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TWO-LAYER SCHEDULING STRATEGY OF WEB-OF-CELLS BASED ON COMPLEX NETWORK

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Abstract: To make full use of cross-region scheduling resources, a two-layer coordinated scheduling model of Web-of-Cells (WoC) based on complex network was proposed. Firstly, the concept of "cell" is introduced to replace different regions, and the complex network theory is used to construct a complex network model for cross-cell scheduling and a two-layer mathematical model for cross-cell scheduling, and the upper model is the scheduling model between Web of Cells, with the goal of maximizing the value of power exchange between Web of Cells. The lower-level model focuses on the economic scheduling within the cell. An improved genetic algorithm based on small-world network was developed to solve the problems of insufficient global search ability and slow convergence speed of multi-objective genetic algorithm when dealing with large-scale scheduling problems. In addition, by analyzing the relationship between the scheduling target and the network modularity, an initial solution generation strategy based on network modularity is proposed to optimize the initial solution of the small-world genetic algorithm. Finally, the effectiveness of the proposed model is verified by the analysis results of numerical examples.
Keywords: Optimized dispatching; Complex network; Web of-Cells; Small world genetic algorithm

1 INTRODUCTION

Due to the uneven geographical distribution of resources and loads, it is difficult to achieve power balance by relying solely on local power grid dispatch resources. This imbalance is even more pronounced especially in regions where renewable energy sources such as wind and photovoltaic power are being developed on a large scale. Through cross-regional scheduling, the allocation of resources can be optimized in a wider region, and the resource complementarity between different regions can be used to alleviate the regional contradiction between power supply and demand, while improving the economic benefits and safety of the system. Cross-regional dispatch relies on inter-regional transmission lines, which are expensive to construct and take a long time. Therefore, it is of practical significance to efficiently use these transmission resources to maximize the economic value of inter-regional power exchange [1-4].
Li and his team [5] propose a two-layer dispatching framework that uses a robust optimization method to develop the connection lines between multi-regional power grids. Robust optimization ensures the safety of grid operation, but the use of uncertain parameter modeling based on extreme cases may lead to the resulting scheduling scheme being too conservative to optimize the economy of the grid as much as possible. The researchers introduced the concept of replacing traditional generator sets with power generation units in order to achieve more precise power regulation on DC transmission lines. Although this method improves the fineness of the regulation, when the temporal resolution of the model decreases, the number of equivalent power generation units increases significantly [6]. This not only enlarges the scale of the model for solving the inter-regional power consumption problem, but also makes the solution time longer.Dr. Cai verifies that the multi-regional networked power system is effective in enhancing the absorption capacity of renewable energy, but the centralized dispatching model is mainly used in this study, which fails to fully consider the requirements of information security and dispatching autonomy of regional power systems [7]. Therefore, the development of decentralized dispatch models and related algorithms has become a new research hotspot in the field of power system, aiming to optimize the resource allocation and dispatch independence between regions, while maintaining the overall efficiency and safety of the system.
Complex network models often exhibit small-world and scale-free characteristics, which allows them to effectively simulate the statistical properties of real-world networks. Zhang, Xue and Zhou [8] used the BA (Barabasi-Albert) scale-free network to explore the impact of carbon trading market, environmental tax and innovation subsidy on the diffusion of green technology in manufacturing enterprises, and the results showed that improving the carbon trading market is conducive to the full diffusion of green manufacturing technology in the alliance. Chen, Zhang and Liu [9] used complex network analysis methods to explore the response of multimodal transport networks to random and targeted attacks. The study focuses on how the average shortest path length and the proportion of the maximum connected subgraph of the network change, so as to assess the vulnerability of the network. This analysis helps to reveal

the stability and resilience of the network structure in the face of threats, thus providing important theoretical support for improving network resistance. Xuan shows how complex network theory can be applied to solve scheduling problems [10]. By examining the local features of the network, these features are used as the heuristic basis for designing scheduling rules, so as to achieve more effective scheduling results than traditional scheduling rules. The advantage of this method is that it can optimize the scheduling strategy according to the structural characteristics of the network itself, and improve the efficiency and effect of scheduling. It is pointed out [11] that large-scale power grids exhibit the characteristics of scale-free networks, which makes the study of power grids based on complex network theory a research hotspot at present. As a complex technical system, the scale-free nature of the network structure of the power grid illustrates the importance of the high connectivity of a few nodes to the operation of the whole network. Studying these characteristics can help optimize the grid design, improve its stability and efficiency, and also better respond to potential failures and attacks.

In this paper, Web-of-Cells (WoC) are taken as the research objects, and the source and load in WoC are used as complex network nodes, and the transmission lines between sources and loads are used as edges, and the corresponding complex network scheduling model is established, and WoC is divided into multiple cells. Then, a mathematical model of two-layer scheduling between and within cells is established. In order to find the optimal solution, this paper designs an improved Small World Genetic Algorithm (SWGA) by combining the advantages of scheduling rules and intelligent algorithms, which can significantly improve the quality of the initial solution by integrating the global features of the complex network into the initial solution generation process of the SWGA [12-13]. This method not only improves the convergence speed of the algorithm, but also improves the quality of the solution. This is because the global characteristics of complex networks, such as node degree distribution, clustering coefficients, and network diameters, can provide deep insights into the network structure, allowing algorithms to more effectively locate and utilize key structural information to optimize solutions.

Furthermore, this improved SWGA is applied to solve the WoC scheduling problem in the network environment. In this application, the algorithm needs to deal with a number of factors, including energy generation, storage, and distribution, which are affected by the structure and dynamics of the network. The use of complex network features, especially when generating initial solutions, enables the algorithm to not only find the best solution faster, but also more accurately reflect and deal with the scheduling challenges in the actual network environment. Therefore, this method not only improves the performance of the algorithm, but also enhances its applicability and efficiency in practical network scheduling problems.

2 WOC CROSS-CELL SCHEDULING FRAMEWORK

The micro-element grid is a highly integrated grid of renewable energy, which contains the connection of a large number of distributed generators (DG) to the grid. This network structure is mainly oriented to the global demand for electricity, and adopts a decentralized and autonomous management method. In such a configuration, the micro-element network covers several network elements, each of which is an autonomous unit. Figure 1 illustrates the framework of the two-layer optimization model for cross-cell power dispatching of micro-element networks, which reveals how power resources can be efficiently allocated and adjusted among multiple cells to support sustainable and efficient grid operations.

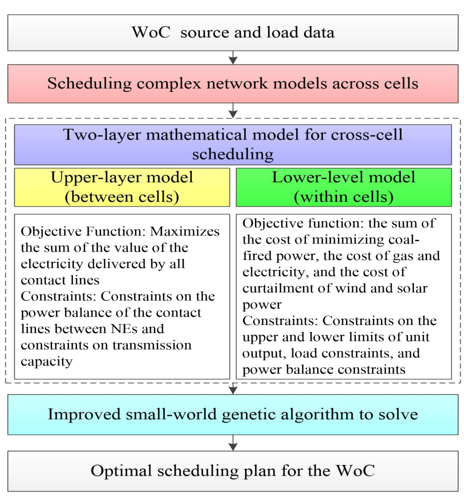


Figure 1 WoC Scheduling Framework

In this paper, the source load in the cell is used as the node, the transmission line between the source and the load is used as the edge, and different cells are used as different modules to construct a complex network model of cross-cell scheduling of micro-element network. Because cross-unit scheduling has different path choices and determines the modularity of complex networks, the overlapping community discriminated algorithm (OCDL) based on graph theory [14] is used to divide modules and increase the size of modularity, which is conducive to reducing the cost and time of cross-unit scheduling in general.

Secondly, a two-layer model of micro-element network scheduling is established, which involves cross-region and intra-cell scheduling problems. In this system, the upper-level model aims to maximize the value of cross-regional dispatch of electricity, and mainly focuses on optimizing the distribution of power resources and the flow of electricity from a macro perspective. Specifically, the design of this layer is mainly from the perspective of the higher-level dispatching agency, whose main responsibility is to determine the amount of power transmitted and received between different network elements. This process not only involves the price of each receiving network element, which is regarded as an indicator of the utility of unit power dispatching, but also needs to consider the unit transmission cost and the price of the transmission network element, the sum of which is used as the basis for cost calculation and is used for electricity dispatching. This approach enables scheduling decisions to take into account both economic and cost efficiency, thereby optimizing the allocation of power resources. By accurately calculating the price difference and transmission costs between cells, dispatching agencies can more effectively develop strategies to ensure the economy and reliability of power delivery. In addition, this strategy helps dispatch agencies maximize economic returns and network efficiency while meeting regional power demand.

The lower-level model aims to minimize the power generation cost of each cell, and focuses on the economics and efficiency issues within the cell. This layer ensures the balance between power supply and demand within the network element from the perspective of the lower-level dispatching organization. The main parameter of this model is to calculate the electricity price of the network element by solving the internal scheduling model based on the power transmission and reception between network elements, and feed this information back to the upper-layer model.

The upper-layer model receives the cell electricity price information from the lower layer, synthesizes the electricity price data between cells, and determines the optimal amount of electricity exchange between cells through further model solving. The design of this two-tier model not only improves the economic operation efficiency of the power grid, but also enhances the flexibility and responsiveness of dispatching, allowing the grid to remain stable and efficient in a complex and changeable operating environment. Through this hierarchical scheduling model, the effective coordination between the upper-layer model and the lower-layer model helps to achieve optimal power allocation between regions, while ensuring that each cell can be economically self-sufficient.

Finally, the improved SWGA was used to solve the model. The improved small-world genetic algorithm optimizes the mating selection mechanism, ensuring the efficient propagation of genetic material and the retention of excellent traits, which is essential for complex and large-scale optimization problems. In addition, by simulating the natural properties of small-world networks, such as short mean paths and high clustering coefficients, SWGA is able to maintain a high degree of diversity during the operation of the algorithm, preventing premature convergence and finding a better solution in the entire search space. This method has shown excellent efficiency and effectiveness in solving scheduling problems, especially in application scenarios that require fast response and accurate scheduling.

3 COMPLEX NETWORK MODEL FOR CROSS-CELLS SCHEDULING

Figure 2 shows the generation process of a directed link network, in which independent nodes are the source loads in the cell and are energy flow relationships, that is, directed links are established based on the energy flow relationships of source and loads.

cell	source（load）			
A	E_1	E_2	E_3	——
B	E_4	E_5	——	——
C	E_6	E_7	E_4	E_3
D	E_9	E_{10}	E_8	E_7

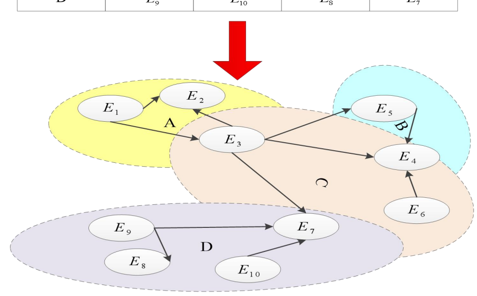


Figure 2 Schematic Diagram of a Directed Link Network

Compared with the traditional K-Means algorithm, the complex network community method can better represent the nonlinear scheduling relationship within and between network elements through the network connectivity graph. This method uses the network index attribute of the graph to quantify the constraint relationship between network elements, which makes the partition result more reasonable and accurate. In particular, the network intermediary centrality index is used to identify and strengthen the synergistic factors in the classification in this method, so as to improve the transparency and efficiency of WoC scheduling. By using these complex network indicators, the partitioning process not only reflects the basic relationship between cells, but also reveals deeper structural characteristics and potential coordination patterns, which is of great significance for optimizing the scheduling strategy of the micro-element network and improving the overall operation efficiency. This network theory-based approach provides a more precise and dynamic solution for dealing with complex and dynamic network data.

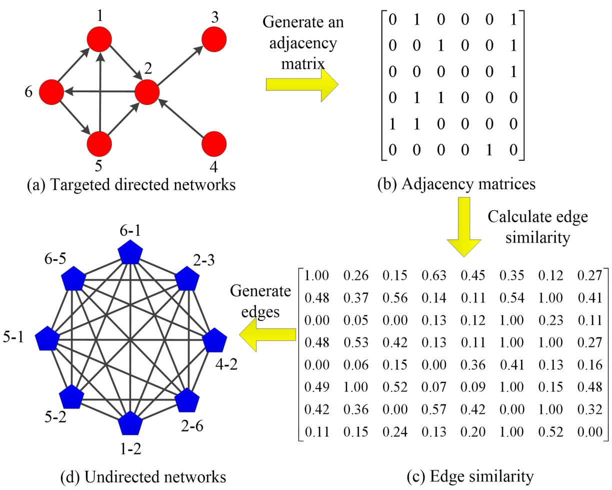


Figure 3 Generation Process of Undirected Weighted Network

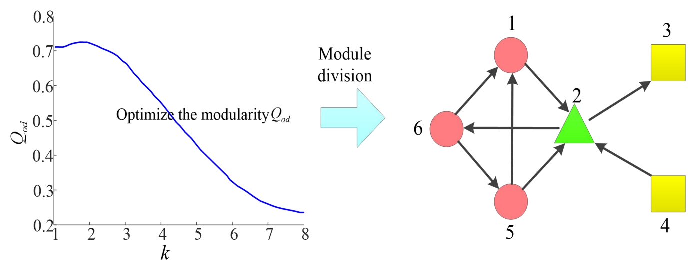
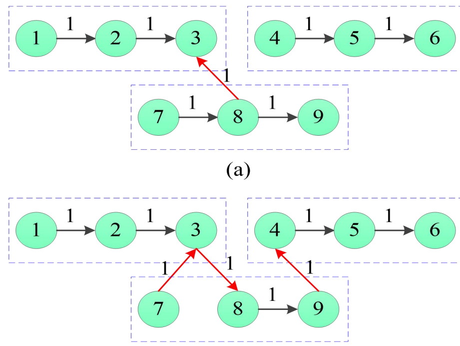


Figure 4 Module Division Process

The OCDL algorithm optimizes the effect of module recognition, which is achieved by calculating the similarity at the edge of the network, effectively maintaining the connection between different clustering modules in the network. Figure 3 depicts the construction process of an undirected weighted network, while Figure 4 shows the process of user clustering and module division. Based on this graph theory-based approach, the OCDL algorithm measures the similarity between nodes by using the characteristics of network edges, and transforms the directionality of the network into the undirected weighting of the new network. In the new network, the algorithm performs hierarchical clustering by calculating the connectivity of each node, and then realizes the division of network modules within the community, and generates the best clustering result with overlapping nodes. The improved version of the OCDL algorithm can be broken down into the following five specific steps:

1) Build a targeted network;
2) Convert to an undirected network;
3) Update the weights of nodes in the undirected network;
4) Calculates the weights of edges in an undirected network;
5) Evaluate the effect of community cluster segmentation.

The cell can choose a variety of cross-unit scheduling paths in the scheduling network, but the complex structure and modularity of the scheduling network are different among different paths, as shown in Figure 5. Figure 5 (a) is higher than Figure 5 (b) in terms of modularity, and the degree of connection between nodes in the same dotted box is closer in Figure 5 (a) than in Figure 5 (b).



(a) (b)

Figure 5 Path Diagram of Different Cross-cell Units

From the above analysis, it can be seen that the selection of a scheduling network with a high degree of modularity can significantly reduce the transportation cost and time across units in general, which not only reduces the overall operating cost, but also significantly improves the scheduling efficiency. It can be seen that there is a close correlation between the modularity of the scheduling network and the scheduling optimization goal. When designing and optimizing the scheduling network, the network structure with a high degree of modularity can more effectively realize the local optimization of resources, reduce unnecessary long-distance transmission, and optimize the performance and response speed of the whole system. Therefore, considering network modularity as a key parameter in scheduling strategy and network design will be crucial to achieve the dual goals of cost efficiency and operational efficiency.

4 MATHEMATICAL MODEL OF CROSS-CELL SCHEDULING

4.1 Upper-Level Model

In the upper-layer model, from the perspective of cell scheduling, the maximization of the value of cross-region dispatching power is regarded as the goal. The model defines the marginal power generation cost of each cell as its electricity price, and its key parameter is the electricity price of each cell. This setup allows the model to more accurately reflect the actual cost of electricity production, thereby optimizing the allocation and use of power resources. By treating the marginal cost of electricity generation as the price of electricity, the model effectively links the cost of production with the market price, ensuring the economic efficiency of electricity trading. Such a configuration not only helps to improve the economy and efficiency of the entire power grid, but also ensures that power dispatch between different network elements is more rational and economical. In addition, considering marginal costs also helps to simulate price signals in a real-world market environment, providing a solid economic basis for decision-making in the electricity market, so that cross-zone dispatch strategies can maximize the value of the entire system while ensuring the safety and cost-effectiveness of power supply. The objective function of the model is:

$$\max F^U = \sum_{t\in T}\sum_{l\in L}\left(p_{l,t}^R Q_{l,t}^R - p_{l,t}^S Q_{l,t}^S - p_l^{TL} Q_{l,t}^S\right) \tag{1}$$

where F^U is the value of the dispatched electricity; T and L are the collection of time periods and contact lines, respectively; $p_{l,t}^R$ and $p_{l,t}^S$ are respectively the electricity prices of the receiving and sending elements of the contact line l in the t period, and their values can be obtained by the corresponding Lagrange multipliers corresponding to the power balance constraints of each network element in the lower model. $Q_{l,t}^R$ and $Q_{l,t}^S$ are respectively the amount of electricity transmitted by the receiving end and the sending end of the contact line l in the t period; p_l^{TL} is the transmission cost of the contact line l.

The constraints are shown below:

$$\begin{aligned} p_{l,t}^R &= -\lambda_{l,t}^R \quad l\in L, t\in T \\ p_{l,t}^S &= -\lambda_{l,t}^S \quad l\in L, t\in T \end{aligned} \tag{2}$$

where $\lambda_{l,t}^R$ and $\lambda_{l,t}^S$ are the Lagrangian multipliers corresponding to the internal power balance constraints of the grid element and the transmission grid element at both ends of the contact line l in the t period.

The constraints of the upper-level model are as follows.

1) Power balance constraints on contact lines between cells:

$$Q_{l,t}^S\left(1-\xi_l\right) = Q_{l,t}^R \quad l\in L, t\in T \tag{3}$$

where ξ_l is the transmission loss of the contact line *l*.

2) Constraints on the transmission capacity of the contact line:

$$\underline{P}_l \Delta t \le Q_{l,t} \le \overline{P}_l \Delta t \quad l \in L, t \in T \tag{4}$$

where $\underline{P}_l$ and $\overline{P}_l$ are the lower and upper limits of the transmission capacity of the contact line *l*, respectively; Δt is the unit time duration, which is taken as $1h$ in this document.

4.2 Lower-Level Model

Considering the constraints of gas turbines, power balance, energy storage, and workload scheduling, the lower-level model takes the lowest total cost as the goal, and optimizes the optimal source-load scheduling plan of each data center in the T period of the next day, and its objective function is as follows.

$$\min C_{DA} = \sum_{t=1}^{T}\sum_{i=1}^{N}\left(C_{i,t}^{grid-DA} + C_{i,t}^{gas-DA} + C_{i,t}^{ch-DA} + C_{i,t}^{\alpha-DA}\right) \tag{5}$$

where C_{DA} is the total economic cost of scheduling; *T* is the number of scheduling moments for the next day; *N* is the number of data centers; $C_{i,t}^{grid-DA}$ is the cost of purchasing electricity from the grid; $C_{i,t}^{gas-DA}$ is the gas turbine operating costs; $C_{i,t}^{ch-DA}$ is the operating cost of energy storage; $C_{i,t}^{\alpha-DA}$ is the latency-sensitive workload scheduling costs. The specific calculation formula is as follows:

$$\begin{cases} C_{i,t}^{grid-DA} = e_{i,t}^{grid-DA} p_{i,t}^{grid-DA} \Delta t \\ C_{i,t}^{gas-DA} = \left(e_{i,t}^{gas} p_{i,t}^{gas1} \big/ H_i^{gas} \eta_i^{gas} + e_{i,t}^{gas} p_{i,t}^{gas2}\right) \Delta t \\ C_{i,t}^{ch-DA} = \left(e_{i,t}^{bc} + e_{i,t}^{bd}\right) p_i^{ch} \Delta t \\ C_{i,t}^{\alpha-DA} = \alpha_{i,t}^{tr} p_i^{tr} \end{cases} \tag{6}$$

where $p_{i,t}^{grid-DA}$ is the predicted electricity price of the market where the center *i* is located; p_i^{gas1} and p_i^{gas2} are the gas purchase cost and operating cost per unit of power generation of the *i* gas turbine of the data center, respectively; H_i^{gas} and η_i^{gas} are the calorific value and power generation efficiency of gas turbine in data center *i*, respectively; p_i^{ch} is the unit operating cost of the energy storage system of the data center *i*; $\alpha_{i,t}^{tr}$ is the number of delay-sensitive load space schedules in data center *i*; p_i^{tr} is the unit latency-sensitive load scheduling fee; Δt is the scheduling cycle time.

5 IMPROVED SMALL-WORLD GENETIC ALGORITHM

SWGA (Small World Genetic Algorithm) is a genetic algorithm that draws on the characteristics of the small world network structure to select mating partners within a population through the connection relationship between nodes in the network. The advantage of this structure is that it can significantly improve the efficiency of mating, thereby accelerating the transmission of genetic information and increasing diversity, which is more efficient than traditional genetic algorithms. In order to further optimize the performance of the algorithm when dealing with large-scale scheduling problems, an improved SWGA algorithm is proposed. This improved method introduces the concept of modularity of the scheduling network to generate a higher quality initial solution. In this way, a good starting point can be ensured at the beginning of the algorithm, and the convergence speed of the whole algorithm and the quality of the final solution can be improved, especially when solving complex and large-scale scheduling problems.

5.1 Chromosome Encoding and Decoding

Coding is the key to the successful implementation of genetic algorithms. This article uses a three-stage encoding, as shown in Figure 6. The code consists of strings of genes from within and between two network elements. Among them, the gene string in the network element determines the transmission path of the power in the network element, the numerical value represents the number of the source (charge) from left to right, and the number *j* in the *i*-th appears indicates the power transmitted from *i* to *j* in the network element. The gene strings between network elements determine the objects of energy transfer between network elements. For example, the first digit 2 that appears from left to right in the gene string in the cell indicates that the source (load) numbered 1 in the cell 1 transmits electricity to the source (load) numbered 2. The first 2 that appears from left to right in the gene string between the first cell indicates that the source (load) numbered 1 of cell 1 transmits electricity to the source (load) numbered 2 in other cells, and the first 1 that appears in the gene string between the second cell from left to right indicates that the source (load) with number 1 of cell 1 transmits electricity to cell 3.

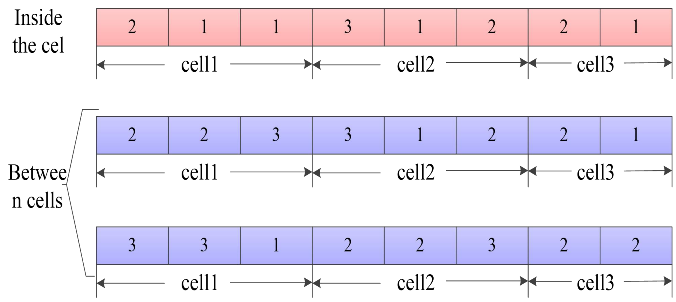


Figure 6 three-stage Coding Gene String

5.2 Initial Solution

Choosing a scheduling network with a high degree of modularity can effectively reduce operating costs and improve scheduling efficiency. In order to further improve the performance of the algorithm and optimize the quality of the initial solution, this paper introduces an initial solution generation mechanism based on the modularity of the scheduling network. This mechanism is broken down into the following steps:
1) Three-stage coding generation: First, a three-stage coding method is used to generate a population of individuals with a size of $2n\times a\%$. This encoding allows each individual to contain multi-dimensional information, helping to more accurately simulate and express the complexity of the problem.
2) Random specimen generation: In the step of generating the initial population, the three-stage coding method is continued and another group of individuals with a size of $n\times(1-a\%)$ is randomly generated. This operation aims to enhance the diversity of the population and provide a broader solution space for the genetic algorithm to explore.
3) Modularity calculation and selection: The modularity of each individual in the first group is calculated, and the modularity is used as an indicator to reflect the structural efficiency of the individual in the network. $n\times a\%$ individuals with the largest modularity were selected and these individuals were merged with the second group to form the final initial population of n size.
Choosing a scheduling network with a high degree of modularity can significantly reduce the overall cost and improve the scheduling efficiency. On this basis, to further improve the performance by improving the quality of the initial solution, this paper proposes an initial solution generation mechanism based on the modularity of the scheduling network. This mechanism optimizes the initial structure of the population through carefully designed steps, including the following:
1) Extended population generation: Firstly, a three-stage coding method was used to generate an individual population with a scale of $2n\times a\%$. The purpose of this step is to create a large pool of candidates so that there is more room for choice to find individuals with a high degree of modularity.
2) Random population generation: Next, the same three-stage code is used, but the random strategy is used to generate a population of $n\times$ (1-$a\%$) in size. This random generation method aims to introduce diversity so that the algorithm does not fall into local optimality early on.
3) Modularity calculation and selection: The modularity is calculated for each individual in the first group of individuals, and the modularity is a key indicator to evaluate the advantages and disadvantages of individual network division, which reflects the independence and cohesion between modules in the network. In this step, select $n\times a\%$ individuals with the largest modularity.
4) Initial population composition: The above-mentioned selected individuals with high modularity are combined with the second group of randomly generated individuals to form the final initial population with a size of n. This merger aims to balance exploration and development, with highly modular individuals providing a good starting point, and random individuals guaranteeing the breadth of the search process.
Through this strategy, the initial solution can not only provide high solution quality, but also enhance the exploration ability of the algorithm in the search space, so as to improve the efficiency and effect of the solution process. This modularity-based initial solution generation mechanism provides a practical solution for complex optimization problems, especially for those application scenarios that require efficient scheduling and cost control.

5.3 Algorithm Steps

1) Firstly, an initial population containing n individuals was constructed by using the initial solution generation mechanism based on the modularity of the manufacturing network. This method takes advantage of the modularity of

the manufacturing network to optimize the quality of the initial solution, so as to provide a strong starting point for the algorithm. In order to promote the effective interaction between individuals in the population and the optimal transfer of genetic traits, we construct a small-world network with n nodes. In this network, each node represents an individual in the population. In addition, the time step is set to t=0, which marks the beginning of the algorithm.
2) In the parent population, individuals mate in pairs according to the structure of the small world network, so as to produce the next generation of offspring population. This type of pairing takes full advantage of the network connection and enhances the genetic diversity of the population.
3) the implementation of elite retention strategies, combining the parent and offspring populations to ensure that excellent genetic traits are retained. In the merged population, non-dominant sorting is implemented, which is a multi-objective optimization method to identify and screen out n individuals with the best performance to form a new round of parent populations. In addition, in order to maintain the efficiency and exploration ability of the algorithm, this strategy also includes regenerating a small-world network with n nodes, ensuring that each network node corresponds to an individual in a population.
4) If n=4, then t=t+1, return to the second step, otherwise the algorithm is terminated.

6 CASE ANALYSIS

6.1 Description of the Study

In this paper, the examples provided [15] are further improved, and the topology of the region is described in detail through the complex network theory, as shown in Figure 7. We divide this area into four modules, each representing an independent network element, for more granular grid management and optimization.

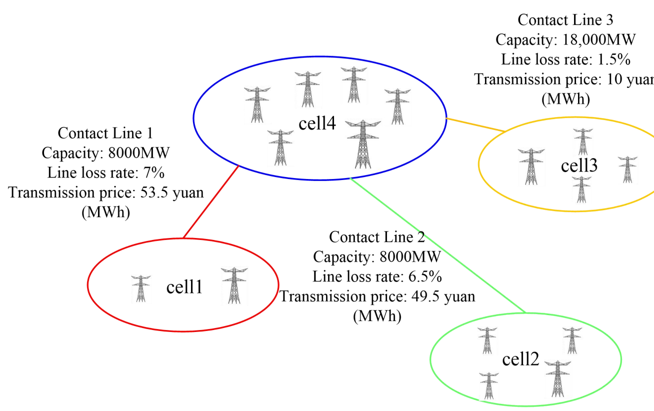


Figure 7 Regional Topology

Among the four cells, cells 1 to 3 are responsible for transmitting power to cell 4. Cell 3 has the highest transmission capacity and the lowest transmission cost due to its largest installed capacity of new energy, making it a key player in regional networks. Table 1 describes the installed capacity and maximum daily load of each cell.

Table 1 Regional Installed Capacity and Maximum Load

cell	Coal-fired power capacity/MW	Installed gas and electricity capacity/MW	Photovoltaic installed capacity/MW	Installed wind power capacity/MW	Maximum load/MW
1	49200	0	12100	12300	51500
2	48000	12900	4300	2100	47200
3	33000	0	12300	25600	38800
4	46500	3000	8000	4000	41600

6.2 Analysis of Operation Results

Figure 8 shows the operation of cell 3 and cell 4, where cell 3 is able to transmit power to cell 4 stably at different times of the day due to its high installed capacity of new energy. In contrast, cell 1 and cell 2 supply power to cell 4 only during peak hours during the day. The detailed operation data shows that the power delivered by cell 3 is equal to that received by cell 4 during the 0-17 hours and 20-23 hours periods, indicating that cell 1 and cell 2 did not transmit power to cell 4 during these time periods.

Observing the trend of electricity price and power generation, the power generation of cell 3 is always equal to the sum of its power transmission and its own load. The characteristics of intraday electricity consumption show that there are two obvious peak hours: the afternoon peak and the evening peak. During the afternoon rush hour, the power demand of cell 4 is fully satisfied by the transmission of cell 3, while during the evening rush hour, the combined transmission of cell 1 to 3 is required to maintain the power balance of cell 4. Although cell3 generates similar power during the afternoon and evening peaks, there is a significant difference in electricity prices, mainly because the output of wind and photovoltaic power is reduced during the evening peak, and more reliance on coal-fired power units to increase power generation to supplement it, which pushes up electricity prices. The intraday electricity price of cell 4 fluctuates greatly. During the off-peak period, coal-fired power units are mainly relied on to maintain power balance, so electricity prices are low. During peak hours, electricity prices rise due to the surge in electricity demand and the need to use higher-cost gas and power units to supplement the supply. During extreme evening rush hours, the output of the gas turbines also reached its upper limit, which further pushed the cell electricity price to the set maximum price. This price and supply-demand dynamics reveal the energy efficiency and economic burden of each cell at different times, emphasizing the importance of optimizing energy allocation and improving the utilization rate of renewable energy.

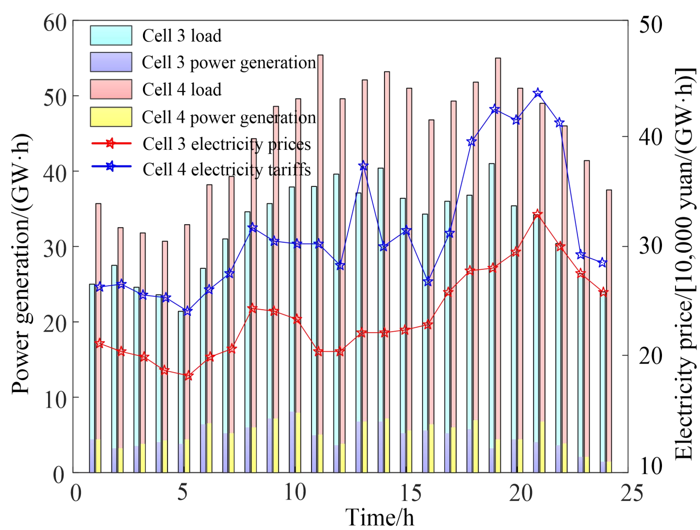


Figure 8 Running Status of Cell 3 and Cell 4

Taking cell 3 as an example, the internal optimal scheduling plan of cell is mainly based on the output of renewable energy, as shown in Figure 9. In day-to-day operations, cell 3 prioritizes the use of renewable energy sources to meet power demand. When the power generation capacity of renewable energy is insufficient to cover the demand, coal power, energy storage equipment and gas turbines will be reasonably arranged to supplement the power supply according to the current electricity price and the cost of different power generation methods.

In particular, during the evening period from 19:00 to 21:00, the load power during this period is significantly higher than that of renewable energy sources, and the electricity price is higher, exceeding the power supply cost of energy storage equipment and gas turbines. Therefore, energy storage equipment and gas turbines will be prioritized for power supply during this period. Even so, if the power supply of these two resources still cannot fully meet the load demand, cell 3 will use coal-fired power units to ensure the continuity and stability of power supply. Conversely, when the output of renewable energy exceeds the real-time load demand, as shown in the figure during the low-load period from 01:00 to 03:00, cell 3 will take advantage of this opportunity to store excess power through the energy storage device. This strategy not only maximizes the utilization of renewable energy, but also reduces the cost of purchasing electricity during peak hours by releasing electricity through energy storage devices during periods of high demand.

This scheduling strategy demonstrates how cell 3 can maximize economic benefits and optimize operating costs by flexibly adjusting the usage ratio of different energy types to cope with price fluctuations in the electricity market and changes in actual power demand. Through this efficient energy management, cell 3 can maintain the high efficiency and economy of power supply, and at the same time provide important support for the stable operation of the entire power grid.

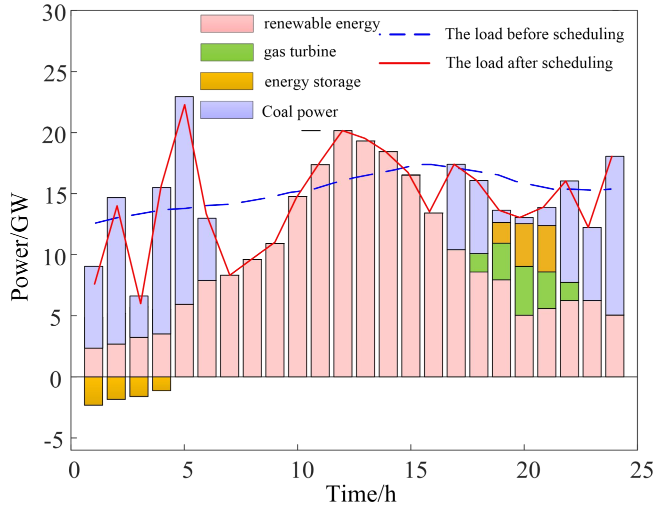


Figure 9 Cell 3 Internal Scheduling Plan

6.3 Model Comparison

The model proposed in this paper (hereinafter referred to as Model 1) is compared with the scheduling model (hereinafter referred to as Model 2)[16]. Figure 10 shows the price changes of each cell in the two models, revealing the differences in the price management strategies of the two models.

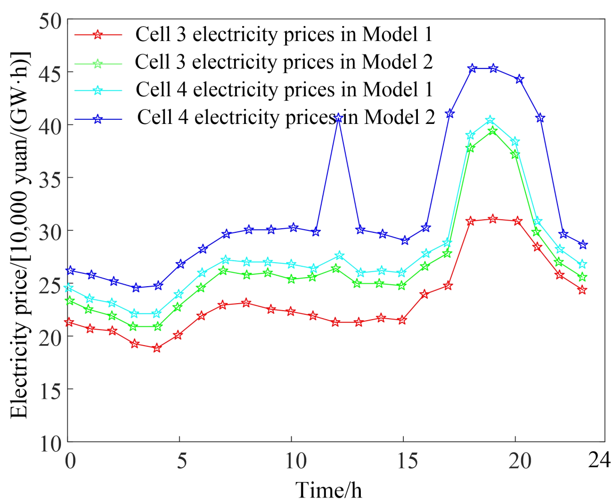


Figure 10 Regional Electricity Prices for the Two Models

Model 1 is characterized by a large price difference between the receiving grid element and the transmission grid element. Especially during the middle and peak hours, the electricity price of the affected grid element 4 is significantly higher than the electricity price of the transmission grid element, which reflects the direct impact of the peak power demand on the electricity price. The electricity price of the transmission grid element is lower at all times of the day, which shows the flexibility of model 1 in electricity price adjustment and the importance of cost control.

In contrast, model 2 relies on the abundant renewable energy supply of cell 3 during the medium and low load periods, so that the electricity price of cell 4 is lower than that of cell 2. In this configuration, the coal-fired power units of cell 4 generate less electricity, which reduces the overall electricity price. The difference in electricity prices is mainly caused by the cost of transmission, showing the advantages of model 2 in utilizing renewable energy. When analyzing the difference in electricity price between cell 3 and cell 4, the difference in electricity price shown in model 1 is generally higher than that in model 2. Especially in the 0-11 hour period when the power supply is sufficient, the electricity price is mainly affected by the marginal power generation cost of coal-fired power units, and the electricity price difference during this period shows relative stability. Further analysis shows that the stability of electricity price during this period is mainly determined by the operating efficiency and cost control level of coal-fired power units. During these hours, coal-fired power units play a key role as a baseload power source due to the relatively sufficient power supply, and their

cost efficiency directly affects the overall electricity price structure. In addition, the stability of the electricity price difference also reflects the difference in the dispatching strategy and energy management of the two cells, where model 1 may focus more on cost efficiency, while model 2 may perform better in maintaining electricity price stability.
However, at 12 hours of the afternoon rush hour, cell 4 in model 1 needs to start the more expensive gas and power units to cope with the surge in power demand, resulting in a sharp increase in electricity prices, further increasing the difference in electricity prices between the two models. At the same time, cell 4 in model 2 mainly relies on the power supply of transmission grid elements, maintaining a relatively stable electricity price level.
In the 18-19 hour period of the evening peak, as the load further increases, the power supply of all cells becomes more tight, and the electricity price of each cell in model 2 also rises to a high level. However, in model 1, only cell 4 has reached the highest level, which further demonstrates the strategy and challenge of model 1 in adjusting electricity prices in response to peak power demand. Through this detailed comparative analysis, it is possible to see the fundamental differences between model 1 and model 2 in terms of tariff management and resource allocation strategies, and how these differences affect the economics and stability of the grid.
Figure 11 illustrates the power transmission behavior of cell 1-3 to cell 4 in both models. The analysis data shows that for most of the time period (0-17 hours and 21-23 hours), both models mainly rely on cell 3 to transmit power to cell 4. This indicates that cell 3 plays the core role of power supply in both models. However, during the 18-20 hours of the evening peak period, due to the increase in the load demand of cell 4, both models require multiple cells to supply power together to meet the demand.

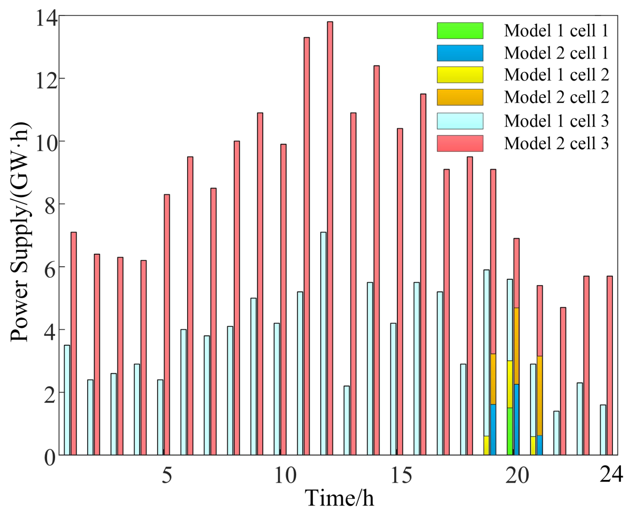


Figure 11 The Amount of Power Sent by Cell 1 to Cell 3 to cell 4 in the Two Models

It is worth noting that model 2 has significantly higher power delivery than model 1 during most periods, such as 2-9 hours. This may be due to Model 2's adoption of a more proactive power dispatch strategy, which adjusts the amount of power delivered more frequently in response to real-time price changes and load conditions. In particular, at 12 hours, the power delivery of model 1 decreases, which is mainly due to the decrease in the photovoltaic power generation output of cell 3 and the increase in load demand. This phenomenon highlights that model 1 may be more dependent on conservative power dispatch strategies in the face of renewable energy generation fluctuations and load changes.
Through this comparative analysis, it is possible to better understand the differences between the strategies of the two models in terms of electricity price management, resource allocation, and response to load fluctuations. This not only helps to evaluate the economics and stability of each model, but also provides practical guidance for future grid management and optimization.

7 CONCLUSIONS

In order to allocate resources in a wide range of micro-meta networks and achieve a balance between power supply and demand, this paper proposes a cross-cell optimal scheduling model of micro-meta networks based on complex networks. This model adopts the complex network theory to build a cross-cell scheduling network that can quickly respond to market demand and improve the overall scheduling efficiency. The model consists of two levels of mathematical framework: the upper-level model aims to maximize the value of electricity between cells, taking into account actual operational constraints such as the transmission capacity of the tie line; The lower-level model focuses on minimizing the power generation cost of each cell, while taking into account the output constraints and load requirements of various power generation resources such as coal, gas, photovoltaic, and wind power. The two layers are tightly coupled with the power transmission and reception and electricity price between cells to ensure policy consistency and efficiency.

In terms of operation, the model alleviates the power supply pressure of the receiving grid elements by adjusting a small number of transmission grid element resources, which not only maximizes the value of cross-grid element power transmission, but also optimizes the allocation and utilization of resources. Especially within the network elements, the model maximizes the consumption of renewable energy while keeping the cost of generating electricity to a minimum. This strategy is particularly effective in environments where the power supply is relatively stable, as it reduces the volatility of power transmission and reception between network elements, thereby reducing the dependence and pressure on tie line adjustments.

In addition, this model is especially suitable for scenarios where power generation resources are tight or the transmission capacity of contact lines between network elements is limited. In these cases, the model can make up for the local resource shortage and improve the overall stability and economy of the system through effective cross-cell scheduling. The application of this optimal dispatch model not only helps grid operators maximize cost-effectiveness, but also improves the adaptability and responsiveness of the power system to market changes.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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