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Optimal Energy Management and Trading Strategy for Multi-Distribution Networks with Shared Energy Storage Based on Nash Bargaining Game

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Abstract

In distribution networks, energy storage serves as a crucial means to mitigate power fluctuations from renewable energy sources. However, due to its high cost, energy storage remains a resource whose large-scale adoption in power systems faces significant challenges. In recent years, the emergence of shared energy storage business models has provided new opportunities for the efficient operation of multi-distribution networks. Nevertheless, distribution network operators and shared energy storage operators belong to different stakeholders, and traditional centralized scheduling strategies suffer from issues such as privacy leakage and overly conservative decision-making. To address these challenges, this paper proposes a Nash bargaining game-based optimal energy management and trading strategy for multi-distribution networks with shared energy storage. First, we establish optimal scheduling models for active distribution networks (ADNs) and shared energy storage operators, respectively, and then develop a cooperative scheduling model aimed at maximizing collaborative benefits. The interactive variables—power exchange and electricity prices between distribution networks and shared energy storage operators—are iteratively solved using the Alternating Direction Method of Multipliers (ADMM). Finally, case studies based on modified IEEE-33 test systems validate the effectiveness and feasibility of the proposed method. The results demonstrate that the presented approach significantly outperforms conventional centralized optimization and distributed robust techniques, achieving a maximum improvement of 3.6% in renewable energy utilization efficiency and an 11.2% reduction in operational expenses. While maintaining computational performance on par with centralized methods, it effectively addresses data privacy concerns. Furthermore, the proposed strategy enables a substantial decrease in load curtailment, with reductions reaching as high as 63.7%.

Keywords: distribution networks; shared energy storage; Nash bargaining game; alternating direction method of multipliers

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1. Introduction

Energy storage is an effective way to smooth out fluctuations in new energy output. Single-user configuration of energy storage has the problems of high cost and low utilization, which limits the application of energy storage devices [1,2]. Shared energy

storage utilizes its economies of scale to meet users' energy storage needs at a low cost. The distribution network can stabilize the fluctuation of its net load by leasing energy storage. The distribution network can incentivize energy storage to participate in peak shaving by setting time-of-use electricity prices. The distribution network, shared energy storage, and microgrid can all be considered relatively independent systems, operated and managed by distribution system operators, shared energy storage operators, and microgrid operators, respectively [3]. The interests of the three parties conflict with each other, and their power interaction affects the distribution of power flow in the distribution network. Therefore, it is necessary to study how to use shared energy storage to promote the on-site consumption of new energy, improve the utilization rate of energy storage, and develop effective scheduling strategies in distribution systems containing shared energy storage to promote the safe and stable operation of the distribution network and solve conflicts of interest among multiple parties [4]. This also has certain engineering reference value for the future investment and use of shared energy storage.

In order to cope with the many adverse effects brought by the integration of a large number of distributed energy sources into the distribution network, traditional distribution networks need to develop towards active control and management. The active distribution network achieves precise control of power flow by comprehensively controlling distributed energy sources such as various distributed power sources, energy storage, and flexible loads within the network, improving the reliability of system operation and greatly promoting the utilization of distributed renewable power sources [5]. At present, there have been many studies on active distribution network (AND) energy optimization management both domestically and internationally, mainly focusing on the economic and reliability aspects of ADN operation. Relevant optimization models have been established and various mathematical methods have been used for simulation research. In the study [6], a multi-objective optimization model is established to study the impact of active power output from power sources on network loss and node voltage offset. The authors of the study [7] designed an active distribution network system with electric vehicle charging stations and proposed a two-layer collaborative planning model, which not only reduces the overall planning cost but also ensures the quality of electrical energy. According to source [8], an ADN active/reactive power joint optimization scheduling strategy with "source grid load storage" interaction is proposed and finely modeled at multiple time scales, which has a significant effect on improving system operation efficiency and reliability. In the study [9], a multi-time scale reactive power dynamic optimization model is established for multiple types of reactive power sources, effectively improving the voltage stability quality caused by wind, solar, and load fluctuations. Starting from the environment of the electricity market, the authors of [10] propose a dual-layer optimization model of "source grid load" multi-stakeholder coordination and interaction using game theory. The upper layer considers the balance of interests among all the stakeholders as the goal, and the lower layer considers the minimum expected annual removal of distributed power sources as the goal. In [11], an ADN optimization scheduling strategy is proposed that takes into account load demand response, fully considers the cost of user satisfaction with electricity consumption, improves user participation, and is more beneficial to the operation of the system. According to reference [12], research focuses on the active/reactive power coordination scheduling method for active distribution networks. The second-order cone and linear techniques are used to model the method, and the relaxation method is adopted to transform the model into a mixed integer linear programming problem for solving, which improves the speed and accuracy of model solving. The authors of [13] studied the multi-level joint expansion planning problem of active distribution networks, jointly considering the investment of distributed power sources, feeders, substations, and other

resources to maximize their operational efficiency. The study in [14] applies the optimal power flow theory to establish a multiperiod optimal power flow model for an active distribution network containing distributed power sources, energy storage, microgrids, and electric vehicles, improving the power quality of the distribution network operation. The study in [15] proposed an active distribution network optimization strategy that considers real-time network reconstruction. By regulating distributed power sources and demand response loads in real time, the operating costs of active distribution networks can be reduced. In the above studies on ADN, most of them have considered the participation of distributed power sources, energy storage, and demand side loads, but have not yet taken into account the impact of uncertainty in new energy sources and loads. In [16], optimization models using scenario clustering, random opportunity constraint, and interval robust optimization methods are established, which, to some extent, reduce the impact of system uncertainty on scheduling. For the integration of electric vehicles into ADN, the authors of [17] studied the impact of electricity price elasticity on electric vehicle charging, constructed an optimization model for electric vehicle charging that takes into account electricity price elasticity, reduced the charging cost for vehicle owners, and improved the load characteristics of the distribution network. The study in [18] applies the time-of-use pricing mechanism to guide the optimization scheduling of flexible loads in active distribution networks, which can reduce power fluctuations on the grid side and is more economical than regulating energy storage.

Currently, numerous scholars have conducted research on the application of shared energy storage in distribution networks. In [19], the specific application of the sharing economy in future smart grids was explored, with shared energy storage being invested and constructed by multiple companies, establishing an energy storage investment model based on non-cooperative game theory and proving the uniqueness of Nash equilibrium solutions. The results of the case analysis show that the proposed model can enable users to arbitrage variable energy prices and allocate their profits. The authors of [20] proposed a master–slave evolutionary hybrid game model for the sharing of electricity and energy storage resources among multiple regions. A master–slave game model was established with operators as leaders and users as followers to optimize decision-making. A revenue and cost model for both operators and users was established, taking into account the interaction between electricity and the grid, as well as the benefits of both parties. The pricing strategy, shared energy storage configuration, and charging and discharging strategy of the operator were obtained. The effectiveness of the proposed operational model was verified through numerical analysis. The study in [21] focuses on the operation mode of shared energy storage, electricity sharing, and capacity sharing. A model considering seasonal differences in user loads and optimization of renewable energy generation is established, and simulation is conducted based on real historical data. The case analysis shows that the operation mode of centralized energy storage investment and electricity sharing is more economical. The authors of [22] conducted research on the demand side shared energy storage operation model, establishing a three-party operation model for shared energy storage power stations, users, and operators. An optimization model was established to minimize system operating costs, and service pricing was based on the Nash negotiation theory. The effectiveness of the proposed operation model was verified by numerical examples. The study in [23] proposed an optimization method for the allocation of shared energy storage capacity among power sales companies under market mechanisms. The objective function of minimizing the purchase cost of multiple power sales companies was established, and the benefit distribution problem of shared energy storage was solved according to the defined contribution degree. The feasibility of energy storage configuration on the sales side was verified through case analysis. The

authors of [24] conducted research on the configuration scheme of shared energy storage for different types of industrial microgrids, with the goal of minimizing the purchase cost of electricity for multiple power sales companies. Based on cooperative game theory and fully considering investment benefits, an energy storage configuration optimization model was established with the full life cycle of energy storage as the time scale, and the benefits generated by cooperation were allocated based on the Shapley value method. The case analysis shows that this energy storage configuration scheme can effectively reduce the investment cost and electricity consumption costs of industrial microgrid users. Authors of [25] conducted research on the configuration scheme of shared energy storage capacity in industrial parks. Considering the uncertainty of power load and new energy output in industrial parks, the scenario tree method was used to model the uncertainty. With the goal of maximizing the operating revenue of shared energy storage operators, a multi-stage stochastic programming model was established. The effectiveness of the proposed model was verified through numerical simulations.

Although numerous scholars have conducted research on coordinated dispatching in distribution networks, challenges such as privacy leakage and overly conservative decision-making persist. Furthermore, deeper issues such as risk-sharing mechanisms in shared energy storage business models and the long-term stability of multi-agent gaming remain underexplored. To address these problems, this paper proposes a Nash bargaining game-based optimal energy management and trading strategy for multi-distribution networks with shared energy storage. The main contributions of this work can be summarized as follows:

First, a cooperative framework based on Nash bargaining game theory is introduced. Targeting the issue where ADNs and SESOs belong to different stakeholders, this paper innovatively employs the Nash bargaining game as a cooperative mechanism, overcoming the drawbacks of traditional centralized dispatching strategies, such as privacy leakage and overly conservative decision-making. This approach achieves mutual benefits for all parties, maximizes overall collaborative gains, and ensures the fair distribution of additional profits from cooperation.

Second, a distributed collaborative optimization solution based on the ADMM is designed. Utilizing ADMM as the core algorithm, this method solves key interactive variables in the cooperative model through distributed iterations. It efficiently addresses complex cooperative optimization problems while protecting private information such as internal costs and operational constraints of all parties. Specifically tailored to handle intricate power exchange and electricity price negotiation between distribution networks and shared energy storage operators, this method enables distributed decision-making, eliminates the need for centralized optimization that requires private information, and ensures both convergence and computational efficiency.

2. Description of Multi-Stakeholder Cooperation Model

Analysis of the operation mode and interest demands of distribution network operators and shared energy storage operators (SESOs): DNO is in a dominant position in the system, and its operational goal is to minimize operating costs. ADN contains new energy sources such as wind turbines and photovoltaics, as well as conventional loads. ADN prioritizes the consumption of its own new energy generation to support its conventional load. In order to reduce the peak valley difference in net load, ADN implements peak shaving scheduling. Based on the peak and off-peak periods of the ADN net load curve, time-of-use electricity prices are formulated to incentivize load participation in demand response, adjust its power interaction with ADN, and achieve peak shaving and valley filling of ADN net load. ADN is connected to the main grid and shared energy storage, and

the remaining load is met by purchasing electricity from the main grid or shared energy storage. Shared energy storage station operators provide energy storage charging and discharging services for multiple distribution networks, and charge energy storage station service fees to each distribution network.

3. Optimization and Scheduling Model of Active Distribution Network with Shared Energy Storage

3.1. Optimal Scheduling Model for Active Distribution Network

The objective function of the distribution network optimization model considers economy, flexibility, and safety, taking into account system flow constraints, distributed power generation operation constraints, system operation constraints, intelligent soft switch operation constraints, and shared energy storage system operation constraints. The objective function is shown in Equation (1):

$$obj = \min(C_{ld} + C_{loss} - C_{ene}) \tag{1}$$

Here, the objective function mainly includes the flexible resource scheduling cost C_{ld}, network loss cost C_{loss}, and shared energy storage scheduling cost C_{ene}. The detailed calculation formulas for each part are shown in (2)–(4) below:

$$C_{ld} = \lambda_g \sum_{t=1}^{T} P_t^g + \lambda_{sop} \sum_{ij \in \Omega_{SOP}} S_{SOP,ij} \tag{2}$$

$$C_{loss} = \lambda_{loss} \left(\sum_{t=1}^{T} P_{ij,t}^{loss} + \sum_{t=1, ij \in \Omega_{SOP}}^{T} P_{SOP,ij,t}^{L} \right) \tag{3}$$

$$C_{ene} = \sum_{t=1}^{T} \left(\lambda_t^{buy} P_{i,t}^{cs,d} - \lambda_t^{sell} P_{i,t}^{cs,c} \right) \tag{4}$$

Here, P_t^g represents the cost of purchasing electricity from the higher-level main grid; $P_{ij,t}^{loss}$ represents the operating loss. λ_g represents the price of electricity purchased from superiors; λ_{sop} represents the operating cost coefficient per unit capacity of SOP; λ_{loss} represents the cost coefficient of unit power loss; $P_{i,t}^{cs,d}$ and $P_{i,t}^{cs,c}$, respectively, represent the discharge power and charging power of shared energy storage devices interacting with the distribution network; and λ_t^{buy} and λ_t^{sell}, respectively, represent the purchase and sale prices of electricity from shared energy storage devices by the distribution network. It should be clarified that this paper addresses real-time dispatch problems. In power system real-time dispatch, the uncertainty of renewable energy generation is not completely ignored, but rather its impact has been significantly reduced and effectively managed at this stage, allowing it to be treated as relatively deterministic input. Real-time dispatch typically refers to operational decisions made very close to the current time (ranging from minutes to tens of minutes), aiming to balance system power in the next time period. The prediction accuracy of renewable energy output improves dramatically as the forecasting time scale shortens. Ultra-short-term forecasting utilizes the latest meteorological observation data, updated numerical weather predictions, and real-time power plant output data, typically yielding much smaller prediction errors compared to medium-/long-term or day-ahead forecasting. At the minute-to-tens-of-minutes scale, drastic changes in weather systems are relatively rare. Variations in renewable energy output predominantly follow gradual trends, enabling ultra-short-term forecasts to capture most fluctuation patterns. Consequently, within the brief time window of real-time dispatch decisions, forecasted values can be reasonably treated as high-confidence inputs with manageable uncertainty levels that the existing

control mechanisms can accommodate, which fundamentally distinguishes our problem framework from longer-term scheduling scenarios dealing with greater uncertainty.

Meanwhile, the distribution network needs to consider the following constraints during operation:

(1) Power flow constraints.

The expression for trend constraints are shown as (5)–(8).

$$\begin{cases} \sum\limits_{ji\in\Omega_B}(P_{ji,t}-r_{ji}I_{ji,t}^2)+P_{i,t}=\sum\limits_{ik\in\Omega_B}P_{ik,t} \\ \sum\limits_{ji\in\Omega_B}(Q_{ji,t}-x_{ji}I_{ji,t}^2)+Q_{i,t}=\sum\limits_{ik\in\Omega_B}Q_{ik,t} \end{cases} \tag{5}$$

$$U_{j,t}^2-U_{i,t}^2-2(r_{ji}P_{ji,t}+x_{ji}Q_{ik,t})+(r_{ji}^2+x_{ji}^2)I_{ji,t}^2=0 \tag{6}$$

$$I_{ji,t}^2U_{i,t}^2=P_{ji,t}^2+Q_{ji,t}^2 \tag{7}$$

$$\begin{cases} P_{i,t}=P_{DG,i,t}+P_{SOP,i,t}-P_{L,i,t}+P_{i,t}^{cs,d}-P_{i,t}^{cs,c} \\ Q_{i,t}=Q_{SOP,i,t}-Q_{L,i,t} \end{cases} \tag{8}$$

Here, $P_{ji,t}$ and $Q_{ji,t}$, respectively, represent the active power and reactive power of the branch ij; $P_{i,t}$ and $Q_{i,t}$, respectively, represent the active power and reactive power injected into the node i; r_{ji}, x_{ji}, and $I_{ji,t}$, respectively, represent branch resistance, branch reactance, and branch current; $U_{i,t}$ represents the node voltage; $P_{L,i,t}$ and $Q_{L,i,t}$, respectively, represent the active power and reactive power of the node load; and $P_{DG,i,t}$ represents the active power injected into the node by renewable energy.

(2) System operation constraints.

The system operation constraints mainly include node voltage and line current constraints, as shown in (9)–(10).

$$U_{i,\min}^2\le U_{i,t}^2\le U_{i,\max}^2 \tag{9}$$

$$I_{ji,t}^2\le I_{ji,\max}^2 \tag{10}$$

Here, $U_{i,\max}$ and $U_{i,\min}$, respectively, represent the maximum and minimum allowable values of the node voltage; and $I_{ji,\max}$ represents the maximum capacity allowed by the branch.

(3) The upper-level main network injects active power constraints.

The injection of active power into the higher-level main network should meet the transmission capacity constraint of the interconnection line, and the expression of the constraint is (11).

$$P_{\min}^g\le P_t^g\le P_{\max}^g \tag{11}$$

(4) New energy output constraints.

The expression for the constraint of new energy output is (12).

$$0\le P_{DG,i,t}\le P_{DG,i,\max} \tag{12}$$

(5) Network side flexibility resource constraints.

The flexibility resources on the grid side mainly consider SOP, which can flexibly, in real time, and safely regulate active and reactive power; effectively solve the problem of system voltage exceeding limits; and enhance the flexibility of the grid structure. SOP replaces traditional interconnection switches and achieves power exchange between feeders through power electronics technology, thereby regulating the power flow distribution and voltage level in the distribution network. There are two VSCs in an SOP, one using PQ control and the other using VdcQ control. The VSC control unit controlled by PQ controls the active power output of SOP and the reactive power injected by VSC, while the VSC

control unit controlled by VdcQ maintains a constant DC bus voltage and injects reactive power. The power control model of SOP is as follows:

$$P_{SOP,i} + P_{SOP,j} + P^L_{SOP,i} + P^L_{SOP,j} = 0 \tag{13}$$

$$\begin{cases} P^L_{SOP,i} = A_{SOP,i}\sqrt{P^2_{SOP,i} + Q^2_{SOP,i}} \\ P^L_{SOP,j} = A_{SOP,j}\sqrt{P^2_{SOP,j} + Q^2_{SOP,j}} \end{cases} \tag{14}$$

$$\begin{cases} \xi_{\min} S_{SOP,ij} \le Q_{SOP,i} \le \xi_{\max} S_{SOP,ij} \\ \xi_{\min} S_{SOP,ij} \le Q_{SOP,j} \le \xi_{\max} S_{SOP,ij} \end{cases} \tag{15}$$

$$\begin{cases} \sqrt{P^2_{SOP,j} + Q^2_{SOP,j}} \le S_{SOP,ij} \\ \sqrt{P^2_{SOP,i} + Q^2_{SOP,i}} \le S_{SOP,ij} \end{cases} \tag{16}$$

Here, $P_{SOP,i}$ and $P_{SOP,j}$ are the transmitted active power at SOP nodes i and j, respectively; $P^L_{SOP,i}$ and $P^L_{SOP,j}$ are the power losses of SOP nodes i and j, respectively; $Q_{SOP,i}$ and $Q_{SOP,j}$ are the transmission reactive power of SOP sections i and j, respectively; $A_{SOP,i}$ is the SOP power loss coefficient; $S_{SOP,ij}$ is the rated capacity for connecting SOP between nodes i and j; and $\xi_{\min}$ and $\xi_{\max}$ represents the minimum and maximum absolute values of the sine wave of the power factor angle, respectively.

Considering that the optimization model contains large-scale nonlinear expressions, which greatly increases the computational burden, in order to reduce complexity, this paper linearizes the SOP model and distribution network power flow constraints.

For the power flow constraint model Equations (5)–(8), by introducing intermediate variables $l_{ji,t}$ and $v_{i,t}$ to replace $I^2_{ji,t}$ and $U^2_{i,t}$, the replaced model is as follows:

$$\begin{cases} \sum\limits_{ji\in\Omega_B} (P_{ji,t} - r_{ji} l_{ji,t}) + P_{i,t} = \sum\limits_{ik\in\Omega_B} P_{ik,t} \\ \sum\limits_{ji\in\Omega_B} (Q_{ji,t} - x_{ji} l_{ji,t}) + Q_{i,t} = \sum\limits_{ik\in\Omega_B} Q_{ik,t} \end{cases} \tag{17}$$

$$v_{j,t} - v_{i,t} - 2(r_{ji}P_{ji,t} + x_{ji}Q_{ik,t}) + (r^2_{ji} + x^2_{ji}) l_{ji,t} = 0 \tag{18}$$

$$l_{ji,t} v_{i,t} \ge P^2_{ji,t} + Q^2_{ji,t} \tag{19}$$

$$U^2_{i,\min} \le v_{i,t} \le U^2_{i,\max} \tag{20}$$

For SOP nonlinear constraint Equations (14) and (16), they are converted into second-order cone constraint (21) and rotational cone constraint (22), respectively:

$$\begin{cases} P^L_{SOP,i} \ge A_{SOP,i}\sqrt{P^2_{SOP,i} + Q^2_{SOP,i}} \\ P^L_{SOP,j} \ge A_{SOP,j}\sqrt{P^2_{SOP,j} + Q^2_{SOP,j}} \end{cases} \tag{21}$$

$$\begin{cases} P^2_{SOP,j} + Q^2_{SOP,j} \le 2\frac{S_{SOP,ij}}{\sqrt{2}}\frac{S_{SOP,ij}}{\sqrt{2}} \\ P^2_{SOP,i} + Q^2_{SOP,i} \le 2\frac{S_{SOP,ij}}{\sqrt{2}}\frac{S_{SOP,ij}}{\sqrt{2}} \end{cases} \tag{22}$$

3.2. Optimal Scheduling Model for Shared Energy Storage Operators

The operating costs of shared energy storage operators (23) mainly consist of two parts: one is the loss cost of shared energy storage charging and discharging, and the other is the

cost of energy exchange between shared energy storage and the distribution network. The detailed mathematical expression is shown in the following Equations (24) and (25).

$$obj = \min(C_{cs,loss} + C_{cs,ene}) \tag{23}$$

$$C_{cs,loss} = \lambda_{cs}^{loss} \sum_{t=1}^{T} (P_{i,t}^{cs,d} + P_{i,t}^{cs,c}) \tag{24}$$

$$C_{cs,ene} = \sum_{t=1}^{T} (\lambda_{cs}^{buy} P_{i,t}^{cs,c} - \lambda_{cs}^{sell} P_{i,t}^{cs,dis}) \tag{25}$$

Here, $C_{cs,loss}$ and $C_{cs,ene}$, respectively, represent the charging and discharging loss cost of shared energy storage, as well as the energy exchange cost between shared energy storage and the distribution network; λ_{cs}^{loss} represents the loss coefficient during energy storage charging and discharging; T takes 24 h; and λ_{cs}^{buy} and λ_{cs}^{sell} represent the purchase and sale price of electricity of shared energy storage devices.

Simultaneously sharing energy storage should meet constraint (26) during operation.

$$\begin{aligned}
&0.1E_{cs}^{\max} \le E_{cs,t} \le 0.9E_{cs}^{\max} \\
&0 \le P_{i,t}^{cs,c} \le \sigma_t^{cs} P_{\max}^{cs,c} \\
&0 \le P_{i,t}^{cs,d} \le (1-\sigma_t^{cs}) P_{\max}^{cs,d} \\
&E_{cs,t} = E_{cs,t-1} + P_{i,t}^{cs,c}\eta^{cs,c} - P_{i,t}^{cs,d}/\eta^{cs,d} \\
&E_{cs,1} = 0.2E_{cs}^{\max} + P_{i,1}^{cs,c}\eta^{cs,c} - P_{i,1}^{cs,d}/\eta^{cs,d} \\
&E_{cs,T} = 0.2E_{cs}^{\max} \\
&\sigma_t^{cs} \in \{0,1\}
\end{aligned} \tag{26}$$

Here, $E_{cs,t}$ and $E_{cs}^{\max}$, respectively, represent the energy stored in the shared energy storage power station at time t and its theoretical upper limit; $P_{\max}^{cs,c}$ and $P_{\max}^{cs,d}$, respectively, represent the upper limits of the charging and discharging power of the energy storage power station; $\eta^{cs,c}$ and $\eta^{cs,d}$, respectively, represent the charging and discharging efficiency of shared energy storage.

4. Multi-Distribution Grid and Shared Energy Storage Collaborative Optimization Operation Model and Solution Strategy Based on Nash Negotiation

4.1. Collaborative Optimization Mathematical Model

In the multi-distribution network shared energy storage collaborative system, each active distribution network and community shared energy storage operator reach an agreement to cooperate and achieve energy synergy, maximizing the benefits of all parties and fairly distributing benefits. According to the definition of the Nash negotiation standard model, the expression of the cooperative game model between multiple distribution grids and shared energy storage in this article is shown in (27).

$$\begin{cases} \max(E^{cs,0} - E^{cs}) \prod_{i=1}^{I} (E_i^{DN,0} - E_i^{DN}) \\ s.t. \begin{cases} E^{cs,0} - E^{cs} \ge 0 \\ E_i^{DN,0} - E_i^{DN} \ge 0 \end{cases} \end{cases} \tag{27}$$

Here, $E^{cs,0}$ and $E_i^{DN,0}$, respectively, represent the negotiation breakdown point between the shared energy storage operator and the distribution network operator i; that is, the independent operating cost of shared energy storage; I represents the number of distribution network operators; and E^{cs} and E_i^{DN}, respectively, represent the costs of each entity after the

cooperation of shared energy storage and distribution network. The constraint conditions indicate that after participating in cooperation, the operating costs of each subject can be reduced and the operating efficiency can be improved. Equation (27) is a non-convex nonlinear problem that cannot be solved directly using a solver. Therefore, it can be equivalently transformed into solving the problems of minimizing alliance cooperation costs and negotiating transactions among various parties.

4.2. Solution of Minimizing Alliance Cooperation Costs Based on ADMM Algorithm

According to the principle of mean inequality, the nonlinear model (27) can be transformed into the solving model shown in (28).

$$\begin{cases} \min\left\{ \sum_{i=1}^{I} C_i^{DN}(P_{i,t}^{DN,cs}) + C^{cs}(P_{i,t}^{cs,DN}) \right\} \\ s.t. \begin{cases} P_{i,t}^{DN,cs} = P_{i,t}^{cs,DN} \\ (5)-(22) \end{cases} \end{cases} \tag{28}$$

Here, C^{cs} represents the shared energy storage operating cost without considering cooperation with the distribution network; C_i^{DN} represents the operating cost of the distribution network i without considering cooperation with shared energy storage. The first row of constraints represents that at time t, the power sold by distribution network i to the shared energy storage power station $P_{i,t}^{DN,cs}$ is equal to the power purchased by the shared energy storage power station from the distribution network $P_{i,t}^{cs,DN}$.

Using the ADMM algorithm for the distributed solution, the optimized cooperation cost is obtained. The auxiliary variables $P_{i,t}^{\Delta}$ are used to decouple the community shared energy storage and the electrical interaction between various distribution networks.

$$P_{i,t}^{\Delta} = P_{i,t}^{DN,cs} = P_{i,t}^{cs,DN} \tag{29}$$

Lagrange multiplier λ_i and penalty factor ρ_i are introduced to construct a distributed optimization model for multiple distribution networks and shared energy storage stations. The distributed optimization operation model of the distribution network is (30).

$$\begin{cases} \min[C_i^{DN}(P_{i,t}^{DN,cs}) + \sum_{i=1}^{I}\sum_{t=1}^{T} \lambda_i(P_{i,t}^{\Delta} - P_{i,t}^{DN,cs}) \\ + \sum_{t=1}^{T} \frac{\rho_i}{2} \left\| P_{i,t}^{\Delta} - P_{i,t}^{DN,cs} \right\|_2^2] \\ s.t.(5)-(22) \end{cases} \tag{30}$$

The distributed optimization operation model for shared energy storage power stations is (31).

$$\begin{cases} \min[C^{cs}(P_{i,t}^{cs,DN}) + \sum_{i=1}^{I}\sum_{t=1}^{T} \lambda_i(P_{i,t}^{\Delta} - P_{i,t}^{cs,DN}) \\ + \sum_{t=1}^{T} \frac{\rho_i}{2} \left\| P_{i,t}^{\Delta} - P_{i,t}^{cs,DN} \right\|_2^2] \\ s.t.(26) \end{cases} \tag{31}$$

The distributed optimization operation model iterates the Lagrange multiplier according to Equation (32). If (33) is satisfied, the iteration terminates, and the minimum alliance cooperation cost of each distribution network and shared energy storage power station at time t are obtained, along with the corresponding exchange energy $P_{i,t}^{cs\sim DN}$ at that moment.

$$\lambda_{i,t+1} = \lambda_{i,t} + \rho_i(P_{i,t}^{cs\sim DN} - P_{i,t}^{DN,cs}) \tag{32}$$

$$\max \sum_{t=1}^{T} \left\| P_{i,t}^{cs\sim DN} - P_{i,t}^{DN,cs} \right\|_2^2 \leq \xi \tag{33}$$

Here, $\lambda_{i,t+1}$ and $\lambda_{i,t}$ represent the Lagrange multipliers corresponding to time $t+1$ and time t, respectively; ξ represents the convergence threshold for minimizing cooperation costs.

4.3. Solution of Transaction Negotiation Problems Among Alliance Parties Based on ADMM Algorithm

By solving the problem of minimizing the cost of alliance cooperation, the optimal energy exchange quantities $P_{i,t}^{DN,cs}$ and $P_{i,t}^{cs,DN}$ between each distribution network and shared energy storage power station are obtained. The cost of operating a shared energy storage power station separately can be directly solved by the solver, expressed as C_0^{cs}. The distribution network scheduling model before the alliance cooperation was solved and expressed as $C_{i,0}^{DN}$. The nonlinear model Equation (28) is transformed into a logarithmic expression as shown in Equation (34).

$$\min \begin{Bmatrix} -[\ln \sum_{i=1}^{I} (C_{i,0}^{DN} - C_{*i}^{DN}(P_{i,t}^{DN,cs}) - C_i^{DN,cs}) + \\ \ln \sum_{i=1}^{I} (C_0^{cs} - C_{*i}^{cs}(P_{i,t}^{cs,DN}) - C_i^{cs,DN})] \end{Bmatrix} \\ s.t. \begin{cases} C_{i,0}^{DN} - C_{*i}^{DN}(P_{i,t}^{DN,cs}) - C_i^{DN,cs} \geq 0 \\ C_0^{cs} - C_{*i}^{cs}(P_{i,t}^{cs,DN}) - C_i^{cs,DN} \geq 0 \\ \underline{p}_t^{grid} \leq p_{i,t}^{cs,DN} \leq \overline{p}_t^{grid} \\ \underline{p}_t^{grid} \leq p_{i,t}^{DN,cs} \leq \overline{p}_t^{grid} \\ (5) - (22) \end{cases} \tag{34}$$

Here, $\overline{p}_t^{grid}$ and $\underline{p}_t^{grid}$, respectively, represent the upper and lower bounds of the interactive electricity price between the microgrid and the distribution network in the park. In model Equation (34), the coupling variables of energy trading prices between various distribution networks and shared energy storage power stations are included, and it is necessary to satisfy that the purchase and sale prices of energy between each distribution network and community shared energy storage are equal. This paper uses the auxiliary variable $p_{i,t}^{\Delta}$ to decouple shared energy storage and electricity transaction prices between distribution networks, as shown in (35).

$$p_{i,t}^{\Delta} = p_{i,t}^{cs,DN} = p_{i,t}^{DN,cs} \tag{35}$$

Using the ADMM algorithm for the distributed solution and introducing Lagrange multipliers, a distributed optimization model is constructed for multiple distribution networks and shared energy storage stations using σ_i and penalty factor γ_i. The distributed optimization operation model of an active distribution network is (36).

$$\begin{cases} \min[-\ln(C_{i,0}^{DN} - C_{*i}^{DN}(P_{i,t}^{DN,cs}) - p_{i,t}^{DN,cs} P_{*i,t}^{\Delta}) \\ + \sum_{i=1}^{I} \sum_{t=1}^{T} \sigma_i (p_{i,t}^{\Delta} - p_{i,t}^{DN,cs}) \\ + \sum_{t=1}^{T} \frac{\gamma_i}{2} \left\| p_{i,t}^{\Delta} - p_{i,t}^{DN,cs} \right\|_2^2)] \\ s.t. C_{i,0}^{DN} - C_{*i}^{DN}(P_{i,t}^{DN,cs}) - p_{i,t}^{DN,cs} P_{*i,t}^{\Delta} \geq 0 \end{cases} \tag{36}$$

The distributed optimization operation model for shared energy storage power stations is (37).

$$\begin{cases} \min[-\ln(C_{i,0}^{DN} - C_{*i}^{DN}(P_{i,t}^{DN,cs}) - p_{i,t}^{cs,DN} P_{*i,t}^{\Delta}) \\ +\sum_{i=1}^{I}\sum_{t=1}^{T} \sigma_i (p_{i,t}^{\Delta} - p_{i,t}^{cs,DN}) \\ +\sum_{t=1}^{T} \frac{\gamma_i}{2} \left\| p_{i,t}^{\Delta} - p_{i,t}^{cs,DN} \right\|_2^2)] \\ s.t. C_{i,0}^{DN} - C_{*i}^{DN}(P_{i,t}^{DN,cs}) - p_{i,t}^{cs,DN} P_{*i,t}^{\Delta} \geq 0 \end{cases} \tag{37}$$

The distributed optimization operation model iterates the Lagrange multiplier according to (38). If (38) is satisfied and the iteration is terminated, the transaction electricity price of the shared energy storage power station at time t can be obtained.

$$\max \left[\sum_{t=1}^{T} \left\| p_{i,t}^{\Delta} - p_{i,t}^{DN,cs} \right\|_2^2 \right] \leq \phi \tag{38}$$

Here, ϕ represents the convergence threshold for transaction negotiations among the various entities in the alliance. The proposed method ensures constraint feasibility through a hierarchical optimization architecture and distributed iterative mechanism. First, local models strictly satisfy physical constraints, with each ADN and SESO independently meeting their respective physical constraints in local optimization subproblems. Specifically, the ADN subproblems rigorously adhere to power balance constraints, node voltage limits, line capacity limits, upstream grid injection power limits, and renewable generation output ranges. The SESO subproblems enforce compliance with energy storage dynamic equations, including SOC boundaries, charge/discharge power limits, and efficiency constraints. During each ADMM iteration, all the entities guarantee strictly feasible solutions to their subproblems through local solvers, eliminating any resource–demand imbalances. On the other hand, global coupling constraints exhibit asymptotic convergence, with system-wide feasibility relying on the satisfaction of two types of coupling constraints: power exchange consistency requires the agreed-upon exchange power between each ADN and SESO to equal the actual transmitted value, while price consistency ensures alignment between the negotiated electricity purchase/sale prices of ADNs and SESO. These coupling constraints progressively converge through ADMM's augmented Lagrangian terms and Lagrange multiplier updates. When the algorithm converges, deviations in coupling constraints approach zero, guaranteeing global feasibility. This dual-layered approach—local constraint enforcement and iterative global coordination—ensures both operational viability and system-wide optimality.

It should be noted that the energy cost function in the paper is convex but not strongly convex. The objective function comprises multiple linear cost terms such as electricity purchase costs, network loss cost coefficients, and energy storage charging/discharging costs, with their linear combination preserving overall convexity. However, the model does not incorporate strictly convex terms and thus does not satisfy strong convexity, meaning there is no unique global minimum point. The ADMM algorithm is applicable to general convex problems and is not limited to quadratic costs. The paper ensures convexity through the following treatments: convex relaxation is applied to nonlinear constraints such as power flow equations, while the objective function maintains a linear convex piecewise form without relying on a quadratic structure. If strict convexity is required in practical scenarios—such as by adding regularization terms—ADMM remains applicable, though the current model does not involve such extensions. The proposed method is suitable for general convex cost functions (including linear, quadratic, or other convex forms). The method itself does not depend on a specific cost structure, as long as the objective function and constraints are convex, which guarantees ADMM convergence. In summary, the model assumes the cost function is convex, and the solution applies to

general convex optimization problems; quadratic costs can be included as a special case but are not a necessary condition. This flexibility ensures broad applicability while maintaining theoretical convergence guarantees.

5. Case Study

5.1. Introduction to the Test System

In order to verify the effectiveness and feasibility of the proposed method, this paper uses three improved IEEE-33 node testing systems to form connections. The systems have their own distributed new energy sources, and shared energy storage devices are connected to the three testing systems through nodes 21, 28, and 28, respectively. The topology of the testing system structure is shown in Figure 1. The output data of various distributed new energy sources are shown in Figures 2 and 3. The shared energy storage parameter settings are shown in Table 1, and the time-of-use electricity prices for the active distribution network to purchase and sell electricity from the higher-level power grid are shown in Table 2.

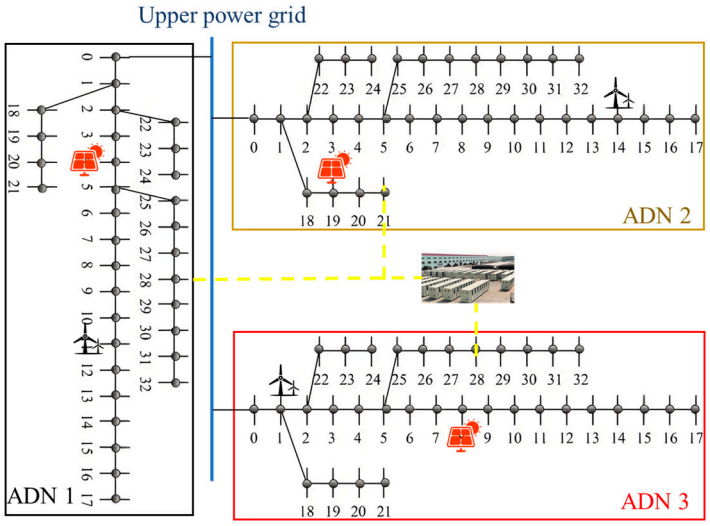


Figure 1. Topology diagram of the test system.

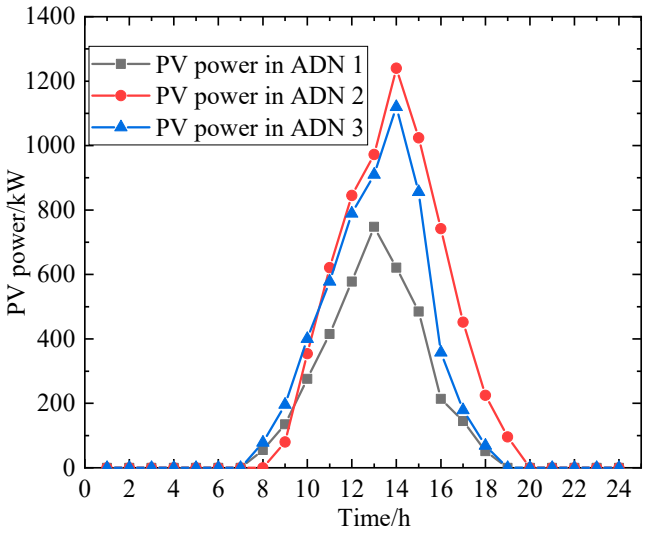


Figure 2. Photovoltaic power in different distribution networks.

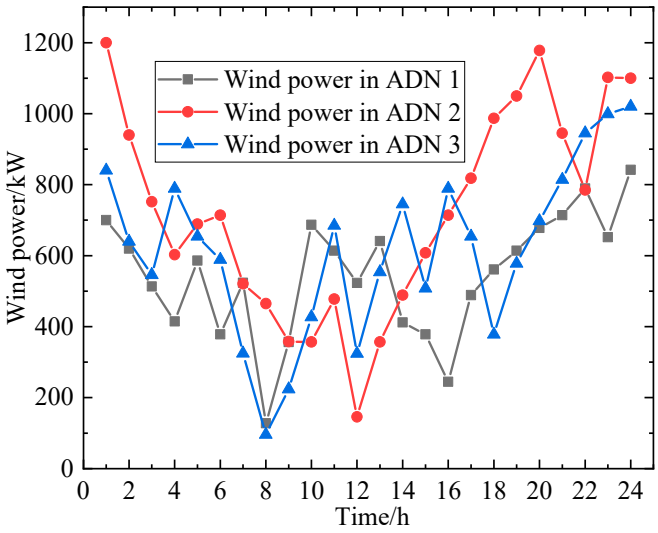


Figure 3. Wind power in different distribution networks.

Table 1. Shared energy storage device parameters.

Parameters and Units	Value
Rated capacity/kWh	7500
Maximum charging and discharging power/kW	2000
Charge/discharge efficiency	0.92
State of Charge Interval	[0.1, 0.9]

Table 2. Time-of-use electricity price for purchasing and selling electricity in the power grid.

Time	Electricity Sell Price/($/kWh)	Electricity Purchase Price/($/kWh)
00:00–05:00, 22:00–24:00,	0.42	0.15
05:00–08:00, 13:00–17:00,	0.85	0.35
08:00–13:00, 17:00–22:00,	1.20	0.45

5.2. Effectiveness Validation of the Proposed Method

To further demonstrate the effectiveness of the method proposed in this article, three different scenarios were set up for comparison. The relevant calculation results are shown in Table 3 below.

Table 3. Comparison results of performance indicators in different scenarios.

Index	Scenario 1	Scenario 2	Scenario 3
Peak valley load difference/kW	1742	1268	458
New energy consumption rate/%	87.4	91.2	97.4
Total operating cost/$	8452.7	7456.4	7137.2
Calculation time/s	35.6	45.8	61.7

Scenario 1: Independent scheduling of each AND without power interaction through shared energy storage.

Scenario 2: Each AND adopts a centralized scheduling strategy to participate in scheduling.

Scenario 3: Each AND adopts the method proposed in this article for energy management.

Observing the above table, it can be found that the strategy proposed in this article can effectively reduce the peak valley load difference, improve the consumption rate of

new energy, and thereby reduce operating costs. The energy storage system smooths the load curve through "low charging and high discharging". Under the traditional mode, the energy storage capacity of a single distribution network is limited, making it difficult to independently cope with large peak valley differences. Shared energy storage can dynamically allocate energy storage charging and discharging power at different time periods through collaborative optimization of multiple distribution networks, enabling more efficient peak shaving and valley filling. Each distribution network interacts with shared energy storage operators based on its own load demand (electricity quantity and price), and achieves global optimal scheduling through iterative adjustments. This mechanism avoids the conservatism of centralized scheduling, allowing energy storage resources to be allocated on demand among multiple distribution networks, further smoothing the total load curve. Nash negotiation game aims to maximize cooperation benefits and incentivize distribution networks and shared energy storage operators to jointly solve the problem of new energy fluctuations. When there is an excess of new energy output, shared energy storage prioritizes storing excess electricity; when the output of new energy is insufficient, energy storage discharge fills the gap and reduces dependence on traditional units. The electricity price signal optimized through ADMM iteration can reflect the real-time supply–demand relationship, guide the distribution network to increase energy storage and charging demand during the peak period of new energy, and thus improve the consumption rate.

In addition, shared energy storage avoids the need for each distribution network to independently configure high-cost energy storage equipment, improves energy storage utilization through large-scale utilization, and dilutes fixed investment costs. The game model ensures that the cooperative benefits are reasonably distributed between the distribution network and energy storage operators, and all parties have the motivation to participate in collaborative scheduling, thereby reducing overall operating costs. Traditional centralized scheduling requires complete information sharing, which may lead to overly conservative decisions. The ADMM algorithm only requires interaction with a small number of key variables, approaching the global optimal solution while protecting privacy and avoiding excessive redundant configuration. The ADMM algorithm does not require the distribution network to publicly disclose all load data, and only updates interactive variables through local model iteration, solving the privacy leakage problem of centralized scheduling. Each subject can independently optimize based on their own constraints, and then coordinate through negotiation games, which is more suitable for the uncertainty of practical scenarios than forced unified scheduling.

The main decisions of energy storage operators include the charging and discharging scheduling of energy storage and corresponding service electricity prices, as shown in Figures 4 and 5, respectively. As shown in Figure 4, the energy storage charging period is concentrated between 9:00 and 14:00, during which the photovoltaic output of each community is relatively high. Energy storage stores the remaining power generated by the community through charging. The charging period also includes 22:00–05:00, during which the power source for energy storage charging comes from the distribution network. Due to the low demand for electricity at night and the lower electricity price of the distribution network, charging energy storage during this period can reduce the cost of purchasing electricity. The main periods for energy storage discharge scheduling are from 06:00 to 08:00 and from 19:00 to 21:00. From the community's photovoltaic output and load demand curves, the photovoltaic output during these two periods is basically zero, while the electricity demand is relatively high. Therefore, each community is in a state of power shortage, and energy storage is discharged to meet the electricity load demand of each community. Therefore, from the power decision results of energy storage, the energy

storage charging and discharging decisions in this article mainly serve the needs of lower-level community alliances, that is, to consume the remaining power when the photovoltaic output is large, and discharge to meet the electricity demand when there is a gap in load power. From Figure 5, it can be seen that the electricity price for energy storage charging and discharging is between the upper and lower limits of the benchmark electricity price, which is in line with the interests and demands of energy storage operators. Compared to directly trading with the power grid, communities can reduce electricity costs through energy storage charging and discharging transactions, and energy storage can also generate profits through low storage and high discharge. Therefore, it is beneficial to incentivize communities and energy storage to participate in energy-sharing trading models.

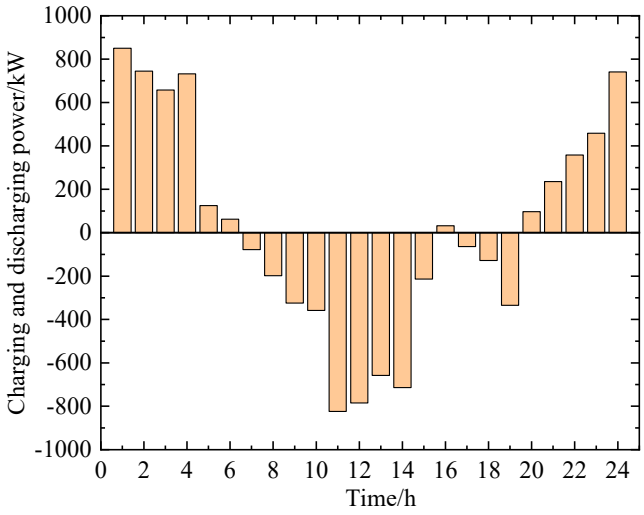


Figure 4. Charging and discharging powers of shared energy storage power station.

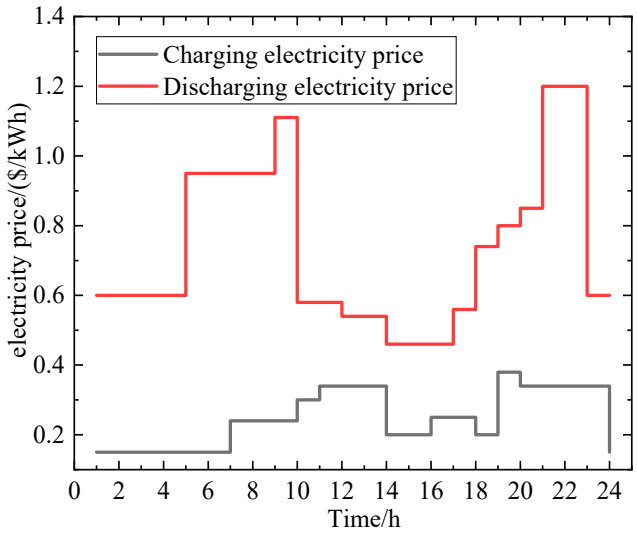


Figure 5. Charging and discharging electricity prices of shared energy storage power station.

Based on the analysis in Figure 4, during the period of concentrated energy storage discharge, the discharge electricity price is relatively high; during the period of centralized energy storage charging, the charging price is relatively low. From the perspective of energy storage operators, it is also a reasonable decision result, as operators have independent pricing power and therefore, tend to raise discharge electricity prices while lowering charging electricity prices as much as possible to increase their own profits. In the master–slave game, energy storage operators hold a higher leadership position, thereby obtaining

greater profits by adjusting electricity prices, which further verifies the market efficiency loss caused by the master–slave game. However, the electricity pricing decisions of energy storage operators also take into account the impact of lower-level community decisions: during periods of abundant new energy output, when there is more surplus power in the community, the demand for energy storage to purchase electricity is significantly reduced, and energy storage discharge services are in a state of oversupply. Therefore, the discharge electricity price has not reached the upper limit of the electricity price or is relatively low, reflecting the trend of energy storage guiding community electricity purchase through price signals.

5.3. Comparison with Other Methods

The proposed distributed Nash bargaining algorithm based on ADMM exhibits polynomial time complexity, ensuring scalability for large-scale systems. Case studies demonstrate its capability to meet real-time scheduling requirements, achieving minute-level response times. Each ADN and SESO independently solve their local optimization problems: the ADN subproblem is formulated as a mixed-integer second-order cone programming problem with a variable number of $O(N_{bus} \times T)$, where N_{bus} represents the number of nodes and T denotes the number of time periods), while the SESO subproblem is a linear programming problem with $O(T)$ variables.

To validate the real-time performance and scalability, verification and analysis were conducted on an expanded system based on the modified IEEE-33 node system. The test system data is shown in Table 4 below, while the computational efficiency results are presented in Table 5.

Table 4. Large-scale test system data.

The Test System Scale	The Number of Distribution Networks	Total Number of Nodes	Number of Time Periods	Total Number of Variables
Small-scale	4	132	24	3168
Medium-scale	10	330	24	7920
Large-scale	50	1650	24	39,600

Table 5. The computational performance test results.

Scales	The Number of Iterations	Time Consumption Per Iteration/s	Total Computation Time/s	The Converged Value of the Objective Function/$
4-distribution network system	46	1.47	67.6	7437.2
10-distribution network system	58	3.21	186.2	23,891.5
50-distribution network system	76	8.95	680.2	118,744.3

The table above demonstrates that when the number of nodes increases by 12.5 times, the computation time only grows by 10 times. For the 50-distribution network system, the total scheduling time remains under 12 min, meeting the typical energy system dispatch cycle which usually ranges from 15 min to 1 h. In detail, ADMM is a distributed optimization algorithm that allows each participant to independently solve their own optimization subproblems locally without exposing their complete internal models, cost functions, constraints, or sensitive data to a central coordinator or other participants. ADMM decomposes

the original complex large-scale centralized optimization problem into multiple smaller and more manageable subproblems—one for each ADN, one for the shared energy storage operator, and a relatively simple coordination problem. Each party only needs to perform local optimization based on their own information and a small amount of globally coordinated data. The model inherently involves multiple independent decision-making entities, each with their own objectives and constraints. ADMM naturally supports this distributed decision-making structure, eliminating the need for a central authority with access to all information. This approach ensures privacy preservation while maintaining computational efficiency, making it particularly suitable for multi-agent energy systems where data confidentiality and scalability are critical. The results confirm that the proposed method achieves practical convergence within operationally acceptable time frames, even as the system scales up significantly. The distributed nature of ADMM not only enhances privacy protection but also improves computational tractability for real-world implementations.

Three different approaches were employed for comparative analysis:

Method A: The proposed method in this paper.

Method B: Centralized scheduling under a centralized framework [1].

Method C: Robust distributed optimization method proposed in [26]

The experimental conditions were set as follows:

Condition 1: Ideal communication.

Condition 2: Time-varying communication delay, with latency following a uniform distribution U (0, 5 s).

Condition 3: Strong nonlinear interference, introducing ±10% random quantization noise to the SOP model.

Condition 4: Load mutation, with a 20% sudden increase in active distribution network load to verify full-period feasibility.

The comparative analysis was conducted across four metrics: economic performance, load-shedding amount, convergence time, and renewable energy accommodation rate. Detailed computational results are presented in Figure 6a–d.

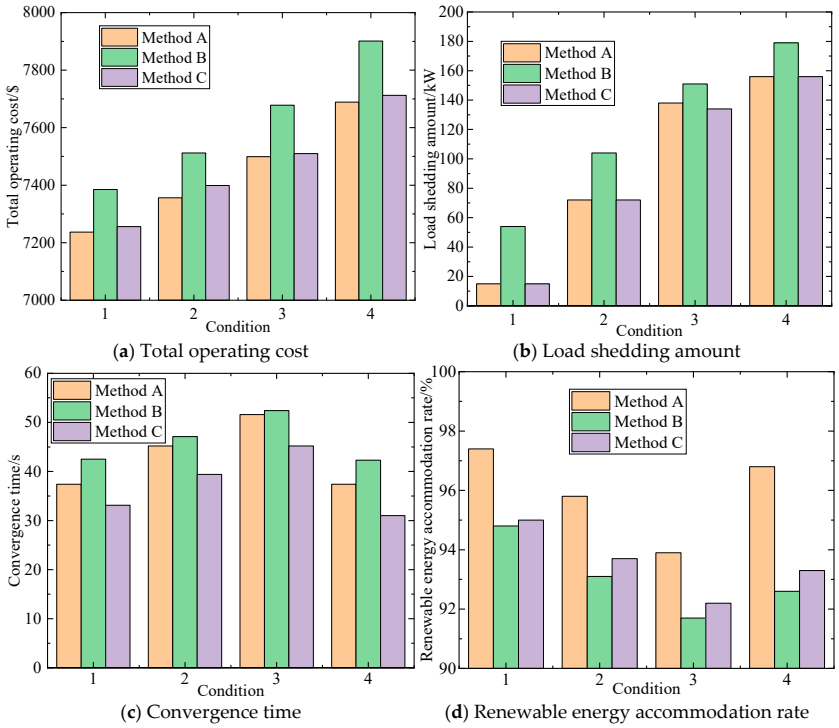


Figure 6. Comparative analysis between different methods.

Under ideal communication conditions, the proposed Nash bargaining approach achieves cooperative surplus allocation with a total cost of 1.0% lower than Method C and 4.3% lower than centralized optimization. When communication delays occur, ADMM's asynchronous iteration feature enables flexible local decision-making based on distributed information, reducing dependence on real-time communication and avoiding the global decision delays or failures inherent in centralized scheduling due to latency. In response to load fluctuations, the Nash bargaining mechanism incentivizes both distribution networks and energy storage operators to proactively optimize local resources—such as adjusting storage charging/discharging—while achieving mutual benefits through electricity price negotiation. Compared to the conservative nature of distributionally robust methods, this approach more actively utilizes storage flexibility to mitigate fluctuations, reducing renewable curtailment and load shedding. In contrast, centralized algorithms cannot access global detailed information due to privacy constraints, making it difficult to achieve equally precise responses. The results demonstrate the superior adaptability of the proposed method across all the test scenarios while maintaining solution optimality.

6. Conclusions

This article proposes a distributed energy management and trading strategy based on the Nash negotiation game and ADMM algorithm to address privacy protection and scheduling optimization issues in the collaborative operation of multiple power grids and shared energy storage systems. By establishing independent optimization models for distribution network operators and shared energy storage operators, respectively, and constructing a collaborative scheduling framework with the goal of maximizing cooperation benefits, efficient energy interaction between both parties has been achieved under the premise of privacy protection. This method iteratively solves coupling variables such as electricity quantity and price through the ADMM algorithm, avoiding the risk of information leakage in centralized scheduling and overcoming the conservatism problem of traditional decentralized decision-making. Through analysis, the proposed method in this paper can increase renewable energy consumption efficiency by up to 3.6% and reduce operational costs by 11.2% compared to traditional centralized optimization methods and distributed robust methods. The computational efficiency is comparable to that of centralized optimization methods while avoiding privacy leakage issues. Additionally, the load-shedding amount can be reduced by up to 63.7%. The simulation results based on the improved IEEE-33 testing system show that the proposed strategy can effectively balance the interests of multiple parties, improve the system economy, and provide a feasible solution for the large-scale application of shared energy storage in the power system. Future research can further consider the impact of uncertainty in renewable energy output on cooperative games.

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