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# Peer-to-Peer Energy Storage Capacity Sharing for Renewables: A Marginal Pricing-Based Flexibility Market for Distribution Networks

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**Abstract**

The distributed renewable energy sources have been rapidly increasing in distribution networks, and some of them are configured with energy storage devices. Indeed, sharing surplus energy storage capacities for subsidizing the investment costs is economically attractive. Although such willingness is emerging, targeted trading mechanisms are less explored. Inspired by the electricity markets, this paper innovates a peer-to-peer energy storage flexibility market within distribution networks, which involves multiple vendors and customers, accompanied by a marginal pricing mechanism to enable the economic reallocation of surplus energy storage capacities in distribution systems. A small-scale market is first studied to show the proposed market mechanism and a larger-scale case is used to further demonstrate the scalability and effectiveness of the mechanism. Case studies set three distinct scenarios: markets with or without deficits and with carryover energy constraints. The numerical simulation validates its ability in reflecting the capacity supply–demand relationship, ensuring revenue adequacy and effectively improving economic efficiency.

**Keywords:** energy storage; marginal price; renewable energy sources; energy storage sharing

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Academic Editors: Giampaolo Manfrida and Osvaldo José Venturini

Received: 29 August 2025
Revised: 19 September 2025
Accepted: 27 September 2025
Published: 30 September 2025

**Citation:** Li, X.; Liu, T.; Liu, Y. Peer-to-Peer Energy Storage Capacity Sharing for Renewables: A Marginal Pricing-Based Flexibility Market for Distribution Networks. *Processes* **2025**, *13*, 3143. https://doi.org/10.3390/pr13103143

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## 1. Introduction

Driven by technological advancements, declining costs, and supportive policies, the development of distributed renewable energy resources has been accelerating globally as part of efforts to create more clean and sustainable energy infrastructures on the distribution side, enable localized renewable energy harvesting, and reduce dependence on centralized power supply. This development, meanwhile, promotes the emergence of peer-to-peer (P2P) trading in the distribution sector, such as Brooklyn Microgrid in the United States and Centrica PLC in the United Kingdom [1]. P2P trading enables solar panel and domestic wind turbine owners to sell energy directly to users bypassing traditional utility companies for monetizing excess electricity and endows electricity customers another supply channel apart from the utility companies. For the distribution level, utilities in many countries still take a dominant role in most cases. Typically, utilities sign medium-term or long-term contracts with distributed energy resources (DERs) willing to feed electricity back to the distribution system for monetizing. The contract allows DERs to inject power at long-term prices that may be seasonally adjusted or vary depending on the type of resources. At the same time, loads in the distribution network are usually settled at fixed or time-of-use tariffs. Intuitively, the fixed and time-of-use tariffs are notably higher than the long-term

prices offered to DERs. From an economic perspective, P2P indeed breaks the domination of the utility in electricity trading, leading to redistribution of the profits generated from the price difference between purchasing and selling electricity.

These driving forces have promoted the exploration of P2P energy trading and pricing mechanisms. Existing trading and pricing mechanisms are mainly auction-based [2–5]. Game theory is widely used to simulate participant interactions and derive prices under equilibrium. A dual auction mechanism for energy trading is proposed by Majumder et al. [2], which can effectively enhance the total social welfare of the distribution system as a whole. In response to the development of renewable energy resources, a blockchain-based distributed double auction mechanism was introduced by Thakur et al. [3], focusing on facilitating the bookkeeping of local energy transfer and settlement and accelerating the convergence of computation. Building upon the previous works, Zhao et al. [4] compared four different double-auction mechanisms, including k-double, Vickrey, McAfee, and maximum volume matching (MVM), and demonstrated that k-double and McAfee auction mechanisms perform better in terms of enlarging participants' surplus, which, traditionally referring to the difference between the price that a participant is willing to pay and the price actually paid, is commonly taken as a key indicator of auction efficiency. Furthermore, considering the budget deficit issue of the VCG mechanism, Cui et al. [5] innovatively proposed a competition padding auction mechanism that can operate sustainably without external subsidies. For energy trading, a high participants' surplus suggests that the auction mechanism is efficient in transferring electricity to those who value it the most. However, in P2P energy auctions, the zero marginal cost leaded low biding prices of distributed renewable energy resources and the publicly undisclosed reserve prices of auctions, which may make many of these auction mechanisms practically inapplicable.

Indeed, game theory, including cooperative game and non-cooperative game, has been extensively applied in analyzing P2P trading. Dixon et al. [6] proposed a P2P trading model that allocates income based on medium market prices on the basis of analyzing with consumer-centric normative coalition game. Tushar et al. [7] proposed a coalition-game-based P2P energy trading scheme where prosumers form alliances for mutual energy exchange. Subsequently, in a later study [8], the authors further refined this approach by developing a detailed coalition formation game framework in which prosumers dynamically form social coalitions by strategically choosing to utilize their batteries for trading based on real-time conditions. Azim et al. [9] designed a coalition graph game-based model to capture the P2P negotiation. Paudel et al. [10] introduced a P2P trading model considering multiple buyers and sellers, where the pricing among sellers is characterized as a non-cooperative game, the selection among buyers as an evolutionary game, and the relationship between buyers and sellers as a leader–follower game. Anoh et al. [11] modeled the coupled P2P market as a risk-averse stochastic Stackelberg game and Yao et al. [12] proposed a virtual microgrid energy trading framework based on Stackelberg game. Moreover, with the advancement of multi-energy systems, Jing et al. [13] proposed a multi-energy P2P trading model, with which participants can submit bids for individual energy commodities, and then the markets of multiple energy commodities are cleared simultaneously with the model that accounts for the coupling between multiple energy forms. Game theory is used to analyze participant interactions.

The intermittent nature of distributed renewable energy resources poses additional challenges for consistent energy supply due to their dependency on dynamic weather conditions. Concurrently, the flexibility brought by energy storage devices in configuration and operation makes energy storage devices an appealing companion to distributed renewable energy resources for managing their intermittent nature [14]. From an operating perspective, energy storage can help suppress power injection fluctuations of distributed

renewable energy resources, while from an economic perspective, it to some extent empowers distributed renewable energy resources with bargaining ability under the time-of-use pricing framework of utility companies as well as in the P2P energy trading. However, for some scattered distributed renewable energy resources, configuring energy storage devices alone may not be economically viable. Indeed, we envision a picture that in a distribution network (i) some distributed renewable energy resources are equipped with energy storage devices while others are not; (ii) for those accompanied with energy storage devices, in many periods of a day and in some seasons, the usage of energy storage capacities could be relatively low and thereby surplus in energy storage capacity exists. As an example, in some regions, wind and solar projects are required to install energy storage sized at 10–20% of their installed capacity, even though such capacity is rarely fully utilized. Therefore, they are willing to lend the surplus to others and compensate for their investment costs naturally sprouts. Moreover, (iii) for distributed renewable energy resources that do not have energy storage devices, they may be interested in leasing some flexible storage capacities to become a controllable asset and actively respond to electricity prices while evading the relatively high one-time investment cost. Meanwhile, driven by the sharing economy, independent energy storage systems are recently emerging, marketing their capacity provision to renewable energy resources while showing the same willingness as energy storage owners. This can create profit channels in addition to the traditional "charging at valley and discharging at peak" pattern, thereby enhancing the economic efficiency of energy storage. Indeed, a multitude of pilot shared energy storage projects have embraced P2P energy trading business models, exemplified by initiatives such as Germany's Lumenaza and Australia's Power Ledger projects [15].

In fact, existing works on energy storage are mainly centered around capacity configuration, operational strategies towards diverse energy storage technologies, and market participation, while works focusing on business models, especially for shared energy storage, are relatively limited. Li et al. [16] investigated the optimal configuration methods for energy storage in grid-connected microgrids, achieving a reduction in the investment costs of energy storage systems. A review provided by Calero et al. [17] examined several rapidly evolving energy storage technologies, offering a comprehensive overview of their modeling. By determining the charging and discharging of energy storage based on market prices, García-Santacruz et al. [18] integrated energy storage in a P2P energy trading market. Han et al. [19] proposed a cooperative game framework based on nucleolus allocation, which minimizes the total cost by centrally optimizing energy storage scheduling in prosumer coalitions. Furthermore, Wang et al. [20] and Gao et al. [21] applied non-cooperative game theory, enabling individual owners of energy storage to decide on the maximum amount of energy to sell in a local market, thereby maximizing their utilities, which reflects the trade-off between energy trading revenue and the associated costs.

The above works mainly focus on independent energy storage, while works on the business model of shared energy storage are still in the early stages. Inspired by the idea of P2P energy trading, energy storage capacity trading and accompanying pricing mechanisms are primarily based on auction models and game theory. Game theory has been relatively widely applied under the topic of shared energy storage. A leader–follower game model is proposed by Mediwaththe et al. [22], where shared energy storage providers and retailers act as the leader and follower, respectively. The Vickrey–Clarke–Groves mechanism is employed for achieving a Stackelberg equilibrium and pricing. Xu et al. [23] introduced a data-driven pricing method, which conducts dynamic pricing through a leader–follower game to enhance the rationality of pricing. In the realm of cooperative game, Chen et al. [24] applied cooperative game to design a day-ahead scheduling model for integrated energy systems that use shared energy storage to reduce the operational

cost and allocate the benefit from accommodating more renewable energy among cooperative alliances. Considering the P2P trading participation of shared energy storage, Zhang et al. [25] proposed a multi-party cooperative game model, utilizing nucleolus and the Shapley value methods to distribute benefits. Similarly, Li et al. [26] also employed the Shapley value to rationally allocate the capacity and costs of shared energy storage systems on the wind farm side. However, the iterative process of the game inevitably involves solving optimization problems repeatedly and multi-party interaction, which may render this approach less practically appealing, especially when a large number of participants engage.

Auction-based energy storage sharing model allows users to bid competitively for energy storage capacity. A model proposed by Zhang et al. [27] allocates the right of use among energy storage resources through an auction mechanism. To address the issue of capacity allocation between multiple providers and residential users, Brijs et al. [28] proposed an improved auction mechanism that captures the interaction between the regulatory commission and the primary entities. Furthermore, Tushar et al. [29] proposed a combinatorial auction approach for the multi-resource allocation of shared energy storage among multiple electricity customers in a residential community, achieving a distributed auction that ensures all users faithfully complete the tasks in an ex post Nash equilibrium. However, matching buyers and sellers may yield uniform or bid-dominated clearing prices, failing to dynamically reflect the defect of energy storage capacity, namely the supply and demand relationship; moreover, bid matching is generally optimized locally at the participant level, which may neglect broader optimization. Additionally, in consideration of the varying behavioral preferences of participants, some works proposed multi-retail package services, where users can choose corresponding packages based on their demands, effectively enhancing the flexibility of users' choices [30,31].

For shared energy storage, providing profit channels through sharing capacity to renewable energy resources can enhance its economic viability, which is of significant importance for further promoting its deployment, especially for distributed energy storage. However, the business model for capacity allocation and pricing is still in its early stage of exploration. As discussed above, most of the existing works on shared energy storage focus on distributing the sharing-generated extra profits or savings, allocating and pricing shared energy storage capacity on the basis of game theory, and designing shared energy storage service packages. We summarize typical existing models that are based on game theory and auction frameworks in Table 1. By contrast, in this paper, inspired by the capacity and electricity markets that have been operated by Independent System Operators (ISOs) for more than decades, an energy storage flexibility market and an accompanying marginal pricing mechanism are innovated, differing from the game theory and auction frameworks.

**Table 1.** Comparison of models and pricing methods from typical references.

| Focused System | References | Based Theory | Model and Pricing Method |
| --- | --- | --- | --- |
| Microgrid | [2–5] | Double auction | The auction platform clears the bids according to certain rules |
| | [6–9] | Cooperative game | Form coalition, revenue is allocated based on member contributions |
| | [10–13] | Non-cooperative game | Nash equilibrium price formed based on game-theoretic strategies |

**Table 1.** *Cont.*

| Focused System | References | Based Theory | Model and Pricing Method |
| --- | --- | --- | --- |
| Independent energy storage | [18] | Double auction | Bilateral pairing method, prices are determined by participant bids |
| | [19] | Cooperative game | Nucleolus-based benefit allocation |
| | [20,21] | Non-cooperative game | Users optimize independently and reach the Nash equilibrium |
| Shared energy storage | [22,23] | Stackelberg game | The energy storage acts as the leader, and the market is settled at the Nash equilibrium |
| | [24–26] | Cooperative game | Cost allocation is based on the principles of the Shapley value or Nash bargaining |
| | [27–29] | Auction | Buyers bid and auctioneer matches supply/ demand to determine prices |
| | [30,31] | Package | Fixed-rate package |

Moreover, it is emphasized that in existing studies, DERs within the distribution system were explored for their participation in electricity markets; further, the potential of DERs to participate in ancillary service markets has been increasingly investigated. Indeed, most of these studies are from the perspective of ISOs, focusing on leveraging the potential of DERs and distributed energy storage for system operational cost reduction, transmission congestion management, and renewable energy accommodation. The absence of a dedicated market trading mechanism continues to hinder the full utilization of energy storage capacity. Therefore, this research aims to design a P2P market framework and a corresponding pricing mechanism to enable DERs to share surplus storage capacity with energy storage systems while ensuring revenue adequacy. To this end, this paper focuses on (1) how to design a scalable market mechanism to facilitate energy storage capacity sharing among DERs and (2) how to design the accompanying pricing mechanism to reflect supply–demand conditions while ensuring revenue adequacy.

The energy storage flexibility market proposed in this paper, adopting the perspective of P2P and sharing, promotes DERs and distributed energy storage to enhance complementarity within the distribution system. The proposed market can involve multiple suppliers and customers. The proposed energy storage flexibility market can involve multiple suppliers and customers. The numerical simulation of the proposed market model shows that it can accurately reflect the supply and demand relationship of capacity and effectively improve the market economic efficiency.

The contributions of this paper are twofold:

- An energy storage flexibility market that allows multiple vendors and customers to bid and be awarded for utilizing the capacity of shared energy storage is innovated.
- On the basis of the proposed energy storage flexibility market, a marginal pricing approach is developed to rationalize pricing and settle the market.

## 2. The Flexibility Market of Shared Energy Storage

### *2.1. The Energy Storage Flexibility Market Design*

Naming the modules that lend the energy storage capacities as vendors and the ones who rent these capacities as customers, this paper aims to innovate an energy storage flexibility market involving multiple vendors and customers as well as to design a marginal pricing approach referring to capacity and electricity markets administrated by the ISO.

ISO day-ahead power markets, although varying in specific operational policies and details for different regions sharing the same market mechanism, are a competitive

marketplace where electricity generation, transmission, and consumption are scheduled for the next operating day in a rolling manner. Participants, including generator owners, load-serving entities, and others (such as virtual traders), submit bids specifying the quantities and paired prices for electricity they are willing to buy or sell. Thereafter, the ISO solves day-ahead security-constrained unit commitment and economic dispatch problems to balance supply and demand while adhering to transmission constraints and satisfying system operational requirements, as well as to produce locational marginal prices on an hourly basis after clearing the market. We draw a parallel between the proposed model and ISO capacity markets considering they both focus on the trading of capacity rights, rather than the delivery of physical energy at a specific location and time. Indeed, the proposed market is designed as day-ahead because of taking into account the limited long-term planning ability of distribution-side participants. Compared to owners of large-scale generators on the transmission side, these participants exhibit greater variability, and shortening the contract duration can better endow them operational flexibility.

For small-scale solar and wind energy resource owners, investing in dedicated energy storage systems is often not the most economically optimal solution. In the established market shown in Figure 1, energy storage owners can separately lend charging and discharging capacities to renewable energy resource owners at individual hours. It is considered that there exists a centralized operator who is responsible for collecting bids, clearing the market, and ultimately settling the market. Energy storage owners who want to lend charging and discharging capacities and renewable energy resources who want to rent those capacities can submit their hourly desired prices and qualities (i.e., bids) in day-ahead during the bidding time window. The traded capacity quantities do not represent the actual power injection or withdrawal to the energy storage during operation, but rather the customers' right to use these amounts of capacity when needed. This market lowers the barrier to entry for managing renewable energy resources and enables broader participation in the energy transition, thereby enhancing social benefits.

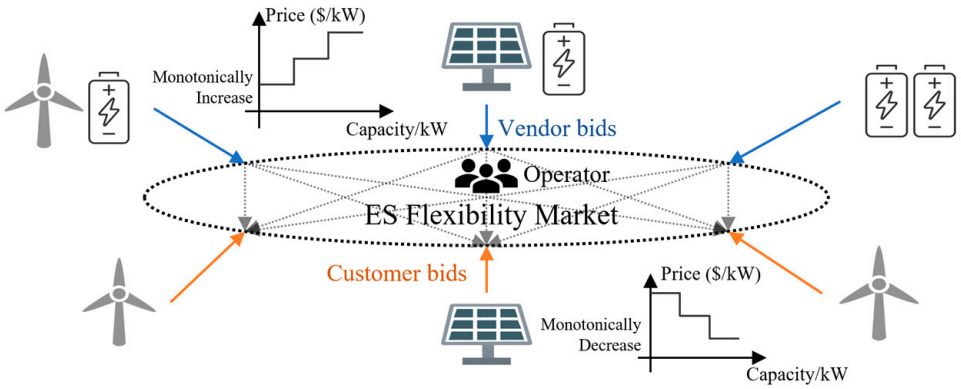



**Figure 1.** The day-ahead hourly energy storage flexibility market.

As shown in Figure 1, bids from vendors are required to be monotonically increasing stepwise curves to describe rising marginal costs, and bids from customers are required to be monotonically decreasing stepwise curves to indicate diminishing marginal returns. The step functions of bids could reflect their price elasticity characteristics. It is also required that bids from customers and vendors can be offered for either charging or discharging exclusively at individual hours. That is, a customer can be awarded as charging, discharging, or unawarded at each hour.

It is worthwhile to emphasize that what is traded in the proposed market is the charging and discharging capacities of shared energy storage, as well as the corresponding storage space. For instance, after being awarded a certain charging capacity in a specific

hour, the customer can utilize the allocated charging capacity of the vendor during that hour to inject energy; similarly, for discharging capacity in a specific hour, the customer can withdraw energy from the vendor at the awarded discharging capacity. Moreover, as energy storage devices are depicted via both power and energy discharging capacities, it is important to note that the product traded in the proposed market design is indeed power capacity as charging and discharging are elaborately distinguished above. Nevertheless, as the traded power capacity is implemented throughout an entire hour, with hourly timespan, it is indeed solidly connected to the energy capacity.

In addition, it is worthwhile to mention that as the market administrator, the operator typically allocates operational costs to the market participants. Considering the limited scale of distribution networks and the corresponding trading volumes, it may be financially unviable for a single distribution-level market to sustain an operator. To this end, multiple distribution-level markets (e.g., dozens or even hundreds) can be administered by a single market operator, thereby reducing the cost burden through shared expenses. Importantly, the distribution-level markets sharing the market operator are not interconnected but are simply operated by the same administrative entity.

### 2.2. The Energy Storage Flexibility Market Model

Although the designed energy storage flexibility market is inspired by the ISO capacity and electricity markets, it fundamentally targets at completely different products, contexts, and participants. As a result, the resulting market models are entirely distinct. It is worthwhile to emphasize that the model focuses on abstract representations of energy storage capacity vendors and customers, without explicitly modeling loads or other generation resources. The proposed energy storage flexibility market model is formulated as in (1)–(21). Similar to the ISO electricity market, Objective (1) is to maximize the social welfare that is equal to the benefit of the customers from purchasing the energy storage capacity minus the total cost of the vendors. We use $i$ to indicate customers and use $j$ to indicate vendors. They are collected, respectively, in sets $I$ and $J$. We use $t$ to indicate hours of a day that are collected in set $T = \{1, 2, \ldots, 24\}$. Step functions $f_{i,t}(\cdot)$ and $f_{j,t}(\cdot)$, as detailed in (2) and (4), represent, respectively, bids at hour $t$ from customers and vendors. $C^{c/d}_{i,t,s}$ ($c/d$ means $c$ or $d$) represent the bidding prices of customers, which should satisfy $C^{c/d}_{i,t,s-1} \geq C^{c/d}_{i,t,s}$, and $C^{c/d}_{j,t,s}$ represent the bidding prices of vendors, which should satisfy $C^{c/d}_{j,t,s-1} \leq C^{c/d}_{j,t,s}$. Subscript $s$ indicates the bidding segments and $[0, P^{c/d}_{i,t,s}]$ and $[0, P^{c/d}_{j,t,s}]$ restrict quantity ranges of $p^{c/d}_{i,t,s}$ and $p^{c/d}_{j,t,s}$.

Variables $p^{c}_{i,t}$ and $p^{d}_{i,t}$ represent the total awarded capacity to customer $i$ from all vendors for charging and discharging. Variables $p^{c}_{j,t}$ and $p^{d}_{j,t}$ are defined similarly for vendors. Constraints (6) and (7) map $p^{c}_{i,j,t}$ and $p^{d}_{i,j,t}$ to $p^{c}_{i,t}$ and $p^{d}_{i,t}$, where $p^{c}_{i,j,t}$ and $p^{d}_{i,j,t}$ represent, respectively, the awarded charging and discharging capacities from vendor $j$ to customer $i$ at hour $t$. In Constraints (8) and (9), $P^{c}_{i,j,t}$ and $P^{d}_{i,j,t}$ represent, respectively, the fixed charging and discharging capacity demands from customer $i$ to vendor $j$. It is worthwhile to mention that to avoid infeasibility, $P^{c}_{i,j,t}$ and $P^{d}_{i,j,t}$ can be converted to bids with high bidding prices. Similarly, Constraints (8) and (9) map $p^{c}_{i,j,t}$ and $p^{d}_{i,j,t}$, as well as $P^{c}_{i,j,t}$ and $P^{d}_{i,j,t}$, to $p^{c}_{j,t}$ and $p^{d}_{j,t}$. Constraints (10) and (11) force $p^{c}_{i,j,t}$ and $p^{d}_{i,j,t}$ to be non-negative, and thereby $p^{c}_{i,t}$, $p^{d}_{i,t}$, $p^{c}_{j,t}$, and $p^{d}_{j,t}$ to be non-negative as well.

Constraints (12) and (13) limit the charging and discharging power with the physical upper bounds of energy storage. Binary variables $I^{c}_{j,t}$ and $I^{d}_{j,t}$, as in (15), are introduced to indicate the charging and discharging modes of vendor $j$ at hour $t$. They could help enforce the minimum charging and discharging power as specified in (12) and (13). Constraint (14) prevents simultaneous charging and discharging. On the one hand, (14) can reduce con-

fusion on simultaneously charging and discharging, and on the other hand may facilitate the solving process, functioning like a cut that excludes a subset of solutions. Moreover, it is worthwhile to emphasize that Constraints (12) and (13) imply the traded charging and discharging capacities can be internally offset. When $p^c_{j,t} > p^d_{j,t}$, the energy storage is in the charging mode, and then $I^c_{j,t} = 1$ and $I^d_{j,t} = 0$, which relaxes Constraint (13) as $-M \leq p^d_{j,t} - p^c_{j,t} \leq 0$; similarly, when $p^c_{j,t} < p^d_{j,t}$, then $I^c_{j,t} = 0$ and $I^d_{j,t} = 1$, and Constraint (12) is relaxed as $-M \leq p^c_{j,t} - p^d_{j,t} \leq 0$. For the extreme case of $p^c_{j,t} = p^d_{j,t}$ at hour $t$, the energy storage is indeed idle. Intuitively, power flows from customers who have excessive energy to the customers who need to charge through the energy storage. For Constraints (16) and (17), in addition to bidding quantities, physical charging and discharging limits of customers are set.

State of charge (SOC) evolution of vendors is represented as in (18) and (19), which is further limited by the lower and upper bounds $\underline{E}_j$ and $\overline{E}_j$ as in (20). In (18) and (19), $r_j$ is the charging/discharging efficiency; and the initial $E_{j,0}$ at $t = 0$ is a given parameter. Constraint (21) is an important formulation that is innovatively added to describe a unique feature of the proposed energy storage flexibility market. Constraint (21) requires that the energy withdrawn by any customer at any time is no greater than the energy it previously stored while accounting for the cycling efficiency, which means the customer is not allowed to borrow any vendor-owned energy, even if it could pay it back at a later time. It eliminates "buy on credit". This feature stems from the consideration that borrowing energy deprives the opportunity of arbitraging from the vendors or other customers with the stored energy, which is not compensated by the pricing in the flexibility market. In Constraint (21), $E_{i,j,0}$ is the carryover energy that represents the remaining energy of customer $i$ in vendor $j$ in the previous day, which is further discussed in detail in the next section. As reflected in the model, loads and other generation resources are not modeled, and therefore flow constraints are not enforced. In fact, in capacity markets of ISOs, power flow constraints are not directly included, and the primary goal of the markets is to ensure resource adequacy at the system level.

The objective of social welfare maximization:

$$\begin{aligned} max & \sum_{t\in T}\sum_{i\in I} f_{i,t}\left(p^c_{i,t}\right) + \sum_{t\in T}\sum_{i\in I} f_{i,t}\left(p^d_{i,t}\right) \\ & -\sum_{t\in T}\sum_{j\in J} f_{j,t}\left(p^c_{j,t}\right) - \sum_{t\in T}\sum_{j\in J} f_{j,t}\left(p^d_{j,t}\right); \end{aligned} \tag{1}$$

The bid function of customers:

$$f_{i,t}\left(p^{c/d}_{i,t}\right) = \sum_{s\in S_{i,t}} C^{c/d}_{i,t,s} \cdot p^{c/d}_{i,t,s}; \tag{2}$$

$$p^{c/d}_{i,t} = \sum_{s\in Si,t} p^{c/d}_{i,t,s}; 0 \leq p^{c/d}_{i,t,s} \leq P^{c/d}_{i,t,s}; \tag{3}$$

The bid function of vendors:

$$f_{j,t}\left(p^{c/d}_{j,t}\right) = \sum_{s\in S_{j,t}} C^{c/d}_{j,t,s} \cdot p^{c/d}_{j,t,s}; \tag{4}$$

$$p^{c/d}_{j,t} = \sum_{s\in S_{j,t}} p^{c/d}_{j,t,s}; \; 0 \leq p^{c/d}_{j,t,s} \leq P^{c/d}_{j,t,s}; \tag{5}$$

Capacity allocation mapping:

$$p^c_{j,t} = \sum_{i\in I} p^c_{i,j,t} + \sum_{i\in I} P^c_{i,j,t}; \quad \forall j \in J, \quad \forall t \in T\left(\lambda^c_{j,t}\right) \tag{6}$$

$$p_{j,t}^{d} = \sum_{i \in I} p_{i,j,t}^{d} + \sum_{i \in I} P_{i,j,t}^{d}; \quad \forall j \in J, \quad \forall t \in T\left(\lambda_{j,t}^{d}\right) \tag{7}$$

Capacity demand mapping:

$$p_{i,t}^{c} = \sum_{j \in J} p_{i,j,t}^{c} + \sum_{j \in J} P_{i,j,t}^{c}; \quad \forall i \in I, \forall t \in T \tag{8}$$

$$p_{i,t}^{d} = \sum_{j \in J} p_{i,j,t}^{d} + \sum_{j \in J} P_{i,j,t}^{d}; \quad \forall i \in I, \forall t \in T \tag{9}$$

Constraints of non-negative variables:

$$p_{i,j,t}^{c} \geq 0; \quad \forall i \in I, \forall j \in J, \forall t \in T \tag{10}$$

$$p_{i,j,t}^{d} \geq 0; \quad \forall i \in I, \forall j \in J, \forall t \in T \tag{11}$$

The power limit constraints of vendors:

$$\underline{P}_{j}^{c} \cdot I_{j,t}^{c} - M \cdot I_{j,t}^{d} \leq p_{j,t}^{c} - p_{j,t}^{d} \leq \overline{P}_{j}^{c} \cdot I_{j,t}^{c}; \quad \forall j \in J, \forall t \in T \tag{12}$$

$$\underline{P}_{j}^{d} \cdot I_{j,t}^{d} - M \cdot I_{j,t}^{c} \leq p_{j,t}^{d} - p_{j,t}^{c} \leq \overline{P}_{j}^{d} \cdot I_{j,t}^{d} \quad \forall j \in J, \forall t \in T \tag{13}$$

The charging and discharging states of vendors:

$$I_{j,t}^{c} + I_{j,t}^{d} \leq 1; \quad \forall j \in J, \forall t \in T \tag{14}$$

$$I_{j,t}^{c}, I_{j,t}^{d} \in \{0,1\}; \quad \forall j \in J, \forall t \in T \tag{15}$$

The power limit constraints of customers:

$$0 \leq p_{i,t}^{c} \leq \overline{P}_{i}^{c}; \quad \forall i \in I, \forall t \in T \tag{16}$$

$$0 \leq p_{i,t}^{d} \leq \overline{P}_{i}^{d}; \quad \forall i \in I, \forall t \in T \tag{17}$$

The SOC constraints of vendors:

$$E_{j,1} = E_{j,0} + p_{j,1}^{c} \cdot r_j - p_{j,1}^{d} / r_j; \quad \forall j \in J \tag{18}$$

$$E_{j,t} = E_{j,t-1} + p_{j,t}^{c} \cdot r_j - p_{j,t}^{d} / r_j; \quad \forall j \in J, \forall t \in T \tag{19}$$

The SOC limit constraint of vendors:

$$\underline{E}_{j} \leq E_{j,t} \leq \overline{E}_{j}; \quad \forall j \in J, \forall t \in T \tag{20}$$

The energy borrowing constraint of customers:

$$E_{i,j,0} + \sum_{\tau=1}^{t} \left( p_{i,j,\tau}^{c} \cdot r_j - p_{i,j,\tau}^{d} / r_j \right) \geq 0; \quad \forall i \in I, \forall j \in J, \forall t \in T \tag{21}$$

## 3. The Carryover Energy and the Marginal Pricing Mechanism

### 3.1. The Carryover Energy

From Constraint (21), it is possible that after the market clearing, the stored energy of some customers is finally not fully discharged, e.g., a customer is awarded for charging at an earlier time but not for discharging at a later time. We refer to the remaining energy as carryover energy, namely $E_{i,j,0}$ in (21). Carryover energy can enable early discharging of customers but correspondingly affects $E_{j,0}$. To this end, a time length-related holding tariff might be applied to motivate customers to bid a higher price for releasing carryover energy on the next operation day. Limiting or completely forbidding carryover energy is also pos-

sible by involving Constraints (22) or (23). In Constraint (22), $E_{i,j,24}$ represents the threshold of the carryover energy. The setting of $E_{i,j,24}$ could be related to the sizes of customer $i$ and vendor $j$. Constraint (22) allows limited carryover energy, while Constraint (23) completely prohibits carryover energy, requiring that all energy stored on the same day should be fully consumed. However, compared with simply including (21), applying (22) or (23) additionally could create more complicated couplings on the clearing result of charging and discharging capacity bids, posing a challenge in analyzing bidding parameters and the consequent market clearing results.

$$E_{i,j,0} + \sum_{\tau=1}^{24} \left( p^c_{i,j,\tau} \cdot r_j - p^d_{i,j,\tau} / r_j \right) \leq E_{i,j,24}; \quad \forall i \in I, \forall j \in J \tag{22}$$

$$\sum_{\tau=1}^{24} \left( p^c_{i,j,\tau} \cdot r_j - p^d_{i,j,\tau} / r_j \right) = 0; \quad \forall i \in I, \forall j \in J \tag{23}$$

### 3.2. The Marginal Pricing Mechanism

Intuitively, the flexibility market Model (1)–(21) is a mixed integer linear programming problem because of the presence of binary variables $I^c_{j,t}$ and $I^d_{j,t}$, and thus the strong duality fails to hold, similar to the day-ahead electricity market, after the unit commitment problem is first solved to obtain the solutions to binary variables. Binary variables are fixed, degenerating the originally mixed-integer linear programming (MILP) into a linear programming problem that holds strong duality and can be efficiently solved by simplex algorithm with the global optimal solution. Therefore, Problems (1)–(21) are solved first for obtaining solutions to variables $I^c_{j,t}$ and $I^d_{j,t}$, and then the degenerated linear programming problem can be obtained. With the strong duality, dual variables can be obtained in solving the linear programming problem. Particularly, dual variables $\lambda^c_{j,t}$ and $\lambda^d_{j,t}$ corresponding to Constraints (6) and (7) are used to derive the marginal price through the Lagrange function.

Referring to the locational marginal price [32], we consider an incremental charging demand that has to be supplied by $p^c_{j,t}$ on vendor $j$ at hour $t$, and the Lagrange function can be written as in (24), where $\Delta P^c_{j,t}$ represents the incremental charge in load. In Lagrange function (24), $\mathcal{O}$ represents the objective function and $\hat{\mathcal{L}}$ compactly represents terms that are not related with $\Delta P^c_{j,t}$. This is indeed analogous to the electricity market. Locating $\sum_{j \in J} P^c_{i,j,t}$ is similar to locating fixed load which exists in the power balance constraints and line flow limit constraints. In the flexibility market Model (1)–(21), the fixed charging demand exists only in Constraint (6). Then, the marginal price of vendor $j$ for charging capacity at hour $t$ can be calculated as in (25).

$$\mathcal{L} = \mathcal{O} + \hat{\mathcal{L}} + \lambda^c_{j,t} \cdot \left( \sum_{i \in I} p^c_{i,j,t} + \sum_{j \in J} P^c_{i,j,t} + \Delta P^c_{j,t} - p^c_{j,t} \right); \tag{24}$$

$$\rho^c_{j,t} = \frac{\partial \mathcal{L}}{\partial \Delta P^c_{j,t}} = \lambda^c_{j,t}; \tag{25}$$

Similarly, considering an incremental discharging load on vendor $j$ at hour $t$ that has to be supplied by $p^d_{j,t}$, the Lagrange function can be written as in (26). Intuitively, $\mathcal{O}$ and $\hat{\mathcal{L}}$ have the same meanings as in (24), where $\Delta P^d_{j,t}$ represents the incremental discharging load. Obviously, in the flexibility market Models (1)–(21), the fixed discharging demand exists only in Constraint (7). Then, the marginal price of vendor $j$ for discharging capacity at hour $t$ can be calculated as in (27).

$$\mathcal{L} = \mathcal{O} + \hat{\mathcal{L}} + \lambda^d_{j,t} \cdot \left( \sum_{i \in I} p^d_{i,j,t} + \sum_{j \in J} P^d_{i,j,t} + \Delta P^d_{j,t} - p^d_{j,t} \right); \tag{26}$$

$$\rho_{j,t}^{d} = \frac{\partial \mathcal{L}}{\partial \Delta p_{j,t}^{d}} = \lambda_{j,t}^{d}; \tag{27}$$

From (25) and (27), the marginal prices are vendor-wise and hour-wise. Indeed, with Constraints (12), (13), (18), and (19), $\rho_{j,t}^{c}$ and $\rho_{j,t}^{d}$ can implicitly reflect power capacity deficit and energy capacity deficit. After market clearing, the market clearing prices are calculated. Vendors are paid and customers pay at the calculated marginal prices. It is straightforward that $\rho_{j,t}^{c}$ and $\rho_{j,t}^{d}$ guarantee revenue adequacy, as they are linked with $p_{i,t}^{c}$ and $p_{i,t}^{d}$ through $p_{i,j,t}^{c}$ and $p_{i,j,t}^{d}$ to ensure that the payment from customers and the income to vendors are always equal. Based on the Karush–Kuhn–Tucker (KKT) complementary slackness condition, (28) can be derived, from which (29) further follows. Therefore, (30) shows the revenue adequacy can be always guaranteed.

$$\begin{cases} \lambda_{j,t}^{c} \cdot \left( \sum_{i \in I} p_{i,j,t}^{c} + \sum_{i \in I} P_{i,j,t}^{c} - p_{j,t}^{c} \right) = 0 \\ \lambda_{j,t}^{d} \cdot \left( \sum_{i \in I} p_{i,j,t}^{d} + \sum_{i \in I} P_{i,j,t}^{d} - p_{j,t}^{d} \right) = 0 \end{cases} \tag{28}$$

$$\sum_{i \in I} \rho_{j,t}^{c/d} \cdot (p_{i,j,t}^{c/d} + P_{i,j,t}^{c/d}) = \rho_{j,t}^{c/d} \cdot p_{j,t}^{c/d} \tag{29}$$

$$\underbrace{\sum_{i \in I} \rho_{j,t}^{c/d} \cdot p_{i,t}^{c/d}}_{\text{Total payments from customers}} = \underbrace{\sum_{j \in J} \rho_{j,t}^{c/d} \cdot p_{j,t}^{c/d}}_{\text{Total revenue to vendors}} \tag{30}$$

By adopting a marginal-cost-based pricing approach, the market clearing price reflects actual supply and demand conditions, leading to a more fair and rational pricing mechanism. In addition, revenue adequacy is ensured, which helps support the financial viability of the market.

## 4. Case Study

The study was initially conducted using a small-scale market that consists of four vendors and six customers to demonstrate the core principles of the proposed market mechanism. For comparison purposes, the four vendors are set with identical physical parameters but with different bids. Specifically, $\overline{P}_{j}^{d}$ / $\overline{P}_{j}^{c}$, $\overline{E}_{j}$, and $r_{j}$ for individual vendors are set as 100 kW, 800 kWh, and 0.9, respectively. The customers are represented merely by bids over time. Then, the study is expanded to a larger-scale scenario involving 50 participants to further evaluate the mechanism's scalability and effectiveness in more extensive market environments. Additionally, simulation results from three different scenarios are compared to verify the rationality of the clearing price. The numerical simulation is conducted with MATLABR2024a.

### *4.1. The Markets Without Power and Energy Capacity Deficit*

In Case 1, the bidding behavior of all customers is specifically defined as follows: they are set to bid for charging in hours 1–8, discharging in hours 9–16, and charging again in hours 17–24. After the market clearing, the vendor-wise and hour-wise charging and discharging prices derived by the marginal pricing mechanism are shown in Figure 2. The charging and discharging prices are the prices that customers need to pay when charging and discharging to the corresponding vendors, respectively. Charging prices rise in hours 1–8 and 17–24 as all customers bid for charging; conversely, for the remaining hours, because of the charging demand being zero, charging prices fall to zero. Discharging prices, on the other hand, present an opposite trend. They rise during hours 9–16 when customers are discharging and fall during the charging hours. With this, the total payment collected from the customers is USD 180.41, equal to the amount payable to the vendors, which verifies the revenue adequacy.




**Figure 2.** The charging and discharging prices in Case 1.

Based on Case 1, we conduct a case study without Constraint (19). It can be seen that, compared to Case 1, the social welfare increases by 1.76%. In the meantime, three out of the four vendors have an increase in their traded volumes. Intuitively, this is because allowing "borrowing" energy enables customers to utilize the stored energy of vendors in advance during the early discharging period and return it later.

In Case 2, the bidding behavior of customers is adjusted based on their energy sources. Customers #1–#3, representing photovoltaic-type customers, keep the same bidding prices as in Case 1, while customers #4–#6, representing wind power-type customers, adopt a different bidding strategy: they bid for discharging, charging, and then discharging again. The resulting charging and discharging prices of Case 2 are depicted in Figure 3. Compared with Case 1 in which no carryover energy is left, the altered bidding patterns in this case lead to a significant difference. Specifically, the previously charged energy is not fully discharged due to the changed bidding patterns, leading to positive carryover energy. In the last 16 h, the charging and discharging behaviors of customers are discrepant. Both $p^d_{j,t}$ and $p^c_{j,t}$ are greater than 0. However, since $p^d_{j,t}$ and $p^c_{j,t}$ are allowed to offset each other, the vendor ultimately presents a comprehensive state. Taking vendor #1 as an example, $p^d_{1,9}$ = 40 kwh and $p^c_{1,9}$ = 60 kwh, which means vendor #1 is in the charging state, while $p^c_{1,17}$ = 40 kwh and $p^d_{1,17}$ = 60 kwh, which means vendor #1 is in the discharging state at hour 17. According to awarded capacities, the carryover energy of vendors is 720 kWh, containing 288 kWh from customer #2 and 432 kWh from customer #3, who bid for charging again in late hours 17 to 24. This additional charging demand in the later hours results in a substantial amount of energy being carried over, as it was not fully utilized during the discharging phase.

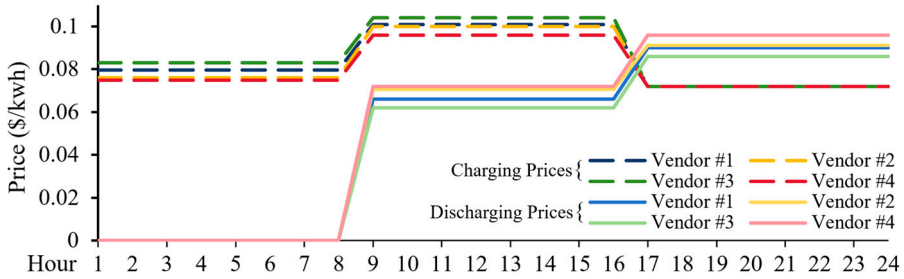



**Figure 3.** The charging and discharging prices in Case 2.

Furthermore, comparing the two cases, several notable differences in the charging and discharging prices can be observed. Specifically, the charging prices are reduced in Case 2 due to the decreased charging demand in the first 8 h. In Case 1, all customers bid for charging during these hours, creating a high demand that drives prices up. Another important factor influencing the prices is Constraint (19), which prohibits arbitraging by borrowing energy from the vendors. This constraint invalidates the discharging bids of customers #4–#6 during the first 8 h, setting discharging prices to zeros at this early stage. In addition, since the bidding prices of customers #4–#6 are higher than those of customers

#1–#3, both charging prices in hours 9 to 16 and discharging prices in hours 17 to 24 increase. High demand, created by homogeneous bids of customers, is the driven force of rising the market clearing prices.

On the basis of Case 2, we extend the number of participants to 50, including 20 vendors and 30 customers and take this case as Case 3. We set customers #1–#14 as photovoltaic-type customers. They bid for discharging for hours 9–16. Customers #15–#30 are wind power-type customers that bid for charging at the same time period. The solving time of Case 2 is 3 s and that of this newly added Case 3 is 47 s. It can be seen that the increased number of participants would increase the solving time of the proposed market model to some extent. However, it can still be solved within tens of seconds, which means computational burden is not a main concern. Moreover, as the market is day-ahead, solving it is not a time-intensive task. In Case 3, the total payments from the customers and finally to the vendors are equal, which verifies the revenue adequacy again. With Case 3, we reduce the energy storage efficiency from 0.9 to 0.8. After clearing the market, the results show that the total traded volume is reduced by 11% and the social welfare is reduced by 4.2%.

### *4.2. The Markets with Power and Energy Capacity Deficit*

In Case 4 and Case 5, all customers are set to bid for charging in the first 8 h and discharging in the remaining 16 h of the operation day. In addition, with the increased demand, Constraints (10) and (18) become binding, causing power and energy capacity deficits in Case 4 and Case 5, respectively. The energy capacity deficit is first investigated, followed by the investigation of the power capacity deficit.

The charging and discharging prices of Case 4 and Case 5 are shown in Figures 4 and 5. These figures provide a detailed view of how prices fluctuate in response to the binding constraints and the overall market conditions. The bidding capacities lead to the binding of Constraint (18) at hour 8 ($E_{j,8} = \overline{E}_j$ = 800 kWh), i.e., an energy capacity deficit occurs. Although Constraint (18) only becomes binding at hour 8, the charging prices in hours 1 to 8 all rise. This is because of the time-coupling nature of Constraint (18), indicating any charging action in hours 1 to 8 causes severe binding of Constraint (18). This also demonstrates that price signals could reflect upcoming energy capacity deficit. Essentially, the market anticipates the deficit and adjusts prices accordingly to reflect the potential strain on capacity. Additionally, pursuing social welfare maximization, the discharging prices are negative in hours 1 to 8 to encourage discharging when possible. Moreover, in this case, the total payments from the customers and to the vendors are equal, i.e., USD 388.49, which further verifies the revenue adequacy even when a deficit happens. This demonstrates that even under conditions of capacity deficits, the system can still achieve financial adequacy. In addition, the demand is suppressed through the high price of charging and supply is stimulated by the negative price of discharging.

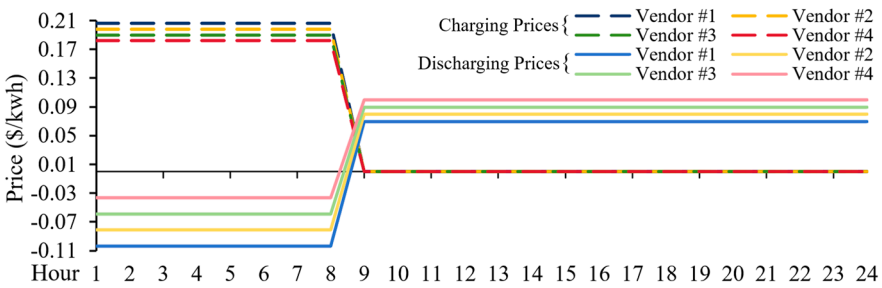



**Figure 4.** The charging and discharging prices in Case 4.




**Figure 5.** The charging and discharging prices in Case 5.

Based on Case 4, in Case 5, $\overline{E}_j$ in Constraint (18) is increased sufficiently to make Constraint (10) bind earlier than (18) in the first 8 h ($p^c_{1-3,1-8} = \overline{P}_j$= 100 kW). In this case, a power capacity deficit happens. Similarly, compared with Case 1, because (10) binds at hours 1 to 8, the charging prices increase, which directly reflects the limited power capacity available for charging during this period. At the same time, negative discharging prices appear to encourage discharging as much as possible to ease the power capacity deficit. Negative prices occur because, as shown in (10), the essence is opportunity cost compensation; charging and discharging powers can offset each other. Furthermore, by analyzing the awarded capacity of each vendor after market clearing, it can be found that during charging, vendor #1 with a higher bidding price has a relatively higher clearing power capacity. Conversely, during the discharging process, vendor #4 with a lower bidding priced is prioritized. This indicates that the clearing power capacity can match the charging and discharging capabilities of vendors with the demands of customers through market clearing. This not only addresses the immediate power and energy capacity deficit but also demonstrates the market's ability to adapt and optimize resource utilization through dynamic pricing mechanisms.

### *4.3. The Markets with the Carryover Energy Constraints*

In Case 6 and Case 7, all customers are set to bid for charging in the first 12 h and for discharging in the remaining 12 h of the operation day, but with Constraint (21) added for Case 7. The charging and discharging prices of Case 6 and Case 7 are shown in Figures 6 and 7, respectively.

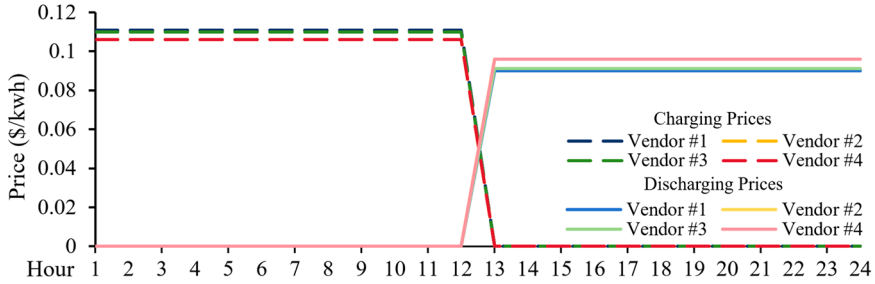



**Figure 6.** The charging and discharging prices in Case 6.

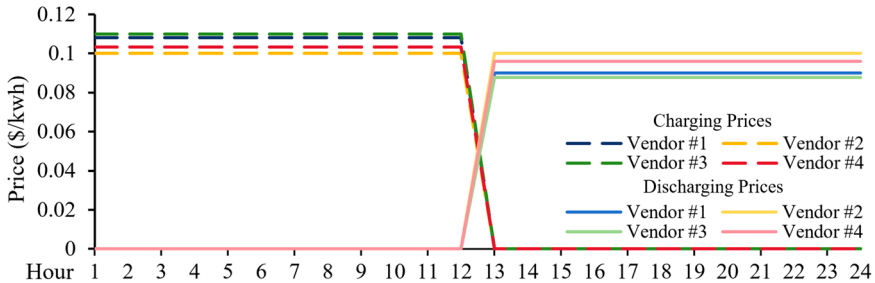



**Figure 7.** The charging and discharging prices in Case 7.

Considering the carryover energy Constraint (21) results in a complete prohibition of carryover energy, and thus at hour 24, $E_{j,24}$ is equal to $E_{j,0}$ (200 kWh) for sure. Compared with Case 6, the market clearing price changes. In the first 12 h, since vendor #3 is awarded more than others, the charging prices of the remaining vendors decrease; conversely, for the remaining hours, vendors #1, #2, and #4 are awarded more, i.e., the usage of vendor #3 decreases in comparison, leading to reduction in its discharging prices. In addition, in order to ensure that the carryover energy of vendor #2 is zero, its energy is consumed more quickly during the discharging process, leading to a slight increase in discharging prices. This also indicates that the carryover energy constraint could alert price signals. The total payments from the customers and to the vendors are equal to USD 74.08, achieving revenue adequacy as well.

## 5. Conclusions

This paper proposes a novel marginal pricing-based energy storage flexibility market, which allows multiple distributed vendors and customers to submit bids for storage capacity rights. By coupling power and energy capacities and adopting the marginal pricing method, which clears the market at the price where the last accepted bid matches the last accepted offer, the market aims to efficiently allocate resources and ensure computational efficiency even as participant numbers increase. Numerical simulation results show that the derived marginal price can properly reflect the supply and demand relationship delivered by the bids, implicitly representing the deficits in power and energy capacities. Furthermore, the mechanism guarantees revenue adequacy regardless of the presence of power and energy capacity deficits, as well as the prohibition of carryover energy.

The market model proposed in this paper focuses on the trading of the right for renewable energy resources to utilize a certain amount of storage and charging/discharging capacity when needed. Accordingly, in terms of modeling, the market participants are simplified as abstract vendors and customers that are represented by their bids only. Considerations of their specific operational constraints could be enhanced and explicit bidding strategies for participants remain to be explored. Future work will further refine the proposed market model and investigate bidding strategies of different participants. Potential directions include incorporating uncertainty associated with renewable generation.

**Author Contributions:** Conceptualization, Y.L.; methodology, X.L.; validation, X.L.; investigation, X.L. and Y.L.; writing—original draft preparation, X.L.; writing—review and editing, T.L. and Y.L.; supervision, T.L. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research received no external funding.

**Data Availability Statement:** The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding authors.

**Acknowledgments:** The authors sincerely thank the editors and reviewers.

**Conflicts of Interest:** The authors declare no conflicts of interest.

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