A Community Sharing Market With PV and Energy Storage: An Adaptive Bidding-Based Double-Side Auction Mechanism

Li He, *Graduate Student Member, IEEE*, and Jie Zhang, *Senior Member, IEEE*

***Abstract*—This article proposes a double auction-based mechanism that captures the interaction within a community energy sharing market consisting of distributed solar power prosumers and consumers. All agents are assumed to have battery energy storage systems, and can use battery for demand response. Agents can optimize the charging/discharging schedules of their battery systems for community sharing to reduce electricity costs. To determine the double-side auction market spot price, a non-cooperative game is formulated among all participants involved in the community sharing. An iterative algorithm is first designed to clear the market and mitigate the uncertainty in supply and demand. Then, an adaptive pricing strategy is designed to assist agents better estimate the market and predict the future price. A case study with 10 agents is provided to evaluate the effectiveness of the proposed community sharing market.**

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

NOMENCLATURE

bid_i, ask_i	Bid and ask price of agent i.
b_i, s_i	Buying and selling quantity of agent i.
p_*	Spot price.
p_i	Bidding price of agent i. $[bid_i, ask_i] \in p_i$
q_i	Quantity of agent i. $[s_i, b_i] \in q_i$
M, N	Numbers of all buyers/sellers.
K, L	Numbers of buyers/sellers who win the auction.
$\sum_{i=1}^{K} b_i$	Aggregated demand of all winners.
$\sum_{i=1}^{L} s_i$	Aggregated supply of all winners.
C_i	Look-ahead cost of agent i in stage one.
U_i	Real-time utility of agent i in stage two.
p_s, p_b	Selling and buying price of utility grid (tariff and buy-back rate).
pv_i, l_i, nl_i	PV, load, and netload of agent i.
x_i	Charging or discharging energy of agent i's storage in stage one.
x_{min}/x_{max}	Lower/upper bound of the charging or discharging energy.
C_{con}	Maximum charging/discharging speed.
η	Charging or discharging efficiency of storage.
Δx_i	Real-time deviation of agent i.
Δx_{-i}	Real-time deviation of all agents except i.
δ^b/δ^s	Total deviation of buyers/sellers in real time.
B_i	Bill of agent i in real time.
SoC_i	State-of-charge of agent i storage.
t	Time period.
h, H	Starting and ending time horizon.
α_i	Reluctance of agent i to adjust its transaction quantity in stage two.
Δx_i^*	Best strategy of agent i's storage in stage two.
β	Short-term estimation rate.
$\hat{p_{s.i}}$	Short-term estimation price.
λ_i	Estimated supply-demand ratio of agent i.
γ	Long-term estimation rate.
$\hat{p_{l.i}}$	Long-term estimation price.
P_{emp}	Empirical bidding prices set.
P_{greedy}	Greedy bidding prices set.
P_{mix}	Mix bidding prices set.
p_{max}/p_{min}	Historical maximum/minimum spot price.
P_*	Estimated spot prices set.
$P_{*.d}$	Spot prices set of recent similar d days.
ω_d	Weighing factor of recent similar d days.

Manuscript received May 8, 2020; revised September 2, 2020 and November 5, 2020; accepted November 29, 2020. Date of publication December 3, 2020; date of current version April 21, 2021. Paper no. TSG-00706-2020. *(Corresponding author: Jie Zhang.)*

Li He is with the Department of Electrical and Computer Engineering, University of Texas at Dallas, Richardson, TX 75080 USA (e-mail: li.he@utdallas.edu).

Jie Zhang is with the Department of Mechanical Engineering, University of Texas at Dallas, Richardson, TX 75080 USA, and also with the Department of Electrical and Computer Engineering (Affiliated), University of Texas at Dallas, Richardson, TX 75080 USA (e-mail: jiezhang@utdallas.edu).

Color versions of one or more figures in this article are available at https://doi.org/10.1109/TSG.2020.3042190.

Digital Object Identifier 10.1109/TSG.2020.3042190

I. INTRODUCTION

AS THE penetration of distributed energy resources (DERs) 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 in the "reverse direction," which may create technical challenges for the grid. Market operators have recently begun to explore transactive energy [1] for a changing environment with an increasing number of DERs and flexible electric 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. However, a critical feature of distributed renewable energy is that its supply is highly variable and uncertain. With the ever-increasing deployment of distributed 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 energy market [2], which is formed among a group of prosumers being willing to share their excess resources. In contrast to the traditional electricity market, where a certain amount of energy is sold at a fixed rate, in the community sharing market the list of buyers and sellers might vary at different times of a day, which highly depends on the agents' netload and sharing prices, thereby making this market more dynamic. While the uncertain and variable nature of DERs creates challenges for energy sharing, energy storage (ES) provides new opportunities in energy planning and load management, reducing uncertainties, and improving energy sharing efficiency due to its flexibility by acting as back-up for DERs in power systems [3]–[5]. ES has been widely installed in community systems, in the form of decentralized household-owned batteries or centralized storage [6], tightly coupling with other DERs, such as PV panels [7], wind turbines [8], combined heat and power system [9], etc. The growing installation of flexible loads and ES has enabled both prosumers and consumers actively participate in the community sharing market [10].

Widespread research has been done on designing and evaluating community energy sharing market in recent years, and various game-theoretic approaches have been explored [11]. For example, as a most widely used game approach, a Nash equilibrium-based game-theoretic approach was applied in energy trading between storage units [12], multiple prosumers [13], aggregators, and DER owners [14]. Zhang *et al.* introduced a simultaneous game-theoretic approach to optimize the market equilibrium and increase the social welfare [15]. With a target of mitigating the intermittency of DERs generation within a community in the absence of ES devices, a cooperative game theory-based solar energy sharing market was developed [16]. When either individual or jointly invested ES is installed, a cooperative game was also shown to be an effective way to promote energy sharing [17]. Moreover, a leader-follower Stackelberg game was applied to cope with a competitive situation between microgrids and a utility grid [18], a combined heat and power community [19], PV and ES sharing between apartments [20], residential units and shared facility controllers [21]. Besides, Paudel *et al.* [22] proposed different game-theoretic models for P2P trading among prosumers and consumers, i.e., non-cooperative game among sellers, evolutionary game of buyers selection and Stackelberg game between buyers and sellers.

Double auction is widely used for market clearing in a energy market consisting of multiple buyers and sellers [23]. For example, the energy exchange price and quantity between ES units and a distribution network were determined via an auction mechanism in [12]. A double-side auction-based energy trading framework among different microgrids using a price anticipation was presented in [24], where the buyers could also adjust their bids based on their market power. Tushar *et al.* [21] developed a modified auction-based ES sharing framework between shared facility controllers and residential units, where the buyers can adjust their quantities via demand response (DR) to different prices. A dynamic economic dispatch algorithm in a community auction microgrid was introduced in [25], where the agents can estimate the market price and dispatch their resources. Bhattacharya *et al.* [26] introduced a staggered clock-proxy auction for online aggregated demand response to adapt multiple users with time-series consumption preferences. A two-stage battery control method in a community microgrid was proposed in [27], and the benefits of P2P energy sharing were assessed from the communities as well as individual customer's perspectives. Khorasany *et al.* [28] proposed an hour-ahead energy market with active participation of prosumers and consumers, which was solved by a double auction with an average mechanism. To better manage the uncertainty in multi-energy trading, two auction mechanisms under the day-ahead and real-time markets were designed by solving a social welfare maximization problem in [29].

Despite the growing number of auction-based P2P energy trading projects, there still exist knowledge gaps between how agents' bidding strategies interact with market conditions. Long *et al.* [30] attempted to close this gap by evaluating various bidding strategies in different P2P energy trading mechanisms, such as supply and auction-based, mid-rate rate and bill sharing. A continuous double auction was introduced in [31], which focused on a prediction-integration adaptive bidding strategy that all prosumers and consumers can perform informed trading. Mengelkamp *et al.* [32] compared two types of bidding behavior, i.e., zero-intelligence agents and intelligently agents in a direct P2P and a double auction market, respectively. Guerrero *et al.* [33] proposed a decentralized P2P energy trading platform based on a continuous double auction considering a physical low-voltage network constraint, where agents with zero intelligence plus bidding strategies were considered. Lin *et al.* [34] proposed two game-theoretic participant bidding strategies (i.e., best-offer approach and market-power approach) and investigated the economic efficiencies of two auction mechanisms (i.e., discriminatory and uniform k-Double-Auction mechanisms).

Therefore, the research gaps are summarized as follows.

i) Some previous works evaluated the benefit of energy sharing either from a cooperative perspective, e.g., [16], [17], or from merely the sellers' (leaders') point of view, e.g., [19]–[21]. However, it's important to consider the interactive and conflicting nature of all flexible ES owners (i.e., both buyers and sellers) who may have privacy concerns with their own optimization goals. Thus in a community sharing market, an effective game theory model that requires limited privacy but is able to realize a strategy-proof double auction market and optimized benefit is needed.

ii) Some previous works have evaluated the benefit of P2P energy sharing, but have not considered the uncertainty in supply and demand, as well as the agents' strategic behaviors, e.g., [13], [15], [20], [22], [25]. Thus a thorough decision-making process that takes account of the previous market behavior and future uncertainty is desired, for analyzing the benefit of the community sharing to each individual agent.

iii) Some previous studies have worked on different pricing mechanisms for community energy sharing, e.g., [3], [12], [15], [21]. However, they don't consider the dynamics in

energy sharing, in which the players are able to observe the market evolution. Besides, most information, such as others' load and PV generation, bidding strategies, and consumption behaviors, are not available in a practical closed auction market, which may bring challenges to some works such as [3], [15], [31]. Therefore, an appropriate and profitable bidding strategy mechanism is required to ensure the benefit of each individual agent without the knowledge of other agents.

In this research, we seek to design a community energy market to promote the energy sharing of surplus solar and ES through economic incentives. Compared to related works on community markets, this study has the following contributions.

i) We model a double auction-based community energy market that provides financial incentives for both prosumers and consumers with ES. In contrast to a static auction which assumes that all agents have a constant bidding price or quantity to trade, this article develops a novel framework that allows all agents to strategically decide their bidding prices and quantities they want to put into the market, thus yielding a dynamic market mechanism.

ii) A two-stage decision-making process is proposed to increase the economic efficiency of the community. In the first stage, the objective is to reduce the total electricity cost by analyzing the supply-demand relationship and estimating price in the look-ahead decision-making. In the second stage, a penalty-charged rule is applied in the real-time market clearing process to address the uncertainty in supply and demand, and the final equilibrium spot price is determined through a non-cooperative game solved by an iterative algorithm.

iii) A dynamic adaptive bidding strategy that incorporates historical records as well as future uncertainty is proposed. In a closed market, the agents can only use limited information to predict the market. Agents are proposed to learn the winning price based on a mixture model, consisting of empirical bidding that leverages historical successful bidding prices, and greedy bidding that considers future market forecasts.

The remainder of this article is organized as follows. Section II describes the architecture of the community energy market. 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 market performance. Section VI concludes the paper and discusses the future work.

II. Market Architecture

A. Community Sharing Market

Fig. 1 presents a typical architecture of a community sharing market. The neighbors, consisting of multiple agents, i.e., prosumers and consumers, are allowed to fairly exchange energy through a centralized sharing platform executed by a non-profit market operator. The community is assumed to be always grid connected, and the utility grid has a continuous supply of energy without interruptions and there is no limit on the feed-in energy from households with excess renewable supply. In each round of auction, the floor price and ceiling price are constrained by the utility grid, i.e., the utility price and buy-back rate. The market operator, acting as a supervisory third party,

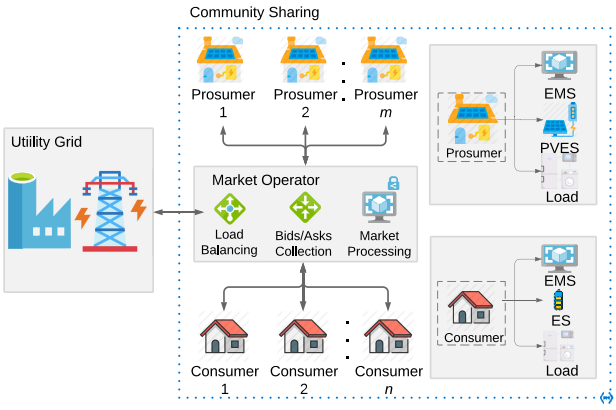

Fig. 1. A community energy sharing market.

is responsible for collecting the bids and asks from the community, processing the market, and balancing the supply and demand between the community and the utility grid [10]. Each household is assumed to have an energy management system (EMS) and ES system to optimize its energy consumption. In practice, PV could be used together with ES to improve the energy efficiency [3], which is referred as PVES in Fig. 1. Prosumers are assumed to first consume its own PV supply, and then if its netload (i.e., load minus PV generation in this article) is negative, this agent has surplus supply to share.

In an open auction market, all agents' bidding prices are publicly available to every agent. However, the extensive deployment of the open market is challenging due to privacy concerns. Compared to the open market, a closed market raises fewer privacy issues, which is more suitable for a community. Market agents send their bidding prices and quantities to the operator in a closed community market, where the spot price is calculated by a local data center to balance demand and supply [35]. The data center only needs the demanded/supplied power and bidding prices from agents, which means the utility and cost function parameters would remain private for each player. Thus, the computational burden in this approach would be low and its cost could be neglected, which makes it suitable for a market with a large number of players.

In a closed market, no information on any agent historical submitted asks/bids is available to its opponents. At the end of each round transaction, the operator will only announce the spot price, the total supply and demand. A potential concern of the proposed framework is that the auction mechanisms discussed in this work rely on a centralized architecture, i.e., all bids and asks are processed through a trustful market operator. Protecting an agent's identity and bidding information is crucial, since each agent's private information can be obtained from the central operator. The problem arises when the operator influences the auction proceedings in a manner that is inconsistent with the supervisory rules. For example, the operator might choose to block bids, insert fake bids, steal payments, prematurely open sealed bids, artificially change prices, etc. Without a trusted authority or notary (e.g., the operator proposed in this work), there are generally two possible approaches to establish trustful auctions. The first approach is to use a decentralized auction platform proposed in [36], where

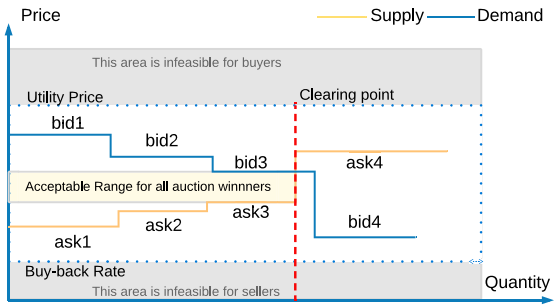

Fig. 2. Aggregation of the bids and asks.

some of the operator-duties are carried out by a mobile token distributed among the participants following a mutual exclusion protocol. The second approach is to use a blockchain technology, such as works [37], [38], to ensure a secure and privacy-preserving energy sharing in the absence of a third party.

B. Double Auction-Based Sharing

Double auction scheme enables multiple buyers and sellers to decide simultaneously and independently how much to bid or ask in the auction through specific decision-making rules without knowing the strategies of others. It should be noted that there exist slight differences in auction terminologies in related references. For example, the authors use terminologies *asks* for sellers and *bids* for buyers in [3], [39], while in [12], [21] the sellers' price is called as *reservation price*; in [25], [28] sellers *offer* what they are willing to sell, and buyers *bid* for what they need to buy; while in [24], bids and asks are not only referring to prices but also quantities. For the sake of clarity in this article, *bids* and *asks* are only referring to prices, and we will use *bidding price* (p_i) to represent the bid_i or ask_i, and *quantity* (q_i) to represent the s_i or b_i of agent i in some equations for simplification.

At each trading period (e.g., 1 h), the buyers announce their quantities to be purchased with their desired bids, and the sellers announce their power to be sold with their asks. The determination rules of the proposed scheme are executed by the market operator via the following steps.

i) The M buyers submit their bids $bid_i, \forall i$ and the amount b_i, then the operator sorts bids in a descending order:

$$bid_1 > bid_2 > \cdots > bid_M$$

ii) The N sellers submit their asks $ask_j, \forall j$ and the amount s_j, then the operator sorts asks in an ascending order:

$$ask_1 < ask_2 < \cdots < ask_N$$

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. 2.

iv) The operator clears the market based on the aggregated supply and demand curves.

Suppose the two curves are intersected by bid_K and ask_L, buyers with an index $i \leq K$ and sellers with an index $j \leq L$ will win the auction (e.g., $K = 3$, $L = 3$ in Fig. 2). The bids and asks beyond the clearing point will be ignored. The market spot price can locate at any point within the range $[ask_L, bid_K]$ (if $ask_L < bid_K$). However, we note that one fixed price may not be considerably beneficial for all the participating agents in the auction scheme. For example, if the spot price is only determined by the operator, the price could be detrimental for some agents. Therefore, to make the auction scheme attractive and beneficial to all the participating agents, also being cost effective for the community, we strike a balance between $[ask_L, bid_K]$ to determine the price p_* based on the supply and demand.

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

where $\sum_{i=1}^{K} b_i$ and $\sum_{j=1}^{L} s_j$ denote the total amount of buying and selling power, respectively, that the auction winners want to put into the market. The reason why we design this price determination rule is that: when the supply is more than demand ($\sum_{i=1}^{K} b_i < \sum_{j=1}^{L} s_j$), the fraction becomes smaller, thus the spot price gets closer to ask_L, and there is a larger gap between the spot price and the buyers' bids. With the increase of the price gap, the buyers are willing to put more demand into the market to increase their utilities (and the utility function will be introduced in Section III-B), thus the overall demand will be increased. On the other hand, when the gap between the spot price and seller's asks gets smaller, the sellers' incentive to sell more energy will decrease. Similarly, the spot price will benefit sellers more when the market is over-demand. When the supply and demand are matched perfectly, Eq. (1) will give a mid-rate of bid_k and ask_L. Further descriptions could be found in Section III-B.

C. Market Clearing Rules

Agents in this work are assumed to have complete knowledge of their 1-hour-ahead (1HA) energy generation and demand with perfect foresight [3]. At the end of each trading period $t-1$, agents submit their desired bids/asks for the next round t, then the market operator will execute the 1HA auction process, announce the spot price p_*^t, and notice all winners the potential energy they can buy or sell (q_i^t) for their submitted bid/ask (p_i^t). Then at the end of t, the final demand/supply and the spot price are used to calculate the bills. However, even with the state-of-the-art forecasting methods, the errors between predictions (1HA) and actuals (real-time) still exist due to agents' increased activities with the flexibility of ES. Thus in practice, the closed auction seems to be vulnerable to non-strategy-proof bidding [12].

To prevent such practices, two clearing rules are added into the market. First, non-iterative bidding is allowed in the market, which means only one-time bidding prices are collected by the market operator at each round. This rule prevents a bidder from placing multiple bids on the same item with the possibility of bid withdrawal. Second, to encourage the energy exchange in the community and maintain a fair and orderly market, a contribution-based penalty-charged rule is proposed to prevent agents from submitting deceptive biddings. The detailed penalty rules will be introduced in Section III-D.

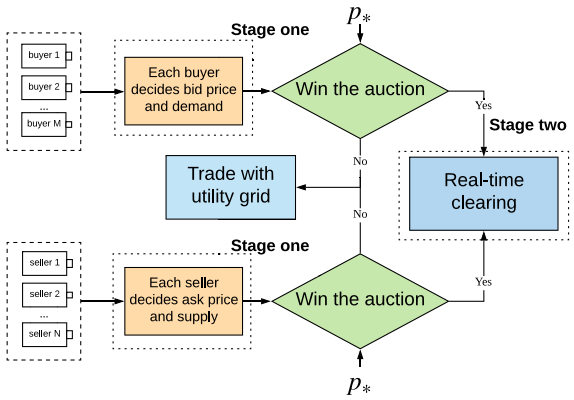

Fig. 3. The proposed community energy sharing scheme.

III. Market Process

For each agent, its optimization goal is to find the best ES schedule to maximize its cost saving. Considering the capabilities of ES in compensating for the unbalance between supply and demand and arbitraging from the utility grid, a two-stage decision-making process is proposed, as shown in Fig. 3. Without loss of generality, the following process is described from the standpoint of agent i.

A. Stage One: Hour-Ahead Market

Hour-ahead arbitrage takes place before real-time market clearing, and it determines the agent's ES schedule. Since the state of charge (SoC) of ES is time dependent, it is reasonable to determine the schedule by look-ahead optimization. The main objective of stage one is to determine the optimal arbitrage schedules, aiming at reducing the customers' current as well as future cost, i.e., charging the battery at a lower rate and discharging it at a higher price period. The objective function of agent i is:

$$min\ C_i^{h\sim H} = \sum_{t=h}^{H}\big[p_s^t \cdot \max\big(nl_i^t + x_i^t, 0\big) + p_b^t \cdot \min\big(nl_i^t + x_i^t, 0\big)\big] \quad (2)$$

$$x_{min} \le x_i^t \le x_{max} \quad (3)$$

$$-C_{con} \le x_i^t \le C_{con} \quad (4)$$

$$SoC_{min} \le SoC^t \le SoC_{max} \quad (5)$$

$$SoC^t = \begin{cases} SoC^{t-1} + x_i^t \cdot \eta, & x_i^t > 0 \\ SoC^{t-1} + x_i^t/\eta, & x_i^t < 0 \end{cases} \quad (6)$$

where H is the whole optimization horizon (i.e., 24 h); h is the current time slot. $C_i^{t\sim H}$ is the look-ahead electricity cost of agent i from current time h to future H; nl_i^t denotes the net-load. x_i^t is the battery charging/discharging schedule; a positive value denotes charging and a negative value denotes discharging. On the first day, all agents have no information of the market. p_s^t and p_b^t are the utility price and buy-back rate, respectively. As the sharing market evolves, new spot prices are settled and then agents will update these two anticipated prices. x_{min} and x_{max} are the lower and upper bounds of the charging energy in a time slot, respectively; C_{con} is the maximum charging/discharging speed of the storage; SoC^t is the SoC of the ES at the end of time slot t; SoC_{min} and SoC_{max} are the lower and upper limits of the ES, respectively.

Due to the energy loss in the charge and discharge process, the relationship between SoC and x is defined in Eq. (6), where η denotes the charging and discharging efficiency, which is chosen as 0.95 following [40]. Since we focus on the energy exchange within a residential community, we use a copper-plate network model in this article.

B. Stage Two: Real-Time Market

We define stage two as a real-time market clearing process. For those auction winners, they need to execute the market-clearing. In real-time market clearing, the spot price and energy quantity turn into decision variables, as introduced in Eq. (1). After being informed to engage in the real-time clearing market, the agents will bargain with each other to maximize their profits [21]. To define the benefit that agent i can earn in the real-time sharing market by adjusting quantity Δx_i, we have modeled a utility function as:

$$\max\ U_i\big(\Delta x_i^t\big) = \big(p_i^t - p_*^t\big)\big(nl_i^t + x_i^t + \Delta x_i^t\big) - \alpha_i \Delta x_i^{t2} \quad (7)$$

where p_i^t and p_*^t denote agent i's bid (or ask) and the spot price, respectively. Since we assume that all agents take 1HA schedules x_i^t as initial strategies, the final quantity after adjustment that agent i puts into the real-time sharing market is $(x_i^t + \Delta x_i^t)$, which should also satisfy constraints (3)-(6). The first part is the utility in terms of its revenue that an agent obtains from sharing energy, and the second term $\alpha_i \Delta x_i^2$ stands for the reluctance of agent i deviating from the 1HA schedule. The proposed utility function also has the following properties: i) the utility of any agent increases as the price gap between the spot price and its bidding price increases; ii) as the reluctance parameter α_i increases, the agent becomes more reluctant to share more energy, and consequently the utility decreases; and iii) for a particular price p_*, the interest to share is decreased if an agent has already shared more energy with others. As a result, by applying the spot price determination rules (1) and utility function (7), the auction participants are more willing to balance the supply and demand voluntarily because of economic incentives.

However, one speculative agent's real-time deviation might prejudice the benefits of others, then other agents will also update their real-time adjustments according to the new settled price, making the market unstable and complicated. One popular solution to this kind of energy trading interaction problem that consists of multiple agents conflicting with each other is non-cooperative game theory.

C. Game Formulation and Equilibrium Analysis

There are several key components in the game-theoretic based real-time market formulation:

i) Players: All auction winners can be regarded as players in the real-time market clearing game (Γ).

ii) Strategies: Players decide the final quantity (Δx_i) they want to bid into the real-time trading.

iii) Benefits: The goal is to maximize the utility (U_i) based on its own strategy as well as the strategies of opponents (Δx_i, Δx_{-i}, p_*).

To ensure that the optimal equilibrium spot price (p_*) can be reached at Nash Equilibrium (NE), the solution of the game should satisfy the following set of conditions:

$$U_i\big(\Delta x_i^*, \Delta x_{-i}^*, p_*\big) \geq U_i\big(\Delta x_i, \Delta x_{-i}^*, p_*\big) \tag{8}$$

Theorem: For the non-cooperative game (Γ), there exists a pure-strategy Nash Equilibrium.

Proof: First, we notice that the quantity strategy set (Δx_i) of the participants is non-empty and the spot prices (p_*) are continuous within an acceptable range $[ask_L, bid_K]$. Hence, there will always exist a non-empty solution. Second, the utility function U_i is strictly concave with respect to Δx_i. Hence for any price within the range $[ask_L, bid_K]$, each agent will have a unique best strategy Δx_i^*, which can be chosen from its strategies set for maximizing its utility U_i. Thus, this iterative process is able to continue until convergence to reach a Nash Equilibrium [12]. The best strategy of agent i can be formulated as:

$$\Delta x_i^* = \arg\max \ U_i(\Delta x_i, \Delta x_{-i}) \tag{9}$$

To solve Eq. (9), first we note that the Δx_i, at which the agent i achieves its maximum utility in response to a price p_*, can be found from the utility function (7),

$$\Delta x_i^* = \frac{p_i - p_*}{2\alpha_i} \tag{10}$$

Now, substituting the value of Δx_i (assuming agent i is a buyer) into (1) and we can get a unique updated spot price (p_*') as follows:

$$p_*' = ask_L + \frac{\sum b + \Delta x_i^*}{\sum b + \Delta x_i^* + \sum s}(bid_K - ask_L) \tag{11}$$

and this new price will be applied to other agents in turn. The process will continue until convergence. ■

As we mentioned in Section II-A, in the market clearing process, the only information that one agent can obtain is the spot price, and the maximum energy to be sold for its bid/ask; no information of its opponents is available. In such a sharing environment, we design an iterative auction approach that allows the buyers or sellers to approximate its quantity to a stable market. The stable market, also called Nash Equilibrium, is a state in which no player has the incentive to deviate from its strategy unilaterally. The overall two-stage market process is shown in **Algorithm 1**, and the bidding strategy in Line 2 will be discussed in the next section.

Algorithm 1 Two-Stage Community Sharing Market

1: **for** t=h:H **do**
2: *Stage one*: Agents initialize quantities according to (2), then submit bidding prices and quantities to the market operator.
3: Market operator collects all asks, bids, quantities.
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 Δx_i according to (7).
8: **end for**
9: The market operator updates the clearing price p_*' according to (11).
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**

D. Penalty Mechanism

At the auction outcome of each time slot, the agents' actual costs may be different from their expectations due to the trading deviation. Hence, we develop a penalty scheme to manage the deviation, which includes two parts: real-time deviations of quantities and corresponding individual contribution. It should be noted that the penalty could be defined either in a *monetary* or *quantitative* way. In this article, the *quantity* allocation is adopted, which means the operator will determine the penalties through quantities rather than bills. For simplicity, we consider the quantities as positive values in this subsection, and the total deviations of buyers (δ^b) and sellers (δ^s) who win the auction are represented as $\delta^b = \sum_{i\in K} \Delta x_i$ and $\delta^s = \sum_{j\in L} \Delta x_j$, respectively, where Δx is the hourly deviation of individual agent determined in the real-time stage.

If $\sum_{i=1}^K b_i + \delta^b < \sum_{j=1}^L s_j + \delta^s$, which means the total supply exceeds the demand at the auction outcome, the operator has to sell the excess part to the utility grid in order to balance the supply and demand. The utility price and quantity are p_b and $(\sum_{j=1}^L s_j + \delta^s) - (\sum_{i=1}^K b_i + \delta^b)$, respectively. The market operator will allocate the quantity q_i to be traded by seller i according to the following rules.

$$q_i = \begin{cases} s_i, & \sum_{i=1}^K b_i + \delta^b \geq \sum_{j=1}^L s_j + \delta^s \\ (s_i - \rho_i)^+, & \sum_{i=1}^K b_i + \delta^b \leq \sum_{j=1}^L s_j + \delta^s \end{cases} \tag{12}$$

where $(\cdot)^+ = max(0, \cdot)$, ρ_i is the allotment of over-supply burden that a seller i must endure, and $s_i = nl_i + x_i + \Delta x_i$. The rule in (12) emphasizes that whenever the total demand exceeds the supply, each seller needs to sell all of the energy s_i bid into the market. However, when the total supply exceeds the total demand, all sellers get an either *equal* or *proportional* share of the over-supply burden. In this article, we use an *equal* burden adopt from [12], [21] to deal with the allocation, thus $\rho_i = \frac{(\sum_{j=1}^L s_j + \delta^s) - (\sum_{i=1}^K b_i + \delta^b)}{L}$. Besides, in some extreme cases, if the penalty exceeds the boundary of one agent's quantity, this agent will not sell any energy and the remaining burden will be allocated among other $L-1$ agents; and this scheme applies to all sellers until each seller has a non-negative quantity. An analogous process can be carried out to find the quantities purchased by the buyers.

Then we can categorize the agents based on their contributions to the community, measured by *positive* or *negative*, to calculate the bills B_i. The penalty charge is the utility price p_s

(or buy-back rate p_b), because this part has to be traded with the utility grid to compensate for the penalty ρ_i.

In an over-supply market: Agent i is a seller and $\Delta x_i > 0$, i.e., more energy has been sold, and its contribution to the community balance is *negative*. Thus there is an extra quantity penalty ρ_i, which implies this part has to be traded with the utility grid with a cost $p_b \rho_i$.

$$B_i = p_*(nl_i + x_i + \Delta x_i - \rho_i)^+ + p_b \rho_i \tag{13}$$

If $(\cdot)^+ = 0$, there is no profit gained because this agent will sell no energy; if $(\cdot)^+ > 0$, the profit increase compared with trading with the utility grid (here ρ_i' is the penalty under this state, and Δx_i is excluded from the penalty) is calculated by:

$$\begin{aligned}\Delta B_i &= B_i - \left[p_*\left(nl_i + x_i - \rho_i'\right) + p_b\left(\rho_i' + \Delta x_i\right)\right] \\ &= (p_* - p_b)\left(\Delta x_i + \rho_i' - \rho_i\right)\end{aligned} \tag{14}$$

Recalling $\rho_i = \frac{(\sum_{j=1}^{L} s_j + \delta^s) - (\sum_{i=1}^{K} b_i + \delta^b)}{L}$, thus $\rho_i' = \frac{(\sum_{j=1}^{L} s_j + \delta^{s/-i}) - (\sum_{i=1}^{K} b_i + \delta^b)}{L}$, and $\rho_i' - \rho_i = -\frac{\Delta x_i}{L}$. The term ΔB_i is always positive since the spot price is always higher than the buy-back rate ($p_* > p_b$), and $\Delta x_i - \frac{\Delta x_i}{L} \geq 0$. In other words, even with penalty-charge, the seller could always guarantee a non-negative profit.

In an over-demand market: Agent i is a seller and $\Delta x_i > 0$, i.e., more energy has been sold, and its contribution to the community balance is positive. Thus there is no extra charge, and the profit increase is given by:

$$\Delta B_i = (p_* - p_b)\Delta x_i \tag{15}$$

In an over-demand market, it's always profitable for a seller to sell more. The proofs under other scenarios can follow an analogous process, which are omitted here.

IV. An Adaptive Bidding Strategy

In this section, an adaptive bidding strategy is proposed to help the participants to prepare their bids/asks. The idea of adaptive bidding is to provide bids or asks as close to the spot price as possible for maximizing the benefit, and provide future price estimation for look-ahead optimization. It's worth noting that the supply and demand are not only influenced by the PV generation and load, but also by other agents' DR incentives as well as bidding strategies, however, these information is not available in a closed market. The limitations of a closed market provide an opportunity to infer the supply and demand from historical trading records.

A. Prediction in the Market Evolution Process

The hypothesis behind predicting the price is that agents can assume that if they lose the auction at the current round, they can potentially win the auction in the future. The adaptive bidding strategy consists of both short-term and long-term estimation mechanisms [41], aiming at providing better bids and asks in response to previous trading price.

1) Short-Term Estimation: In the short-term learning, agents aim to adapt their prices by following the latest spot price. In a simple approach introduced in [25], agent i can track the spot price using:

$$\hat{p_{s.i}}^{t+1} = p_i^t + \beta \cdot \left(p_*^t - p_i^t\right) \tag{16}$$

where $\hat{p_{s.i}}^{t+1}$ is the short-term estimated price, p_*^t is the spot price that the agent wants to follow, p_i^t is the last bid/ask of this agent, and β is the short-term estimation rate, which is chosen to be 0.3 following [25].

2) Long-Term Estimation: Besides short-term estimation, agents should also consider future PV supply and load demand to have a better estimate of the future market. The relation between price and supply-demand relationship is inverse-proportional [42], which means the agents will predict a price hike for an upcoming over-demand market and a price drop for an over-supply market. This long-term estimation rule for agents is defined as:

$$\hat{p_{l.i}}^{t+1} = \begin{cases} \hat{p_{s.i}}^{t+1} + \left(p_s^t - \hat{p_{s.i}}^{t+1}\right) e^{\frac{-1}{\lambda_i^{t+1}}}, & \lambda_i^{t+1} > 1 \\ \hat{p_{s.i}}^{t+1}, & \lambda_i^{t+1} = 1 \\ p_b^t + \left(\hat{p_{s.i}}^{t+1} - p_b^t\right) e^{\frac{-1}{\lambda_i^{t+1}}}, & \lambda_i^{t+1} < 1 \end{cases} \tag{17}$$

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 spot price, respectively. λ_i^{t+1} denotes the predicted supply-demand ratio in the sharing market. The market power of an agent reflects its ability to influence the overall outcome of the auction. 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 utility price to earn more profit. Similarly, if there is only one buyer to dominate the market ($\lambda_i^{t+1} \to 0$), it will set a price close to the buy-back rate to reduce the cost. However, in the sharing market, each agent only has limited information regarding others. At the beginning, the following simple inferring approach is proposed to help predict the future market behavior.

$$\lambda_i^{t+1} = \frac{\sum_{i=1}^{K} b_i^t}{\sum_{j=1}^{L} s_j^t} \times \frac{l_i^{t+1} \times pv_i^t}{l_i^t \times pv_i^{t+1}} \tag{18}$$

where parameters l_i ad pv_i denote the load and PV generation of agent i, respectively. Inside a sharing community, all PV prosumers might have similar generation trends but with varying capacities due to strong spatial correlations, so agents can use their own PV generation to help predict others'. It is more challenging to predict the load demand of other agents due to various energy consumption behaviors, however, the aggregated load of the community is rather consistent and its daily pattern is relatively easier to predict. This simple inferring method is only useful when the market is just established and there is no historical records for reference. However, as the sharing market operates, new equilibrium prices are settled and trading records are stored, then agents will update this simple inferring method with a more accurate strategy. Combining the short-term (16) and long-term estimations (17), the final bidding price of agent i is given by:

$$\hat{p_i}^{t+1} = \gamma \cdot \hat{p_{l.i}}^{t+1} + (1 - \gamma) \cdot \hat{p_{s.i}}^{t+1} \tag{19}$$

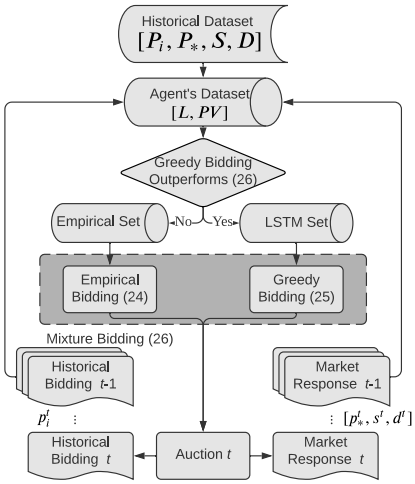

Fig. 4. Overall process of the proposed adaptive bidding strategy at time t.

where γ is a weighing factor between two estimations. In this article γ is chosen to be 0.3.

B. Long Short-Term Memory Forecasting

In addition to the aforementioned simple prediction method, when enough historical data is available, the agents can use other approaches to predict the supply and demand. Long short-term memory (LSTM) is an artificial recurrent neural network (RNN) architecture with feedback connections. It can process not only single data points, but also entire date sequences. A common LSTM unit is composed of a memory cell $\mathbf{c}$, an input gate $\mathbf{i}$, an output gate $\mathbf{o}$, and a forget gate $\mathbf{f}$. The cell remembers values over arbitrary time intervals and the three gates regulate the flow of information into and out of the cell. The formulations of an LSTM structure are expressed as:

$$\mathbf{f}_t = \sigma\left(\mathbf{W}_f\left[\mathbf{h}_{t-1}, \mathbf{X}_t\right] + \mathbf{b}_f\right) \tag{20}$$

$$\mathbf{i}_t = \sigma\left(\mathbf{W}_i\left[\mathbf{h}_{t-1}, \mathbf{X}_t\right] + \mathbf{b}_i\right) \tag{21}$$

$$\tilde{\mathbf{c}}_t = \tanh\left(\mathbf{W}_c\left[\mathbf{h}_{t-1}, \mathbf{X}_t\right] + \mathbf{b}_c\right) \tag{22}$$

$$\mathbf{c}_t = \mathbf{f}_t * \mathbf{c}_{t-1} + \mathbf{i}_t * \tilde{\mathbf{c}}_t \tag{23}$$

$$\mathbf{o}_t = \sigma\left(\mathbf{W}_o\left[\mathbf{h}_{t-1}, \mathbf{X}_t\right] + \mathbf{b}_o\right) \tag{24}$$

$$\mathbf{h}_t = \mathbf{o}_t * \tanh(\mathbf{c}_t) \tag{25}$$

where $\mathbf{W}_f$, $\mathbf{W}_i$, $\mathbf{W}_c$, $\mathbf{W}_o$ are the input weight matrices, while $\mathbf{b}_f$, $\mathbf{b}_i$, $\mathbf{b}_c$, $\mathbf{b}_o$ are the corresponding bias vectors; $\sigma(\cdot)$ and $\tanh(\cdot)$ are the logistic sigmoid and hyperbolic tangent activation functions, respectively; $\mathbf{h}$ is a hidden state, which is also the output of the LSTM hidden layer; $\tilde{\mathbf{c}}$ is a new state candidate vector; and the bracket is a concatenation operator.

As a sequence-based model, LSTM is able to abstract residents' pattern, maintain the memory of the states, and establish the temporal correlations between information and the current circumstances. Such characteristic is ideal for market forecasting since the residential power consumption and PV generation have been proven to follow certain routines during a day. In this study, the following input features are used:

i) The sequence of load consumptions L_i and solar generation PV_i for the past time steps.

ii) The historical published supply S and demand D in the sharing market for the past time steps.

iii) The hourly stage of a day (1-24 h).

The data pre-processing and parameters selection are executed following [43], and the simulation is run in the MATLAB Deep Learning Toolbox.

C. Empirical Bidding and Greedy Bidding

An empirical method means agents predict the supply and demand on the past values by searching historical data, which has been applied in [3], [15]. In this work the empirical prediction is performed by averaging the previously recorded prices from past similar weather days. Based on the PV production percentage (of the full clear-sky generation) during a day, the historical data could be classified into three groups: i) above 70%, ii) between 30% and 70%, and iii) below 30%. It's worth noting that when enough data is available, the group numbers can be increased to consider more features, such as temperature, holiday, etc. Therefore the spot price estimation can be obtained as:

$$P_* = \sum_{d=1}^{n} (\omega_d \cdot P_{*.d}) \tag{26}$$

where ω_d is a weighing factor of the most recent n similar days, which can be selected based on personal preference, market fluctuations, and weather similarity. $P_{*.d}$ is the spot prices set of day d. Similarly, the historical successful bidding prices set P_i can also be calculated by this method. The empirical method learns from the historical spot price as well as the historical successful bidding prices, then in the empirical bidding, the bid/ask can be conducted as:

$$P_{emp} = P_i + \beta \cdot (P_* - P_i) \tag{27}$$

Besides the empirical method that only aims at making the bids/asks win since it learns from previous successful strategies, a greedy method allows an agent to put a bid or ask close to the spot price by forecasting the future supply and demand. In an over-supply market, the greedy bidding will put a price close to the historical minimal spot price (p_{min}); similarly, in an over-demand market, it will put a price close to the maximum spot price (p_{max}).

$$P_{greedy} = \begin{cases} P_* + (p_{min} - P_*)e^{\frac{-1}{\lambda_i^{t+1}}}, & \lambda_i^{t+1} > 1 \\ P_*, & \lambda_i^{t+1} = 1 \\ p_{max} + (P_* - p_{max})e^{\frac{-1}{\lambda_i^{t+1}}}, & \lambda_i^{t+1} < 1 \end{cases} \tag{28}$$

D. Mixture Bidding

In the previous subsection, we introduced the empirical bidding and greedy bidding. In practice, following the empirical method usually underestimates the winning price, because there is always a gap between the successful bidding and the final spot price. Greedy bidding usually provides a higher estimation than the empirical bidding, however, this aggressive behavior might decrease the bidding success rate due to price matching failure. To bridge the gap, we propose an adaptive mixture strategy to help agents provide bidding prices.

$$P_{mix} = Pr(\Xi)P_{greedy} + (1 - Pr(\Xi))P_{emp} \tag{29}$$

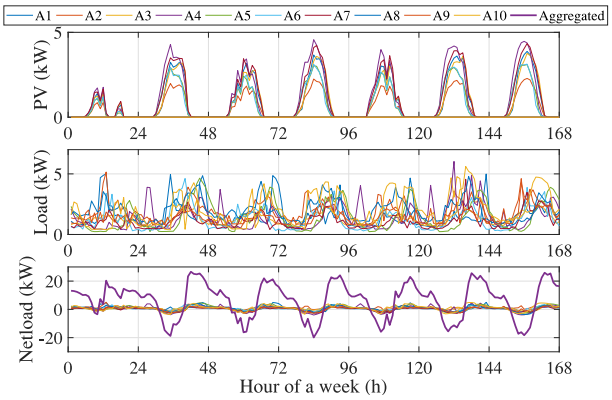

Fig. 5. PV, load, netload (including aggregated) profiles of the 10 agents within the first week.

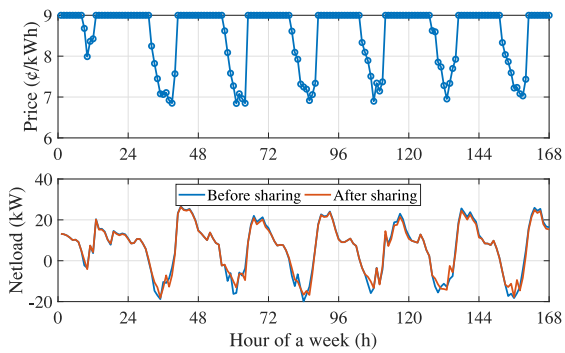

Fig. 6. Evolution of the market spot price and the aggregated netload within the first week.

where $Pr(\Xi)$ is a probability that the greedy method provides a better bids/asks than the empirical method in the previous round. The mixture model can provide better bids/asks when the greedy bidding outperforms the empirical bidding. When the greedy bidding strategy doesn't have a good accuracy, the agent can choose empirical bidding to ensure a success. Fig. 4 depicts the overall process of the proposed adaptive bidding strategy. As per Fig. 4, for agent i in round t, given a dataset consisting of historical trading records, bidding and market response, it first constructs the supply and demand forecasts in the empirical and LSTM sets. Then through a proper choice of the bidding strategy (29), the agent finally decides its bidding price at time t. After the agent submits its bidding price into the auction market and the new market response occurs, this pair will be recorded and added to the historical dataset. The mixture model aggregates the merits of these two estimators and provides a better estimation. We will compare these bidding strategies in the case study.

V. Case Study

The developed sharing market is evaluated with a case study of 10 agents within a community in Austin, Texas, from May 30 to July 11, 2016 (6 weeks) [44]. Agents 1-7 are PV prosumers and agents 8-10 are pure consumers. It is assumed that all agents are equipped with a 3 kWh battery storage system. In this article the energy charge is set to be 9 ¢/kWh [45], and the buy-back rate is set to be 6 ¢/kWh [33]. The PV, load, and netload curves of the 10 agents within the first week are plotted in Fig. 5. It is noted that due to the proximity of agents, the solar power generation profiles are similar and only vary in magnitude. For each individual agent, the load and netload profiles vary greatly from one household to another, and this is due to the different consumption behavior. However, the aggregated community netload is rather consistent.

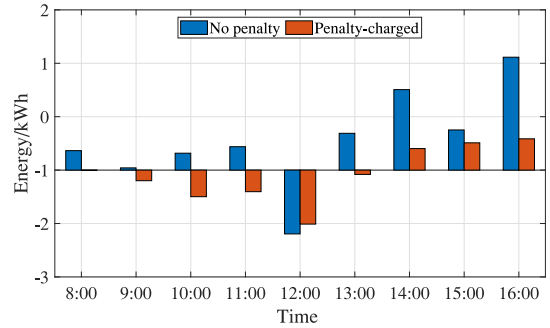

Fig. 7. Energy trading with the utility grid before and after penalty regulation.

A. Market Evolution

Fig. 6 shows the evolution of the market spot price over the first week and the aggregated netload change before and after the energy sharing. It is observed that the energy sharing almost occurs from 10:00 a.m. to 4:00 p.m. on sunny days. For the rest hours, all agents need to meet their demand relying on the utility grid. It is seen that the market spot prices are always between the utility price and buy-back rate, which means all agents are willing to participate in the community sharing scheme. We also observe that the spot price profile is closely following the PV generation curves in Fig. 5. On day 1 when there is no sufficient PV generation for sharing, the spot price is almost equal to the utility price.

Under the sharing framework, the aggregated netload during peak solar hours is increased on sunny days, which means the excess solar generation is shared among the community and less power is sent back to the utility grid. However, there is still some negative values in netload, which means the community can't consume all the excess PV due to limited ES capacity. Besides, the night load peak is shaved with ES discharging, which can also be regarded as an arbitrage-based DR. Fig. 7 depicts the energy trading quantity with the outside utility grid under two different scenarios in a single day: without penalty and penalty-charged. Positive values mean the community has to purchase energy from outside, and negative values indicate selling energy. And these unbalanced quantities will be shared among buyers or sellers. It is seen that our proposed method with penalty-charge is able to better balance the supply and demand in the community market, since less energy is traded with the utility grid.

B. Sensitive Analysis of Parameters β and γ

The parameters β and γ are used to quantify the agents' willingness to update their bidding prices in market estimation process. A larger β means that the agent is more willing to provide biddings close to the market spot price, and a larger γ

TABLE I
SENSITIVE ANALYSIS OF PARAMETERS β AND γ

	β=0.1		β=0.3		β=0.5		β=0.7		β=0.9	
	SB	*CS*	*SB*	*CS*	*SB*	*CS*	*SB*	*CS*	*SB*	*CS*
γ=0.1	349	782	***350***	785	349	773	344	771	344	778
γ=0.3	340	790	**345**	**813**	342	***814***	344	789	338	781
γ=0.5	344	772	340	776	342	771	344	773	340	780
γ=0.7	342	776	343	767	344	771	336	750	338	759
γ=0.9	338	752	339	737	335	737	333	725	327	724

Note: *SB* and *CS* indicate the aggregated numbers of successful bidding, and cost savings (¢) of the community in the first 5 days, respectively. **Bold values** indicate the parameters combination we use in this paper, and ***bold italic values*** indicate the best individual value.

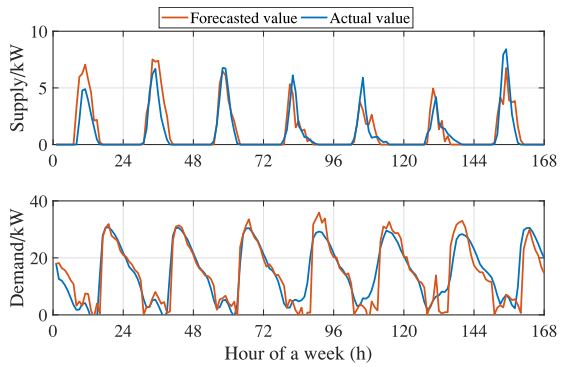

Fig. 8. Supply and demand forecasting validation of agent 4.

means that the agent is more confident in its long-term estimation. With the change of β and γ, the results are compared in Table I. It's first found that the number of successful bidding and cost savings are reduced with larger β and γ. The combinations of $\beta = 0.3, \gamma = 0.1$ and $\beta = 0.5, \gamma = 0.3$ yield the best performance in successful bidding and cost savings, respectively. The parameters combination we choose in this article $\beta = 0.3, \gamma = 0.3$ can increase the number of successful bidding, while only reduce the cost savings slightly, which confirms the effectiveness of parameters selection.

C. LSTM Results

The historical trading records are split into three subsets for training (fist 4 weeks), validating (fifth week), and testing (sixth week). The training set is used to train LSTM networks, and the validating set is used to evaluate, while the testing set is used for future price estimation. Fig. 8 shows the forecasted supply and demand curves of Agent 4, and Table II gives the forecasting summary of all prosumers. We use the normalized mean root square error (nRMSE) as an evaluation index, and RMSE is normalized based on the maximum supply or demand in this article. For most agents, the demand forecasting accuracy is satisfactory considering that the community only consists of 10 participants. The forecasts of the supply are not as accurate as the forecasts of the demand. Based on different load levels and PV capacities, some agents perform better in demand forecasting while others have higher accuracies in supply forecasting, which may also reflect diverse agents' market power in influencing the market. This level of accuracy is anticipated because the supply is affected by multiple factors, such as weather, users' consumption behavior, and bidding strategies, which are not available in such a closed market. Overall, in our case, the accuracy achieved by LSTM is more reasonable compared with the empirical method.

TABLE II
FORECASTING ERRORS [%] SUMMARY

Agent	1	2	3	4	5	6	7
nRMSE LSTM supply forecasts	18.61	22.18	16.37	18.68	20.60	19.00	15.53
nRMSE LSTM demand forecasts	8.92	9.31	9.45	8.07	10.81	11.46	14.59
nRMSE empirical supply forecasts	25.22						
nRMSE empirical demand forecasts	18.55						

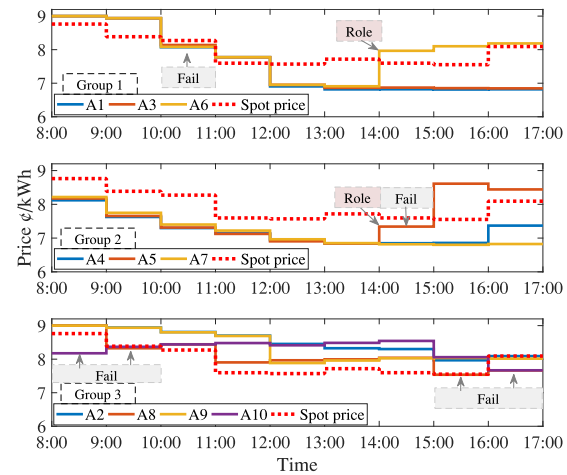

Fig. 9. Bids and asks of all agents in day 37.

D. Overall Performance of the Community Sharing Market

1) The Market Performance in a Single Day: Fig. 9 depicts the bids and asks of all agents in day 37 (sixth week) in the mixture bidding scenario. The 10 agents are divided into three groups, and the red dashed lines indicate the market spot price. Basically, bidding prices above the spot line indicate the agents are buyers while below the spot price indicate the agents act as sellers in the market. *Role* indicates the role of this agent has changed, either from buyer to seller or vice versa; *Fail* indicates this agent loses this round auction. Group 1 consists of agents 1, 3, and 6, and they mainly act as buyers in the morning while sellers in the afternoon; group 2 includes agents 4, 5, and 7, who act as sellers during most time of the day; while in group 3, agents 2, 8, 9, and 10 act as buyers due to the lack of PV generation.

2) ES Profiles Under Different Scenarios in a Single Day: To evaluate the effectiveness of our proposed community energy sharing market, three different scenarios are compared in this section. In Scenario 1, the empirical (*Emp*) forecasting is applied, the proposed mixture method is applied in Scenario 2 (*Mix*), and the greedy bidding is applied in Scenario 3 (*Greedy*). Fig. 10 depicts the energy charging/discharging profiles of three representative agents from each group in three different bidding scenarios. It is observed that the operation of ES can be roughly divided into three stages. First, in the time period 0-8, there is no obvious activity for the ES since there is no energy sharing inside the market. Second, in the time period 8-16, the ES works in different sharing modes for

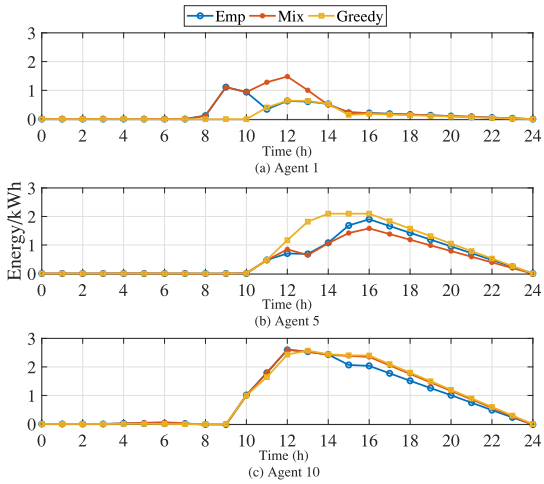

Fig. 10. ES profiles of three agents 1, 5, and 10 in day 37.

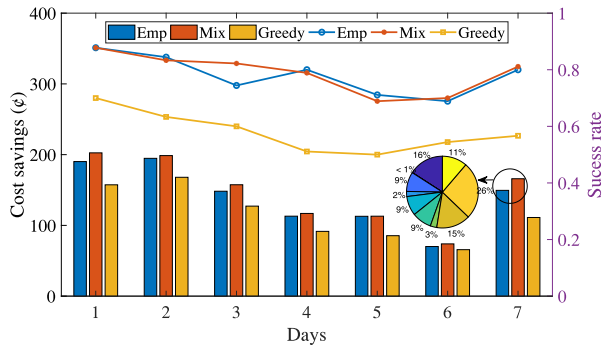

Fig. 11. Cost savings (bars) and bidding success rate (lines) of the community for the last week.

the three agents. More specifically, for agent 5 in the seller group, and agent 10 in the buyer group, their ESs work in a buffered mode, i.e., buffering energy in their anticipated low-prices period. For agent 1 in the first group, its ES works in a more flexible mode, i.e., charging/discharging more frequently based on the market fluctuation. Third, all agents choose to use their buffered energy in the evening. Besides the ES activities of different agents, bidding scenarios also have impacts on the ES profiles, especially for agent 1. Since agent 1 can flexibly determine when to charge/discharge based on their desired prices, there is no obvious routine for its opportunistic arbitrage. However, other two agents have a similar trend in the ES profiles under different bidding scenarios, i.e., buffering energy in the low-price period for future usage.

3) Market Performance in a Week: To validate the effectiveness of different bidding strategies, success rate is introduced as an evaluation factor, which is calculated based on the value of accumulated winning bids/asks divided by all submitted bids/asks in the market. Fig. 11 compared the cost savings as well as the bidding success rate in the sixth week under the three scenarios. The cost saving without community energy sharing is 0, which is used as a benchmark. It is observed that compared with the other two bidding strategies, the mixture bidding has improved the cost saving without damaging the bidding success rate through the whole week.

Improvement details on day 7 for each agent are also summarized as a pie chart in Fig. 11. Compared with the empirical method, the mixture method contributes to a 10% (from 150 to 165) increase in community cost saving, and all agents achieve higher benefits, from 1% to 26%. Although the greedy bidding can be profitable for single household during certain times when it has a higher market power, the whole welfare of the community is damaged due to price matching failure, so the bidding success rate is pretty low. Please note that since the sixth day during this week is a rainy day, the PV generation is seriously limited, which causes almost no cost saving change among these three scenarios.

TABLE III
COMPUTATION TIME WITH DIFFERENT NUMBERS OF AGENTS

Numbers of agents	10	25	50	100
Average time in stage one (s)	0.077	0.087	0.095	0.106
Maximum time in stage one (s)	0.112	0.113	0.135	0.154
Average time in stage two (s)	0.95	1.36	1.65	3.15
Maximum time in stage two (s)	2.32	3.05	6.31	7.27

E. Algorithm Performance and Scalability Analysis

To analyze the practical feasibility and computation cost of the proposed method, the case studies are conducted on a laptop with an Intel Core i7-6600U CPU running at 2.8GHz and with 16.0 GB RAM. Each agent can solve the stage one optimization independently, thus the speed of information transmission and computation cost are satisfactory at this stage. For the real-time stage, the model works in an iterative manner, and the agents need to get p_* from the market operator, which depends on other agents' strategies to optimize their own utilities. The average computation cost of both stages is summarized in Table III. It is observed that the two-stage optimization can be completed within a short time. The increase of the agents number will only slightly increase the computation complexity in stage two, however, the computational cost is still within a reasonable range in an hour-ahead market [3]. The computational burden in this approach is relatively low, which makes the proposed method scalable to a larger community market that may consist of hundreds of agents.

VI. CONCLUSION

This article investigated the energy sharing between PV prosumers and consumers within a community assisted with distributed energy storage. The proposed double auction-based sharing market consists of multiple dynamic buyers and sellers. A two-stage decision-making strategy was developed 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 real-time 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 supply and demand forecasting. The case study demonstrated the effectiveness of the proposed community energy sharing market in cost saving, and showed that the adaptive bidding strategy was able to increase agent's benefit without reducing the bidding success rate. Potential future work will further explore more sophisticated models that could improve the price prediction. Also,

methodologies for individual load and demand response ability forecasting can be developed to further enhance the cost saving of the community.

REFERENCES

[1] S. Chen and C.-C. Liu, "From demand response to transactive energy: State of the art," *J. Mod. Power Syst. Clean Energy*, vol. 5, no. 1, pp. 10–19, 2017.

[2] E. Mengelkamp, J. Gärttner, K. Rock, S. Kessler, L. Orsini, and C. Weinhardt, "Designing microgrid energy markets: A case study: The Brooklyn microgrid," *Appl. Energy*, vol. 210, pp. 870–880, Jan. 2018.

[3] A. M. Alabdullatif, E. H. Gerding, and A. Perez-Diaz, "Market design and trading strategies for community energy markets with storage and renewable supply," *Energies*, vol. 13, no. 4, p. 972, 2020.

[4] D. Krishnamurthy, C. Uckun, Z. Zhou, P. R. Thimmapuram, and A. Botterud, "Energy storage arbitrage under day-ahead and real-time price uncertainty," *IEEE Trans. Power Syst.*, vol. 33, no. 1, pp. 84–93, Jan. 2018.

[5] D. Kalathil, C. Wu, K. Poolla, and P. Varaiya, "The sharing economy for the electricity storage," *IEEE Trans. Smart Grid*, vol. 10, no. 1, pp. 556–567, Jan. 2019.

[6] A. Lüth, J. M. Zepter, P. C. del Granado, and R. Egging, "Local electricity market designs for peer-to-peer trading: The role of battery flexibility," *Appl. Energy*, vol. 229, pp. 1233–1243, Nov. 2018.

[7] D. Parra, M. Gillott, S. A. Norman, and G. S. Walker, "Optimum community energy storage system for PV energy time-shift," *Appl. Energy*, vol. 137, pp. 576–587, Jan. 2015.

[8] P. C. Del Granado, S. W. Wallace, and Z. Pang, "The value of electricity storage in domestic homes: A smart grid perspective," *Energy Syst.*, vol. 5, no. 2, pp. 211–232, 2014.

[9] A. Ali, N. Liu, and L. He, "Multi-party energy management and economics of integrated energy microgrid with PV/T and combined heat and power system," *IET Renew. Power Gener.*, vol. 13, no. 3, pp. 451–461, Feb. 2019.

[10] F. Moret and P. Pinson, "Energy collectives: A community and fairness based approach to future electricity markets," *IEEE Trans. Power Syst.*, vol. 34, no. 5, pp. 3994–4004, Sep. 2019.

[11] M. Pilz and L. Al-Fagih, "Recent advances in local energy trading in the smart grid based on game-theoretic approaches," *IEEE Trans. Smart Grid*, vol. 10, no. 2, pp. 1363–1371, Mar. 2019.

[12] Y. Wang, W. Saad, Z. Han, H. V. Poor, and T. Başar, "A game-theoretic approach to energy trading in the smart grid," *IEEE Trans. Smart Grid*, vol. 5, no. 3, pp. 1439–1450, May 2014.

[13] Y. Chen, S. Mei, F. Zhou, S. H. Low, W. Wei, and F. Liu, "An energy sharing game with generalized demand bidding: Model and properties," *IEEE Trans. Smart Grid*, vol. 11, no. 3, pp. 2055–2066, May 2020.

[14] J. Wang, H. Zhong, C. Wu, E. Du, Q. Xia, and C. Kang, "Incentivizing distributed energy resource aggregation in energy and capacity markets: An energy sharing scheme and mechanism design," *Appl. Energy*, vol. 252, Oct. 2019, Art. no. 113471.

[15] Z. Zhang, H. Tang, P. Wang, Q. Huang, and W. Lee, "Two-stage bidding strategy for peer-to-peer energy trading of nanogrid," *IEEE Trans. Ind. Appl.*, vol. 56, no. 2, pp. 1000–1009, Mar./Apr. 2020.

[16] L. He and J. Zhang, "Distributed solar energy sharing within connected communities: A coalition game approach," in *Proc. IEEE Power Energy Soc. Gen. Meeting (PESGM)*, Atlanta, GA, USA, USA, Aug. 2019, pp. 1–5.

[17] P. Chakraborty, E. Baeyens, K. Poolla, P. P. Khargonekar, and P. Varaiya, "Sharing storage in a smart grid: A coalitional game approach," *IEEE Trans. Smart Grid*, vol. 10, no. 4, pp. 4379–4390, Jul. 2019.

[18] J. Lee, J. Guo, J. K. Choi, and M. Zukerman, "Distributed energy trading in microgrids: A game-theoretic model and its equilibrium analysis," *IEEE Trans. Ind. Electron.*, vol. 62, no. 6, pp. 3524–3533, Jun. 2015.

[19] N. Liu, L. He, X. Yu, and L. Ma, "Multiparty energy management for grid-connected microgrids with heat- and electricity-coupled demand response," *IEEE Trans. Ind. Informat.*, vol. 14, no. 5, pp. 1887–1897, May 2018.

[20] A. Fleischhacker, H. Auer, G. Lettner, and A. Botterud, "Sharing solar PV and energy storage in apartment buildings: Resource allocation and pricing," *IEEE Trans. Smart Grid*, vol. 10, no. 4, pp. 3963–3973, Jul. 2019.

[21] W. Tushar *et al.*, "Energy storage sharing in smart grid: A modified auction-based approach," *IEEE Trans. Smart Grid*, vol. 7, no. 3, pp. 1462–1475, May 2016.

[22] A. Paudel, K. Chaudhari, C. Long, and H. B. Gooi, "Peer-to-peer energy trading in a prosumer-based community microgrid: A game-theoretic model," *IEEE Trans. Ind. Electron.*, vol. 66, no. 8, pp. 6087–6097, Aug. 2019.

[23] M. Khorasany, Y. Mishra, and G. Ledwich, "Market framework for local energy trading: A review of potential designs and market clearing approaches," *IET Gener. Transm. Distrib.*, vol. 12, no. 22, pp. 5899–5908, Dec. 2018.

[24] M. N. Faqiry and S. Das, "Double-sided energy auction in microgrid: Equilibrium under price anticipation," *IEEE Access*, vol. 4, pp. 3794–3805, 2016.

[25] P. Shamsi, H. Xie, A. Longe, and J.-Y. Joo, "Economic dispatch for an agent-based community microgrid," *IEEE Trans. Smart Grid*, vol. 7, no. 5, pp. 2317–2324, Sep. 2016.

[26] S. Bhattacharya, K. Kar, J. H. Chow, and A. Gupta, "Extended second price auctions with elastic supply for PEV charging in the smart grid," *IEEE Trans. Smart Grid*, vol. 7, no. 4, pp. 2082–2093, Jul. 2016.

[27] C. Long, J. Wu, Y. Zhou, and N. Jenkins, "Peer-to-peer energy sharing through a two-stage aggregated battery control in a community microgrid," *Appl. Energy*, vol. 226, pp. 261–276, Sep. 2018.

[28] M. Khorasany, Y. Mishra, and G. Ledwich, "Auction based energy trading in transactive energy market with active participation of prosumers and consumers," in *Proc. Aust. Univ. Power Eng. Conf. (AUPEC)*, Melbourne, VIC, Australia, 2017, pp. 1–6.

[29] W. Zhong, K. Xie, Y. Liu, C. Yang, and S. Xie, "Auction mechanisms for energy trading in multi-energy systems," *IEEE Trans. Ind. Informat.*, vol. 14, no. 4, pp. 1511–1521, Apr. 2018.

[30] C. Long, J. Wu, C. Zhang, L. Thomas, M. Cheng, and N. Jenkins, "Peer-to-peer energy trading in a community microgrid," in *Proc. IEEE Power Energy Soc. Gen. Meeting*, Chicago, IL, USA, 2017, pp. 1–5.

[31] K. Chen, J. Lin, and Y. Song, "Trading strategy optimization for a prosumer in continuous double auction-based peer-to-peer market: A prediction-integration model," *Appl. Energy*, vol. 242, pp. 1121–1133, May 2019.

[32] E. Mengelkamp, P. Staudt, J. Garttner, and C. Weinhardt, "Trading on local energy markets: A comparison of market designs and bidding strategies," in *Proc. 14th Int. Conf. Eur. Energy Market (EEM)*, Dresden, Germany, 2017, pp. 1–6.

[33] J. Guerrero, A. C. Chapman, and G. Verbič, "Decentralized P2P energy trading under network constraints in a low-voltage network," *IEEE Trans. Smart Grid*, vol. 10, no. 5, pp. 5163–5173, Sep. 2019.

[34] J. Lin, M. Pipattanasomporn, and S. Rahman, "Comparative analysis of auction mechanisms and bidding strategies for P2P solar transactive energy markets," *Appl. Energy*, vol. 255, Dec. 2019. Art. no. 113687.

[35] M. Khorasany, Y. Mishra, and G. Ledwich, "Distributed market clearing approach for local energy trading in transactive market," in *Proc. IEEE Power Energy Soc. Gen. Meeting (PESGM)*, Portland, OR, USA, 2018, pp. 1–5.

[36] A. M. Marufu, A. V. Kayem, and S. D. Wolthusen, "A distributed continuous double auction framework for resource constrained microgrids," in *Proc. Int. Conf. Critical Inf. Infrastruct. Security*, 2015, pp. 183–196.

[37] V. Hassija, G. Bansal, V. Chamola, V. Saxena, and B. Sikdar, "BlockCom: A blockchain based commerce model for smart communities using auction mechanism," in *Proc. IEEE Int. Conf. Commun. Workshops (ICC Workshops)*, Shanghai, China, 2019, pp. 1–6.

[38] S. A. Abeyratne and R. P. Monfared, "Blockchain ready manufacturing supply chain using distributed ledger," *Int. J. Res. Eng. Technol.*, vol. 5, no. 9, pp. 1–10, 2016.

[39] P. Huang, A. Scheller-Wolf, and K. Sycara, "Design of a multi–unit double auction e–market," *Comput. Intell.*, vol. 18, no. 4, pp. 596–617, 2002.

[40] H. Wang and J. Huang, "Incentivizing energy trading for interconnected microgrids," *IEEE Trans. Smart Grid*, vol. 9, no. 4, pp. 2647–2657, Jul. 2018.

[41] P. Vytelingum, "The structure and behaviour of the continuous double auction," Ph.D. dissertation, Dept. Elect. Comput. Sci., Univ. Southampton, Southampton, U.K., 2006.

[42] N. Liu, X. Yu, C. Wang, C. Li, L. Ma, and J. Lei, "Energy-sharing model with price-based demand response for microgrids of peer-to-peer prosumers," *IEEE Trans. Power Syst.*, vol. 32, no. 5, pp. 3569–3583, Sep. 2017.

[43] W. Kong, Z. Y. Dong, Y. Jia, D. J. Hill, Y. Xu, and Y. Zhang, "Short-term residential load forecasting based on lstm recurrent neural network," *IEEE Trans. Smart Grid*, vol. 10, no. 1, pp. 841–851, Jan. 2019.

[44] *Pecan Street Inc*, Dataport, Altenholz, Germany, 2018. [Online]. Available: https://dataport.cloud

[45] (2020). *Public Utility Commission of Texas*. [Online]. Available: https://www.puc.texas.gov/industry/electric/rates/RESrate/RESratearc.aspx