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Research article

Distributed optimization and scheduling strategy for source load storage distribution grid based on alliance chain

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Abstract: With the high penetration of renewable energy, the addition of a large number of energy storage units, and flexible loads, the source-load-storage structure of active distribution networks is becoming increasingly complex, making optimization and scheduling more challenging. In response to issues as difficult global information acquisition, less consideration of flexible load and energy storage unit access, individual deception, and insufficient security in the optimization scheduling process of active distribution networks, this paper constructed a distribution network optimization scheduling model that includes sources, loads, and storage. It proposed a distributed optimization scheduling strategy for source-load-storage distribution networks, combined with alliance chains. This strategy is based on the FISCO BCOS consortium chain platform, with blockchain multi-agent nodes forming a consortium chain network. The consistency variables are the incremental cost of distributed power generation and the incremental benefits of flexible loads. Distributed scheduling calculations were carried out using a consensus algorithm that includes leadership nodes. By combining the data storage mechanism and consensus algorithm advantages of the consortium chain, the centrality of leadership nodes is eliminated, achieving optimal power allocation in the distribution network at a minimum economic cost. The simulation results show that the distributed optimization scheduling strategy proposed in this paper can achieve optimal allocation of minimum cost in the distribution network and converge quickly in various scenarios such as non-flexible load fluctuations, leader node switching, node joining or leaving, and changes in power exchange instruction in the distribution

network. It demonstrates good robustness and stability.

Keywords: distributed optimal scheduling; alliance chain; FISCO BCOS; consistency algorithm; distribution network

1. Introduction

With the high penetration of renewable energy, the addition of a large number of energy storage units, and flexible loads, the source-load-storage structure of the active distribution network is becoming more and more complex, and its optimal scheduling becoming more challenging. Optimal scheduling of the distribution network refers to the distribution of the total load to the output of each generating unit under the premise of meeting certain constraints of the power system. This is done to achieve the balance between the supply and demand of the system and minimize the total generation cost [1]. The optimal control methods of the active distribution network are generally divided into centralized and distributed. In centralized control, the central node collects system information, performs unified calculations, and finally issues instructions to control each distributed power supply. This method generally has issues such as poor reliability, high communication, and computing pressure in the control center, and is not suitable for the current scenario of fully distributed power supply. The distributed control mode can exchange information with neighboring multi-agents and update its own state autonomously with strong reliability and uniform computing pressure. It can adapt well to the decentralized characteristics of distributed power generation. However, distributed control faces challenges in the overall optimization of the distribution network. The decentralization of control rights has created security problems and individual deception problems [2,3]. For example, malicious nodes may invade and steal distribution network information, or even pretend to be leading nodes to manipulate economic dispatching operations, posing significant security risks. Additionally, some legitimate nodes in the network may exchange false information with neighboring nodes to seek more benefits, leading to the deviation of optimal distribution network scheduling and the inability to reach the optimal state—that is, the problem of individual deception.

In order to achieve distributed optimal scheduling under the complex structure of the distribution network, researchers have proposed various methods. In [4], a particle swarm algorithm was used to solve the power grid scheduling model in the established solar thermal-wind power joint dispatching model, aiming to achieve optimal economic dispatching [5]. A distributed optimal scheduling model was established with multiple decision-makers for multi-park integrated energy systems. The model introduces power coordination variables to decouple mutual power between parks and calculates economic scheduling through the alternating direction multiplier method. In [6], economic droop control was employed to achieve economic dispatching. The method introduces the system operation cost into the control parameters and alters the power distribution characteristics by adjusting the droop coefficient, enabling the distribution of power based on cost considerations. In [7], the operational optimization problem of active distribution networks was addressed by establishing a distribution network model that considers photovoltaic, energy storage systems, the number of actions of regulating equipment, network losses, and node voltage deviations. A multi-objective co-location optimization algorithm based on comprehensive crowding distance sorting, Bernoulli chaotic mapping, external archiving, and non-dominated sorting mechanisms was proposed to achieve optimal economic dispatch of the distribution network. In [8], a multi-objective tuna swarm optimization algorithm was used to establish the ADN energy optimization model, which includes dynamic reconstruction, reactive power compensation, on-load tap changer, and controllable load coordinated control. In [9], a sustainable airport energy ecosystem framework was proposed, consisting of hydrogen-based renewable energy, power grid, and energy storage. The airport energy system model is solved through single-objective and multi-objective optimization, as well as multi-criteria decision-making methods, providing ideas for achieving sustainable transformation. In [10], a stochastic vehicle scheduling model was established for demand response and grid flexibility in renewable energy building transportation microgrids. It uses chi-square distribution and normal distribution to quantify the distribution of vehicle numbers, optimize vehicle travel arrangements, and achieve optimal economic and environmental scheduling.

The consistency algorithm is a commonly used method for optimal scheduling in distribution networks, known for its high computing efficiency and minimal network traffic. However, mainstream consistency algorithms typically necessitate a leader node to gather information from neighboring nodes and global sources [11]. This leader node is crucial for overseeing the implementation of optimal scheduling, introducing a certain level of centrality and dependence on this leader. For instance, an improved discrete first-order consistency algorithm for iterative calculations was employed in [12]. Under the leadership of the designated leader node, it ensures the consistency of incremental costs for each distributed generation, facilitating optimized scheduling in the autonomous region but relying heavily on the leader node. In a similar vein, a virtual generator was designated as the leading node [13], which devised a distributed economic dispatching strategy with incremental costs as the consistency variable. While addressing the issue of individual deception, the strategy incorporates a correction vector to counteract the impact of deceptive information, yielding positive outcomes but exhibiting high dependence on the virtual power plant. In [14], system power gaps were identified using system frequency to eliminate the leader node. However, dynamic regulation may fail when load power variations in the system are approximately balanced. Alternatively, a robust consistency coordination algorithm based on a gain adjustment function was proposed in [15]. The introduction of a power adjustment term enables real-time detection of system active power deficiencies, eliminating the need for a leader node. Nevertheless, the algorithm's complexity should be noted.

In this paper, we propose a source-load-storage optimal scheduling strategy based on the alliance chain and a consistency algorithm. The alliance chain network for distributed power and flexible load is constructed using the FISCO BCOS platform. Leveraging the technical characteristics of the alliance chain, this strategy addresses challenges related to accessing global information, enhancing security, and mitigating individual deception. It significantly improves the security and reliability of the system, eliminates the centrality of leading nodes in the consistency algorithm, and achieves fast and effective distributed optimal scheduling. Simulation experiments and analyses demonstrate that the distributed optimal scheduling strategy presented in this paper achieves rapid convergence and performs exceptionally well across various experimental scenarios. The outstanding contributions of this study are as follows. First, a distribution network optimization scheduling model including source, load, and storage is constructed, and a distributed optimization scheduling strategy based on consortium chain technology and consistency algorithm is proposed. Second, the proposed strategy combines consortium chain technology with distributed optimization scheduling, where nodes directly obtain neighbor node information and global information from local sources during the scheduling process, reducing information exchange with neighboring nodes; after about 40 iterations, the consistency variable can achieve the global optimal power allocation, achieve system supply-demand balance, and quickly and efficiently achieve coordinated optimization scheduling goals. Third, the proposed strategy can effectively cope with non-flexible load fluctuations, leader node switching, node joining or leaving, and changes in power exchange instructions in the distribution network, with good robustness and stability.

The structure of the rest of this article is as follows. Section 2 introduces blockchain and FISCO BCOS platform, as well as the rPBFT algorithm of FISCO BCOS platform. Section 3 introduces a distributed optimization scheduling algorithm based on the consistency algorithm. Section 4 discusses the distributed optimization scheduling strategy based on consortium chain. Section 5 presents the simulation experiment results and analyzes the effectiveness of the strategy proposed in this paper. Section 6 summarizes the entire text.

2. Alliance chain

2.1. Blockchain and alliance chain

Blockchain originated from Bitcoin and is a decentralized, tamper-proof, and highly secure distributed network. Its core technologies include distributed storage, consensus mechanisms, smart contracts, and asymmetric encryption algorithms [16,17]. Distributed data storage ensures that each node on the blockchain stores complete chain data, preventing tampering. The consensus mechanism ensures data consistency among multiple nodes in a distributed architecture. Smart contracts, described in computer language, function as program algorithms to arbitrate and execute contracts autonomously, ensuring high transaction security without external influence. The asymmetric encryption algorithm encrypts and decrypts messages through paired private and public keys, ensuring the security of message transmission between blockchain nodes.

Blockchain is categorized into public chains, alliance chains, and private chains. The alliance chain is typically initiated and maintained jointly by several institutions (allies). It is only open to alliance members and limited third parties, functioning as an access-controlled blockchain. The entry of new nodes and data access undergoes strict authority authentication. Consensus participants in the alliance chain are nodes pre-approved through a specific agreement, jointly determining the generation of each block. Other nodes can participate in transactions but do not engage in the bookkeeping process. The alliance chain exhibits characteristics such as fast transaction speed, low transaction cost, absence of mining, reduced computing power consumption, absence of forks, and enhanced data privacy protection. Currently, it finds widespread application in finance, commodity traceability, e-government, the Internet of Things, and other fields.

2.2. FISCO BCOS

FISCO BCOS is an enterprise-level financial alliance chain platform developed by Chinese enterprises and open-sourced to the public. It is designed to be safe and controllable, considering the specific needs of alliance chains. FISCO BCOS prioritizes performance, security, operational ease, and scalability, allowing for quick realization of chain building, development, and deployment. FISCO BCOS adopts a high-throughput scalable multi-group architecture, enabling dynamic management of multiple chains and groups. This design caters to the expansion and isolation requirements of various business scenarios. The platform implements a robust distribution network mechanism based on the concept of load balancing, effectively minimizing bandwidth overhead. Figure 1 shows the architecture diagram of FISCO BCOS. In terms of overall architecture, FISCO BCOS is divided into a foundation layer, a core layer, a management layer, and an interface layer:

(1) Basic layer: Provides the basic data structure and algorithm library of blockchain.

(2) Core layer: Implements the core logic of blockchain, which is divided into two parts. The chain core layer implements the chain data structure, transaction execution engine, and storage driver of blockchain, and the interconnection core layer implements the basic P2P network communication, consensus mechanism, and block synchronization mechanism of blockchain.

(3) Management: Implements the management functions of blockchain, including parameter configuration, ledger management, and AMOP.

(4) Interface layer: Targeting blockchain users, it provides RPC interfaces, SDKs, and interactive consoles for multiple protocols.

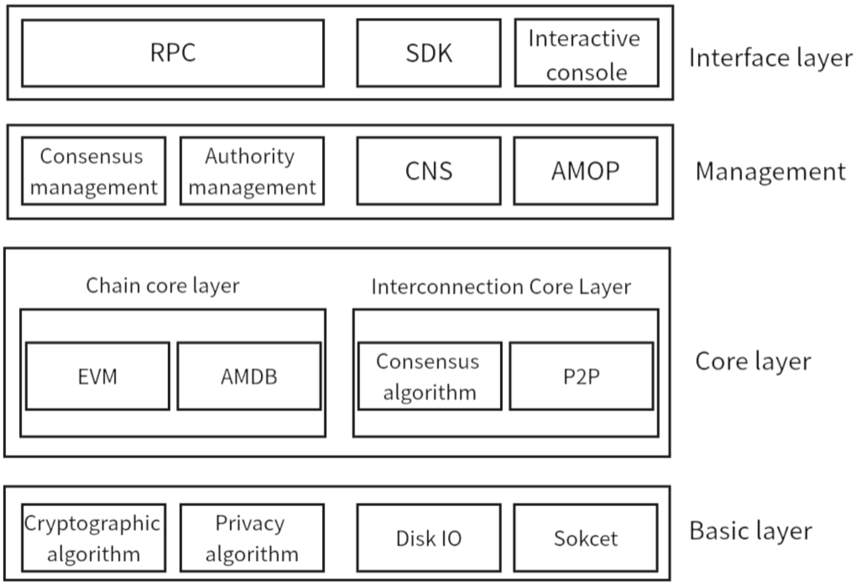

Figure 1. FISCO BCOS architecture diagram.

2.3. Rpbft consensus algorithm

The rpbft consensus algorithm of the FISCO BCOS alliance chain is an improvement of the practical byzantine fault tolerant (PBFT) algorithm. It boasts second-level transaction confirmation delay, final consistency, high throughput, and low resource consumption. It can handle scenarios where nodes act maliciously and can operate normally when the number of malicious nodes is less than one-third. The PBFT algorithm requires all nodes to participate in the consensus, and its complexity is related to the node size. The supported network size is limited, greatly constraining the node size of the alliance chain [18,19]. In contrast, the rpbft consensus algorithm selects specific nodes as the consensus committee to execute the consensus process. The consensus committee is constantly rotated, ensuring decentralization and eliminating restrictions on the node size.

The rpbft consensus algorithm categorizes alliance chain nodes into two types: consensus members and verification nodes. The consensus committee carries out the consensus process, while the verification nodes only verify the legitimacy of the consensus node and the block. During the operation of the alliance chain, several consensus members are selected for each round of the rpbft algorithm's consensus process. These consensus members are periodically replaced according to the block height to ensure system security.

The consensus process of the rpbft algorithm is similar to the PBFT algorithm [20], with the main difference lying in the set of nodes executing the consensus. As illustrated in Figure 2, the core process is primarily divided into five stages.

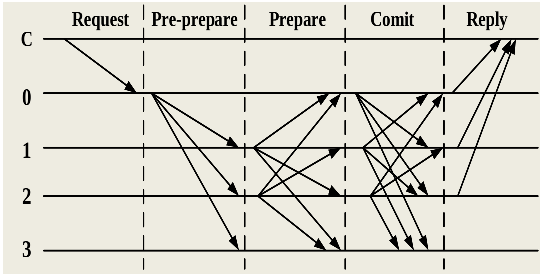

Figure 2. Rpbft algorithm consensus process.

(1) Request: Client C sends a request to Master Node 0.

(2) Pre-prepare: Upon receiving C's request, Node 0 verifies the signature of the request message. If no errors are found, it signs and broadcasts the pre-prepare message, propagating C's request to Nodes 1, 2, and 3.

(3) Prepare: After receiving the pre-prepare message, Nodes 1, 2, and 3 verify the signature's validity and broadcast it. However, Node 3, experiencing downtime, cannot broadcast at this stage. The Prepare phase aims to prevent the master node from sending different requests to different slave nodes, thus thwarting any malicious behavior by the master node.

(4) Commit: In the Prepare phase, if each node receives more than 2F (F being the number of tolerable Byzantine nodes, i.e., one-third of the total number of nodes) identical requests, it proceeds to the commit phase, broadcasting the commit request.

(5) Reply: If each node receives more than 2F + 1 identical commit requests, it executes the request from client C and provides feedback to C upon completion. Thus, the consensus is achieved.

3. Optimal scheduling algorithm based on consistency algorithm

3.1. Consistency algorithm

The main idea of the consistency algorithm is as follows: In a distributed system, each agent node exchanges information with its neighboring nodes, updates its own state value based on the states of the neighbor nodes [21], and achieves convergence of consistency parameters across all nodes through multiple iterations.

Each node in the active distribution network is interconnected by the communication network to form a distributed network topology structure. This structure can be represented by an undirected graph

G. Each agent node corresponds to the node in the undirected graph. The relationship between the node and the edge is through the adjacency matrix $M=(a_{ij})_{n\times n}$ express. The elements in matrix *M* are:

$$a_{ij}=\begin{cases}1,(v_i,v_j\in E)\\0,(v_i,v_j\notin E)\end{cases} \tag{1}$$

where *E* is the edge set of graph *G*, v_i and v_j are nodes in *G*.

Then, the Laplace matrix of an undirected graph can be defined as:

$$L=\begin{cases}-a_{ij},i\neq j\\ \varphi_i,i=j\end{cases} \tag{2}$$

where φ_i is the degrees of nodes *i*.

For the convenience of calculation, the elements of Laplace matrix are transformed as follows:

$$l_{ij}'=\frac{|l_{ij}|}{\sum_{j=1}^{n}|l_{ij}|} \tag{3}$$

where l_{ij} is the original element of *L*, and l_{ij}' is the transformed value of l_{ij}.

As $X=[x_1,x_2,x_3,\cdots,x_n]$ is the vector of the consistency variable of the distributed generation, then the vector is iteratively updated by Eq (4):

$$X(k+1)=-LX(k) \tag{4}$$

where $X(k)$ is the vector of the *k*-th round consistency variable.

3.2. Optimal scheduling strategy based on consistency algorithm

The active distribution network consists of a thermal power unit (TP), a wind turbine unit (WP), a photovoltaic unit (PE), an energy storage unit (SS), flexible load (FL), and non-flexible load (RL). Its structure is shown in Figure 3. Each node deploys a blockchain agent, which is responsible for collecting node status information, participating in coordination and control, and sending control instructions to the units. This is done to finally realize the optimized dispatching of the distribution network, ensuring the supply and demand balance of the entire distribution network and minimizing the operational cost.

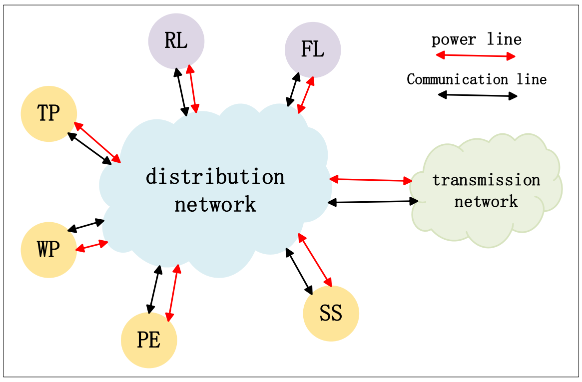

Figure 3. Structure diagram of active distribution network.

The objective function of active distribution network optimal dispatching is defined as follows:

$$\min F = \min \sum_{i=1}^{n} F_i\left(P_i\right) = \min\left(F_{TP} + F_{WP} + F_{PE} + F_{SS} + F_{FL}\right) \tag{5}$$

where F is the total generation cost, F_i is the cost of nodes i, P_i is the power of nodes i, F_{TP} is the sum of generation costs of all thermal power sources, and F_{WP}, F_{PE}, F_{SS}, and F_{FL} are the power generation costs of all WP, PE, SS, and FL, respectively.

The power generation cost of thermal power supply [22], wind power photovoltaic power supply [23], and energy storage unit, and the power consumption benefit function [24] of flexible load are calculated as follows:

$$F_{i,TP} = a_{i,TP} P_i^2 + b_{i,TP} P_i + c_{i,TP} \tag{6}$$

$$F_{i,PE} = F_{i,WP} = a_{i,PE/WP}\left(P_i^2 + 2P_i^r P_i\right) \tag{7}$$

$$F_{i,SS} = a_{i,SS} P_i^2 \tag{8}$$

$$F_{i,FL} = \gamma_{i,FL} + \beta_{i,FL} P_{FL} + \alpha_{i,FL} P_{FL}^2 \tag{9}$$

where $a_{i,TP}$, $b_{i,TP}$, and $c_{i,TP}$ are the correlation coefficients of the quadratic term, the primary term, and the constant term of the i-th thermal power unit, respectively; $i = 1, 2, 3 \ldots, n$; $a_{i,PE/WP}$ is the cost coefficient of wind power and photovoltaic units; $a_{i,ss}$ is the cost coefficient of the energy storage unit; $\gamma_{i,FL}$, $\beta_{i,FL}$, and $\alpha_{i,FL}$ are the constant term, the primary term, and the secondary term coefficients of the power consumption benefit function of the flexible load, respectively; P_i^r is the maximum adjustable power of wind power and photovoltaic power supply.

The equation constraint [23] for optimal dispatching of the distribution network is Eq (10).

$$P_{TP} + P_{WP} + P_{PE} + P_{SS} + L_e = P_{FL} + P_{RL} \tag{10}$$

where P_{TP} is the total output power of all thermal power sources, P_{WP}, P_{PE}, and P_{SS} are the total output power of wind power, photovoltaic, and energy storage units, respectively; P_{FL} and P_{RL} are the sum of the power of flexible load and non-flexible load, respectively; and L_e is the power exchange instruction between the transmission network and the distribution network.

The inequality constraint of each node is Eq (11):

$$P_i^{\min} \le P_i \le P_i^{\max} \tag{11}$$

where $P_i^{\min}$ and $P_i^{\max}$ are the lower and upper power limits of corresponding nodes, respectively. The system rotation alternate constraint is [25]:

$$\sum P_{i,pow}^{\max} - \sum P_{i,pow} \ge R(t) \tag{12}$$

where $P_{i,pow}^{\max}$ is the power cap of the ith power supplies, $P_{i,pow}$ is the current power of the ith power supplies, and $R(t)$ is the rotating reserve capacity of the system at the current time.

Under the condition of Eq (10), the original objective function Eq (5) can be transformed by the Lagrange multiplier method into:

$$\begin{aligned} &\min F = F_{TP} + F_{WP} + F_{PE} + F_{SS} + F_{FL} \\ &+\lambda(P_{TP} + P_{WP} + P_{PE} + P_{SS} + L_e - P_{FL} - P_{RL}) \end{aligned} \tag{13}$$

The partial derivative of Eq (13) is the optimal conditions for the optimal dispatching of the active distribution network:

$$\begin{cases} \lambda_{i,TP} = 2a_{i,TP}P_{TP} + b_{i,TP} \\ \lambda_{i,WP} = 2a_{i,WP}(P_{i,WP} + P_{i,WP}^r) \\ \lambda_{i,SS} = 2a_{i,SS}P_{i,SS} \\ \lambda_{i,PE} = 2a_{i,PE}(P_{i,PE} + P_{i,PE}^r) \\ \lambda_{i,FL} = 2\alpha_{i,FL}P_{FL} + \beta_{i,FL} \end{cases} \tag{14}$$

where $\lambda_{i,TP}$, $\lambda_{i,WP}$, $\lambda_{i,SS}$, and $\lambda_{i,PE}$ are incremental costs of TP, WP, SS, and PE, respectively; and $\lambda_{i,FL}$ is the power consumption benefit of flexible load. The above parameters are taken as consistent variables to realize coordinated optimal dispatching.

According to Eq (14), when the consistency variable of each node meets the following conditions, the system reaches the optimal state, and the total power generation cost is the minimum:

$$\lambda_{i,TP} = \lambda_{i,WP} = \lambda_{i,SS} = \lambda_{i,PE} = \lambda_{i,FL} = \lambda \tag{15}$$

In the process of coordinated and optimized dispatching, it is necessary to constantly update the consistency variables of each node. The specific method is to select one power node as the leader node and the rest as the slave nodes. The master and slave nodes update the values of the consistency variables according to different update formulas with the help of the Laplace matrix, ensuring that the consistency variables of each node gradually reach consistency. The update formula of the leading node includes the system power difference parameter to balance the supply and demand of the whole system.

The consistency variable update formula of the leading node and flexible load is:

$$\lambda_i(k+1) = \sum_{j=1}^{n} l_{ij}{}' \lambda_j(k) + \varepsilon \Delta P \tag{16}$$

where $\lambda_i(k)$ and $\lambda_i(k+1)$ are the consistency variable of the *i*th node in rounds k and rounds $k+1$, respectively; ε is the convergence coefficient; and ΔP is the system power difference with the following calculation method:

$$\Delta P = P_{FL} + P_{RL} - (P_{TP} + P_{WP} + P_{PE} + P_{SS} + L_e) \tag{17}$$

The consistency variable update formula of the slave node is:

$$\lambda_i(k+1) = \sum_{j=1}^{n} l_{ij}{}' \lambda_j(k) \tag{18}$$

When the consistency variables of all nodes converge to the same value, the system state is optimal, and the economic cost is minimal, that is, the distributed coordinated optimal dispatching goal of the active distribution network is realized.

4. Distributed optimal scheduling strategy based on alliance chain

4.1. Design of optimal scheduling framework based on alliance chain

The blockchain-based distributed optimal scheduling framework is shown in Figure 4. The lowest layer is the alliance chain network composed of multiple agents and communication lines, which serves as the hardware foundation of the entire system. The second layer is the bottom layer of the FISCO BCOS architecture, primarily including level-DB (a non-relational database), smart contract, rpbft consensus algorithm, and encryption mechanism. The third layer is the middle layer Java SDK, providing Java APIs for accessing FISCO BCOS nodes. Through these APIs, you can call smart contracts to query the data on the chain and the status of nodes. The fourth layer is the management layer, which achieves functions like data governance, node management, group management, contract management, and account management by embedding webize. The top layer is the presentation layer, composed of the Vue front end and FISCO BCOS console.

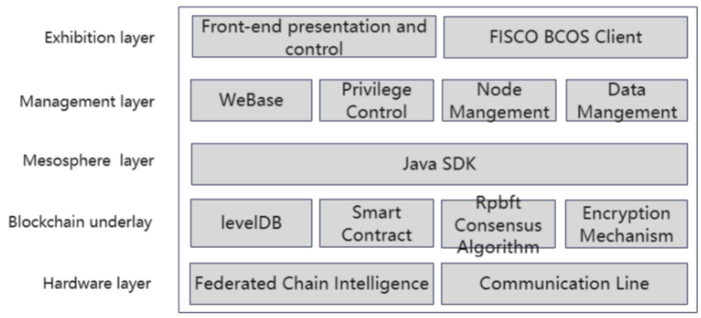

Figure 4. Distributed economic dispatch framework diagram of distribution network combined with FISCO BCOS platform.

4.2. Optimized scheduling process based on alliance chain and consistency algorithm

The optimal scheduling process of the active distribution network based on alliance chain and consistency algorithm is as follows:

(1) Initialize system parameters, including characteristic coefficients of each power supply and flexible load, upper and lower limits of each node power $P_i^{\min}$, $P_i^{\max}$, initial value of consistency variable $\lambda_i^{(0)}$, etc.

(2) Verify the validity of the parameters passed in by the requester, and then call the smart contract to obtain the power distribution $P_i^{(k-1)}$ and consistency variable values $\lambda_i^{(k-1)}$ of the last round from the local alliance chain nodes.

(3) According to the consistency variable value of the previous round $\lambda_i^{(k-1)}$, calculate the power of each node in the current round $P_i^{(k)}$ and system power difference ΔP.

(4) Update the consistency variables of the leader node and the slave node according to the Laplace matrix $\lambda_i^{(k)}$.

(5) Update the power of this round $P_i^{(k)}$ and consistency variables $\lambda_i^{(k)}$ to each node database through rpbft consensus algorithm, that is, data uplink.

(6) Continue the above iterative process until the consistency variables of each node are equal. At this time, the power distribution of each node reaches the global optimal state, and the total power generation cost is the minimum.

The flowchart of optimization scheduling based on the alliance chain and consistency algorithm is shown in Figure 5.

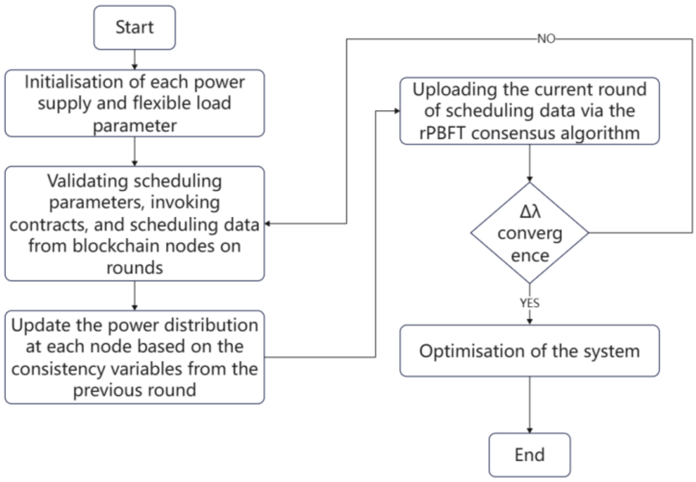

Figure 5. Flowchart of optimization scheduling based on the alliance chain and consistency algorithm.

The optimal dispatching process of the active distribution network based on the alliance chain and consistency algorithm is written as an intelligent contract and deployed on the alliance chain composed of multi-agent nodes. The scheduling calculation process is taken over by the smart contract throughout the process. It operates atomically in the sandbox environment and is not affected by the external environment to ensure the security of execution. The initiator of the scheduling request only passes in the necessary parameters, such as iteration rounds. The chain node verifies the source and legitimacy of the request according to the signature mechanism and admission mechanism. The node directly obtains the global information and the last round scheduling results from the local database, effectively avoiding individual deception and reducing the centrality of the leading node. The scheduling results generated in each round are synchronously updated to the local database of each node through the rpbft consensus mechanism. Then, each node updates its output or load according to the scheduling results until the system reaches the optimal state.

4.3. Global information acquisition and centrality weakening mechanism of leading nodes

Conventional consistency algorithms typically require a leader node to collect information from neighbor nodes to obtain the system power difference and dictate the convergence direction of consistency variables. Collecting information from all nodes places significant communication pressure on the leader node and grants it greater control. If the leader node engages in malicious behavior, such as adding a deviation value to the power difference or experiencing communication issues that prevent it from collecting information from all nodes, inaccurate calculation of the system power difference may occur. This can result in deviations in the overall optimal scheduling, leading to a failure to reach the optimal state.

In this strategy, data storage adopts the redundant storage mode of the alliance chain. Each round of scheduling data is synchronized to all nodes through the rpbft consensus algorithm, achieving final consistency. Consequently, each node can directly obtain the power distribution of all nodes from the local database, and the leading node does not need additional operations to collect the power information of other nodes.

Simultaneously, because all consensus members verify the correctness of the system power difference in the consensus process, the leader node will no longer make decisions independently to lead the optimal scheduling process, significantly reducing centrality and control power. The distinction between the leader node and the slave node lies only in updating the consistency variable using different formulas. Through this mechanism, dependence on the leader node and the centrality of the leader node are diminished, achieving a more decentralized distribution.

4.4. Individual deception control mechanism

In distributed optimal scheduling based on multi-agents, each node typically exchanges information with its neighbor nodes and updates its own state by relying on the exchanged information. The correctness of the exchanged information directly determines the accuracy of the optimal scheduling, making it the weakest link in the scheduling process. In actual scheduling scenarios, some nodes may engage in individual deception, deliberately exchanging incorrect self-information with neighbor nodes, such as adding a constant deviation to their own consistency variable to reduce their output and economic cost. Other normal nodes, unaware of the deception, may increase their output to maintain the supply-demand balance of the distribution network. The result is that deceptive nodes gain additional benefits, normal nodes suffer losses, the entire distribution network fails to reach the optimal state, and the optimal dispatching goal remains unmet.

In this strategy, the scheduling results of each round are ultimately consistent on all nodes through rpbft consensus. Each node can directly obtain information about neighbor nodes locally, avoiding information errors or losses caused by individual deception or exchange failures in the process of information exchange. Therefore, ordinary nodes cannot engage in individual spoofing. For the leader node, there are two potential ways to cheat; one is to tamper with the scheduling data of the last round in the local database before executing the smart contract, and the other is to tamper with the data during the execution of the scheduling optimization algorithm. In the first case, if the leader node tampers with the last round of scheduling data in the local database, resulting in incorrect scheduling calculation results, then in the subsequent implementation of rpbft consensus, the consensus committee verifies the calculation results of the leader node. Only after more than two-thirds of the nodes successfully verify the results, can the calculation results of the leader node be deemed effective; otherwise, the calculation result will be discarded, and the individual deception will be invalid. For the second case, the optimal scheduling algorithm in this strategy is executed atomically in the form of a smart contract and operates in a sandbox environment, making it immune to disturbance and modification. Therefore, the leader node cannot engage in individual deception during the execution of the optimal scheduling algorithm.

In conclusion, this strategy effectively prevents individual deception and ensures the accuracy of optimal scheduling.

5. Example analysis

5.1. Simulation environment

The active distribution network consists of two thermal power units, one wind turbine unit, one photovoltaic power supply, one energy storage unit, and one flexible load node. Refer to Table 1 for the basic parameters of each power supply and Table 2 for flexible load parameters. The VMware virtual machine is used to simulate six blockchain node agents in the distribution network. The hardware environment of the node virtual machine is as follows: Linux operating system, 2 GB memory, 10 GB external memory, and the CPU is Intel(R) Core(TM) i5-10400f CPU @ 2.90 GHz. The programming software is as follows: November 2019 release of Visual Studio Code and FISCO BCOS 2.0 Alliance Chain Platform.

Table 1. Parameters of distributed power supply.

Node number	Power supply type	Pimin/MW	Pimax/MW	a_i	b_i	P_i^r /MW
1	Thermal power 1	50	300	13.065	0.0618	-
2	Photovoltaic	30	150	0.42	-	65
3	Energy storage	−30	60	0.390	-	-
4	Thermal power 2	50	400	13.360	0.0475	-
5	Wind power	50	180	0.290	-	40

Table 2. Parameters of flexible load.

Node number	Pimin/MW	Pimax/MW	α_i	β_i
6	50	450	10.305	0.0623

5.2. Experiment scenario

(1) Non-flexible load fluctuation scenario

Make the initial consistency variable of each node [23.00, 20.00, 22.00, 27.00, 21.00, 28.00]. The initial output power is calculated based on the consistency variable, and the power exchange command is 0 MW. The leading node is node 1. In the iterations from 0 to 99, the non-flexible load is 300 MW, which suddenly changes to 400 MW in the 100th round and remains constant until the 199th round. At the 200th round, the non-flexible load suddenly changes back to 500 MW and remains constant until the 300th round of iteration. Under these experimental conditions, the convergence results of the node consistency variables and node power are verified when the non-flexible load fluctuates.

(2) Leader node switching scenario

Let the non-flexible load be 400 MW, the power exchange command be 0 MW, and the initial leading node be node 1. Then, switch the leading node to node 4 in the 10th round when convergence has not been reached, and switch to node 2 in the 100th round. Under the above conditions, verify the impact of leader node switching on the optimal scheduling process in the non-convergent stage and the convergent stage.

(3) Node exit and join scenario

The non-flexible load of the system is 300 MW, the exchange power command is 0 MW, and the leading node is node 1. When iterating to 100 rounds, node 2 is out of order and exits the scheduling, and the output changes to 0. At the 200th round, node 2 returns to normal and rejoins the scheduling. Under the above conditions, verify the impact of node exit and join on consistency variables and power allocation.

(4) Power exchange command change scenario

The non-flexible load of the system is 400 MW, and the initial leading node is node 1. The initial power exchange command is −100 MW. When iterating to the 100th round, the power exchange command becomes 0 MW, and when iterating to the 200th round, the power exchange command becomes 100 MW. Under the above conditions, verify the influence of power exchange command changes on consistency variables and power allocation.

(5) Comparison of consensus algorithms rPBFT and PBFT for forwarding traffic

Compare the communication volume of nodes using rPBFT algorithm and PBFT algorithm at different nodes and verify the impact of different consensus algorithms on the communication cost between nodes.

5.3. Experimental results and analysis

(1) Analysis of experimental results of non-flexible load fluctuation scenarios

Under the scenario of non-flexible load fluctuation, the variation trend of consistency variable and node power is shown in Figures 6 and 7.

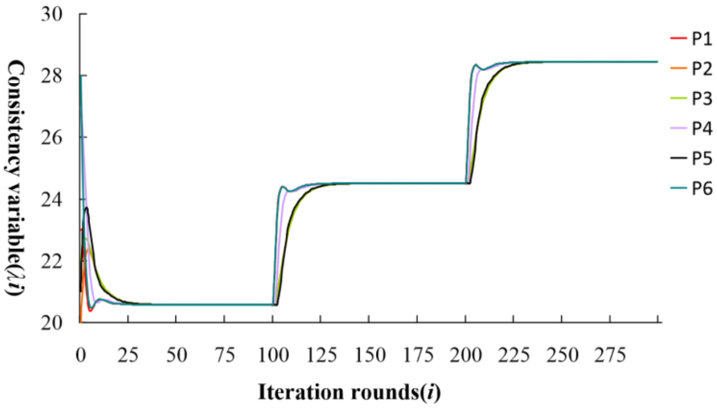

Figure 6. Convergence curve of consistency variable under load fluctuation.

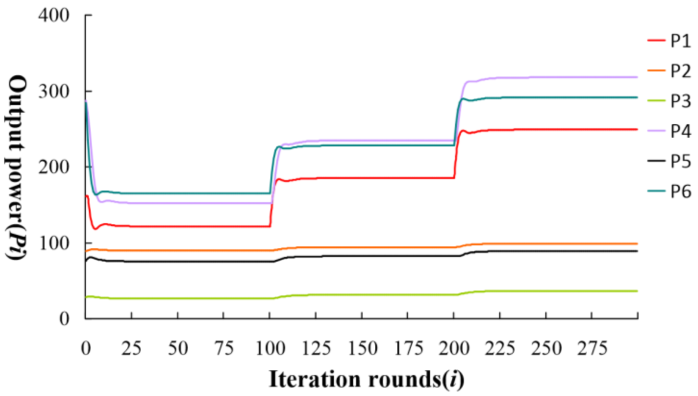

Figure 7. Power change curve of each node when non-flexible load fluctuates.

It can be seen from Figures 6 and 7 that under the initial condition with a non-flexible load of 300 MW, when iterating to the 39th round, the consistency variable converges to 20.61, and the power of each node stabilizes. The power distribution of the six nodes is [122.15, 89.54, 26.43, 152.71, 75.54, 165.47] MW, reaching the optimal distribution. The total power that the system can provide, i.e., the sum of the output power of each power supply and power exchange command, is 466.37 MW, which is balanced with the sum of flexible load and non-flexible load. When the iteration reaches the 100th round, the non-flexible load suddenly changes to 400 MW. After 38 rounds of iteration, the consistency variable returns to convergence, which is 11.89. At this time, the power distribution of each node is [184.78, 94.14, 31.39, 234.22, 82.21, 227.60] MW, and the system reaches the balance between supply and demand. At the 200th round, the non-flexible load rises to 500 MW, and the system becomes unbalanced again. After 38 rounds of iteration, the consistency variable finally converges to 28.43, and the power distribution stabilizes at [248.60, 98.84, 36.44, 317.27, 89.01, 290.91] MW. The system reaches the optimal state and realizes the balance of supply and demand. The above results have proved the effectiveness of this strategy in the case of non-flexible load fluctuation.

(2) Experimental results and analysis of leader node switching scenarios

The experimental results in the case of leader node switching are shown in Figures 8 and 9. In the initial state, the leading node is node 1. The system has not reached convergence when iterating to the 10th round. At this time, the leading node is switched to node 4. When iterating to the 27th round, convergence is achieved. At this time, the consistency variable is 24.48, the power of each node is [184.77, 94.14, 31.39, 243.23, 82.11, 227.60], and the total output power and the total load of the system are balanced. In the 100th round, when the system is stable, the leading node is switched to node 2, and the system remains stable, with the consistency variable and power distribution unchanged. The above experiments show that the consistency variable and power distribution can still converge well in the case of leader node switching.

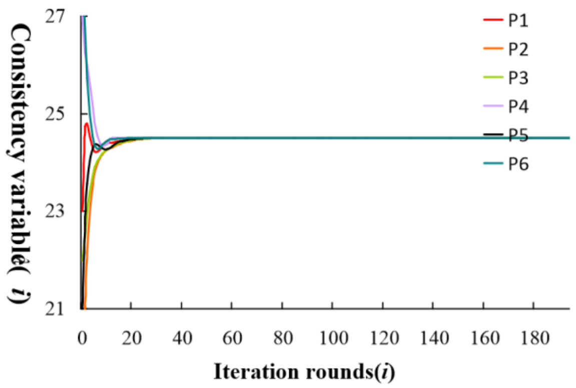

Figure 8. Convergence curve of incremental cost in the case of leader node switching.

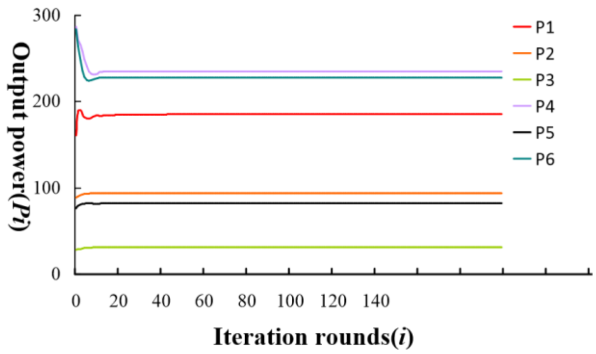

Figure 9. Power change curve of each node when the leader node changes.

(3) Analysis of experiment results of node exit and join scenarios

The simulation experiment is carried out when the node exits and joins, and the experimental results are shown in Figures 10 and 11.

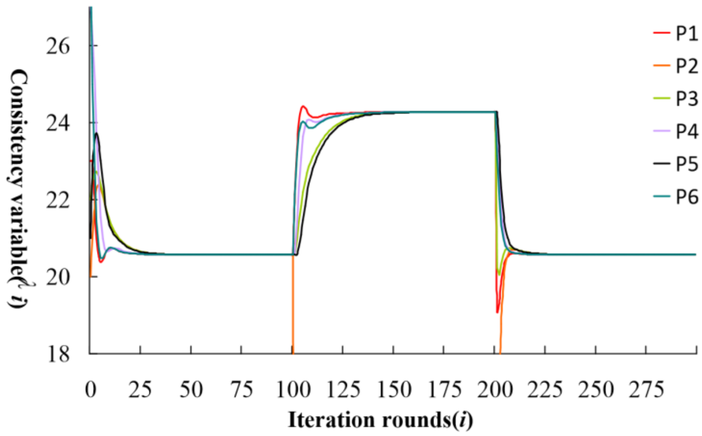

Figure 10. Curve of consistency variable in case of node exit and join.

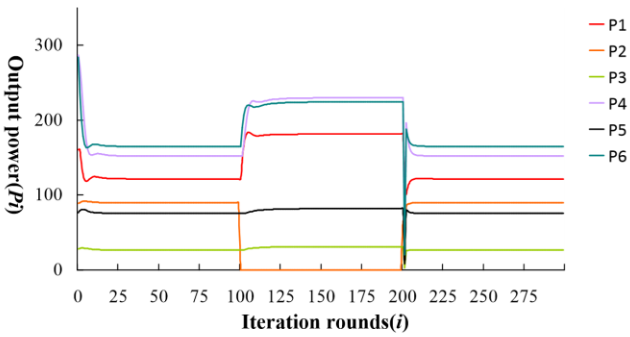

Figure 11. Power of each node in case of node exit and join.

It can be seen from Figures 10 and 11 that at the beginning, when all nodes are normal, the consistency variable converges to 20.61, and the power of each node also reaches a stable value of [122.15, 89.54, 26.43, 152.71, 75.54, 165.47] MW when iterating to the 39th round. In the 100th round, node 2 exits, the output returns to zero, and the distribution network status is unbalanced. The remaining five nodes are coordinated for dispatching. After 55 rounds of iteration, the consistency variable converges to 24.25, and the system is stable again. At this time, the power of each node is [180.93, 0.00, 31.08, 229.19, 81.80, 223.78] MW, reaching the optimal distribution and supply-demand balance. In the 200th round, node 2 joins the scheduling again. After 31 rounds of iteration, the consistency variable converges to 20.61, and the power of each node is [122.07, 89.54, 26.43, 152.56, 75.54, 165.38] MW, that is, the state before node 2 exited is restored. The above results show that this strategy can quickly adapt to the scenario of nodes joining and exiting.

(4) Analysis of experimental results of power switching command change scenarios

When the power exchange command changes, the experimental results are shown in Figures 12 and 13.

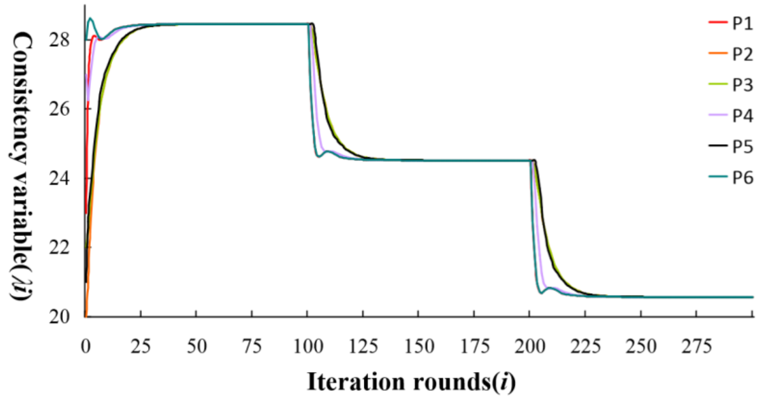

Figure 12. Consistency variable curve when power exchange command changes.

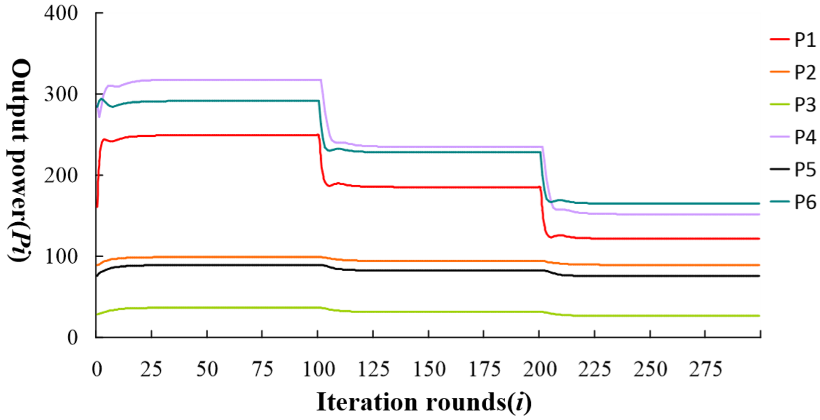

Figure 13. Power of each node when the power exchange command changes.

According to Figures 12 and 13, in the initial state, the consistency variable converges to 28.42 after 41 rounds of iteration, and the power of each node converges to [248.53, 98.84, 36.44,317.16, 89.01,290.84] MW. The supply and demand are balanced. In the 100th round, the power exchange command becomes 0 MW, and after 41 rounds of iteration, the consistency variable converges to 24.55, and the power of each node converges to [185.91, 94.23, 31.48,235.67, 82.34,228.72], restoring the supply-demand balance. At the 300th round, the power exchange command becomes 100 MW. After 37 rounds of iteration, the consistency variable finally converges to 20.61, and the power of each node is [122.07, 89.54, 26.43,152.56, 75.54,165.38] MW. The system is balanced and reaches the optimal state. The above results show that this strategy has a good scheduling effect in the scenario of power exchange command change.

(5) Comparison of forwarding traffic between consensus algorithms rPBFT and PBFT at different node sizes

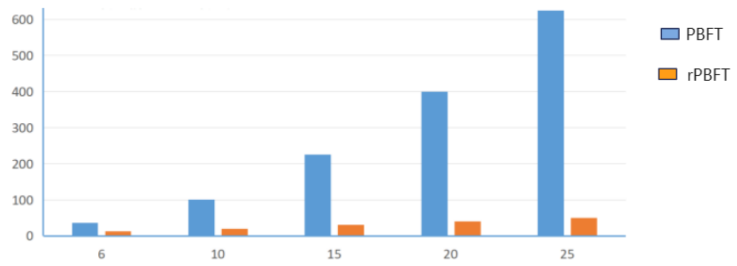

Figure 14. Comparison of forwarding traffic between consensus algorithms rPBFT and PBFT at different node sizes.

As shown in Figure 14, with the increase in node size, the communication volume using rPBFT consensus algorithm is much smaller than that using the PBFT consensus algorithm. This article uses the rPBFT consensus algorithm to store the scheduling data of each round in the distribution network and synchronize it to each node. Each node can obtain the power distribution of all nodes from local data, which can reduce the communication cost between nodes.

6. Discussion

From the above example analysis, it can be seen that the distributed coordinated optimal scheduling strategy proposed in this paper based on the alliance chain and consistency algorithm can cope well with the non-flexible load fluctuations of the distribution network, the switching of leading nodes, the joining or exiting of nodes, and the change of power exchange instructions, with good robustness and stability.

7. Conclusions

In this paper, a distributed optimization scheduling strategy based on alliance chain and consistency algorithm is proposed. Through the alliance chain mechanism, the problems of individual deception, difficulty in obtaining global information, and strong centrality of leading nodes are solved, and a fast and effective optimization scheduling is realized. The effectiveness of the scheduling strategy is verified in a variety of scenarios. Based on the theoretical analysis and simulation results, the following conclusions are drawn:

(1) A distribution network optimal dispatching model including source, load, and storage is constructed, and a distributed optimal dispatching strategy based on alliance chain technology and consistency algorithm is proposed.

(2) The strategy proposed in this article combines alliance chain technology with distributed optimization scheduling. During the scheduling process, nodes directly obtain neighboring node information and global information from local sources, reducing information interaction with neighboring nodes and avoiding individual deceptive behavior; The consistency algorithm has been improved through the rPBFT consensus algorithm, significantly weakening the centrality of the leader node and eliminating the dependency of the consistency algorithm on the central node.

(3) The strategy proposed in this article can achieve global optimal power allocation and achieve system supply-demand balance by iterating consistency variables for about 40 rounds. Similarly, using

consistency algorithms requires about 50 rounds [9], indicating that this strategy can quickly and efficiently achieve coordinated optimization scheduling goals.

(4) This strategy can deal well with the non-flexible load fluctuation, leading node switching, node joining or exiting, and power exchange command change of distribution network, and has good robustness, stability, and scalability.

This article only considers power balance constraints in the global constraints, without considering other constraints. In the future, network loss and other constraints can also be considered. In addition to economic factors, the objective function to be considered in the subsequent scheduling research can also take into account environmental factors, user satisfaction, etc. The constraint conditions can also consider reactive power, voltage, frequency, etc., to improve and supplement existing power scheduling strategies.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Acknowledgments

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Conflict of interest

The authors declare no conflicts of interest.

Author contributions

Conceptualization, Jinhua Tian; methodology, Bihan Fan, Cheng Zhang and Qiqi Zang; validation, Yueyuan Zhang and Yanan Gao; formal analysis, Cheng Zhang, Yu Qin and Bihan Fan; writing—original draft preparation, Cheng Zhang; writing—review and editing, Qiqi Zang; supervision, Jinhua Tian and Yueyuan Zhang. All authors have read and agreed to the published version of the manuscript.

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