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Design of load-side resource scheduling model based on hierarchical market mechanism and study of distributed computing methodology

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Abstract Aiming at the optimal scheduling of load-side resources in smart grids, this study proposes a multilevel collaborative scheduling framework based on a hierarchical market mechanism, which combines an improved hybrid genetic algorithm with a distributed model predictive control method to achieve the global optimization and dynamic response balance of load resources. First, a spot market load resource dispatch model based on dynamic cross-probability adjustment is constructed to reduce the total dispatch cost by optimizing the objective function, which covers the operating cost, network loss and power supply/demand balance. For the aggregation control demand of temperature-controlled load TCL, a distributed model predictive control LDMPC method based on Lyapunov function is designed to reduce the system delay by 9.19ms through localized communication, which is 25.6% lower than the traditional method, and at the same time, safeguard the comfort of users. In addition, an improved thermoelectric load resource allocation algorithm is proposed to coordinate the weight allocation of electric and thermal loads, which reduces the operating cost of the plant to 9860 RMB, saving 24.1% compared with the traditional algorithm. Simulation experiments show that the proposed method significantly outperforms the traditional scheduling strategy in terms of delay performance, integrated system output and cost optimization.

Index Terms hierarchical market mechanism, load-side resource scheduling, distributed computing, LDMPC function

I. Introduction

With the continuous advancement of the country's "dual carbon" goals, the proportion of new energy power generation has gradually increased. It shows considerable randomness and intermittency due to factors such as seasons and weather, which has a significant impact on the safe and stable operation of the power system. Flexible load-side resource scheduling in the power grid has become an effective means to smooth out fluctuations in wind and solar power and respond to the regulation and control demands of the new power system [1]-[5]. Scheduling the load side according to the need for generation and consumption balance is an important part of the source-grid-load interaction model. With the new power system and economic and social development, the volatility of the generation side is increasing, and the peak-to-valley difference of the load side is increasing. The total system dispatch potential is limited, so strengthening the load-side dispatch capability has become a key research direction to comprehensively improve the dispatch capability and flexibility of the power system and realize the goal of “double carbon” [6], [7]. Load-side scheduling has also gradually changed from the orderly use of electricity under the planning system to a market-based approach [8], [9]. Therefore, the research on the market-oriented dispatch method of load-side resources and its role mechanism is of great significance.

The demand for load-side resource dispatch is no longer accidental and fixed, but dynamically generated and constantly changing [10]. With the development of the electricity market, the forms of demand response not only include time-of-day tariffs, invitational and interruptible demand response, but also can be aggregated to directly participate in the spot market and capacity market transactions in the form of “load curtailers”, while the participation of load-side resource scheduling capacity in ancillary services transactions has been comprehensively carried out [11]-[13]. Broadly speaking, demand response, medium- and long-term and spot market trading of electricity, as well as load-side participation in the relevant auxiliary service transactions, should all belong to the scope of load-side resource dispatch. The overall demand response is generally categorized into tariff-type and incentive-type based on the difference of scheduling instruments [14]. On the basis of tariff-type and incentive-type demand response classification, load-side resource dispatch also needs to consider dispatch objectives, dispatch signal sources, and other factors, in order to cover the scheduling role of multiple transaction types on the load side in different markets [15].

This study proposes a multilevel cooperative scheduling framework that combines market mechanisms with distributed control, aiming to achieve global optimization and dynamic response balancing of load-side resources. Firstly, a load resource scheduling model based on improved hybrid genetic algorithm for the spot market is constructed, which improves the resource allocation efficiency by dynamically adjusting the crossover probability and variance strategy. Second, for the aggregation control demand of temperature-controlled load TCL, a distributed model predictive control LDMPC method based on Lyapunov function is designed to reduce communication dependence and guarantee user comfort. Aiming at the multi-energy coupling characteristics of the cogeneration system, an improved resource allocation algorithm for thermoelectric loads is proposed to realize the synergistic optimization of plant economics and energy consumption by coordinating the weight allocation of electric and thermal loads.

II. Multi-level load resource co-dispatch for smart grid based on distributed model predictive control

II. A. Establishment of load resource scheduling model for smart grid spot market

In the design of smart grid spot market load resource scheduling method based on improved hybrid genetic algorithm, constructing smart grid spot market load resource scheduling model is the core link. The smart grid spot market load resource scheduling model is constructed by calculating the objective function and setting constraints. The following are the specific contents of the grid market load resource scheduling model:

The grid market load scheduling model aims to simulate the transaction and operation process of the electricity market in order to optimize resource allocation and improve market efficiency. The decision objective function in the model includes the dispatch quantities of various types of load resources, such as generation, storage, and demand response, while the model constraints include limitations such as power balance, network security, and resource capacity.

The objective function is the core of the dispatch model and is used to quantify the dispatch effect. Define the decision variables and constraints of the dispatch problem. The decision variables include the dispatch quantities of various load resources in each time period, while the constraints include power balance constraints, network security constraints, resource capacity constraints and so on. These variables and conditions form the basis of the objective function.

In this model, the objective function is constructed in order to efficiently and accurately achieve the optimal allocation of load resources by considering multiple aspects such as operating costs, network security, and power supply and demand balance. The following are the specifics of the objective function establishment:

The objective function of the scheduling problem is established, which is used to although the scheduling effect. The objective function integrally considers multiple aspects such as power supply and demand balance, network loss, operation cost, etc., and can be expressed as:

$$F = \frac{T}{MN} C_n + L_n - (P_n + Q_n) \frac{R_n}{S_n} \partial \tag{1}$$

where F is the total dispatch cost; T is the number of scheduling periods; N is the number of load resource types; M is the number of lines in the network; C_{ti} and L_{ti} are the active and reactive tariffs of the load resource i for time period t, P_{ti} and Q_{ti} are the active and reactive dispatch quantities of load resource i's active and reactive dispatch; R_{tj} is the resistance of line j in time period t; S_{tj} is the apparent power of line j in time period t; and ∂ is the weighting coefficients of network losses. It is used to adjust the relative importance of different cost terms in the objective function. The objective function takes into account the operating costs, network losses and the balance between power supply and demand, aiming at minimizing the dispatching costs.

Based on the above objective function, excellent individuals are selected into the next generation in accordance with their fitness values. Multiple crossover methods such as multi-point crossover and uniform crossover are introduced to increase the diversity of the population. A non-uniform mutation strategy is adopted, and the mutation step is dynamically adjusted according to the number of evolutionary generations in order to balance the global search and local search capabilities, and the smart grid spot market load resource scheduling model is established as follows:

$$P_c(f) = P_{c\max} - \frac{(P_{c\max} - P_{c\min}) \times (f_{svg} - f(x))}{F(f_{\max} - f_{svg})} \tag{2}$$

where $P_{c\max}$ and $P_{c\min}$ are the maximum and minimum values of the crossover probability of the trading strategies, and $f_{\max}$ and f_{avg} are the maximum and average fitness values of the individuals in the current resource allocation.

The following constraints are imposed on the modeling above.

(1) The crossover probability should be close to its minimum value of $P_{c\min}$ when the individual's fitness value is close to or exceeds the current maximum fitness value of $f_{\max}$, when the model is constrained:

$$P_f(f) = P_{c\min} + \frac{f_{avg} - f}{f_{avg} - f_{\max}} \times (P_{c\max} - f_{c\min}) \tag{3}$$

where f is the fitness value of the current individual. This equation ensures that $P_c(f)$ is close to $P_{c\min}$ when f is close to or exceeds $f_{\max}$

(2) When the individual's fitness value is much lower than the current maximum fitness value, but higher than the average fitness value f_{avg}, the crossover probability should lie between $P_{c\min}$ and $P_{c\max}$ and increase as the individual's fitness value decreases.

(3) When an individual's fitness value is close to or lower than the current average fitness value f_{avg}, the crossover probability should be close to its maximum value $P_{c\max}$ in order to increase the diversity of the search.

Ensure that the value of $P_c(f)$ is always in the range $[P_{c\min}, P_{c\max}]$, which can be achieved by applying a truncation function after computing $P_c(f)$:

$$P_c(f) = \max(\min(P_{cf}, P_{c\max})P_{c\min}) \tag{4}$$

This equation ensures that the value of $P_c(f)$ will not exceed its allowed range. Through the above steps, the smart grid spot market load resource scheduling model is constructed.

II. B. Predictive control of aggregated temperature-controlled load model based on Lyapunov function

Although the spot market scheduling model constructed in the previous section can effectively optimize the global allocation of load resources, its reliance on a centralized communication architecture exposes the shortcomings of high cost and low real-time performance when coping with massive temperature-controlled load TCL. For this reason, this section introduces the distributed model predictive control DMPC strategy, which improves the dynamic response capability while reducing the system complexity through localized communication and Lyapunov stability theory.

II. B. 1) Introduction of distributed control

An efficient, reliable and ideal communication system is the solid foundation for accomplishing the control objectives.In the CMPC method, since the dispatching center and each aggregator need to establish contact with each other, the requirements for the communication system are higher, and for the “massive” TCL, the cost of building such a communication system is extremely high in reality.DMPC greatly reduces the requirements for the communication system due to the use of local communication between aggregators to replace the upper and lower level communication between some aggregators and the dispatching center, thus reducing the huge amount of information transmission and communication delay, and also has high tracking accuracy. DMPC uses the local communication between aggregates to replace the upper and lower level communication between some aggregates and the dispatching center, which greatly reduces the huge amount of information transmission and communication delay, thus reducing the requirements for the communication system, and at the same time has a higher tracking accuracy.

In addition, in the traditional centralized control, all TCL aggregators receive the same optimal temperature regulation control signal, and accordingly complete the target tracking. In distributed control, the TCL aggregators in different regions can adaptively track the target according to the power assigned by the load aggregator, and calculate and obtain different optimal temperature adjustment quantities as the control signals, which can better satisfy the user comfort while accomplishing the target tracking task.

In summary, in this paper, DMPC-based ATCL control will be used to provide load power balancing services as a way to reduce the impact of non-ideal communication environments, to reduce the amount of information transmission, and to reduce the impact on user comfort while ensuring good target tracking results.

II. B. 2) LDMPC controller design

When the DMPC implementation scheme based on the Lyapunov function (hereinafter referred to as LDMPC) is implemented, all ATCLs respond to the secondary frequency modulation instructions of power grid dispatching as a whole, and for grid dispatching, ATCL can be regarded as a "virtual" AGC unit to complete the secondary frequency modulation task of scheduling together with other conventional units. In addition, in case of emergencies such as faults, in order to cooperate with the existing low-frequency or low-voltage load-shedding devices, according to the pre-consultation agreement between the electric utility and the load aggregator, and provided that the cost is feasible, the dispatch may consider prioritizing the removal of the TCL, and then using the original low-frequency or low-voltage load-shedding measures until the system frequency is restored to the permissible range.

The use of a large number of ATCLs for power system dispatch control can be in the form of a TCL aggregate. It can be considered as a TCL aggregate, assuming that there is c TCL aggregate in a certain area, including a total of n TCL devices, n_i is the number of i th aggregate loads, $n = n_1 + n_2 + \cdots + n_i + \cdots + n_c$, the control signal u_i of the i th TCL aggregate is generated by its MPC controller to monitor its output power P_{Ti} and fed back to the MPC for optimization of the prediction model, and it needs to track the power reference signal of $P_{refi} = w_i P_{ref}$, P_{ref} is the regulated scheduling power command,

$w_i = n_i P_i / P_{TZ}$ is the proportion of the adjustable capacity of the i th TCL aggregator to the total adjustable capacity of the temperature-controlled load, P_i is the power of a single TCL device of the i th aggregator, and P_{TZ} is the total ATCL power in the region.The MPC prediction model adopts the ISBAM constructed in Chapter 2, and then the total ATCL power P_{TZ} in the region can be written as:

$$P_{TZ} = \sum_{i=1} P_{Ti} \tag{5}$$

where P_{Ti} is the output power of each TCL aggregate.

For the i th TCL aggregator, the MPC controller based on Lyapunov function is designed as follows:

(1) Build the prediction model

According to construct the ISBAM expression of TCL and discretize it, the discretized bilinear state space equation can be obtained as:

$$x_i(k+1) = A_{Ii} x_i(k) + B_{Ii} x_i(k) u_i(k) \tag{6}$$

$$P_{Ti}(k) = C_{Ii} x_i(k) \tag{7}$$

where $x_i(k), u_i(k), P_{Ti}(k), A_{Ii}, B_{Ii}$ and C_{Ii} are the i th TCL aggregates $X(t), U(t), P_T(t), A, B$ and C after discretization, respectively. form, $A_{Ii} = I + \tau A_i, B_{Ii} = \tau B_i, C_{Ii} = C_i$, with τ being the sampling step size, and I being the unit array of order $L \times L$.

(2) Rolling Optimization

For $k+1$ moments, if the output power is expected to track the reference signal, the objective function can be written as:

$$e_i(k+1) = | P_{refi}(k+1) - P_n(k+1) | \tag{8}$$

Define the Lyapunov function as follows:

$$L(e(k)) = \frac{1}{2} e_i^T(k) e_i(k) \tag{9}$$

The rate of change of the Lyapunov function is:

$$\begin{aligned} \Delta L(e(k+1)) &= L(e(k+1)) - L(e(k)) \\ &= \frac{1}{2}(P_{refi}(k+1) - P_{Ti}(k+1))^T (P_{refi}(k+1) - P_{Ti}(k+1)) - \frac{1}{2} e_i^T(k) e_i(k) \end{aligned} \tag{10}$$

Substituting Eqs. (6) and (7) into Eq. (10) above yields:

$$\begin{aligned} \Delta L(e(k+1)) &= \frac{1}{2}(P_{refi}(k+1) - C_{Ii} A_{Ii} x_i(k) - C_{Ii} B_{Ii} x_i(k) u_i(k))^T \\ &\times (P_{nefi}(k+1) - C_{Ii} A_{Ii} x_i(k) - x_i B_{Ii} x_i(k) u_i(k)) - \frac{1}{2} e_i^T(k) e_i(k) \end{aligned} \tag{11}$$

In order to control the output power to track the reference signal accurately, the derivative of the Lyapunov function should be negatively definite, which can be made:

$$P_{refi}(k+1) - C_{Ii} A_{Ii} x_i(k) - C_{Ii} B_{Ii} x_i(k) u_i(k) = \lambda e_i(k) \tag{12}$$

where, λ is the control gain. Substituting Eq. (12) into Eq. (11), it is able to obtain the value range of λ as $-1 \le \lambda \le 1$.

II. C. Improved algorithm for heat and power load resource allocation

After completing the distributed cooperative control of temperature-controlled loads, how to further coordinate the coupling of electric and thermal loads becomes the key to improve the comprehensive energy efficiency of power plants. This section focuses on the multi-energy flow characteristics of the cogeneration system, and breaks through the limitations of the traditional single-load optimization by improving the resource allocation algorithm to achieve the joint optimal allocation of electricity and heat loads.

The regulation of heat pumping units is based on the amount of electricity used by users and the amount of heat used for heating, and the scheduling of different situations is realized according to the amount of heat provided by the power plant; therefore, enterprises need to rationally arrange the thermoelectric loads between the machines in the workshop providing heat according to the needs of the heat-user and the electricity-user.

For a given thermoelectric load, how to adjust the type of machine and the difference in machine efficiency, as well as the resource allocation of thermoelectric load among machines, so as to minimize the heat consumption rate of the whole plant and make the economic efficiency of the whole plant as good as possible, is an urgent problem facing the operation of the power plant. Therefore, the power plant has to maximize the use of resources for the electrical and thermal loads between the machines in the workshop providing heat in the power plant, giving the specific values of electrical and thermal loads for each machine.

When the power plant optimizes the allocation of resources for the electrical and thermal loads between machines in the workshop that provide heat, it will have a great impact on the overall machine, the rate of heat extraction and the amount of steam used for power generation. In addition to affecting the amount of steam used for power generation, it is also sensitive to changes in the back pressure of the condenser, and therefore, when maximizing the allocation of resources for the electrical and thermal loads between machines in the workshop that provide heat in the plant, it is necessary to well incorporate the factor of back pressure.

Following the extensive research above, the mathematical model for resource maximization allocation of thermoelectric loads is studied to obtain the required function:

$$\min F=\sum_{i=1}^{8} w_i \times H\,C_i \tag{13}$$

Among them:

$$HC=f(p,s) \tag{14}$$

$$w_i=\frac{p_i}{P} \tag{15}$$

The heat consumption in the above equation is a function of power and vapor extraction, w_i is the ratio of the power of the i th machine to the total power, and HC_i is the consumption of heat by the i th machine. Further processing of the function results in making the weighted average heat consumption of several machines extremely small.

For the thermoelectric load configuration may occur when a specific value of the constraints, such as the extreme value of the power of each machine can be achieved, the extreme value of the heat load of each machine and the total power of all the machines in the plant, the total heat load, all of the above constraints, the constraints for the construction of the final thermoelectric load resource allocation are as follows:

$$\begin{gathered} F_{\min}=\sum_{i=1}^{n}\frac{p_i}{P}\times f(p_i,s_i) \\ \begin{cases} p_{\min i}\le p_i\le p_{\max i} \\ s_{\min i}\le s_i\le s_{\max i} \\ \sum\limits_{i=1}^{n} s_i=S \\ \sum\limits_{i=1}^{n} p_i=P \end{cases} \end{gathered} \tag{16}$$

$F_{\min}$ is the minimum constraint value, p_i is the power of the i th machine, s_i is the heat load of the i th machine, and P and S are the total power and total heat load.

III. Experiment on Load Characterization and Optimization of Distribution Grid Dispatch Based on Hierarchical Market Mechanism

After completing the design of the multilevel load resource cooperative scheduling model based on distributed model predictive control, in order to verify the applicability and effectiveness of the model in the actual power system, this chapter will carry out an experimental study of load resource scheduling for distribution networks in conjunction with the analysis of specific load characteristics. First, the typical daily load curves of residential loads and commercial/office loads are analyzed in depth to reveal their power usage patterns and their impact on grid scheduling. Second, based on the above load characteristics, an experimental environment is constructed to compare and analyze the delay performance and cost optimization effect of different scheduling methods, in order to comprehensively evaluate the comprehensive scheduling capability of the proposed model.

III. A. Load Characterization

III. A. 1) Residential load

With the popularization and application of some energy-consuming household electrical equipment such as air-conditioners, electric heaters, electric stoves and electric water heaters, the electricity consumption of the residents has been growing rapidly, which can be divided into two parts, namely, the basic load and the seasonal load, in terms of the change pattern. Basic load mainly refers to refrigerators, electric stoves, lighting, television sets, electric water heaters, washing machines, computers and other household appliances; while air conditioners, heaters, electric fans and so on are typical seasonal load. Air conditioners and heaters, as heating loads, are generally concentrated in the evening peak hours, with a short continuous running time; the operation of equipment such as air conditioners and electric fans, as cooling loads, is closely related to the temperature, with their duration, daily continuous running time being positively proportional to the duration of high temperatures, and the higher the temperature is in the summer, the higher the cooling load is. Lighting power consumption within the day changes, but the lighting load between the time difference is small, while the rate is high, the formation of the so-called light peak. Such as the above power equipment caused by a short period of peak load has become an important factor in restricting the size of the installed power system and power system operation mode.

Figure 1 shows the typical daily load curve of a residential building in a residential neighborhood in 2024.

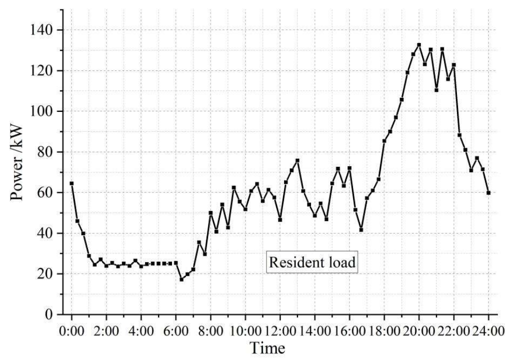

Figure 1: The daily load curve of a residential building in 2024

As can be seen from the figure, the evening peak of the residential load is obvious, which is consistent with the current living habits of urban residents, and the load curve can better reflect the residents' work and rest patterns. From the data in the figure, it can be seen that the peak and valley difference of electricity consumption of urban residents is large and fluctuates seriously, generally the peak and valley difference is between 70% and 80%; the duration of the maximum load is shorter, generally 2~3h, and the average load rate is small.

III. A. 2) Commercial/office loads

The major load elements in commercial/office buildings are incandescent lamps, fluorescent lamps, heat pumps, central air conditioners, window air conditioners, fans, and electric motors. Commercial loads have obvious single-peak and single-valley characteristics, with peak load times corresponding to the opening and closing times of stores. Through the commercial load power consumption characteristics and purely residential move smaller, generally the peak and valley difference will be larger; peak load duration is relatively long, the average load rate is higher.

Figure 2 shows a typical daily load profile for an office building in a commercial office district for the year 2024, which reflects the typical commercial load electricity use characteristics described above.

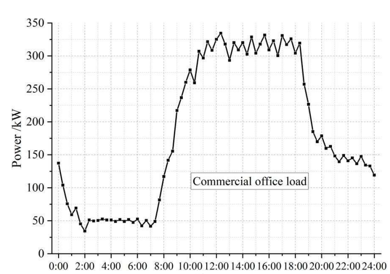

Figure 2: The daily load curve of a commercial office building in 2024

Power consumption in the commercial office area is mainly concentrated in the office hours from 9:00 to 18:00, and the average load power in this period is about 320kW.

III. B. Distribution network load resource scheduling study

After clarifying the electricity consumption characteristics and fluctuation patterns of different types of loads, this section will design an experimental scheme for load resource scheduling in distribution networks based on these characteristics. The actual grid operation environment is simulated by simulation software to compare the performance differences between the Lyapunov function-based DMPC method proposed in this paper and the traditional scheduling method in terms of time delay, integrated system output and scheduling cost.

III. B. 1) Test preparation

In this paper, simulation software is used to simulate and analyze for the two load resource scheduling methods, and the parameters of the energy power station used in the test are the same, with the installed capacity of 1150kW in the usual state and 2500kW in the operational state.

The tree topology is used to simulate the database in the above distribution network load resources, and the time delay and power of different circuits are set to simulate the grid communication resources under the same line, and then the actual process of resource scheduling is simulated by using the DMPC load resource scheduling based on the Lyapunov function of this paper and the traditional load resource scheduling, respectively.

III. B. 2) Time delay simulation results

In order to more clearly and concretely verify the actual effect of the load-side resource scheduling model based on hierarchical market mechanism designed in this paper, it is compared with the traditional load resource scheduling method of the distribution network, and the results of the time-delay simulation are compared.

In the test process, by designing two kinds of load resource scheduling to work in the same environment at the same time, the method of this paper and the traditional method of simulation, set the different flow meter clearing period, simulate the distribution network load resource scheduling, and analyze the changes in the delay simulation results, the different methods of delay simulation results comparison is shown in Figure 3.

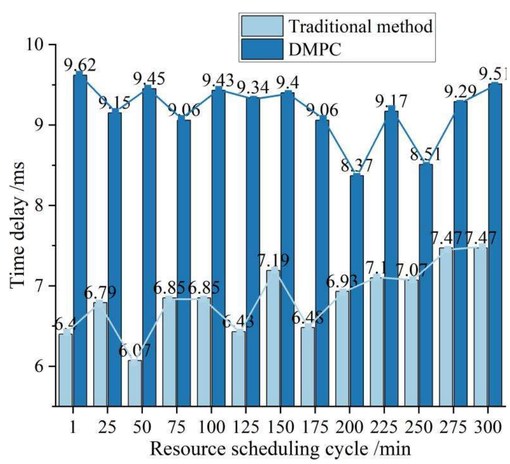

Figure 3: Delay simulation results under different methods

The test results show that the difference between the two scheduling methods is mainly reflected in the frequent distribution network load resource redistribution under the premise of the introduction of the communication delay is still ms level, but the design method in this paper shows more flexibility in the implementation, with an average delay of 9.19 ms, while the average delay of the traditional method is 6.85 ms, which indicates that the DMPC implementation based on Lyapunov function designed in this paper It shows that the program designed in this paper based on Lyapunov function DMPC implementation can be adapted to the actual needs of distribution networks, give full play to the controllable power of the new generation of distribution automation master system, and support the safe operation of the distribution network in the complex environment.

III. B. 3) Study of the combined output of the system before and after scheduling

After verifying the time-delay performance of the scheduling method, the impact of scheduling on the integrated system output is further analyzed. The improved thermoelectric load resource allocation algorithm is used to optimize the coordinated operation of thermal power generation and renewable energy in the smart grid, and to evaluate the power curve of the electric load and the trend of the remaining battery power after dispatch.

In this paper, an improved algorithm based on thermoelectric load resource allocation is used to optimize the integrated power output of the smart grid as well as the electricity load for scheduling. Within the algorithm, the population size is set to n=50, the particle dimensions are controlled by the nodes of the input layer, the implicit layer, and the output layer, the compression factor a=0.5, the inertia weight factor ω=0.1, the acceleration constants c1=c2=2, and the maximum of the particle search speed Vmax The minimum value is taken, the number of training times is 800, and the learning rate is 0.1. Within this power load scheduling decision-making system, the PV arrays and wind turbines are all connected to the AC bus, and at the same time, the information transmission line is connected to the grid load scheduling control center, which is intelligently regulated, and the integrated power output curve of the power loads and the residual power inside the batteries after the scheduling are shown in Fig. 4 and Fig. 5, respectively.

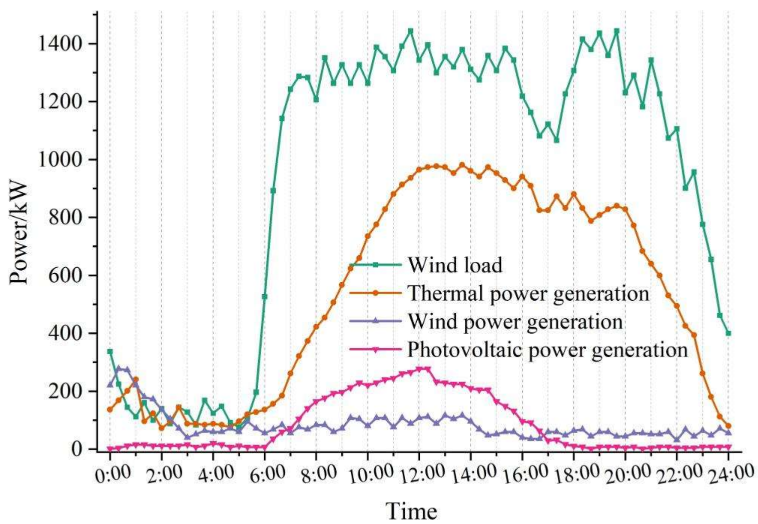

Figure 4: The comprehensive output curve of power load after dispatching

After scheduling the smart grid electricity load, photovoltaic power generation, and wind power generation system does not change, but the thermal power generation system has a large change in the operating power. From the original just stabilized power, it is changed to follow the predicted electricity load power. It can be clearly seen through Fig. 3 that in 0:00-6:00, the electricity load is at a lower value with an average of 143 kW, and at this time, the thermal power generation system output also stays at a lower degree with an average of 121 kW. However, after 6:00 the electricity load increases sharply and fluctuates around 1300kW, the thermal power generation also increases synchronously with the electricity load and fluctuates between 800-1000kW, and when the electricity load decreases at 20:00, the value of thermal power generation also decreases.

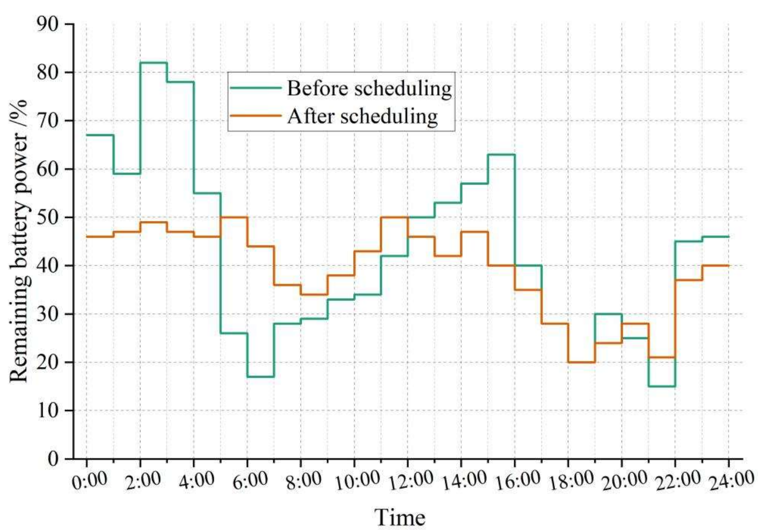

Figure 5: The remaining power inside the battery

Under such a scheduling decision-making method, there is a significant change in the remaining battery power, with a minimum value of about 20%, a maximum value of 50%, and a maximum difference of about 30%, with a significant downward trend before scheduling. Although photovoltaic power generation and wind power generation are greatly affected by the natural environment and are difficult to be regulated by artificial control, they can be generated by thermal power generation and reduce unnecessary losses.

III. B. 4) Comparison of dispatch cost optimization

After clarifying the optimization effect of scheduling on the integrated system output, this section will focus on comparing the operating costs of different scheduling methods. Through the iterative optimization of particle swarm algorithm, the advantages of this paper's method in reducing the cost of power load dispatch are analyzed, and the performance is compared with the traditional algorithm.

Through the grid operation and maintenance coefficient set above, test the operating cost required for power load output under the comprehensive processing curve before scheduling, and at the same time, use the particle swarm algorithm designed in this paper to make scheduling decisions for power loads, and obtain the operating cost after scheduling under 800 iterations. The cost of this paper's power load scheduling decision-making method is compared with the cost of several other scheduling methods, and the operating costs under different scheduling methods are shown in Fig. 6.

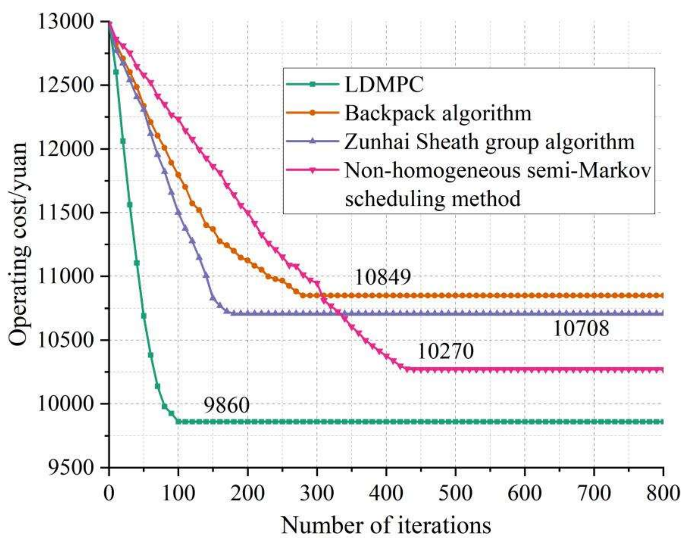

Figure 6: Operating costs under different scheduling methods

In Fig. 4, after the 100th iteration, the algorithm can get the optimal solution, and at this time, the operating cost has been reduced from the original 13,000 yuan to 9,860 yuan. It can be seen that the power load scheduling decision-making method designed in this paper is effective, which can improve the output efficiency and reduce the power load scheduling cost to a certain extent. As for the three traditional power load scheduling decision-making methods, the non-chiral semi-Markov scheduling method obtains the final training result at the 430th iteration, at which time its operating cost is reduced to 10,270 yuan. The Bottle Sea Sheath swarm algorithm reaches the lowest value of the system's operating cost at the 170th iteration, which is 10,708 dollars. The backpack algorithm obtains the optimal solution at the 270th iteration, at which point the running cost of the algorithm is 10,849 yuan. Comparing the above three algorithms, the proposed power load scheduling method has the lowest operating cost and the smallest number of iterations to reach the optimal solution, which shows that the method has the best scheduling effect.

IV. Conclusion

In this paper, a complete set of load-side resource scheduling optimization scheme is proposed by combining hierarchical market mechanism and distributed control.

(1) The spot market scheduling model based on improved hybrid genetic algorithm can dynamically adjust the crossover probability, improve the resource allocation efficiency, and reduce the scheduling cost by 24.1%.

(2) The LDMPC method realizes distributed cooperative control of temperature-controlled loads through Lyapunov stability theory, and the average system delay is reduced to 9.19ms while reducing communication dependence.

(3) The improved thermoelectric load resource allocation algorithm optimizes the comprehensive energy efficiency of the power plant by coordinating the weight allocation of electric and thermal loads, and the thermal power generation output is

dynamically matched with the electricity consumption load, and the fluctuation range of the remaining battery power is reduced to 30%.

Compared with traditional methods, the proposed framework shows significant advantages in terms of delay, cost and energy utilization, and provides a new idea for real-time scheduling and multi-energy coupling optimization of smart grid.

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