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# Bidding Strategy for the Alliance of Prosumer Aggregators in the Distribution Market

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**Abstract:** Photovoltaic energy storage system (PV-ESS) prosumer aggregators are characterized by a large number but small scale in the distribution system and are not competitive enough to participate in market transactions. For this reason, a prosumer aggregator alliance is proposed to participate in the distribution market bidding strategy. Firstly, based on the framework for prosumer aggregator alliances participating in distribution market trading, a bilevel bidding model is constructed. The upper level represents the optimal decision-making model for the prosumer aggregators, while the lower level constitutes the distribution market-clearing model. Secondly, the additional benefits obtained by the alliance are distributed more fairly using the improved Shapley value based on the PV self-consumption rate. Given the problem that the traditional diagonalization algorithm (DA) has an excessive number of iterations when solving the game equilibrium problem of multiple subjects, the DA is improved by optimizing the initial value of the inputs. Finally, case studies are conducted based on the improved IEEE-33 bus distribution system to validate the feasibility and economic viability of the proposed strategy. The case study results show that forming cooperative alliances to participate in market bidding can significantly increase overall profits. The improved DA reduces the number of bids and computation time by 75% and 80%, respectively. Additionally, the improved Shapley value facilitates compensation for some of the aggregators.

**Keywords:** prosumer aggregators; distribution markets; improved Shapley values; improved diagonalization algorithm



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## 1. Introduction

In recent years, there has been a notable surge in the advancement of distributed generation, represented by distributed photovoltaics (PVs) [1]. Numerous distributed PV aggregators are now participating in electricity spot market trading [2]. Due to their small individual capacities and fluctuating output, distributed PV aggregators face challenges in market competitiveness, compounded by significant curtailment issues [3]. However, energy storage systems (ESSs) enable time-shifted reuse of energy [4]. PV systems combined with ESSs can effectively reduce curtailment issues when participating in the market as a whole [5]. However, the number of distributed PV-ESSs is large but typically small in scale [6]. Compared to traditional units, their market competitiveness remains limited. These PV and ESS resources can be managed and scheduled by prosumer aggregators or virtual power plants. This approach allows for better resource utilization and increased overall revenue [7]. This paper primarily considers the agency of prosumer aggregators for these PV and ESS resources.

As new market entities, prosumer aggregators have attracted significant attention from researchers. Reference [8] proposes a trading strategy for prosumer aggregators based on P2P technology to participate in microgrid transactions. However, due to the small scale of prosumers and user demand, they can only engage in transactions within limited areas. Reference [9] proposes a mechanism based on a novel transactive energy framework. However, their research focuses only on the energy market. In contrast, reference [10] considers the production–consumption characteristics of PV-ESSs and proposes a two-stage bidding strategy for prosumers in the energy-reserve market. Reference [11] highlights the excellent frequency modulation (FM) capabilities of ESSs and presents a two-stage bidding framework for prosumers participating in the energy–FM auxiliary service market. However, references [8–11] treat prosumer aggregators as price takers, neglecting their influence on clearing prices. With the continuous improvement of auxiliary service market rules and the increasing number of prosumer aggregators, those with strong regulation capabilities are becoming competitive in the electricity market, and their bidding strategies can impact clearing outcomes. Therefore, references [12,13] propose a bidding strategy for prosumer aggregators participating in the market, with the market operator responsible for calculating and announcing the final clearing price. However, these studies consider prosumer aggregators as independent entities directly participating in market bidding, without accounting for the potential collaboration among storage stations of different aggregators to enhance overall returns. References [14,15], respectively, study the formation of alliances by combining wind ESSs and virtual power plants for market transactions. However, no studies in the literature have examined prosumer aggregators as members of an alliance yet. Therefore, this study is highly significant. Furthermore, after forming an alliance, fair profit distribution is crucial for maintaining cooperation stability. The Shapley value is a commonly used method for profit distribution in cooperative games [16]. However, in practical scenarios, reallocation based on the contributions and sacrifices of alliance members is necessary.

Multi-agent participation in electricity markets is often modeled as an Equilibrium Problem with Equilibrium Constraint (EPEC), where traditional approaches include intelligent algorithms [17] or the combination of KKT conditions with diagonalization algorithms (DAs) [18–20] for the solution. Reference [17] employs a prioritized experience replay deep deterministic policy gradient method to address this issue. However, this method is based on reinforcement learning, making the training process complex. Moreover, its convergence is influenced by numerous factors. As the number of market participants and constraints increases, the number of iterations required for such intelligent algorithms will increase significantly, leading to a dramatic rise in solution time, which makes them less suitable for practical problem-solving. Conversely, leveraging KKT conditions and strong duality transforms the EPEC into solving a Mixed-Integer Linear Programming (MILP) problem for multiple agents. Subsequently applying the DA effectively mitigates these issues. The core idea of the DA involves iteratively solving each market participant's optimal decision model while keeping other participants' decision variables fixed, iterating until strategies stabilize or reach a maximum iteration limit. References [18–20] specifically address strategic bidding by multiple market participants, utilizing the DA to find Nash equilibrium solutions. This methodical approach ensures robust convergence towards market equilibrium, maintaining stability in competitive electricity markets. However, significant discrepancies between the initial operational strategies chosen by each agent and their optimal strategies can result in excessive iteration. Moreover, the assumption of knowing other participants' strategies during iterative self-strategy optimization does not reflect real-world scenarios. Therefore, this paper proposes an improved DA to address these issues, where each agent optimizes its bidding strategy by predicting other agents' bidding strategies, thereby significantly reducing the solution time to just one bidding round.

In summary, a bidding strategy is developed for a coalition of prosumer aggregators to engage in distribution market bidding. The key contributions of the paper are as follows:

A framework for prosumer aggregator alliances to participate in electricity market trading is proposed. This framework uses an improved DA and KKT conditions to solve the EPEC problem. It ensures that the solution's accuracy remains within an acceptable range while significantly reducing computation time.

Additional revenues earned by the alliances are allocated based on improved Shapley values. This approach effectively compensates the ESS for the losses incurred from participating in the FM market to support PV generation.

## 2. Trading Framework of Prosumer Aggregator Alliance Participation in Market

With the deepening reform of the electricity market, more and more new market players are involved in the market competition. Distributed PVs and distributed ESSs cannot directly participate in electricity market transactions due to their small volume, decentralized layout, and difficult regulation and management. Therefore, distributed PVs and distributed ESSs can be aggregated by aggregators in a certain region for unified scheduling. However, the capacity of distributed PVs and distributed ESSs represented by a single aggregator remains limited, with minimal market competitiveness. Therefore, forming alliances through cooperative gaming can leverage resource complementarity and enhance overall revenue. The distribution market trading framework based on cooperative gaming with the participation of multiple prosumer aggregators is shown in Figure 1, and this paper mainly considers the multi-market joint bidding of prosumer aggregators in the energy–FM market.

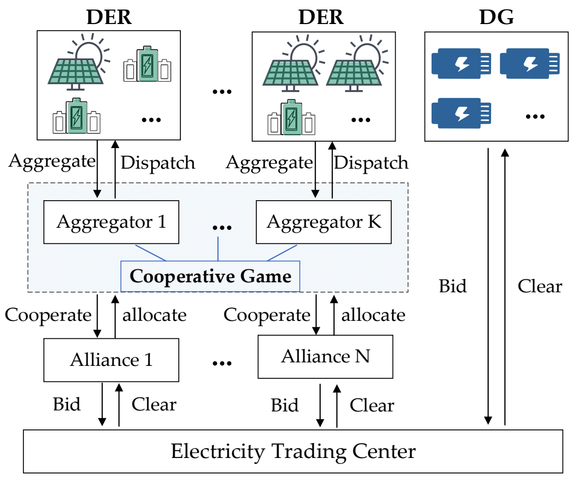



**Figure 1.** Cooperative game-based distribution market trading framework with the participation of prosumer aggregator alliances.

The specific market trading process is as follows:

1. Each market participant is required to verify unit parameters and relevant details concerning FM auxiliary service provision capabilities.
2. On declaration day, the electricity trading center releases information to all market participants about the next day's active power demand, frequency modulation demand, bidding limits for power, and similar details. Subsequently, the operator organizes market participants to participate in the declaration process.
3. The trading period is set at 15 min, totaling 96 periods. Microturbine (MT) units declare bids based on their respective generation costs, while prosumer aggregators search for optimal alliances. These alliances then collectively submit unified "price-quantity" bids.
4. Considering the secure functioning of the distribution network and physical constraints, the objective is to meet day-ahead market load and FM requirements. Electricity trading centers strive to optimize day-ahead market clearing, with the primary objective of minimizing energy costs, thus determining the day-ahead clearing results.
5. The electricity trading center announces the final clearing result to all market members.

## 3. Optimal Decision Model for Upper-Level Prosumer Aggregator

The upper-level model is a trading decision model for prosumer aggregators, with the objective of maximizing aggregator profits. This model generates the optimal bidding strategies for each aggregator. The uncertainty of PV power generation is characterized through scenario analysis.

### *3.1. Objective Function of Prosumer Aggregator*

The objective function of the aggregated prosumer aggregator is described in Equation (1), which includes participation in energy–FM market revenues and curtailment penalty costs.

$$\max F_k = \sum_{s}^{N_s} \rho_s \left\{ \sum_{t=1}^{T} \left[ \lambda_{t,s}^{\text{en}} P_{k,t,s}^{\text{en}} + \lambda_{t,s}^{\text{cap}} P_{k,t,s}^{\text{cap}} + \lambda_{t,s}^{\text{mil}} P_{k,t,s}^{\text{mil}} - C_{k,t,s}^{\text{PV}} \right] \right\} \tag{1}$$

$$C_{k,t,s}^{\text{PV}} = \sum_{v=1}^{V_k} c^{\text{PV}} \left( P_{k,v,t,s}^{\text{PV,fore}} - P_{k,v,t,s}^{\text{PV}} \right) \tag{2}$$

$$\begin{cases} P_{k,t,s}^{\text{en}} = \sum\limits_{v=1}^{V_k} P_{k,v,t,s}^{\text{PVe}} + \sum\limits_{e=1}^{E_k} P_{k,e,t,s}^{\text{dis}} - \sum\limits_{e=1}^{E_k} P_{k,e,t,s}^{\text{ch}} \\ P_{k,t,s}^{\text{cap}} = \sum\limits_{v=1}^{V_k} P_{k,v,t,s}^{\text{Pcap}} + \sum\limits_{e=1}^{E_k} P_{k,e,t,s}^{\text{Ecap}} \\ P_{k,t,s}^{\text{mil}} = \sum\limits_{v=1}^{V_k} P_{k,v,t,s}^{\text{Pmil}} + \sum\limits_{e=1}^{E_k} P_{k,e,t,s}^{\text{Emil}} \end{cases} \tag{3}$$

$$P_{k,v,t,s}^{\text{PV}} = P_{k,v,t,s}^{\text{PVe}} + P_{k,v,t,s}^{\text{Pcap}} \tag{4}$$

Here, $\rho_s$ is the probability of scenario $s$; $P_{k,t,s}^{\text{en}}$, $P_{k,t,s}^{\text{cap}}$, and $P_{k,t,s}^{\text{mil}}$ are the amount of awarded electricity, the FM capacity, and mileage in the market by the aggregator $k$ at time $t$ under scenario $s$, respectively. $\lambda_{t,s}^{\text{en}}$, $\lambda_{t,s}^{\text{cap}}$, and $\lambda_{t,s}^{\text{mil}}$ are the price of electricity, the FM capacity, and the mileage clearing price, obtained through the joint clearing of the lower-level market, respectively; $C_{k,t,s}^{\text{PV}}$ is the costs incurred in the process of participating in market transactions for distributed PV; $V_k$ and $E_k$ are distributed PV and distributed ESS quantities represented by aggregator $k$, respectively; $c^{\text{PV}}$ is the penalty factor for PV abandonment; $P_{k,v,t,s}^{\text{PV}}$ and $P_{k,v,t,s}^{\text{PV,fore}}$ are the aggregators' planned PV output and predicted PV output. Equation (3) represents the allocation of the aggregator $k$ allocating the awarded quantities of charging, discharging, the FM capacity, and the FM mileage to each member, where $P_{k,v,t,s}^{\text{PVe}}$, $P_{k,e,t,s}^{\text{dis}}$, and $P_{k,e,t,s}^{\text{ch}}$ represent the planned output of distributed PVs and the planned charging and discharging power of distributed ESSs by aggregator $k$; and $P_{k,v,t,s}^{\text{Pcap}}$, $P_{k,v,t,s}^{\text{Pmil}}$, $P_{k,e,t,s}^{\text{Ecap}}$, and $P_{k,e,t,s}^{\text{Emil}}$ are aggregator $k$ planned FM capacity and FM mileage output for distributed PVs and distributed ESSs in the FM market, respectively.

### *3.2. Constraints*

#### 3.2.1. Constraints of Prosumer Aggregators' Declared Power

Constraints (5) limit the declared power range of the prosumer aggregator in the energy–FM market.

$$\begin{cases} -\sum\limits_{e=1}^{E_k} P_{k,e,\max}^{\text{ch}} \le p_{k,t,s}^{\text{en}} + p_{k,t,s}^{\text{cap}} \le \sum\limits_{v=1}^{V_k} P_{k,v,t}^{\text{PV,fore}} + \sum\limits_{e=1}^{E_k} P_{k,e,\max}^{\text{dis}} \\ 0 \le p_{k,t,s}^{\text{cap}} \le \sum\limits_{v=1}^{V_k} P_{k,v,\max}^{\text{Pcap}} + \sum\limits_{e=1}^{E_k} P_{k,e,\max}^{\text{Ecap}} \\ 0 \le p_{k,t,s}^{\text{mil}} \le \sum\limits_{v=1}^{V_k} s_{\text{pv},v}^{\text{mc}} P_{k,v,\max}^{\text{Pcap}} + \sum\limits_{e=1}^{E_k} s_{\text{ess},e}^{\text{mc}} P_{k,e,\max}^{\text{Ecap}} \end{cases} \tag{5}$$

Here, $p^{\mathrm{en}}_{k,t,s}$, $p^{\mathrm{cap}}_{k,t,s}$, and $p^{\mathrm{mil}}_{k,t,s}$ are the power declared by aggregator $k$ in the energy market and the FM capacity and mileage declared in the FM market, respectively; $P^{\mathrm{dis}}_{k,e,\max}$ and $P^{\mathrm{ch}}_{k,e,\max}$ are the maximum charging and discharging power of distributed ESSs; $P^{\mathrm{Pcap}}_{k,v,\max}$ and $P^{\mathrm{Ecap}}_{k,e,\max}$ are the maximum FM capacity for distributed PVs and distributed ESSs, respectively; $s^{\mathrm{mc}}_{\mathrm{pv},v}$ and $s^{\mathrm{mc}}_{\mathrm{ess},e}$ are mileage-to-capacity ratios for distributed PVs and distributed ESSs, respectively.

#### 3.2.2. Constraints of Prosumer Aggregators' Declared Price

Constraints (6) limit the declared price range of the prosumer aggregator in the energy–FM market.

$$\begin{cases} 0 \le b^{\mathrm{en}}_{k,t,s} \le b^{\mathrm{en}}_{k,\max} \\ 0 \le b^{\mathrm{cap}}_{k,t,s} \le b^{\mathrm{cap}}_{k,\max} \\ 0 \le b^{\mathrm{mil}}_{k,t,s} \le b^{\mathrm{mil}}_{k,\max} \end{cases} \tag{6}$$

Here, $b^{\mathrm{en}}_{k,t,s}$, $b^{\mathrm{cap}}_{k,t,s}$, and $b^{\mathrm{mil}}_{k,t,s}$ are the price of electric energy, the FM capacity, and the mileage price declared by the aggregator, respectively; and $b^{\mathrm{en}}_{k,\max}$, $b^{\mathrm{cap}}_{k,\max}$, and $b^{\mathrm{mil}}_{k,\max}$ are the maximum prices declared by aggregator $k$ in the energy–FM market, respectively.

#### 3.2.3. Constraint of Distributed PVs

Constraint (7) means that the planned PV output of the aggregator cannot exceed the forecasted output.

$$0 \le P^{\mathrm{PV}}_{k,v,t,s} \le P^{\mathrm{PV,fore}}_{k,v,t} \tag{7}$$

#### 3.2.4. Constraints of Distributed ESSs

Constraints (8) describe the range of ESSs' charging and discharging, along with the non-simultaneous charging and discharging characteristics.

$$\begin{cases} 0 \le P^{\mathrm{dis}}_{k,e,t,s} \le \alpha^{\mathrm{dis}}_{k,e,t,s} P^{\mathrm{dis}}_{k,e,\max} \\ 0 \le P^{\mathrm{ch}}_{k,e,t,s} \le \alpha^{\mathrm{ch}}_{k,e,t,s} P^{\mathrm{ch}}_{k,e,\max} \\ \alpha^{\mathrm{dis}}_{k,e,t,s} + \alpha^{\mathrm{ch}}_{k,e,t,s} \le 1 \end{cases} \tag{8}$$

Here, $P^{\mathrm{dis}}_{k,e,t,s}$ and $P^{\mathrm{ch}}_{k,e,t,s}$ are the planned charging and discharging power of aggregator $k$ for the distributed ESS, respectively; $\alpha^{\mathrm{dis}}_{k,e,t,s}$ and $\alpha^{\mathrm{ch}}_{k,e,t,s}$ are binary variables representing the discharge and charge states of the ESS; $E_{k,e,t,s}$ is the state of charge of the distributed ESS; $E_{k,e,\min}$ and $E_{k,e,\max}$ are the minimum and maximum capacities allowed by the ESS, respectively; and $\eta^{\mathrm{ch}}_{k,e}$ and $\eta^{\mathrm{dis}}_{k,e}$ are charge and discharge efficiency, respectively.

## 4. Integrated Clearing Model for Lower-Level Energy–FM Market

The lower-level model is a joint clearing model for the energy–FM market. Its objective function aims to minimize operational costs while determining clearing prices and the quantities allocated to various market participants.

### *4.1. Objective Function of Joint Market Clearing*

The objective function of the energy–FM market clearing is described in Equation (10), which includes the operational costs of MT units and prosumer aggregators.

$$\min F_L = \sum_{s}^{N_S} \rho_s \left\{ \begin{array}{l} \sum\limits_{t=1}^{T} \sum\limits_{m=1}^{N_{\mathrm{DG}}} (b^{\mathrm{Ge}}_{m,t,s} P^{\mathrm{Ge}}_{m,t,s} + b^{\mathrm{Gcap}}_{m,t,s} P^{\mathrm{Gcap}}_{m,t,s} + b^{\mathrm{Gmil}}_{m,t,s} P^{\mathrm{Gmil}}_{m,t,s}) + \\ \sum\limits_{t=1}^{T} \sum\limits_{k=1}^{N_{\mathrm{AG}}} (b^{\mathrm{en}}_{k,t,s} P^{\mathrm{en}}_{k,t,s} + b^{\mathrm{cap}}_{k,t,s} P^{\mathrm{cap}}_{k,t,s} + b^{\mathrm{mil}}_{k,t,s} P^{\mathrm{mil}}_{k,t,s}) \end{array} \right\} \tag{9}$$

Here, $N_{\mathrm{DG}}$ and $N_{\mathrm{AG}}$ are the quantities of MT units and prosumer aggregators in the system, respectively; $P^{\mathrm{Ge}}_{m,t,s}$, $P^{\mathrm{Gcap}}_{m,t,s}$, and $P^{\mathrm{Gmil}}_{m,t,s}$ are the winning bid in the energy market and the winning bid in the FM market for FM capacity and FM mileage for MT $m$, respectively; $b^{\mathrm{Ge}}_{m,t,s}$, $b^{\mathrm{Gcap}}_{m,t,s}$, and $b^{\mathrm{Gmil}}_{m,t,s}$ are the declared generation price, FM capacity, and mileage price for MT $m$, respectively.

### *4.2. Constraints*

#### 4.2.1. Constraints of Network Operation

Constraint (10) ensures nodal power balance, constraint (10) limits branch transmission capacity, and constraint (12) establishes the balance node.

$$\begin{array}{l}\sum\limits_{m\in\Phi_{\mathrm{g}}(i)} P^{\mathrm{G}}_{m,t,s} + \sum\limits_{e\in\Phi_{\mathrm{ess}}(i)} (P^{\mathrm{dis}}_{k,e,t,s} - P^{\mathrm{ch}}_{k,e,t,s}) + \sum\limits_{v\in\Phi_{\mathrm{pv}}(i)} P^{\mathrm{PVe}}_{k,v,t,s} - \sum\limits_{d\in\Phi_{\mathrm{d}}(i)} P^{\mathrm{L}}_{d,t} \\ = \sum\limits_{j\in\Phi(i)} B_{ij}(\theta_{i,t}-\theta_{j,t}), \forall i, \forall t : \lambda_{1,i,t,s}\end{array} \tag{10}$$

$$-P_{ij,\max} \le B_{ij}(\theta_{i,t}-\theta_{j,t}) \le P_{ij,\max}, \forall i, \forall q \in \Psi(i) : \mu^{\min}_{1,ij,t,s}, \mu^{\max}_{1,ij,t,s} \tag{11}$$

$$\theta_{1,t} = 1 : \lambda_{1,1,t,s} \tag{12}$$

Here, $\Phi_{\mathrm{g}}(i)$, $\Phi_{\mathrm{ess}}(i)$, $\Phi_{\mathrm{pv}}(i)$, and $\Phi_{\mathrm{d}}(i)$ represent the aggregation of MT units, distributed ESSs, distributed PVs, and loads set at node $i$, respectively; $\Phi(i)$ is the set of nodes connected to node $i$; $\Psi(i)$ is the set of all branches connected to node $i$; $P^{\mathrm{L}}_{i,t}$ is the load of node $i$; $B_{ij}$ is the line conductance between nodes $i$ and $j$; $\theta_{i,t}$ and $\theta_{j,t}$ are the phase angles of node $i$ and node $j$, respectively; $P_{ij,\max}$ represents the maximum transmission capacity of the branch ($i$,$j$); and $\lambda_{1,i,t,s}$, $\mu^{\min}_{1,ij,t,s}$, and $\mu^{\max}_{1,ij,t,s}$ are the pairwise multipliers corresponding to the equality constraint and the inequality constraint, respectively, where $\lambda_{1,i,t,s}$ is the clearing price of node $i$.

#### 4.2.2. Constraints of FM Capacity and Mileage Demand

Constraints (13) ensure that the awarded quantities of various market participants in the FM market meet the system's FM requirements.

$$\begin{cases} \sum\limits_{m=1}^{N_{\mathrm{DG}}} P^{\mathrm{Gcap}}_{m,t,s} + \sum\limits_{k=1}^{N_{\mathrm{AG}}} P^{\mathrm{cap}}_{k,t,s} = R^{\mathrm{SVS}}_t : \lambda_{2,t,s} \\ \sum\limits_{m=1}^{N_{\mathrm{DG}}} P^{\mathrm{Gmil}}_{m,t,s} + \sum\limits_{k=1}^{N_{\mathrm{AG}}} P^{\mathrm{mil}}_{k,t,s} = M^{\mathrm{SYS}}_t : \lambda_{3,t,s} \end{cases} \tag{13}$$

Here, $R^{\mathrm{SVS}}_t$ and $M^{\mathrm{SYS}}_t$ are the system's FM capacity, and mileage requirements, respectively; $\lambda_{2,t,s}$ and $\lambda_{3,t,s}$ are dual variables corresponding to the constraints of the distribution system, namely FM capacity and mileage clearing price.

#### 4.2.3. Constraints of Market Clearing

Constraints (14)–(15) limit the clearing power of MT units and aggregators in the energy–FM market, respectively.

$$\begin{cases} P^{\mathrm{Ge}}_{m,t,s} \ge P^{\mathrm{G}}_{m,\min} + P^{\mathrm{Gcap}}_{m,t,s} : \mu^{\min}_{2,m,t,s} \\ P^{\mathrm{Ge}}_{m,t,s} \le P^{\mathrm{G}}_{m,\max} - P^{\mathrm{Gcap}}_{m,t,s} : \mu^{\max}_{2,m,t,s} \\ 0 \le P^{\mathrm{Gcap}}_{m,t,s} \le p^{\mathrm{Gcap}}_{m,t,s} : \mu^{\min}_{3,m,t,s}, \mu^{\max}_{3,m,t,s} \\ 0 \le P^{\mathrm{Gmil}}_{m,t,s} \le p^{\mathrm{Gmil}}_{m,t,s} : \mu^{\min}_{4,m,t,s}, \mu^{\max}_{4,m,t,s} \\ 0 \le P^{\mathrm{Gmil}}_{m,t,s} \le s^{\mathrm{mc}}_{\mathrm{g,m}} P^{\mathrm{Gcap}}_{m,t,s} : \mu^{\min}_{5,m,t,s}, \mu^{\max}_{5,m,t,s} \end{cases} \tag{14}$$

$$\begin{cases} 0 \le P^{\mathrm{en}}_{k,t,s} \le p^{\mathrm{en}}_{k,t,s} : \mu^{\min}_{6,k,t,s}, \mu^{\max}_{6,k,t,s} \\ 0 \le P^{\mathrm{cap}}_{k,t,s} \le p^{\mathrm{cap}}_{k,t,s} : \mu^{\min}_{7,k,t,s}, \mu^{\max}_{7,k,t,s} \\ 0 \le P^{\mathrm{mil}}_{k,t,s} \le p^{\mathrm{mil}}_{k,t,s} : \mu^{\min}_{8,k,t,s}, \mu^{\max}_{8,k,t,s} \\ 0 \leqslant P^{\mathrm{mil}}_{k,t,s} \leqslant \sum\limits_{v=1}^{V_k} s^{\mathrm{mc}}_{\mathrm{pv},v} P^{\mathrm{Pcap}}_{k,v,t,s} + \sum\limits_{e=1}^{E_k} s^{\mathrm{mc}}_{\mathrm{ess},e} P^{\mathrm{Ecap}}_{k,e,t,s} : \mu^{\min}_{9,k,t,s}, \mu^{\max}_{9,k,t,s} \end{cases} \tag{15}$$

Here, $P_{m,\max}^{\mathrm{G}}$ and $P_{m,\min}^{\mathrm{G}}$ denote the maximum and minimum output for MT $m$, respectively; $s_{\mathrm{g},m}^{\mathrm{mc}}$ is the FM mileage-to-capacity ratio for MT $m$; and $\mu_{o,m,t,s}^{\min}, \mu_{o,m,t,s}^{\max}, o \in (2,10)$ are dual variables.

## 5. Formation of Cooperative Alliances and Benefit-Sharing Methods

As a single prosumer aggregator participates in market transactions, its capacity is small compared to other units, and it does not have an advantage in market competition, while the quantity of PVs and ESSs represented by some aggregators do not match, which can cause serious light abandonment problems in the transaction process. Therefore, aggregators are encouraged to cooperate to form an alliance, which increases the market competitiveness of aggregators and reduces the problem of light abandonment at the same time. How to fairly apportion the additional benefits generated after the formation of a cooperative alliance is the key to maintaining the stability of the alliance.

### *5.1. Improved Shapley Value Method Based on PV Self-Consumption Rate*

The Shapley value method is the average marginal contribution of a particular alliance member in the alliance, and the Shapley value of aggregator $k$ is assumed to be the cooperative game $G = \langle N, v \rangle$, with $|N| = n$ denoting the number of all aggregators:

$$\varphi_k(v) = \sum_{S \in N_n} \frac{(|S|-1)!(n-|S|)!}{n!}[v(S) - v(S - \{k\})] \tag{16}$$

Here, $\varphi_k(v)$ is the revenue apportioned to aggregator $k$ from the total revenue of alliance $S$; set $N_n$ is the n aggregators that can participate in the alliance $S$; $v(S)$ is the total revenue of the union $S$; and $v(S - \{k\})$ is the total revenue of the affiliate after removing the aggregator $k$.

This paper introduces the concept of a PV self-absorption rate, which represents the rate at which prosumer aggregators strategically charge ESSs during the bidding process in the market to accommodate the PV systems. Therefore, to encourage aggregator entities with greater distributed ESS capacity to join the alliance and enhance overall PV integration rates, a certain compensation for lost profits in the FM market will be provided. This involves adjusting the Shapley value method for profit distribution based on each aggregator's self-consumption rate of solar energy. Let the PV self-consumption rate of aggregator $k$ when bidding independently be $\omega_k$:

$$\omega_k = \frac{\sum\limits_{t=1}^{T} \sum\limits_{e=1}^{E_k} P_{k,e,t}^{\mathrm{PV-ESS}}}{\sum\limits_{t=1}^{T} \sum\limits_{v=1}^{V_k} P_{k,v,t}^{\mathrm{PV,fore}}} \tag{17}$$

Here, $P_{k,e,t}^{\mathrm{PV-ESS}}$ is the energy absorbed from the PV system by the energy storage in aggregator $k$ at time $t$.

The new weight $m_k$ of aggregator $k$ is shown in Equation (18) and the gain $M_k$ of the improved aggregator $k$ is shown in Equation (19).

$$m_k = \frac{\omega_k}{\sum\limits_{k=1}^{n} \omega_k} \tag{18}$$

$$M_k = \varphi_k(v) + (m_k - \frac{1}{n}) \sum_{k=1}^{n} \varphi_k(v) \tag{19}$$

Here, $m_k - \frac{1}{n}$ is the correction factor for each aggregator $k$. The sum of the correction factors for each aggregator is zero, so the total return after reallocation for each aggregator is the same as before correction, as demonstrated in Appendix A.

### 5.2. Model Transformation and Solution

The prosumer aggregator day-ahead market bidding model presented in the preceding section can be formulated as a multi-objective bilevel optimization problem.

$$\begin{cases} \max\limits_{x_S} & F_S(x_S, y)\ \forall S \in N_S \\ \text{s.t.} & P_S(x_S) \geq 0 \\ & Q_S(x_S, y) = 0 \\ & y = \underset{y}{\operatorname{argmin}}\ F_L(x, y) \\ & \text{s.t.} p(x, y) \geq 0 \\ & \ q(x, y) = 0 \end{cases} \tag{20}$$

Here, $F_S(\cdot)$ is the objective function of the aggregator alliance $S$; $x_S$ is a decision variable for the aggregator alliance $S$; y is a variable that is part of the market-clearing problem; and $N_S$ is a collection of aggregators. $P_S(\cdot)$ and $Q_S(\cdot)$ are inequality constraints and equality constraints for the aggregator alliance $S$; $F_L(\cdot)$ is an objective function of the market-clearing problem; $x$ is a decision variable for all aggregator alliances in the distribution system; and $p(\cdot)$ and $q(\cdot)$ are inequality constraints and equation constraints on the market-clearing problem.

The lower-level market-clearing problem is structured as a linear programming model. Therefore, it can be reformulated into its corresponding KKT conditions, which serve as constraints in the upper-level optimal decision model for prosumer aggregators.

$$\begin{cases} \max\limits_{x_S, y, \lambda, \mu} & F_S(x_S, x'_S, y, \lambda, \mu)\ \forall S \in N_S \\ \text{s.t.} & P_S(x_S) \geq 0 \\ & Q_S(x_S, y) = 0 \\ & \{y, \lambda, \mu\} \in \mathbf{C}^{\mathrm{KKT}} \end{cases} \tag{21}$$

Here, $\lambda$ and $\mu$ are the dyadic variables of the equilibrium and inequality constraints in the market-clearing problem; $x'_S$ is the decision-making of alliances other than alliance $S$; and $\mathbf{C}^{\mathrm{KKT}}$ is the set of constraints corresponding to the KKT condition for the market-clearing problem.

Using KKT conditions and strong duality theory, the bilevel model is transformed into a single-level model, thereby converting the multi-agent bilevel programming problem into an EPEC problem. The DA is a commonly used method for solving such problems. Furthermore, this paper improves upon traditional DAs. The improved DA first determines the optimal bidding strategy set $\left\{x_k^{(0)}\right\}$ when all prosumer aggregators form a cooperative alliance, using it as the initial input, and then sequentially compute the bidding strategy sets $\left\{x_k^{(f)}\right\}$ for each agent. For each aggregator, while fixing the bidding strategies of the other aggregators, the strategies are subsequently updated until convergence or reaching the maximum iteration count for each agent. This process decomposes the global problem into independent subproblems, allowing each agent to independently seek its optimal strategy and thereby achieve the global optimal solution. The specific steps for solving are detailed as follows:

Step 1: Obtain initial values. Obtain the bidding strategy when all aggregation merchants form an alliance as initial values $\left\{x_k^{(0)}\right\}$.

Step 2: Parameter settings. Set the maximum number of iterations $f^{max}$ and convergence criteria $\varepsilon$.

Step 3: Iterative solving. Let the iteration count be $f = 1$, and input the optimized initial values $\left\{x_k^{(0)}\right\}$. Update each aggregator merchant's solution by fixing the bidding strategy of the remaining aggregator merchants.

Step 4: Convergence criteria. If for all $k$, three consecutive iterations satisfy $\left|x_k^{(f)} - x_k^{(f-1)}\right| \leq \varepsilon$, terminate and report the $F_k, p_{k,t,s}^{\mathrm{en}}, p_{k,t,s}^{\mathrm{cap}}, p_{k,t,s}^{\mathrm{mil}}$. Else if $f = f^{max}$, terminate and report non-convergence. Otherwise, $f = f + 1$ and return to Step 3.

## 6. Case Study

### *6.1. Example Setup*

This case study is tested on the improved IEEE-33 node system, incorporating four MT units and three prosumer aggregators, as shown in Figure 2. The parameter information for the MT units and prosumer aggregators is provided in Appendix B [21]. Distributed PVs managed by Aggregator 1 are situated at nodes 3, 4, and 20; those managed by Aggregator 2 are at nodes 11 and 13; and those managed by Aggregator 3 are at nodes 9 and 28, with equal installed capacities. The PV output scenarios are set to five, with typical PV output scenarios shown in Figure 3 and their corresponding probabilities listed in Table 1. Assuming the total system FM requirement equals 10% of the total load, with a curtailment penalty cost of 0.6 CNY/kWh, the system daily load profile is depicted in Figure 4 [22,23]. To avoid vicious competition, given the offer range of the PV-ESS alliance, the electric energy offer is [0.1, 0.3] CNY/kWh, and the FM capacity and FM mileage offer range is [0, 0.02] CNY/kWh [24]. The convergence criterion for the solving process is set such that the difference between successive iterations is less than or equal to 1.5%. Convergence is considered achieved if this criterion is met for three or more consecutive iterations [25]. This paper uses Gurobi 10.0 in MATLAB R2021b to solve the problem.

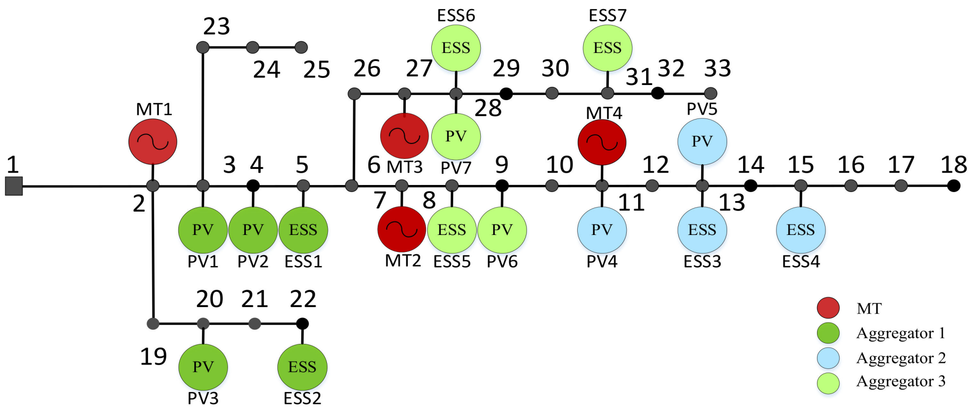



**Figure 2.** Schematic diagram of improved IEEE-33 node system topology.

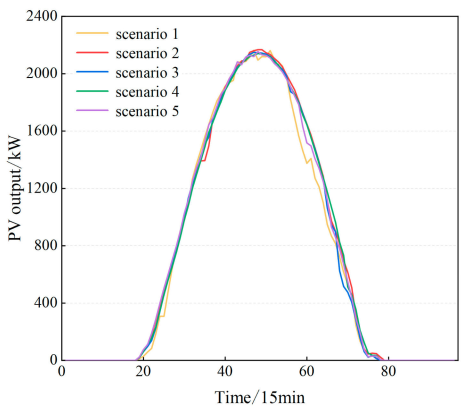



**Figure 3.** Typical set of scenarios for PV output.

**Table 1.** Probabilities corresponding to each scenario.

| Scenario | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Probability | 0.19 | 0.21 | 0.21 | 0.22 | 0.17 |

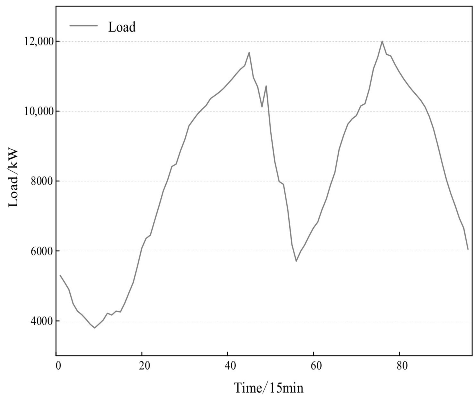



**Figure 4.** System daily load profile.

### *6.2. Algorithm Comparison Analysis*

The upper limit values of declared prices in each market were used as initial inputs for solving the traditional DA and compared with the improved DA proposed in this paper. Taking the case of three independent aggregators participating in market bidding as an example, a comparative analysis was conducted. The analysis focused on iteration count, solution time, and overall profit, as shown in Figure 5. The improved DA reduced the number of bidding attempts by three and significantly shortened the total solution time. Due to the sensitivity of the diagonalization algorithm to initial values, the iteration count increases substantially as the initial inputs deviate further from optimal results. Furthermore, an increase in the number of target entities leads to an exponential rise in iteration count. In terms of overall profits, the improved algorithm shows a decrease of 0.37% in total profits compared to the equilibrium solution after the first round of bidding. Combined with actual solving times, utilizing the improved algorithm for a single bidding round can significantly enhance solving efficiency. Therefore, subsequent case studies in this paper employ the improved DA, which only requires one round of bidding for solving.

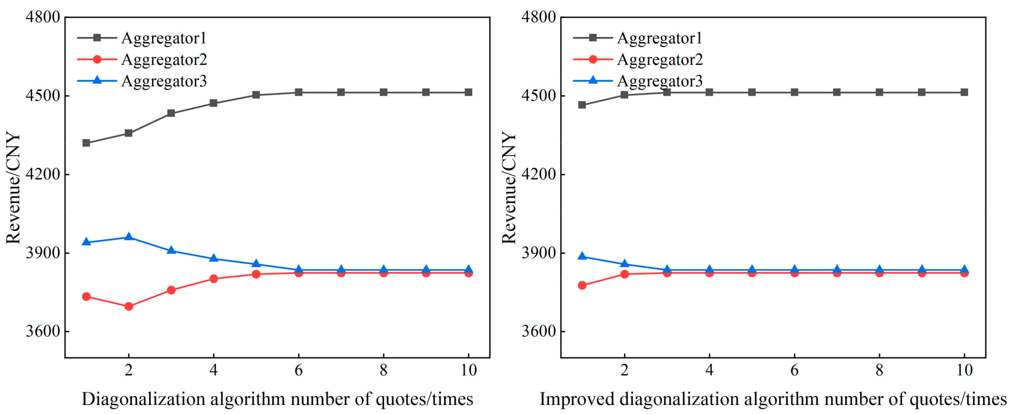



**Figure 5.** Algorithm performance comparison results.

### *6.3. PV-ESS Alliance Bidding Results*

Based on the merge–split rule introduced in Section 5.1, the optimal alliance combination identified is $\{(1),(2,3)\}$. Specifically, prosumer Aggregator 1 forms Alliance 1, while prosumer Aggregators 2 and 3 form Alliance 2. The bidding outcomes of each alliance in the energy–FM market are illustrated in Figures 6 and 7.

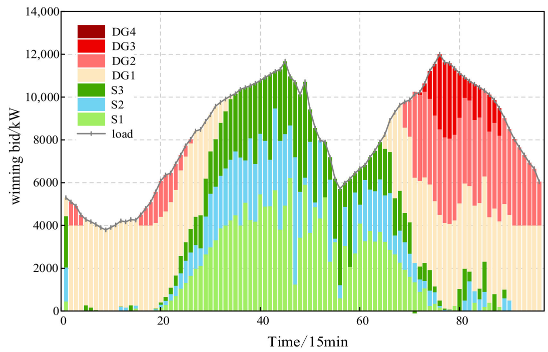



**Figure 6.** Winning bids in the energy market for each subject.

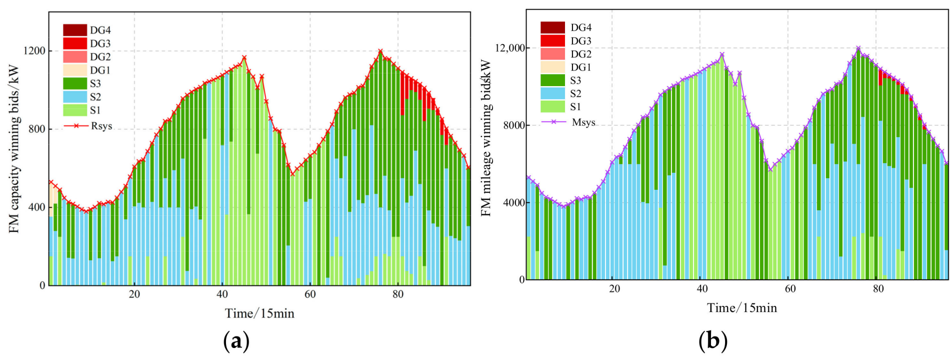
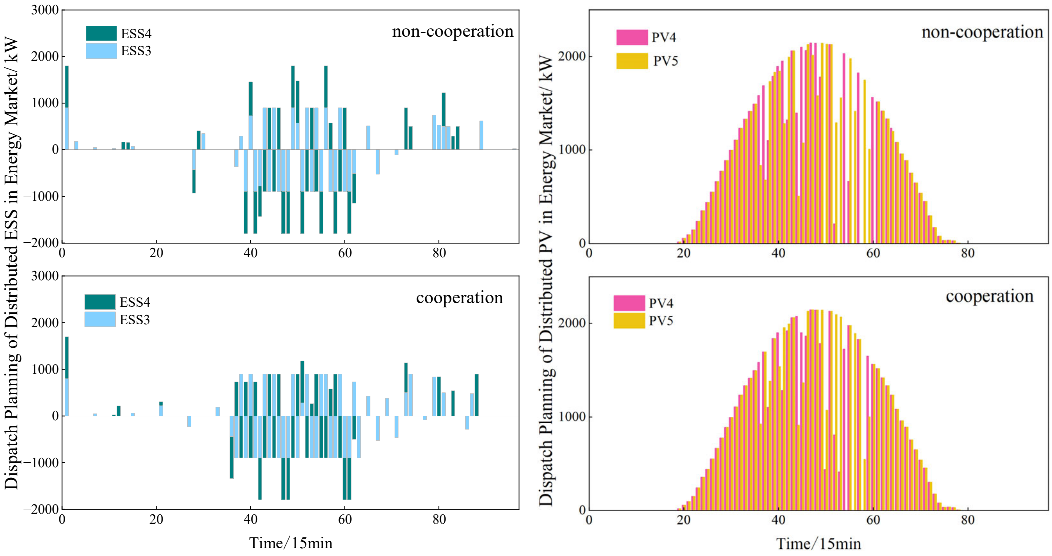



**Figure 7.** Winning bids in the FM market for each subject. (**a**) FM capacity. (**b**) FM mileage.

Figure 6 depicts the bidding outcomes of various MT and PV-ESS alliances in the energy market. It can be observed that the two PV-ESS alliances account for approximately 50% of the total energy demand cumulatively across different periods, primarily concentrated during hours 20–77. Due to the higher solar generation during this period, the solar-storage alliances aim to minimize curtailment penalties. They achieve this by offering prices slightly below those of MT units to capture market share while maximizing overall revenue. MT units predominantly generate power during early morning and evening hours when distributed PVs are not producing power. MT unit 1 is cleared first due to having the lowest bid. When its output reaches the upper limit, units 2 and 3 with relatively lower bids supplement the generation capacity.

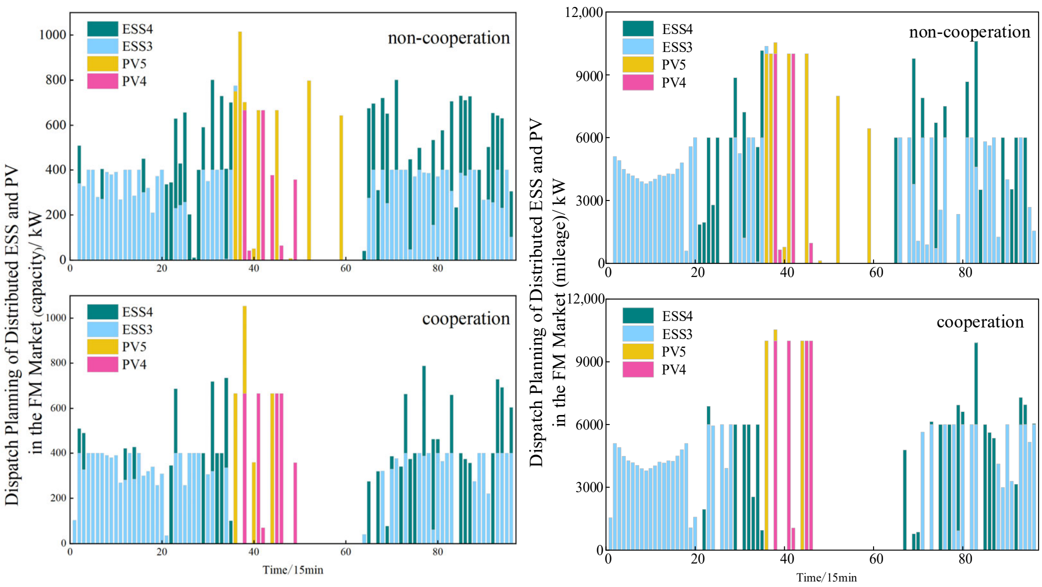
The winning bids of each market player in the FM market for each time period are shown in Figure 7. As can be seen from the figures, the FM capacity and mileage provided by the two PV-ESS alliances account for about 99% of the system demand, respectively. Since the distributed PVs and distributed ESSs in the alliance have a higher FM mileage-capacity factor and can provide more FM mileage than MT units when providing the same FM capacity, the PV-ESS alliance with stronger FM responsiveness is preferentially called upon to provide FM services in the FM auxiliary service market.

Taking Aggregator 2 as an example, a comparative analysis of the scheduling plans of the distributed PVs and distributed ESSs that it represents in the case of bidding independently and bidding after allying is conducted, and the results are shown in Figures 8 and 9. The dispatch of distributed PVs and distributed ESSs by the aggregator increased by 6% and 10% during the 36–67 time period in the energy market, respectively. During midday hours, PV generation is high while load demand is low. Therefore, to maximize overall revenue, excess electricity generated by PV systems represented by Aggregator 2 is partially stored in distributed ESS 3 and ESS 4. Subsequently, it is sold during the nighttime peak load periods.




(**a**) (**b**)

**Figure 8.** Prosumer Aggregator 2 scheduling plan in the energy market. (**a**) ESS. (**b**) PV.




(**a**) (**b**)

**Figure 9.** Prosumer Aggregator 2 scheduling plan in the FM market. (**a**) FM capacity (**b**) FM mileage.

As shown in Figure 9a,b, it can be observed that when participating in the FM market, the aggregator's dispatch of PVs and ESSs is reduced in almost all time periods. Simultaneously, distributed PV outputs remain concentrated during the midday period, whereas distributed ESSs exhibit an opposite trend, with their output times displaying complementary characteristics. In the energy market, the unit power price is significantly higher than in the FM market. Aggregators prioritize participation in the energy market to pursue greater profits, thereby increasing their involvement as much as possible. This inevitably reduces the capacity available for participation in the FM market. Additionally, aggregators primarily utilize dispatchable distributed ESSs to participate in the FM market, accounting for 83% of total ESS output. During peak PV generation periods, the primary task of distributed ESSs is to absorb excess solar power and opportunistically sell it. During periods of low PV generation, the main task shifts to frequency modulation.

Figure 10 depicts the cumulative curtailment of distributed PV systems for Aggregator 2 and Aggregator 3 across different time periods, under cooperative and non-cooperative scenarios. The total curtailment without cooperation amounts to 11.13 MWh, whereas with cooperation in forming an alliance, the total curtailment decreases to 7.99 MWh, a reduction of 28.22% in curtailed energy.

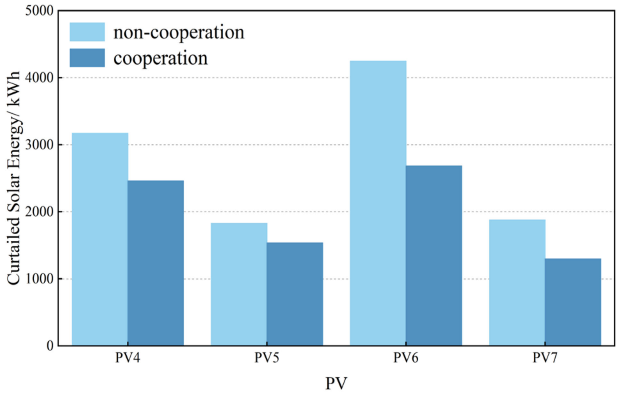



**Figure 10.** The curtailed solar energy amount for cooperation and non-cooperation.

### *6.4. Benefits of the PV-ESS Alliance*

The PV-ESS alliance currently participates primarily in the energy market and FM market. To illustrate the necessity of the PV-ESS alliance's participation in the energy–FM market, comparisons were also made regarding the daily revenue performance of the PV-ESS alliance in different market cases, as detailed in Table 2.

**Table 2.** Comparison of cases for prosumer aggregator participation in various markets.

| Case | Energy Market | FM Ancillary Service Market |
| --- | --- | --- |
| Case 1 | YES | NO |
| Case 2 | NO | YES |
| Case 3 | YES | YES |

The comparative results are shown in Table 3. It is clear from the table that the alliance generates higher revenue by participating in the combined market. Compared to participating in only one market, the total revenue increases by CNY 8361.55 and CNY 16,556.78, respectively. Therefore, actively participating in the combined energy–FM market is beneficial for the alliance to obtain higher revenue, encouraging their engagement in market competition and promoting the development of PV-ESSs.

**Table 3.** Benefits of the alliance when participating in different markets.

| Benefits/CNY | Case 1 | Case 2 | Case 3 |
| --- | --- | --- | --- |
| Alliance 1 | 4105.99 | 1941.92 | 7681.34 |
| Alliance 2 | 8650.39 | 2619.23 | 13,436.58 |
| All Benefits | 12,756.38 | 4561.15 | 21,117.93 |

In existing research, there are cases where only distributed ESSs are considered as individual market entities participating in bidding. Therefore, this paper considers all ESSs as being represented by a single ESS aggregator. It compares and analyzes the revenues of the ESS aggregator participating in market bidding independently under this scenario. The comparison results are presented in Table 4. The table indicates that the total revenue of the integrated prosumer aggregator exceeds the combined revenue of the ESS aggregator and the PV generator by CNY 1682.06. When the ESS aggregator participates in the market independently, it competes with the distributed PV generator, which results in both ESS and PV resources being underutilized. The aggregator can minimize resource wastage by conducting unified scheduling and management of ESSs and PVs.

**Table 4.** Benefits of ESS and PVs managed by different entities.

| Benefits/CNY | ESS | PV | PV-ESS |
|---|---|---|---|
| Energy Benefits | 802.71 | 12,036.58 | 14,584.24 |
| FM Capacity Benefits | 289.74 | 149.47 | 464.04 |
| FM Mileage Benefits | 4062.11 | 2095.26 | 6069.65 |
| All Benefits | 5154.56 | 14,281.31 | 21,117.93 |

Table 5 presents the revenue outcomes for each aggregator under cooperative and non-cooperative conditions. According to the table, forming alliances through mutual cooperation increases the total revenue for prosumer aggregators by CNY 887.72. Moreover, to highlight the benefits of cooperation, the revenue includes not only market participation earnings but also curtailment penalty costs. When allocating additional revenue gained by the alliance using Shapley values, Aggregator 2 and Aggregator 3 see revenue increases of CNY 495.65 and CNY 402.07, respectively. Utilizing the improved Shapley values for revenue distribution, the new weights for Aggregator 2 and Aggregator 3 are 0.47 and 0.53, resulting in revenue increases of CNY 239.14 and CNY 648.58, respectively. Under both allocation methods, aggregators experience enhanced revenue, with Aggregator 3 showing a higher growth rate in revenue when using the improved Shapley values. As analyzed earlier, the ESS in Aggregator 3 sacrifices some revenue from FM markets for overall benefit by accommodating more PV power. Compared to non-cooperation, this cooperation results in a loss of CNY 150.62 in frequency modulation revenue. The use of improved Shapley values compensates Aggregator 3, encouraging more aggregators to join the alliance through fairer revenue distribution.

**Table 5.** Benefits in case of cooperation and non-cooperation.

| Subject | Benefits/CNY | | Benefit Allocation/CNY | |
|---|---|---|---|---|
| | Non-Cooperation | Cooperation | Shapley Value | Improved Shapley Value |
| Aggregator 1 | 4464.83 | 4464.83 | - | - |
| Aggregator 2 | 3776.71 | 8550.39 | 4272.36 | 4015.85 |
| Aggregator 3 | 3885.96 | | 4288.03 | 4534.54 |
| All Benefits | 12,127.50 | 13,025.22 | - | - |

## 7. Conclusions

This paper addresses the bidding strategy problem of prosumer aggregators participating in multi-species electricity markets, proposing a bilevel bidding model for prosumer aggregators considering uncertainty. A revenue allocation method based on the improved Shapley value of the PV self-consumption rate is proposed and solved using the improved DA. The following conclusions can be obtained from the case study:

1. Compared to traditional algorithms, the improved DA proposed in this paper achieves market equilibrium solutions more rapidly. Considering the actual computation time, using this improved DA approach requires only one round of bidding, which greatly boosts solution efficiency.
2. Taking Aggregator 2 as an example, after forming the optimal alliance, the scheduling volume of distributed PVs increases by 6% and distributed ESSs by 10%. Furthermore, Alliance 2 demonstrates a 28% reduction in total curtailed solar energy, leading to a more efficient utilization of all resource types.
3. After forming the optimal alliance, total revenue increased by 7.3%. Considering the structural differences in the composition of prosumer aggregators, an improved

Shapley value based on PV self-consumption rates was proposed. This approach allows for compensating aggregators that handle a higher proportion of distributed ESSs, thereby achieving a more equitable distribution of benefits.

In the subsequent work, further consideration will be given to the participation of prosumer aggregators in the operation of the real-time market within cooperative alliances. Additionally, a bidding strategy for the participation of prosumer aggregators in the day-ahead–real-time market will be proposed, taking into account the strong coupling between day-ahead and real-time markets. Additionally, when studying the real-time market, it is important to consider the impacts of special situations, such as the forced disconnection of photovoltaic sources under adverse operating conditions.

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**Data Availability Statement:** The original contributions presented in the study are included in the article, further inquiries can be directed to the corresponding author.

**Conflicts of Interest:** Author Chunyi Wang was employed by the company State Grid Shandong Electric Power Company. Authors Jiawei Xing and Yuejiao Wang were employed by the company State Grid Shandong Electric Power Research Institute. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

## Abbreviations

The abbreviations used in this manuscript are as follows:

| | |
|---|---|
| PV | photovoltaic |
| ESS | energy storage system |
| DA | diagonalization algorithm |
| FM | frequency modulation |
| EPEC | Equilibrium Problem with Equilibrium Constraint |
| MILP | Mixed-Integer Linear Programming |

## Appendix A

It has been shown through previous studies that when an ESS participates in the electric energy–FM market, most of its revenue comes from the participating FM market. It is assumed that the aggregator $k_1$ acts as an agent for a larger number of distributed PV with a smaller number, while the aggregator $k_2$ acts as an agent managing a larger number of distributed PV systems alongside a smaller number of energy storage units, and a cooperative game is played to ally the aggregators $k_1$ and $k_2$. Aggregator $k_1$ allocates a portion of its energy storage capacity originally intended for FM market participation to store excess energy from distributed PV systems within aggregator $k_2$ during peak solar generation periods. This ESS is subsequently sold during nighttime hours, generating additional revenue for the alliance in the energy market. Using the traditional Shapley value method for revenue allocation only considers the average marginal contribution of aggregators $k_1$ and $k_2$ and ignores the sacrifices made by aggregator $k_1$ in the alliance. Therefore, this paper proposes an improved Shapley value.

The proof regarding the sum of correction factors for all aggregators being zero is as follows:

$$
\begin{aligned}
\sum_{k=1}^{n}(m_k \quad -\frac{1}{n}) &= \sum_{k=1}^{n}\left(\frac{\omega_k}{\sum_{k=1}^{n}\omega_k}\right) - \sum_{k=1}^{n}\left(\frac{1}{n}\right) = \frac{\sum_{k=1}^{n}\omega_k}{\sum_{k=1}^{n}\omega_k} - 1 = 0 \\
\sum_{k=1}^{n} M_k &= \sum_{k=1}^{n}\left[\varphi_k(v) + (m_k - \frac{1}{n})\sum_{k=1}^{n}\varphi_k(v)\right] = \sum_{k=1}^{n}\varphi_k(v) + \sum_{k=1}^{n}\left[(m_k - \frac{1}{n})\sum_{k=1}^{n}\varphi_k(v)\right] \\
&= \sum_{k=1}^{n}\varphi_k(v) + \left[\sum_{k=1}^{n}(m_k - \frac{1}{n})\right]\sum_{k=1}^{n}\varphi_k(v) = \sum_{k=1}^{n}\varphi_k(v)
\end{aligned} \tag{A1}
$$

## Appendix B

**Table A1.** The parameter information of MT units.

| MT Units | G1 | G2 | G3 | G4 |
|---|---|---|---|---|
| Rated power/kW | 4000 | 4000 | 3500 | 3000 |
| Power generation quotation/CNY/kWh | 0.183 | 0.190 | 0.208 | 0.218 |
| Frequency modulation capacity quotation/CNY/kWh | 0.012 | 0.012 | 0.016 | 0.013 |
| Frequency modulation mileage quotation/CNY/kWh | 0.016 | 0.015 | 0.015 | 0.017 |
| Mileage and capacity ratio | 12 | 10 | 7 | 12 |

**Table A2.** The parameter information of distributed ESSs.

| Aggregators | 1 | | 2 | | 3 | | |
|---|---|---|---|---|---|---|---|
| ESS ID | ESS1 | ESS2 | ESS3 | ESS4 | ESS5 | ESS6 | ESS7 |
| Charge/Discharge Power/kW | 400 | 200 | 900 | 900 | 800 | 800 | 800 |
| Capacity/kWh | 2000 | 800 | 3600 | 3600 | 3200 | 3200 | 3200 |
| Maximum Storage Capacity | 0.9 | 0.9 | 0.9 | 0.9 | 0.9 | 0.9 | 0.9 |
| Minimum Storage Capacity | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| Charge/Discharge Efficiency | 0.9 | 0.9 | 0.9 | 0.9 | 0.9 | 0.9 | 0.9 |
| Energy Density Ratio | 15 | 15 | 15 | 15 | 15 | 15 | 15 |

**Table A3.** The parameter information of distributed PVs.

| Aggregators | 1 | | | 2 | | 3 | |
|---|---|---|---|---|---|---|---|
| PV ID | PV1 | PV2 | PV3 | PV4 | PV5 | PV6 | PV7 |
| Capacity/kW | 2000 | 2000 | 2000 | 2000 | 2000 | 2000 | 2000 |
| Energy Density Ratio | 15 | 15 | 15 | 15 | 15 | 15 | 15 |

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