{K} b_i^t}{\sum_{i=1}^{L} s_i^t} \times \frac{l_i^{t+1} \times pv_i^t}{l_i^t \times pv_i^{t+1}} \tag{9}$$

where $\sum_{i=1}^{K} b_i^t$ and $\sum_{i=1}^{L} s_i^t$ denote the total demand and supply in the last round, respectively. Inside a sharing community, all PV prosumers might have similar generation trends and only vary in capacity due to the strong weather impacts, so agents can use their own PV generation to predict others'. However, it is more challenging to predict the load demand of other agents due to various energy consumption behaviors. Combining the short-term and long-term estimations, the final bidding price of agent i is given by:

$$p_i^{t+1} = \gamma_i \cdot \hat{p_{l.i}}^{t+1} + (1 - \gamma_i) \cdot \hat{p_{s.i}}^{t+1} \tag{10}$$

where γ_i is a weighing factor between the short-term and long-term estimations. In this paper, both β_i and γ_i are chosen to be 0.3 by following [2].

B. Price Anticipation

As the sharing market operates, new equilibrium prices are settled and then agents will update their price anticipation p_b' and p_s' in (2) according to following rules:

$$p_b' = p_s' = \sum_{t=m-n}^{m} \left(\omega_t \cdot p_*^t \right) \tag{11}$$

where ω_t can be a weighing factor of the most recent t rounds of trading, which is selected based on personal preference, market fluctuations, and weather similarity. For example, agents should put more weights on similar days to have a better price forecast. In this paper, we put average weights ($\omega_t = 1/t$) on the most recent t days.

V. Case Study

The developed sharing market is tested with a case study of 10 agents inside a community in Texas from Aug. 21 to Aug. 27, 2016 [10]. Agents 1-7 own PV panels and agents 8-10 are pure consumers. It is assumed that all agents are equipped with a 3 kWh battery storage system. The PV, load, and netload curves of the ten agents are plotted in Fig. 3. It is noted that due to the proximity of agents, the solar power generation profiles are similar and only vary in magnitude. For the ToU prices, the on-peak hours are from 6 a.m. through 8 a.m. and from 3 p.m. through 8 p.m. for the selected week, and the energy charge is 18.4 ¢/kWh for on-peak, 9 ¢/kWh for off-peak hours, and the buy-back rate is 6 ¢/kWh [11].

Fig. 4 shows the evolution of the market clearing price over the week. It is observed that most of the times energy sharing occurs from 10:00 a.m. to 4:00 p.m., when the prosumers' PV panels can produce energy. For the rest hours, all agents need to meet their demand relying on the utility grid. It is seen

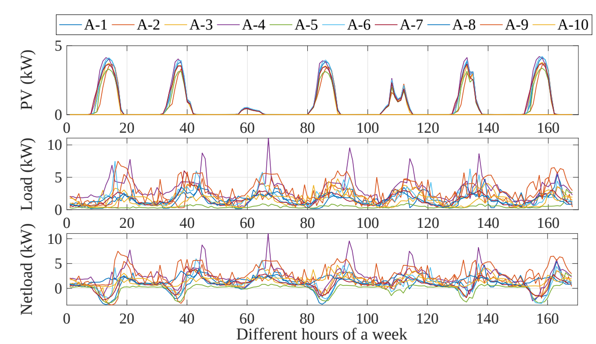

Fig. 3. PV, load, and netload profiles of the 10 agents within one week.

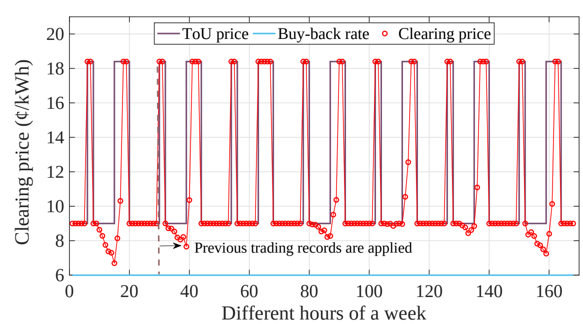

Fig. 4. Evolution of the market clearing price within one week.

TABLE I
COST SAVINGS OF ALL AGENTS IN DIFFERENT DAYS

	Day 1			Day 3			Day 5			Day 7		
Agents	Cost 1 (¢)	Cost 2 (¢)	Saving (%)	Cost 1 (¢)	Cost 2 (¢)	Saving (%)	Cost 1 (¢)	Cost 2 (¢)	Saving (%)	Cost 1 (¢)	Cost 2 (¢)	Saving (%)
1	150.13	90.03	40.03	567.50	527.25	7.09	509.44	438.22	13.98	503.36	427.42	15.09
2	383.08	318.39	16.89	651.73	609.90	6.42	619.30	529.29	14.53	609.67	521.94	14.39
3	300.54	227.53	24.29	630.86	591.21	6.28	607.71	507.11	16.55	380.84	329.29	13.53
4	867.71	704.96	18.76	1017.54	964.42	5.22	1033.88	870.83	15.77	672.48	564.07	16.12
5	-40.14	-77.83	93.91	137.42	109.82	20.08	68.96	34.45	50.05	77.70	26.05	66.47
6	345.19	240.97	30.19	647.69	612.57	5.42	431.50	371.67	13.87	274.03	212.10	22.60
7	216.02	165.62	23.33	553.97	514.32	7.16	449.35	380.75	15.27	276.53	231.13	16.42
8	480.10	413.56	13.86	632.35	592.73	6.27	545.04	477.13	12.46	470.62	394.09	16.26
9	1017.80	969.68	4.73	1211.00	1171.37	3.27	1039.16	965.01	7.14	1205.19	1104.69	8.34
10	359.48	314.15	12.61	509.04	476.41	6.41	419.00	365.90	12.67	450.92	392.30	13.00

**Cost 1 denotes cost without sharing and cost 2 denotes cost with sharing.*

that the market clearing prices are always between the utility grid's ToU price and buy-back rate, which means all agents are willing to participate in the community sharing scheme. We also observe that the clearing price profile is closely following the PV power generation profile. On day 3 and day 5, there is no sufficient PV generation for sharing, so the clearing price is almost equal to the ToU price.

The aggregated community netload profiles are shown in Fig. 5, where the positive values mean buying and negative values mean selling. Under the energy sharing framework, the amount of trading with the utility during on-peak hours is significantly reduced, which means the community sharing can help reduce the electricity costs of the participating agents, since less energy is purchased from the grid during peak hours. As can be seen, part of the on-peak load has been shifted to the off-peak period, which can also be regarded as a types of demand response.

To demonstrate how the proposed sharing market helps to reduce energy cost, Table I summarizes the total energy costs of four different days. The costs of each agent are compared between scenarios with and without PV/storage sharing. We observe that there are more cost savings during sunny days (i.e., day 1 and day 7) compared to cloudy days (i.e., day 3 and day 5). When the market establishes on the first day, all agents earn considerable profits with the sharing market compared with no sharing scenario, especially for sellers. While the percentage saving of all sellers is slightly decreased in other days, we notice that buyers earn more profits on day 7. This is because as the market operates, buyers acquire an estimate of the market. Although day 1 and day 7 have similar PV generation curves, agents have higher load demand on day 7, which benefits more for buyers. Nevertheless, overall the energy sharing within a community has significantly reduced the energy costs of all agents.

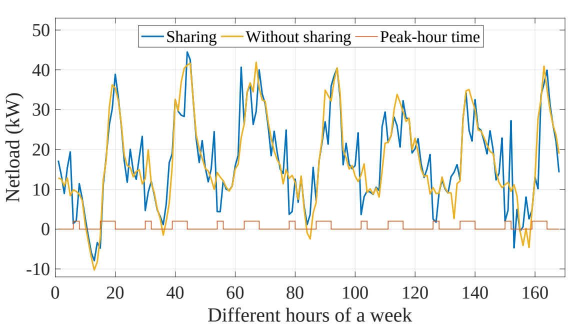

Fig. 5. Aggregated netload of the community within one week.

VI. CONCLUSION

This paper investigated the energy sharing of PV owners within a community assisted with distributed battery energy storage. A double auction-based sharing market was proposed, which consists of multiple dynamic buyers and sellers. We developed a two-stage decision-making strategy to minimize the energy costs of consumers, where the first stage is arbitrage with the utility grid, and the second stage is real-time market clearing. An iterative algorithm was proposed to solve the non-cooperative game for market-clearing. In addition, an adaptive pricing strategy was also developed to allow agents to update their bids and asks adaptively based on the historical transaction records as well as load and PV power forecasting. The case study showed the proposed energy sharing framework could significantly reduced the energy costs for the community agents. Potential future work will further explore how the sharing market is affected by different factors such as weather, PV and battery sizing, and differing market learning abilities among the agents.

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