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Energy Storage Sharing for Multiple Services Provision: A Computable Combinatorial Auction Design

Bo Wei [1], Wenfei Liu [2], Chong Shao [1], Yong Yang [2], Yanbing Su [3] and Zhaoyuan Wu [3,*]

[1] State Grid Gansu Electric Power Company, Lanzhou 730030, China; edisonjoke@163.com (B.W.); shaoch_dkzx@gs.sgcc.com.cn (C.S.)
[2] State Grid Gansu Electric Power Research Institute, Lanzhou 730070, China; liuwenfeitgh@163.com (W.L.); yy8801@163.com (Y.Y.)
[3] State Key Laboratory of Alternate Electrical Power System with Renewable Energy Sources, North China Electric Power University, Beijing 102206, China; 120212201183@ncepu.edu.cn
* Correspondence: wuzy@ncepu.edu.cn

Abstract: Given the profound integration of the sharing economy and the energy system, energy storage sharing is promoted as a viable solution to address the underutilization of energy storage and the challenges associated with cost recovery. While energy storage sharing offers various services for system operation, a significant question remains regarding the development of an optimal allocation model for shared energy storage in diverse application scenarios and the proposal of efficient solving algorithms. This paper presents the design of a computable combinatorial mechanism aimed at facilitating energy storage sharing. Leveraging the distinct characteristics of buyers and sellers engaged in energy storage sharing, we propose a combinatorial auction solving algorithm that prioritizes and incorporates the offers of shared energy storage, accounting for temporal variations in the value of energy resources. The numerical results demonstrate that the proposed solving algorithm achieves a computation time reduction of over 95%, adequately meeting the practical requirements of industrial applications. Importantly, the proposed method maintains a high level of computational accuracy, ranging from 92% to 98%, depending on the participants and application scenarios. Hopefully, our work is able to provide a useful reference for the further mechanism design for energy storage sharing.

Keywords: computational algorithms design; combinatorial auction; energy storage sharing; multiple services provision

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1. Introduction

1.1. Motivation

Driven by the dual carbon goal, building a new type of power system that adapts to the gradually increasing proportion of new energy has become the development form of future electrical energy development [1]. The integration of a large number of new energy sources has also brought new challenges to the flexible and efficient operation of the power system [2]. In recent years, with the development and maturity of energy storage, new energy storage resources with rapid response capability, represented by electrochemical energy storage, are regarded as the key to weakening the uncertainty of both supply and demand and ensuring the low-carbon, safe and flexible operation of the new power system [3–5]. On the one hand, energy storage can achieve spatiotemporal translation of electrical energy, transforming the original electrical balance of the power system into surface balance, improving the supply- and demand-matching ability of the power system. On the other hand, it can also delay investment in transmission and distribution assets to a certain extent, which can play a non-wire alternative value [6–8].

Although energy storage resources can provide multi-dimensional support capabilities for the system, they can fundamentally solve the challenges posed by large-scale new energy integration to the adequacy of the power system [9]. However, in practical operation, the imperfect market mechanism of auxiliary services limits the profitability of energy storage in the market, and also leads to significant differences in the systematic value and actual monetization value of energy storage [10]. On the other hand, due to the limitations of energy storage ownership and different market access conditions, the current energy storage utilization rate is relatively insufficient, further limiting the cost recovery of energy storage. The energy storage system has characteristics such as high investment cost, long investment payback period, and poor self-sufficiency. Scholars have proposed the model of shared energy storage, which is essentially the application of the shared economy in the energy field, aiming to improve the utilization rate of energy storage resources. Compared to traditional energy storage configuration methods, energy storage sharing has a series of characteristics such as easy scheduling, diversified returns, high utilization rate, and short investment payback period [11–13].

Not only limited to theoretical research in academia, shared energy storage has shown strong application potential and value in various aspects of the power supply chain. Generally speaking, energy storage sharing is a commercial operation model in which a third party or manufacturer is responsible for investment, operation and maintenance, and leases the power and capacity of the energy storage system to the target user in the form of commodities as a lessor, adhering to the principle of "who benefits, who pays" to collect rent from the lessee [14,15]. Users can utilize the power of shared energy storage charging and discharging to meet their own energy supply needs within the service time limit, without the need to independently build energy storage power stations, greatly reducing the original capital investment [16]. Compared with the high investment cost and poor controllability of traditional energy storage power stations, shared energy storage has the advantages of high emptiness, improved utilization rate and guaranteed cost dispersal. In recent years, with the advancement of digital technologies such as blockchain, energy storage sharing among large-scale market members has become possible [17–20]. In detail, the advancement of the shared energy storage business model holds significant economic value. Firstly, it enhances the flexibility of system operation and facilitates the integration of renewable energy sources within the system. Moreover, it benefits energy storage investors by improving the utilization rate of energy storage and reducing the investment payback period. Secondly, shared energy storage contributes to the establishment of an independent market presence for energy storage and fosters market mechanisms tailored to energy storage participation.

1.2. Literature Review

In recent years, numerous studies have concentrated on the operational models of shared energy storage in various application scenarios. These models can be broadly categorized into two main approaches. (1) The first approach utilizes auction theory to allocate shared energy storage resources among different market members or implements distributed peer-to-peer trading to enhance the utilization rate of energy storage resources and mitigate investment risks [21–23]; in [21], the authors proposed an application scenario for energy storage sharing among configured distributed PV users, and altogether quantitatively assessed the potential benefits of a shared energy storage model in urban energy systems. In [22], the authors proposed an overall framework for adapting energy storage sharing under peer-to-peer trading model, based on which, the authors of [23] further designed a corresponding transaction settlement mechanism under the framework of distributed peer-to-peer trading, aiming to stimulate the sharing of idle energy storage resources in seeking and thus the utilization of energy storage resources. (2) The second approach, based on cooperative game theory, involves the formation of alliances among energy storage and other market participants to collectively engage in the market. Within these alliances, energy storage resources are shared, and the resulting cooperative surplus is distributed among the alliances based on their respective contributions [24–26]. Admittedly, the above research provides a very valuable reference for promoting the development of shared energy storage. For the optimization research of shared energy storage, however, the key issue ignored in the literature is that if the shared energy storage is regarded as a new business model, and the right to use the power/capacity parameters of the shared energy storage in a specific period of time is taken as the subject matter, the auction of the right to use energy storage is inseparable from the traditional electricity energy trading. Actually, the demand of different users for shared energy storage is a certain combination of charge and discharge power and capacity, and its essence is a combinatorial auction process, which is specifically reflected in the mathematical model. The power and capacity parameter demands of energy storage resources declared by users at different times must be met simultaneously instead of only partially. Therefore, what it needs is a dynamic matching process between energy storage demand and corresponding idle and shareable energy storage resources.

In this context, the problem of energy storage sharing considering multi-dimensional attribute coupling has also been studied from the perspective of combinatorial auctions. The authors of [27] focus on the auction problem of energy storage sharing considering both the capacity and power allocation of energy storage. In [28], a combinatorial double auction mechanism for energy storage sharing is proposed, the complex offer constraint of the combinatorial auction is simplified to a mixed integer linear programming model. However, in fact, the combinatorial auction of energy storage sharing is a typical NP-hard problem that is difficult to solve in polynomial time, and its computational complexity will grow exponentially with the increase of market members, which poses a challenge to practical applications. In [29], a greedy-based algorithm is designed for the combinatorial auction of energy storage sharing. However, only the single-side auction is taken into account, which cannot meet the practical requirements for many-to-many in energy storage sharing. In [30], a fully polynomial-time approximation algorithm is designed that can achieve the solution of the combinatorial auction problem in polynomial time, however, its scenario is limited to peak-valley spread arbitrage on the user side with limited generalization capability. It is difficult to adapt to the practical system requirements for multi-application scenarios, which makes the proposed combinatorial auction mechanism for energy storage much less meaningful.

1.3. Contributions

To fill the aforementioned gap, this paper will deeply research the combinatorial auction mechanism of shared energy storage considering multiple application scenarios. The contributions are summarized as follows:

(1) We establish a framework for a shared energy storage combinatorial auction that incorporates multi-dimensional parameter coupling. The allocation of shared energy storage entails matching resource supply and demand across various dimensions, including storage capacity, charging and discharging power, and stored energy for each operational period. These resources exhibit coupling characteristics, akin to a combinatorial auction. Furthermore, we analyze the correlation between different application scenarios and the shared energy storage combinatorial auction, taking into account the multiple scenarios in which shared energy storage can be applied. Our analysis focuses on resource demand and time scale.

(2) Building upon the distinct characteristics of buyers and sellers engaged in energy storage sharing, we design a combinatorial auction solving algorithm that ranks the offers of shared energy storage from these participants. This algorithm effectively captures the variations in the value of energy resources across different time periods. The proposed solving algorithm significantly reduces the search space of the model, enabling a rapid solution to the combinatorial auction model, while maintaining high accuracy even in conventional scenarios.

(3) Additionally, we design a settlement model based on bundle pricing. This model calculates pricing results based on the priority matching outcomes of buyers and sellers, incentivizing participants in the combinatorial auction to disclose their true

information. Case studies using real-world datasets reveal notable variations in the demand for shared energy storage resources across different application scenarios. The shared energy storage combinatorial auction, when applied to multiple scenarios, demonstrates a substantial enhancement in resource allocation efficiency.

The remainder of the paper is organized as follows. Section 2 introduces the framework of energy storage sharing from the perspective of combinatorial auction. Section 3 presents the system model for combinatorial auction of energy storage sharing. Section 4 provides the pricing mechanism for combinatorial auction. Section 5 conducts the cases studies and Section 6 draws the conclusions. Hopefully, our work is able to provide a useful reference for the further mechanism design for energy storage sharing.

2. Framework of Energy Storage Sharing

2.1. The Overall Combinatorial Auction for Energy Storage Sharing

Generally speaking, the operation of energy storage mainly involves the charge and discharge of energy storage, energy storage capacity, net change value of electricity and charge and discharge efficiency and other parameters. Demand scenarios for shared energy storage mainly include peak cutting and valley filling, frequency modulation, and backup. In this paper, we will focus on the combinatorial auction problem between different energy storage characteristics and demand scenarios. In other words, shared energy storage operators are faced with the problem of how to optimally allocate shared energy storage parameters according to the different demands of market members. Considering the synergistic coupling between the charge and discharge power and capacity of energy storage, it is only meaningful to obtain the corresponding right allocation at the same time. Therefore, the essence of shared energy storage operation is a combinatorial auction problem. As mentioned above, this paper constructs the operation mode of shared energy storage based on combinatorial auction as shown in Figure 1 to achieve the optimal allocation of shared energy storage resources in different periods.

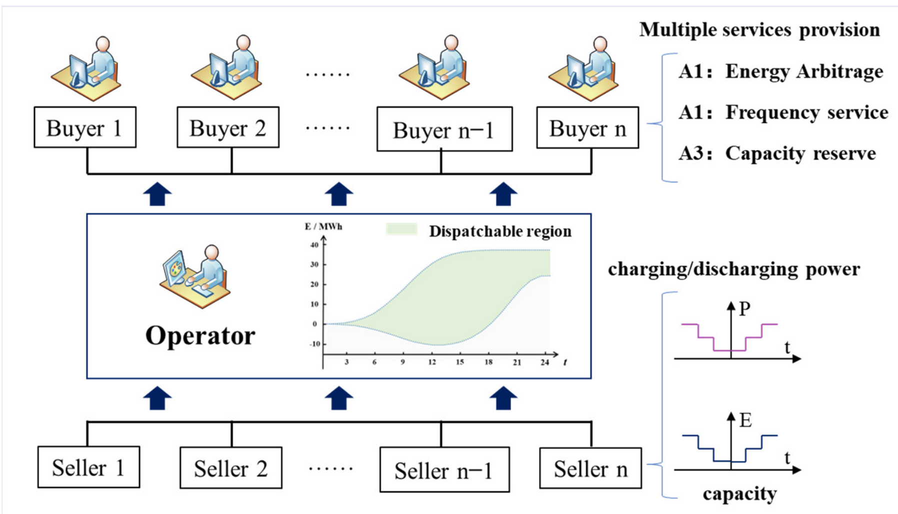

Figure 1. The framework of combinatorial auction for energy storage sharing.

(i) Energy storage sellers

A supplier of energy storage is the seller in the auction of shared energy storage and provides services to the demander according to different resource holdings in the combinatorial auction process. In practice, energy storage providers can be large-scale centralized energy storage resources, while the shared energy storage in urban energy systems is mostly reflected in distributed energy storage resources with small individual capacity.

(ii) System operator for energy storage sharing

An operator of energy storage sharing is responsible for organizing the shared storage auction, collection and matching the different demand of shared storage bidders scenarios offer, according to the result of the auction and shared storage resources allocation under different demand scenarios and settlement, the distribution of the shared storage involves energy storage capacity of each operational time, charge and discharge power and energy storage to store the energy of the multidimensional resource allocation. Moreover, there are coupling characteristics among resources, so its essence is a kind of combinatorial auction, which can be performed by power grid operators or third-party aggregators in the current market of China.

(iii) Energy storage buyers

The users of energy storage are the buyers; the buyer in the auction of shared energy storage needs to submit relevant demand parameters and quotations to the operator of shared energy storage according to the flexible adjustment demand scenarios, such as peak shaving and valley filling, frequency modulation, standby application, etc. The quotation should meet its own needs and guarantee expected revenue at the same time. The specific combinatorial auction model will be analyzed in detail in Section 3.

2.2. Correlation between Multiple Services Provision and Energy Storage Sharing

As mentioned above, energy storage sharing runs through all aspects of the power supply chain in potential application scenarios, providing multi-dimensional support capabilities for the system, such as peak shaving and frequency services provision etc. Generally speaking, the operation of energy storage mainly involves parameters such as energy storage charging and discharging, energy storage capacity, net change in electricity quantity, and charging and discharging efficiency. However, it should be noted that the requirements for shared energy storage operation vary among different application scenarios. The essence of energy storage sharing is the dynamic matching of supply and demand with different dimensional parameters of energy storage resources at different time periods. Considering the coupling effect of capacity and charging and discharging power in energy storage operation, it is necessary to obtain corresponding allocation of usage rights simultaneously in order to be meaningful. In other words, energy storage sharing can be understood as a type of combinatorial auction problem.

Considering the differences in shared energy storage requirements among different application scenarios, this article mainly considers the following three types of application scenarios, denoted as A1–A3, respectively.

(i) A1, Energy arbitrage: this application scenario is commonly used for energy storage sharing on the user side or power supply side. The corresponding shared energy storage buyer needs to simultaneously bid for the charging and discharging power usage rights of valley and peak hours, respectively, as well as the capacity between valley and peak hours. From a systemic perspective, arbitrage behavior also helps peak shaving and valley filling, which can reduce the system operation cost.

(ii) A2, Frequency services provision: this application scenario is commonly used for variable renewable stations to mitigate real-time energy imbalances. The corresponding shared energy storage buyer has a low demand for capacity, but it is necessary to ensure the right for charging and discharging power during the corresponding period of time.

(iii) A3, Capacity reserve: this application scenario has wide applicability and can be used as a conventional backup reserve or non-wire alternatives. The corresponding shared energy storage buyer requires discharge capacity during a specific period of time, so both discharge power and capacity usage rights are required.

Overall, the differences in application scenarios will be reflected in the differential demands of shared energy storage buyers for charging power, discharging power, and energy storage capacity at different time periods, as shown in Table 1. "+" indicates the correlation between different shared energy storage application scenarios and corresponding parameters, with more "+" indicating stronger correlation.

Table 1. The correlation between different shared energy storage application scenarios and corresponding parameters.

	Application	Capacity	Charging Power	Discharging Power
A1	Energy arbitrage	+++	Only valley hours	Only peak hours
A2	Frequency services provision	+	++	++
A3	Capacity reserve	++	+	Specific hours

3. System Model for Combinatorial Auction

In this section, we first introduce the combinatorial auction model of energy storage sharing, including the bid submission and winner determination process. Then, the corresponding computationally manageable algorithm is designed.

3.1. Bids Submission Considering Multi-Application Scenarios

The concept of package bidding is adopted in the design combinatorial auction for both energy storage buyers and sellers. As mentioned above, there are significant differences in the requirements for energy storage in different application scenarios, which will also lead to the diversity of submission bids from shared energy storage buyers. In practice, due to the coupling characteristics of multi-dimensional resources such as energy storage capacity and charging and discharging power, the bids submission in combinatorial auction is composed of energy storage resource demands of different dimensions in multiple periods. Among them, the requirement of multi-resources of shared energy storage in each period can be regard as the basic bids, i.e., atomic bids, and can be expressed as follows.

$$\mathbf{Q}_n = [p_n^c, p_n^d, e_n] \tag{1}$$

where subscript n represents the serial number of the combinatorial auction bids, $\boldsymbol{Q}_n$ represents the atomic bid vector and p_n^c, p_n^d, e_n denote the required charging power, discharging power and the capacity of energy storage of the combinatorial auction bids.

Considering the coupling of shared energy storage in practical applications, buyers of shared energy storage often require energy storage resources in multiple time intervals simultaneously, that is, only the submission bids in all bidding periods are selected at the same time can meet their needs. As a result of this, the above atomic bids can be extended to the following form:

$$x_n = [\mathbf{Q}_n, b_n] \tag{2}$$

$$\mathbf{Q}_n = [p_{n,t}^c, p_{n,t}^d, e_{n,t}] \tag{3}$$

where x_n^b and b_n denotes the actual bid and the corresponding bidding price of the combinatorial auction.

It should be noted that the above bidding submission is applicable to both the buyer and seller in energy storage sharing, but the corresponding bidding price has the opposite physical meaning. To facilitate differentiation, we will use superscripts "*B*" and "*S*" to distinguish the bidding information from the buyer and seller of shared energy storage, respectively. Moreover, there are also studies related to combinatorial auctions that discuss other bids submission forms such as OR-bid and XOR-bid, which correspond to different logical relationships between multiple atomic bids. However, in the shared energy storage combinatorial auction, these order configurations can be equivalent to multiple independent combinatorial auction quotations, which will not affect the matching and solution of the shared energy storage combinatorial auction. More details of the order configurations in combinatorial auction can be found in [31–33].

3.2. Winner Determination Process

After the bidding stage of the combinatorial auction, the energy storage sharing operator needs to determine the winning bids from the shared energy storage buyer and seller. The corresponding winner determination model of the energy storage sharing can be formulated as follows:

$$\text{Max } R = \sum_{n \in \Phi^B} b_n^B \cdot y_n^B - \sum_{n \in \Phi^S} b_n^S \cdot y_n^S \tag{4}$$

$$y_n^S \in [0, 1] \tag{5}$$

$$y_n^B \in \{0, 1\} \tag{6}$$

$$0 \leq \sum_{n \in \Phi^B} (p_{n,t}^{B,c} \cdot y_n^{B,c}) \leq \sum_{n \in \Phi^S} (p_{n,t}^{S,c} \cdot y_n^{S,c}) \tag{7}$$

$$0 \leq \sum_{n \in \Phi^B} (p_{n,t}^{B,d} \cdot y_n^{B,d}) \leq \sum_{n \in \Phi^S} (p_{n,t}^{S,d} \cdot y_n^{S,d}) \tag{8}$$

$$0 \leq \sum_{n \in \Phi^B} (e_{n,t}^B \cdot y_n^B) \leq \sum_{n \in \Phi^S} (e_{n,t}^S \cdot y_n^S) \tag{9}$$

where Φ^B and Φ^S denote the set of buyers and sellers in the energy storage sharing. y_n^S and y_n^B are the state variables for buyers and sellers in the combinatorial auction.

The objective function (4) is to maximize the overall social welfare and achieve efficient matching between the buyer and seller in energy storage sharing. Constraints (5) and (6) show the limit of the state variables in the combinatorial auction. Note that y_n^B is a binary variable, while y_n^S is not. This means that the needs of the shared energy storage buyer must be fully met, and the resources of the shared energy storage seller can be split, which is consistent with the introduction of the shared energy storage combinatorial auction mentioned earlier. Constraints (7)–(9) show the multi-resource limits in the combinatorial auction of energy storage sharing.

The above winner determination model of the combinatorial auction in energy storage sharing can be equivalent to a constrained multi-dimensional 0–1 knapsack problem, that is, for the submission from the energy storage buyer, its energy storage resource demand in each period must be met at the same time. It is a typical NP hard problem, and it is difficult to find the optimal solution at multiple times. That is, in practice, when there are many market members participating in the shared energy storage lease, it will be difficult to obtain an effective allocation method by using a conventional optimization algorithm. In Section 3.3, we will design the corresponding computationally manageable algorithm to solve the NP-hard winner determination model. We will design a computationally manageable algorithm for the proposed combinatorial auction for energy storage sharing in Section 3.3.

3.3. Computationally Manageable Algorithm Design

Actually, there is always an inherent contradiction between the economic efficiency of the auction and the computational complexity of solving the winner determination model in the mechanism design of the combinatorial auction. To reduce the time complexity of solving the winning bid problem, it is often necessary to sacrifice a certain allocation efficiency. Only by sacrificing a small amount of economic efficiency of the auction to impose some restrictions on the bid, can we successfully realize the combinatorial auction, that is, take a compromise way to quickly obtain an approximate optimal allocation scheme at the expense of solving accuracy.

As a result of this, we use the idea of the greedy algorithm to identify the priority of different combinatorial auction bids in energy storage sharing, so as to reduce the decision space as much as possible and improve the search speed. By using this method, the combinatorial auction of energy storage sharing can solve the combinatorial auction model in polynomial time while ensuring that the results obtained are closer to the optimal value as much as possible.

As mentioned above, the bids submission in energy storage sharing include the required storage resources and the corresponding prices. For the participants in energy storage sharing, the attractiveness of a bid does not only depend on the price that the bidder is willing to pay for the unit energy storage resources, but it is also affected by the scarcity of storage resources in different periods, that is, relatively higher payment prices are required in some periods of scarce energy storage resources. The specific priority analysis method of bid submissions for buyers and sellers of in energy storage sharing can be expressed as follows.

For the energy storage sellers, the opportunity cost of participating in the shared energy storage combinatorial auction can be measured by its profitability in the electricity market, which can be presented as follows.

$$\text{Max } R_n^S = \sum_{t\in\Phi^T}\sum_{n\in\Phi^S}(\lambda_t p_{n,t}^{S,c} - \lambda_t p_{n,t}^{S,d}) \tag{10}$$

$$0 \le p_{n,t}^{S,c} \le p_{\max}^{S,c} \tag{11}$$

$$0 \le p_{n,t}^{S,d} \le p_{\max}^{S,d} \tag{12}$$

$$SOC_{n,t}^S = SOC_{n,t-1}^S + \frac{1}{e_{n,t}^S}\left(\psi_n^{S,c}\cdot p_{n,t-1}^{S,c} - \frac{p_{n,t-1}^{S,d}}{\psi_n^{S,d}}\right) \tag{13}$$

$$0 \le SOC_{n,t}^S \le 1 \tag{14}$$

$$\sum_{t\in\Phi^T}(\psi_i^{S,c}\cdot p_{n,t-1}^{S,c} - \frac{p_{n,t-1}^{S,d}}{\psi_i^{S,d}}) = 0 \tag{15}$$

where R_n^S and λ_t denote the expected market revenue of shared energy storage seller n and the clearing price in the day-ahead market, respectively. $\psi_n^{S,c}$ and $\psi_n^{S,d}$ are the charging and discharging efficiency of the energy storage seller. $SOC_{n,t}^S$ denotes the state of the charge.

Based on the above market profitability evaluation model of different sellers in energy storage sharing, the bidding priority of shared energy storage sellers can be calculated as follows:

$$\chi_n^S = \frac{b_n^S}{R_n^S} \tag{16}$$

where b_n^S denotes the priority of bidding and the equivalent bidding unit of sellers in energy sharing. The economic rationale of the above priority analysis method is that for two bid submission with same bid prices, if the required energy storage resources are more profitable in the market, the corresponding bid in combinatorial auction should be given higher priority. From the perspective of incentive compatibility, energy storage sharing sellers hope that their bids will have strong profitability in the market to improve the priority, so they are willing to fully share their energy storage resources in the submission bid.

For the energy storage buyers, the situation is quite different. The above evaluation method based on market profitability is not applicable. This is mainly because shared energy storage buyers can strategically submit multiple discrete energy storage resource demands to reduce their profitability in the electricity market, and thus improve the priority of their own quotations.

As a result of this, we can only start from the physical meaning of energy storage resources. Considering the differences in the scarcity of multi-dimensional energy storage resources in different periods, we introduced the concept of resource scarcity. When the electricity price is low, that is, when the power supply is relatively abundant, market members are more inclined to store energy at this time. Therefore, it can be considered that charging power is more valuable than discharging power, and vice versa. For energy storage capacity, this attribute is a necessary condition for realizing the time-space transfer of electric energy. It is easy to know that the value of energy storage capacity is higher in scenarios with strong price volatility. Based on this idea, the scarcity of attributes of each dimension of shared energy storage can be calculated by the following formula:

$$\mu_t^{B,c} = \varpi \cdot \lambda_t \tag{17}$$

$$\mu_t^{B,d} = \frac{\varpi}{\lambda_t} \tag{18}$$

$$\mu_t^{B,e} = \frac{1}{2} \cdot (\varpi \cdot \lambda_t + \frac{\varpi}{\lambda_t}) \tag{19}$$

$$\varpi \cdot = \frac{T}{\sum\limits_{t \in \Phi^T} \lambda_t} \tag{20}$$

where T denotes the total number of time periods. ϖ is a parameter representing the distribution of electricity prices. In practice, the shared energy storage operator can replace it with other indicators or parameters that can represent the scarcity of electric energy according to the actual situation.

In energy storage sharing, the attractiveness of a shared energy storage bidding is not only determined by the price that the bidder is willing to pay for the unit energy storage resources, but also affected by the scarcity of shared energy storage resources in different periods, that is, in some energy storage resource scarce periods, a relatively higher payment price is required. Based on the quantification method of resource scarcity in different dimensions of shared energy storage mentioned above, the bidding priority of shared energy storage buyers can be calculated as follows:

$$\chi_n^B = \frac{b_n^B}{\overline{Q}_n^B} \tag{21}$$

$$\overline{Q}_n^B = \sum_{t \in \Phi^N} (\mu_t^{B,c} \cdot \frac{p_{n,s,t}^c}{p_{\max}^c} + \mu_t^{B,d} \cdot \frac{p_{n,s,t}^d}{p_{\max}^d} + \mu_t^{B,e} \cdot \frac{e_{n,s,t}}{c_{\max}^{ES}}) \tag{22}$$

where b_n^B and $\overline{Q}_n^B$ indicate the priority of bidding and the equivalent bidding unit of buyers in energy sharing, respectively.

Compared with the traditional method that simply relies on bidding information of the combinatorial auction, the above priority evaluation method takes into account the scarcity of multi-dimensional energy storage parameters and the interest needs of the buyers and sellers of the shared energy storage, and establishes a connection with the electricity market price, which can effectively reduce the potential strategic bidding behavior. On this basis, the proposed computable algorithm for combinatorial auction of energy storage sharing can be presented via the following steps:

(1) Input relevant submission data from both the buyers and sellers from the combinatorial auction of energy storage sharing, calculate the priority of buyer and seller quotations.
(2) Sort the priority of buyer and seller quotations in descending order, respectively. Calculate the unit parameter value corresponding to each quotation. Matching is only allowed when the buyer's unit value is higher than the seller's unit value. This is mainly to ensure incentive compatibility for subsequent settlement. The specific shared energy storage combinatorial auction settlement mechanism will be explained in the next paragraph.
(3) Starting from the buyer with the highest priority, with buyer's serial number G = 1, select all sellers that meet the matching requirements to form an available shared energy storage set, determine whether the demand can be met, and if it can be met, output 1. At the same time, allocate resources for each dimension of shared energy storage according to the seller's priority, and update the remaining unmatched seller quotes.
(4) Buyer's serial number G = G + 1, select the remaining shared energy storage sellers to form an available shared energy storage set, determine whether the demand can be met, and if it can be met, output 1. At the same time, allocate resources for each dimension of shared energy storage according to the seller's priority, update the remaining unmatched seller quotes, determine whether the serial number is greater than N, if Y, then next step, if not, return 3.
(5) Output combinatorial auction results.

As mentioned above, the combinatorial auction of energy storage sharing is typical NP-hard problem that is difficult to solve in polynomial time, and its computational complexity will grow exponentially with the increase of market members. The essence of algorithm design in combinatorial auction is to make a tradeoff between efficiency and computational complexity of auction. The computational complexity of the proposed priority-based algorithm is analyzed in the next section.

3.4. Computational Complexity Analysis

The most cumbersome part of the algorithm for solving the shared energy storage combinatorial auction model mentioned above is to calculate the priority of each offer, and sort all the combinatorial auction offers according to the priority (that is, step 2 in the algorithm process). Assuming that the number of offers of the shared energy storage buyer or seller is K_1 and K_2, respectively, which is without loss of generality, we define the problem scale K as follows:

$$K = \mathrm{Max}(K_1,\ K_2) \tag{23}$$

Taking the classic merge sort method as an example, the merge sort method is a stable sorting algorithm, and its core idea is the 'divide and conquer' idea. If you want to sort an array, you need to first divide the array into the front and back parts, then sort the front and back parts, respectively, and then merge the two parts in the order together, which is the final result. Through recursive analysis, it is easy to know that the calculation time is:

$$T_2(K) = \alpha_2 \log 2K + K \log 2K \tag{24}$$

where α_2 is a constant coefficient, $T_2(K)$ represents the calculation time of algorithm step (2) when the corresponding problem size is K.

In contrast, for shared energy storage buyers, the computational complexity of step (1) is only related to the number of time periods T, with T = 24 in a shared energy storage combinatorial auction with hourly time periods in the day-ahead market; for the seller of shared energy storage, although the optimization problem shown in (10)–(15) needs to be solved, it is essentially a linear programming problem, and the computational complexity is a polynomial level related to the number of variables. Compared with the combinatorial auction quotation scale K, it can be expressed by constant coefficients. The computational complexity of steps (3) and (4) is linearly related to the problem size K, and the total solving time of the proposed algorithm is as follows:

$$T(K) = \alpha_1 + \alpha_3 K + \alpha_2 \log 2K + K \log 2K \quad (25)$$

where α_1 and α_3 are all constant coefficients. When the big O mark method is used, because O(KlogK) > O (K) > O(logK), the corresponding time complexity of the proposed algorithm can be expressed as O(KlogK). In contrast, the computational complexity of the traditional exhaustion-based method and dynamic programming-based method for solving the problem of shared energy storage combinatorial auction is O (2^K) and O (K^2), respectively, which will grow exponentially with the expansion of the problem scale.

3.5. Pricing the Shared Storage in Combinatorial Auction

The essence of shared energy storage combinatorial auction can be understood as the dynamic matching of supply and demand of energy storage resources at different time periods. For a winning shared energy storage seller, its auctioned energy storage resources may be obtained by multiple energy storage buyers. Similarly, the energy storage resources purchased by a shared energy storage buyer may also come from multiple shared energy storage sellers. The matching settlement price for each transaction can be calculated based on the unit price quoted by both parties. The specific pricing and settlement results are as follows:

$$\zeta_n^S = \frac{b_n^S}{\sum\limits_{t\in\Phi^T}\left(\left|p_{n,t}^{S,c}\right| + \left|p_{n,t}^{S,d}\right| + \left|e_{n,t}^{S}\right|\right)} \quad (26)$$

$$\zeta_n^B = \frac{b_n^B}{\sum\limits_{t\in\Phi^T}\left(\left|p_{n,t}^{B,c}\right| + \left|p_{n,t}^{B,d}\right| + \left|e_{n,t}^{B}\right|\right)} \quad (27)$$

$$\lambda_{i,j} = \frac{\zeta_j^S + \zeta_i^B}{2} \quad (28)$$

$$R_i^B = \sum_{j\in\Phi^S} \lambda_{i,j} \sum_{t\in\Phi^T}\left(\left|p_{i,j,t}^{c*}\right| + \left|p_{i,j,t}^{d*}\right| + \left|e_{i,j,t}^{*}\right|\right) \quad (29)$$

$$R_j^S = \sum_{i\in\Phi^D} \lambda_{i,j} \sum_{t\in\Phi^T}\left(\left|p_{i,j,t}^{c*}\right| + \left|p_{i,j,t}^{d*}\right| + \left|e_{i,j,t}^{*}\right|\right) \quad (30)$$

where ζ_n^S and ζ_n^B represent the value of the seller and the buyer's unit resources in energy storage sharing. $|\cdot|$ represents the dimensionless numerical value of the corresponding parameter. $\lambda_{i,j}$ represents the settlement price corresponding to the matching part between the shared energy storage buyer *i* and seller *j*. R_i^B and R_j^S represent the benefits that shared energy storage buyer i and seller j need to pay or receive, respectively. It should be noted that in order to maintain consistency with the aforementioned bid density calculation, all dimensional parameters are also represented by dimensionless numbers.

Different from the unified clearing price used in most power market clearing, the transaction settlement mechanism proposed above is to calculate the settlement price separately for each matching pair formed by the buyer and the seller in the shared energy storage combinatorial auction, which can be understood as the social welfare of each matched energy storage sharing transaction being shared equally by the buyer and the seller. The significance of calculating the settlement price separately in this way is to incentivize both buyers and sellers of shared energy storage to quote truthfully. For example, for combinatorial auction participants, they can try to choose a quote that is lower than their true needs, in order to obtain higher benefits. This "free riding" phenomenon is particularly common in unified settlement prices. However, in the above settlement mode, deviating from the true evaluation price may lead to a decrease in the priority of the quotation. On the one hand, it may reduce the likelihood of winning the bid in one's own quotation, and on the other hand, for shared energy storage buyers or sellers, it may increase or decrease the final settlement price. That is to say, the proposed energy storage combinatorial auction pricing and settlement mechanism helps to suppress strategic bidding behavior and improve resource allocation efficiency to a certain extent.

It should be noted that our proposed model is technology-neutral, focusing on achieving the optimal allocation of energy storage resources using the declaration information provided by buyers and sellers. The shared energy storage combination auction model and solution method presented in this article can, in theory, be applied to any type of energy storage.

4. Case Studies

In this section, two cases with different problem sizes are adopted to validate the effectiveness of the designed combinatorial auction of energy storage sharing.

4.1. Basic Case

For simplicity, in the basic case, we first only consider three buyers and five sellers in the combinatorial auction of energy storage sharing, denoted as B1–B3 and S1–S5, respectively. The combinatorial auction includes five time periods, of which three buyers of shared energy storage correspond to the three types of application scenarios described in Section 2.2. The relevant parameters of the shared energy storage combinatorial auction are shown in Table 2, where the light yellow background is the quotation information from the combinatorial auction participants, the light red background is the market price information in the day ahead, which is used to calculate the quotation priority of each combinatorial auction, and the light blue part is the calculated information. It includes quotation priority and unit value, which are used in the winner determination and settlement processes in the combinatorial auctions, respectively.

Table 2. Relevant information in combinatorial auction of energy storage sharing.

No.		Bid Information ($p^{c,(\cdot)}_{n,t}$, $p^{d,(\cdot)}_{n,t}$, $e^{(\cdot)}_{n,t}$)					Bid Price	Priority	Unit Value
		T1	T2	T3	T4	T5	$b^{(\cdot)}_n$	$b^{(\cdot)}_n$	$\zeta^{(\cdot)}_n$
	B1 (A1)	(2,0,2)	(2,0,4)	(0,0,4)	(0,4,4)	-	70	3.46	3.89
	B2 (A2)	(1,1,1)	(1,1,1)	(1,1,1)	-	-	30	3.12	3.33
	B3 (A3)	-	-	(3,0,3)	(0,0,3)	(0,3,3)	48	2.77	3.19
	S1	(1,1,2)	(1,1,2)	(1,1,2)	-	-	33	1.2	2.75
	S2	-	(1,1,2)	(1,1,2)	(1,1,2)	-	35	0.92	2.91
	S3	-	-	(1,1,2)	(1,1,2)	(1,1,2)	35	2.33	2.91
	S4	(2,2,4)	(2,2,4)	(2,2,4)	(2,2,4)	(2,2,4)	120	0.95	3.0
	S5	(2,2,4)	(2,2,4)	-	-	-	8	2	0.5
Price	λ_t($/MWh)	25	27	50	65	30	-	-	-
	μ^d_t	0.64	0.69	1.27	1.65	0.76	-	-	-
Scarcity	μ^c_t	1.58	1.46	0.79	0.61	1.31	-	-	-
	μ^e_t	1.11	1.07	1.03	1.13	1.04	-	-	-

As can be seen in Table 2, the scarcity of storage resources in different periods are various, for example, the scarcity index of discharging power is higher in T_3 and T_4, which results from relatively high market prices in the above two periods. Regarding the scarcity of storage resources, for the buyers of shared energy storage, the scarcity of energy storage resources also leads to different priorities and unit prices corresponding to each bidding information, that is, relatively higher payment prices are required in some periods of scarce energy storage resources. From the perspective of shared energy storage sellers, we can also clearly note that although the energy storage resources owned by S1–S3 are similar to the quotations, there are obvious differences in the corresponding priorities, which is mainly because the differences in market prices in different periods determine the different profitability of each seller's energy storage.

Based on the bidding information of both buyers and sellers of shared energy storage mentioned above, the shared energy storage operator can obtain the final matching transaction winning result by solving the combined auction model, as shown in Table 3. For shared energy storage sellers, there may be a possibility that their bids may not be fully auctioned out. The values in the table represent the transaction proportion of declared parameters for each time period, denoted as y_n^B and y_n^S, respectively.

Table 3. Winner determination results of the combinatorial auction.

	No.	**Winner Determination Results**					**State Variables**		**Priority**	**Unit Value**
		$\mathbf{T_1}$	$\mathbf{T_2}$	$\mathbf{T_3}$	$\mathbf{T_4}$	$\mathbf{T_5}$	y_n^B	y_n^S	$b_n^{(\cdot)}$	$\zeta_n^{(\cdot)}$
Buyer	B1 (A1)	(2,0,2)	(2,0,4)	(0,0,4)	(0,4,4)	-	1	-	3.46	3.89
	B2 (A2)	(1,1,1)	(1,1,1)	(1,1,1)	-	-	1	-	3.12	3.33
	B3 (A3)	-	-	(3,0,3)	(0,0,3)	(0,3,3)	1	-	2.77	3.19
Seller	S1	(1,0,0)	(0,0,0)	(1,0,2)	-	-	-	33.3%	1.2	2.75
	S2	-	(1,0,1)	(1,0,2)	(0,1,2)	-	-	75%	0.92	2.91
	S3	-	-	(0,0,0)	(0,1,1)	(0,1,0)	-	25%	2.33	2.91
	S4	(2,1,3)	(2,1,4)	(2,1,4)	(0,2,4)	(0,2,3)	-	51.7%	0.95	3.0
	S5	(0,0,0)	(0,0,0)	-	-	-	-	0	2	0.5

From the winner determination results, it can be seen that except for S5, all other shared energy storage sellers have varying degrees of energy storage resource transactions. Among them, all buyers have completed the transaction, which means the corresponding state variable is 1, while the state variable of the seller may be a non-integer, which is consistent with the physical meaning of the shared energy storage combination auction we mentioned earlier. From the proportion of shared energy storage sellers' transactions, it can be clearly seen that the transaction situation and priority are basically inversely correlated. Shared energy storage sellers with relatively low quotations have more trading opportunities. Although S5 has a higher priority compared to S3, there are still no resources winning the bid. This is mainly because S5 only covers the first two periods, and the first two periods have higher priority energy storage resources, namely S1 and S4, which resulted in the bid not winning. However, it should be noted that the quotation of S5 is relatively low. In fact, if S5 wins the bid, more social benefits will be generated. This also indicates that the algorithm proposed in this paper is an approximation algorithm, which will lose some calculation accuracy while improving the solution speed. We will further analyze it in Section 4.2.

4.2. Large-Scale Combinatorial Auction of Energy Storage Sharing

In this subsection, large-scale combinatorial auction scales with the 24 operation hours of the next operating day are considered. To demonstrate the rationality and effectiveness of the proposed combinatorial auction solving algorithm in this paper, three scenarios are designed for comparation, denoted as M1–M3, respectively.

(1) M1 is a benchmark, in which branch and bound method is adopted to obtain the results of energy sharing, and can considered as the theoretical optimal solution of the corresponding combinatorial auction.
(2) M2 is the proposed computable combinatorial auction in this paper, we use the idea of the greedy algorithm to identify the priority of different combinatorial auction bids to achieve the solution in polynomial time while ensuring that the results obtained are closer to the optimal value as much as possible.
(3) M3, similar to the algorithm proposed in [16], is a conventional greedy algorithm based on the unit parameter value which is adopted to solve the shared energy storage combinatorial auction model. Compared to the M2 scenario, the method in M3 does not consider the differences in the value of shared energy storage resources in different time periods.

In essence, the combinatorial auction solution algorithm proposed in this paper is a kind of approximation algorithm, which realizes the fast solution of the combinatorial auction model at the cost of sacrificing part of the calculation accuracy. In large-scale problems, it may make the net winning bid decision result deviate from the theoretical optimal solution. In this section, we use the approximate ratio (AR) index to measure the difference between the combinatorial auction result and the theoretical optimal social welfare, that is, the ratio of the combinatorial auction social welfare (M2 or M3) obtained by the approximation algorithm and the theoretical optimal social welfare (M1).

The changes in the efficiency of shared energy storage combinatorial auctions under different participation scales are shown inFigure 2. The participation scale of shared energy storage combinatorial auctions is the total number of quotes from shared energy storage buyers and sellers. We assume that the number of shared energy storage buyers and sellers is equal, and the three types of application scenarios in the declaration information of shared energy storage buyers are generated at a ratio of 1:1:1.

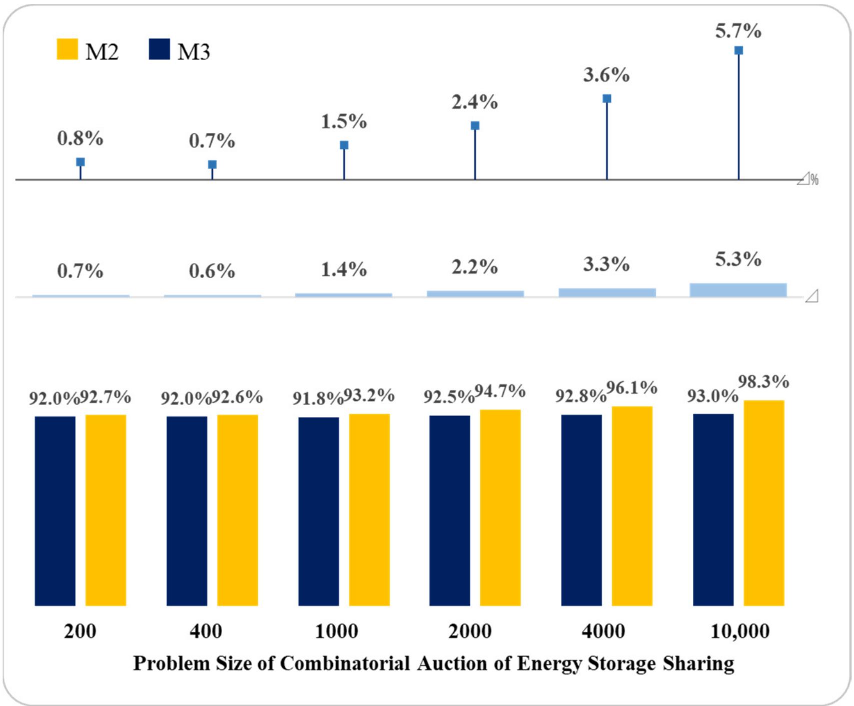

Figure 2. The approximate ratio under M2 and M3 scenarios with different combinatorial auction scales.

From the results in the figure, it can be clearly seen that with the continuous expansion of the participation scale of the shared energy storage combinatorial auction, the difference in economic efficiency between M2 and M3 shows a gradually increasing trend. This is mainly because the participation of large-scale market members reduces the possibility of individual extreme situations, ensuring the difference in energy storage demand between time periods. It should be noted that the economic effectiveness of the M2 and M3 scenarios is related to the actual declaration information of combinatorial auction and the value of scarcity index. In some cases, the social welfare of the M2 scenario is lower than that of the M3 scenario. We will further investigate key influence factors of the combinatorial auction of energy storage sharing in Section 4.3.

4.3. The Influence of Services Provision and Market Conditions

In practice, the efficiency of shared energy storage combinatorial auctions is influenced by various factors. In this subsection, we will analyze the impact of different service offerings and market conditions, namely resource scarcity, on the shared energy storage combinatorial auctions from the perspective of market demand.

Considering the correlation between multiple services provision and energy storage sharing, different services provision portfolios of energy storage buyers are generated. The approximate ratio of the combinatorial auction with different services provision (A1-A3) portfolios with a total problem size of 2000 are presented in Figure 3. The vertical axes in the figure represent the proportion of frequency services provision (A2) and capacity reserve among shared energy storage buyers (A3), indicating that the remaining application scenario is energy arbitrage. The horizontal axis represents the approximate ratio obtained by solving the combinatorial auction model in the M2 scenario.

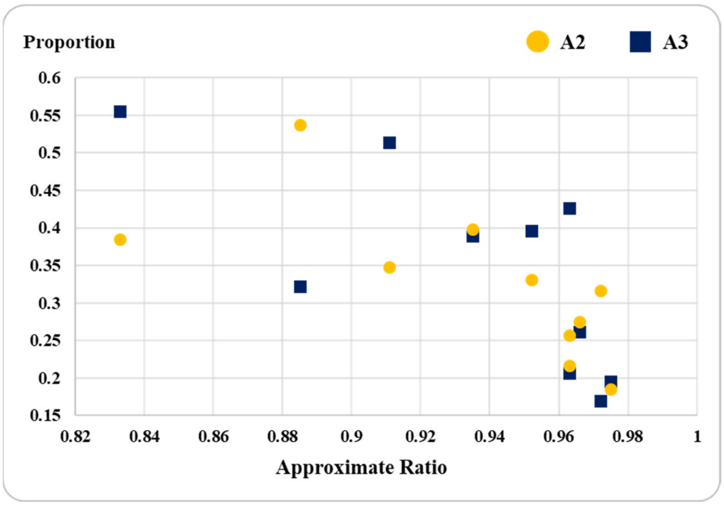

Figure 3. Approximate ratio under M2 with different application portfolios.

As one can observe, the scatter plot shows a downward trend, indicating that as the proportion of A2 and A3 increases, the approximate ratio of combinatorial auctions gradually decreases. In other words, when the proportion of A1, i.e., energy arbitrage, is high, the proposed solution algorithm can guarantee higher accuracy. This result is intuitive, mainly because the evaluation method used in this article for the ranking of shared energy storage seller quotes is based on market profitability. This method is essentially similar to the energy storage operation in the A1 arbitrage scenario. Therefore, when the A1 scenario has a high proportion, the corresponding approximation ratio is also higher.

In addition to the multiple application scenarios, market conditions can affect the scarcity of shared energy storage resources in different periods, which may also exert influence on the combinatorial auction efficiency of energy storage sharing. To compare and analyze the impact of market demand differences on the results of combinatorial auctions, we have introduced the proportion coefficient y in this subsection to represent the proportion of the expansion or reduction of the original shared energy storage resource scarcity parameter. Figure 4 shows the economic efficiency index of different scarcity proportional coefficients under M2 and M3 when the participation scale of combinatorial auctions is 1000. Note that the proportional coefficient is 1.0, indicating the basic shared energy storage resource scarcity scenario, and the distribution function of the corresponding declaration information generation is also adjusted with the change in the proportional coefficient y.

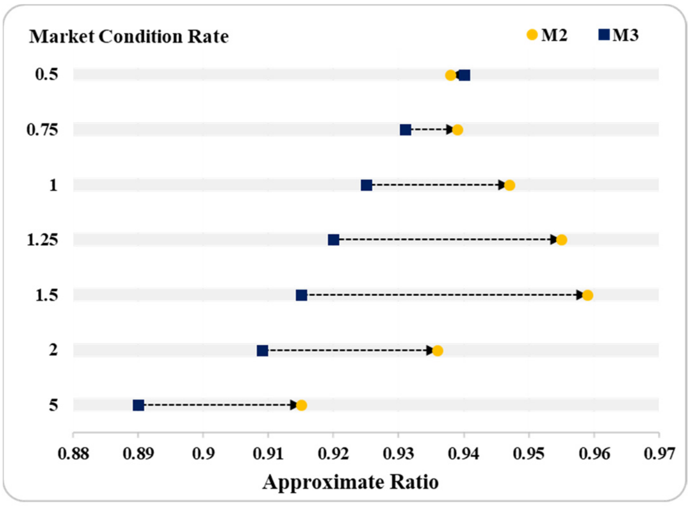

Figure 4. Combinatorial auction results in M2 and M3 scenarios under different market conditions.

As can be seen from the above figure, when the proportion coefficient y gradually decreases, the difference between the combinatorial auction results corresponding to the M2 and M3 scenarios gradually decreases. This is mainly because the continuous decrease of y means that the scarcity of energy storage resources in different time periods gradually converges. When there is no difference in scarcity in each time period, the algorithms corresponding to M2 and M3 scenarios are equivalent.

In addition, it can also be found that with the increase in the proportion coefficient y, M3′s economic efficiency gradually decreases, while M2 shows a trend of first increasing and then decreasing. This is mainly because M3 does not consider the differences between periods, so when the proportion coefficient y is large, M3 performs poorly. M2 corresponds to the greedy algorithm based on scarcity proposed in this paper, so it performs well to a certain extent.

5. Discussion

As previously mentioned, the allocation of shared energy storage entails the multi-dimensional matching of resource supply and demand, encompassing storage capacity, charging and discharging power, and stored energy for each operational period. The fundamental principle of energy storage sharing lies in the dynamic alignment of supply and demand using diverse parameters of energy storage resources across varying time intervals. Recognizing the interdependence between capacity, charging and discharging power in energy storage operations, it becomes imperative for energy storage buyers to acquire the corresponding allocation of usage rights that align with their specific storage needs, such as energy arbitrage, frequency services provision, and capacity reserve.

These interconnected characteristics of diverse storage resources can be viewed as a type of combinatorial auction. In this article, we propose a method that ranks the offers from buyers and sellers of shared energy storage, effectively capturing the value disparities of energy resources across distinct time periods. Compared to traditional methods for solving combinatorial auction problems, the solution algorithm proposed in this paper can reduce the search space of the model by more than 90%, and the solution accuracy can reach up to 98.3% in conventional scenarios. Compared with the conventional greedy algorithm based on unit parameter value in energy storage sharing, the economic efficiency of the proposed energy storage combinatorial auction solving algorithms can be improved by approximately 5.7% with a relatively high combinatorial auction scale, e.g., 10,000.

It is important to acknowledge that the crux of designing combinatorial auction-solving algorithms lies in striking a balance between solution speed and computational accuracy, commonly referred to as the approximation ratio. We are delighted to report that our proposed algorithm consistently achieves high accuracy across various scenarios. We find that the proposed computable combinatorial auction demonstrates better adaptability to the application of energy arbitrage, with a maximum difference in approximate ratio combi-nations for different scenarios of approximately 0.15. As the field of combinatorial auction models continues to expand, the solving accuracy of the methods presented in this paper demonstrates a progressive improvement, indicating the efficacy of our proposed approach in addressing practical application requirements.

Furthermore, the accuracy of combinatorial auction-solving algorithms can be influenced by various factors, including variations in application scenarios and resource scarcity within the market. Notably, energy arbitrage demonstrates greater suitability for the proposed computable combinatorial auction. This is primarily due to the evaluation method employed in this study, which ranks shared energy storage seller quotes based on market profitability. Compared with the traditional greedy algorithms, the economic effectiveness improvement brought by the proposed method in our work can reach up to approximately 5% in situations of high market scarcity. These findings underscore the significance of carefully selecting the evaluation method during the algorithm design of shared energy storage portfolio auctions. Market operators conducting shared energy storage portfolio auctions can optimize auction efficiency by choosing the most suitable evaluation method aligned with the diverse requirements of potential shared energy storage buyers.

6. Conclusions

The integration of the sharing economy and energy system has led to the advocacy of energy storage sharing as an effective solution for addressing the low utilization rate of energy storage and the challenges related to cost recovery. This paper presents the construction of a framework for the shared energy storage combinatorial auction that incorporates multi-dimensional parameter coupling. Furthermore, we analyze the correlation between different application scenarios and the combinatorial auction of shared energy storage, taking into account the diverse application scenarios and examining the resource demand and time scale. A computable combinatorial auction solving algorithm is designed based on the distinctive characteristics of buyers and sellers in energy storage sharing. This algorithm effectively reduces the model search space and enables a rapid solution to the combinatorial auction model.

The case studies compare three scenarios, revealing the following: firstly, the proposed solving algorithm significantly reduces the computation time by over 95% com-pared to the traditional method for solving combinatorial auction, while ensuring high accuracy in the conventional case. Secondly, increasing the problem size of the combinatorial auction of energy sharing improves the stability and accuracy of the method proposed in this paper. Notably, as the combinatorial auction scale grows from 200 to 10,000, the approximate ratio progressively rises from 92.7% to 98.3%. Compared to conventional greedy algorithms, the proposed method in this paper achieves a maximum accuracy improvement of 5.7%. Moreover, the combination of different application scenarios affects the economic effectiveness of shared energy storage combinatorial auctions to a certain extent. Lastly, the proposed temporal value in this article effectively captures the temporal disparities among different energy storage resources, surpassing traditional greedy algorithms. Consequently, in situations of high market scarcity, the approximation difference can reach a maximum of approximately 5%.

Hopefully, our work is able to provide a useful reference for the further mechanism design for energy storage sharing. Based on the main findings of our work, further in-depth research can be expanded from the following three aspects: (1) a novel energy storage sharing framework considering network constraints and system operation; (2) energy storage sharing mechanism considering the investment process of different types of energy storage; (3) energy storage sharing mechanism design covering multiple power supply chain links.

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