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Approach to Multi-Timescale Optimization for Distributed Energy Resources Clusters Considering Flexibility Margin

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Abstract: The disordered access of massively distributed energy resources (DERs) brings great challenges to the operation stability of the power grid. This paper puts forward the concept of a cluster, which gathers DERs in large quantities, small capacities, dispersion and disorder to form a large, centralized and orderly whole, namely cluster, with certain incentive measures. In this paper, a multi-timescale optimization method of day-ahead planning and intra-day rolling optimization is proposed according to the characteristics of aggregated clusters and the requirements of China's power grid architecture. Specifically, the day ahead model is proposed in two steps: the first step is to establish an optimization model with the goal of optimal fitting the target load curve and maximizing the utilization of DERs; The second step is to establish a potential game model considering the reasonable distribution of cluster benefits. Taking the minimum percentage of output correction of each cluster as the objective, considering the deviation of load forecasting and the deviation of day ahead instruction execution, an intra-day rolling optimization model is established. Finally, the application scenario of cluster participation in power grid auxiliary peak shaving is simulated and verified. The simulation results show that the cluster collaborative optimization method proposed in this paper can effectively reduce the load peak valley difference and maximize the use of cluster resources. The optimization tasks can be reasonably allocated while ensuring the stable and reliable operation of the power grid.

Keywords: cluster; optimization; multiple-timescale; flexibility margin

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1. Introduction

With the rapid growth of society's energy demands and the gradual depletion of traditional fossil energy sources worldwide, one of the most pressing problems is to gradually replace traditional fossil energy with renewable energy [1–4]. According to the development of renewable energy, the access forms of renewable energy can be mainly divided into two types: large-scale centralized access and distributed small-capacity access. In China, large-scale centralized renewables are mainly developed in the northwest area. Conversely, the southeast coastal area, which has heavy in load requirements but lacks space, is more suitable for distributed renewables [5]. Therefore, developing distributed renewable energy has become an important way to promote low-carbon transformation for the power grid manager of the southeast coastal area in China. Once a large amount of decentralized, small capacity renewables connected to the grid in a disorderly manner, the randomness and uncertainty of the power grid operation will increase greatly. The stability and security of the power system will be seriously challenged.

In order to deal with such problems, local management and utilization of DERs in a certain area has become an ideal solution. Most existing research focuses on the utilization and complementary use of internal resources to obtain economic [6] or environmental [7] benefits. The general methods are through microgrid and virtual power plant (VPP). Microgrid is a small-scale power generation and distribution system consisting of DERs, energy storage devices, energy conversion devices, loads, etc., using independent energy management system (EMS) to achieve self-control [8,9]. In [10], a day-ahead optimization model is proposed to optimize the power interaction between multi-microgrid and the distribution network. Several microgrids were coordinated on the upper optimization model and the lower optimization model focuses on economic optimized operation of the multi-microgrid system. In [11], a two-layer real-time optimization model is proposed for a microgrid, with the upper layer using look-ahead data to determine the initial dispatching plan and the lower layer updating strategy based on real-time data. Virtual power plant refers to the equivalent virtual aggregation of DERs, controllable loads and energy storage in the distribution network to participate in the operation and dispatch of the power system as a whole [12–14]. In [15], a stochastic bilevel optimization is proposed to achieve optimal economics of VPP participation in the day-ahead and the balancing markets. With proper utilization of renewable power and the day-ahead biding strategy, the cost can be greatly reduced. In [16], a bidding strategy for VPPs while taking part in demand response is proposed by taking current market price and uncertainty of inner resources into consideration, when the VPPs participate in demand response. In [17], an economic operating model is proposed to aggregate resources inside VPPs and join the power market as a flexible resource. The operating characteristics of internal resources of VPP are analyzed and integrated into a unified operation model of the VPP. They are combined as a whole to stabilize power fluctuation and obtain economic benefits from the power grid. However, public power grids only play the role of demand issuer or a supporter of providing stable power to microgrid or VPP in this research. It is a pity that the microgrid or VPP's flexible adjustment ability is unknown to the grid, since this ability is a valuable flexibility resource for the power grid. Therefore, mismatch between grid demand and microgrid or VPP's capacity may occur. In addition, the development of microgrid and VPP are in the initial development stage in China and their flexible resources are not enough to maintain external and pre-agreed power transactions. The less regulable resources in a microgrid or VPP, the less reliable its plan of interaction with the power grid, which may result in imbalance of a wider area.

Recently, layered and clustered grid architectures have been widely studied and are supposed to be an effective way for China to deal with the uncertainty caused by DERs. A concept of an interconnected system is proposed in [18]. An interconnected system consists of several independent power systems (also called balance area, BA) connected by contact lines or other equipment. Each BA should maintain its external and pre-agreed power transaction and cope with randomness of load and renewables by internal regulation. With these requirements, interconnected system will be able to achieve power balance locally. In addition, the external and pre-agreed power transaction should be formed at the lowest possible system level to avoid frequent optimization. Therefore, we define a "cluster" to coordinate the local DERs and form an external characteristic for power grid to take part in power grid optimization. The cluster manager would establish an external power interaction plan according to the information reported by inner DERs. There are many distributed coordination and optimization approaches to achieve the agreement among the cluster manager and DERs, such as game theory [19] and distributed robust optimization [20]. Then, the cluster manager would report the external power interaction plan, including planned aggregation curve and adjustable range, to the local power grid to take part in power grid optimization. The power grid would coordinate the output between clusters and issue instructions for each cluster to follow. Finally, the cluster manager should adjust the optimization strategy for DERs to satisfy the instructions from the power grid. A typical process of the interaction of plans and decisions among DERs-clusters-power grid is illustrated in Figure 1. From Figure 1, the cluster becomes the bridge between the public grid and the large amount of DERs. The optimization has been simplified into two parts: the coordination among DERs integrated by the cluster manager and the optimization for clusters coordinated by the power grid manager. Therefore, to the public power grid, the optimization process has been greatly simplified, since the management of large amounts of distributed resources turns into the optimization and management of several clusters. Great efforts have been done on the intra-cluster coordination [6–20]. In this paper, we focus on the strategy made by the power grid to better optimize the clusters.

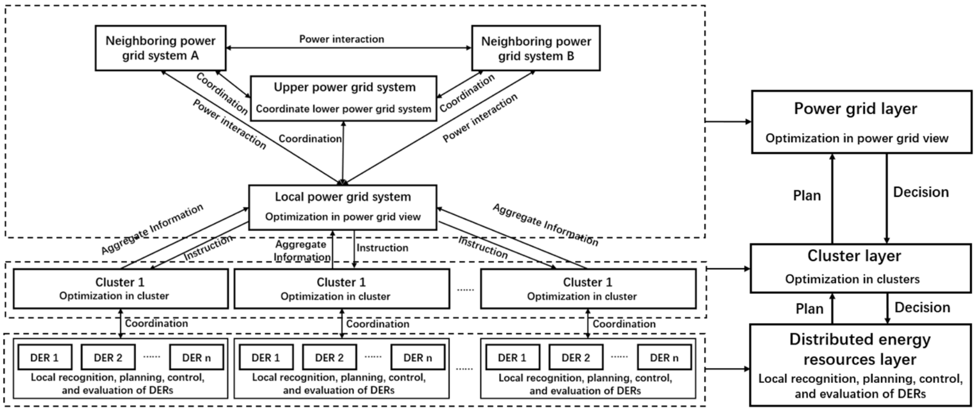

Figure 1. A typical process of interaction of plans and decisions among DERs-clusters' power grids.

After receiving the planned aggregation curve and adjustable range from clusters, the local power grid will play global collaboration and optimization by taking the cluster's adjustable range as constraints into consideration. Then, a key issue is how to keep the balance of cluster, since the flexibility of cluster is influenced by uncertainty of inner resources. As a result, a multi-timescale optimization to cluster is proposed to maintain the external stability of the power grid, according to the changing time-scale of inner DERs. A multi-timescale optimization model including day-ahead optimization and intra-day rolling optimization is established in this paper. The day-ahead optimization model is established via two steps. The first step of day-ahead optimization determines the total output of clusters. A day-ahead optimization model is established with the objectives of the best fitting of the target load curve and the best utilization of cluster resources. The second step of day-ahead optimization determines instruction curves for every cluster to follow, considering the ability willingness and economic benefit of each cluster. The intra-day rolling optimization takes into account the deviation of the load forecast and the deviation of the execution of the day-ahead order of each cluster. The intra-day rolling optimization model is established with the objective of minimizing the correction percentage of the output of each cluster to determine the optimized order adjustment to each cluster. Through the combination of day-ahead optimization and intra-day rolling optimization, the maximum utilization of DERs in clusters and the economic operation of the power grid are realized.

The remainder of the paper is organized as follows. In Section 2, the concept of interconnected system is described and the multi-timescale optimization architecture for clusters is proposed. In Section 3, the day-ahead optimization model is proposed, considering the reliability of the grid and cluster resource maximized utilization. A potential game is also proposed in Section 3 to assign optimization tasks and benefits. In Section 4, the intra-day optimization model is proposed, considering the flexible capacity and economic efficiency of each cluster. Section 5 proposes the algorithm solving process. Section 6 presents the experimental results to prove the effectiveness of the proposed method. Section 7 concludes the paper.

2. Multi-Timescale Optimization Architecture for Clusters

Treating clusters and regional loads involving optimization as a system, a two-stage cluster optimization strategy including day-ahead optimization and intra-day rolling optimization is developed to realize the full utilization of cluster resources and ensure the executability of optimized instructions. The multi-timescale optimization architecture is shown in Figure 2.

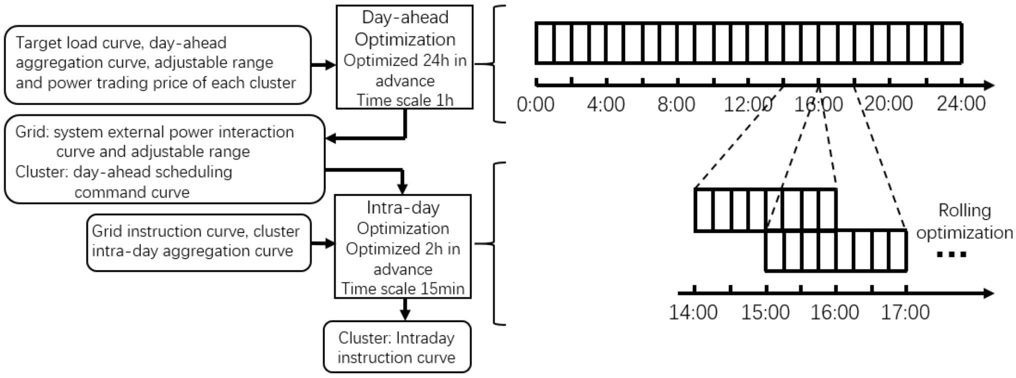

Figure 2. Framework of multi-timescale optimization method for clusters.

The first stage is the day-ahead optimization stage, which is carried out 24 h in advance with a time granularity of 1 h. Considering each cluster has its own optimal strategy, the instruction should be limited to an inferior level. Therefore, clusters should upload not just their aggregation curve, but also their adjustable range [21–23] (the range of ability to reach and that they are willing to accept instruction from) to the power grid before grid optimization. Then, an instruction should be determined within the adjustable range to satisfy the cluster's benefits. The objective is to develop the day-ahead power trading plan for each cluster based on the aggregation curve and the day-ahead adjustable reported by the clusters, the target load prediction curve and other information. The targets include the best effect of fitting the target load curve, the maximum utilization of cluster resources and the optimization economy. It also decides the external power interaction curve and adjustable range of the system and provides reference for the grid to carry out coordination between systems.

The second stage is the intra-day scale rolling optimization stage, which is carried out 2 h in advance with a 15 min interval. The optimization instructions are updated every 1 h to ensure the executability of the optimization instructions. Before intra-day rolling optimization, it is necessary to collect the information of intra-day aggregation curve of each cluster and the scheduling instruction curve information of the upper power grid system. The optimization instruction correction plans for each cluster are determined with the goal of minimizing the output correction percentage of each cluster, considering the economic benefits of each cluster and its ability to execute the instruction.

3. Day-Ahead Scale Optimization Model

Considering that the day-ahead long time-scale optimization should meet the grid's demand for stability and maximum utilization of DERs while achieving a reasonable distribution of cluster benefits, the day-ahead long time-scale optimization is divided into two steps.

In the first step, the optimization model is established with the objective of best fitting the target load curve and maximizing the utilization of cluster resources of multiple clusters. The sequential solution method is used to solve the model and determine the optimal total cluster output.

The second step is to consider the conflicting interests of the cluster decision makers and construct a non-cooperative potential game model. The achievement of a Nash equilibrium through the game allows the cluster managers to consider the satisfaction of each cluster to maximize their own interests.

3.1. Day-Ahead Optimization Model Considering Reliability and Cluster Resource Maximizations

The first step of the day-ahead optimization is to determine the total output of all clusters. Considering the day-ahead aggregation curve and adjustable range of the clusters, the optimization model is established with the objective function of best fit to the target load curve and maximum utilization of cluster resources. The sequential solution method is used to solve the model and determine the optimal total cluster output.

1. Objective functions
   - Best fit to the target load curve

$$f_1 = \min\sum_{t=1}^{\mathrm{T}} \{L_t - (\sum_{n=1}^{\mathrm{T}} W_{n,t} + R_t^{\mathrm{se}}) - \frac{\sum\limits_{t=1}^{\mathrm{T}} [L_t - (\sum\limits_{n=1}^{\mathrm{N}} W_{n,t} + R_t^{\mathrm{se}})]}{\mathrm{T}}\}^2 \tag{1}$$

where T represents the total number of optimization periods, considering a single optimization period of 1 h in length, T = 24; N represents the set of clusters; L_t represents the power in time period t of the target output curve; $W_{n,t}$ represents the day-ahead aggregated power of cluster n in time period t; R_t^{se} is the decision variable of this model that represents the sum of the flexibility margin usage of the cluster in period t, and uses the flexibility upward margin if positive and the flexibility downward margin if negative.

   - Maximum utilization of cluster resources

$$f_2 = \max\sum_{n=1}^{\mathrm{N}} W_{n,t}{+}R_t^{\mathrm{se}} \tag{2}$$

2. Constraints
   - Adjustable margin constraint for each time period

$$\sum_{n=1}^{\mathrm{N}} R_{n,t}^{\mathrm{se,up}} \geq R_t^{\mathrm{se}} \geq \sum_{n=1}^{\mathrm{N}} R_{n,t}^{\mathrm{se,dn}} \tag{3}$$

where $R_{n,t}^{\mathrm{se,up}}$ and $R_{n,t}^{\mathrm{se,dn}}$ represent the upward and downward flexibility margins of cluster n at time t, respectively. Then, the overall flexibility margin provided by the system to the grid can be expressed as

$$R_t^{\mathrm{en,up}} = \sum_{n=1}^{\mathrm{N}} R_{n,t}^{\mathrm{se,up}}{-}R_t^{\mathrm{se}} \tag{4}$$

$$R_t^{\mathrm{en,dn}} = R_t^{\mathrm{se}} - \sum_{n=1}^{\mathrm{N}} R_{n,t}^{\mathrm{se,dn}} \tag{5}$$

where $R_{n,t}^{\mathrm{en,up}}$ and $R_{n,t}^{\mathrm{en,dn}}$ are the upward and downward flexibility margins provided by the system to the grid at time t, respectively.

   - System power balance

$$\sum_{n=1}^{\mathrm{N}} W_{n,t} + R_t^{\mathrm{se}} + W_{\mathrm{ch},t} = L_t \tag{6}$$

where $W_{\mathrm{ch},t}$ represents the amount of power that the system interacts with the grid at time t. When positive, the system obtains power from the grid, and when negative, it outputs power to the grid.

The cluster day-ahead timescale optimization is a multi-objective optimization problem. Considering the significant differences in the importance of the two objectives in this optimization problem, the sequential solution method is used to solve the problem, setting the objectives with different priorities: the best fit to the target load curve is the prerequisite for the problem, with higher priority; the maximum utilization of cluster resources is the requirement for responding to the energy transition, with lower priority. The optimal value of the objective function with high priority is sought first, then the objective function with low priority is sought under the condition that the objective with high priority is not lower than the optimal value, and the pareto optimal solution is finally obtained.

3.2. Profit Optimization Distribution Model of Day-ahead Cluster Based on Potential Game

Game theory is the study of conflict and cooperation between rational decision makers and is divided into cooperative and non-cooperative games depending on whether binding agreements can be reached between decision makers. The non-cooperative game focuses on how to make decisions to maximize one's own benefits in situations where interests interact and is discussed and applied in more contexts. Considering the competitive relationship between cluster operators, this paper adopts the complete potential game in the non-cooperative game to model the problem.

Theorem 1. [24] *For a game* $\Gamma =< N, \{Y_n\}_{n\in N}, \{U_n\}_{n\in N} >$, *if there exists a function* $P : Y \to R$, *with* $\forall n \in N, \forall y^{-n} \in Y^n, \forall x, z \in Y^n$, *satisfying the following equation:*

$$u_n(x, y^{-n}) - u_n(z, y^{-n}) = P(x, y^{-n}) - P(z, y^{-n}) \tag{7}$$

Then, game Γ *is called a full potential game,* N *is the insider,* Y_n *is the strategy space of the insider and* U_n *is the payoff function of the insider. Where* y^n *is the strategy of the nth inning,* y^{-n} *represents the combination of strategies of all inning players except the nth inning player, and the strategy of all inning players* $y(y \in Y)$ *can be expressed as* $y = (y^n, y^{-n})$.

In this paper, we model the mapping of cluster participation in power grid optimization from three elements of the game: the insider, the payoff function, and the strategy space. The details are as follows.

- The insider

Considering the self-interest and autonomy of clusters participating in power grid optimization, each cluster is mapped as an insider, and the decision variable for each cluster is the flexibility margin usage $r^{\mathrm{se}}_{n,t}$. The goal is to maximize its own benefit in a mutual game, while promoting optimal system efficiency.

- The payoff functions

The efficiency functions of the insiders are their respective corresponding economic operation models, which can be expressed as:

$$U(y^n, y^{-n}) = \sum_{t=1}^{\mathrm{T}} (W_{n,t} + r^{\mathrm{se}}_{n,t}) c_{n,t} \tag{8}$$

where $c_{n,t}$ represents the price of electricity traded between the grid and cluster n in time slot t on the second day.

- The strategy spaces

The flexibility margin used by each aggregator should not exceed its adjustable range, which can be expressed as:

$$R^{\mathrm{se,up}}_{n,t} \geq r^{\mathrm{se}}_{n,t} \geq R^{\mathrm{se,dn}}_{n,t} \tag{9}$$

where $r^{\mathrm{se}}_{n,t}$ represents the upward and downward flexibility margins for cluster n at time slot t.

In addition, in order to protect the interests of clusters, the direction of flexibility usage should be the same for all clusters, i.e., to avoid the situation where one cluster's output is required to increase while another cluster's output is required to decrease, which can be expressed as:

$$r^{\mathrm{se}}_{i,t} \times r^{\mathrm{se}}_{j,t} \geq 0, \forall i, j \in \mathrm{N} \tag{10}$$

Despite the different types and quantities of DERs within clusters, their grid-oriented characteristics are still presented in the form of their overall planned output and adjustable range, which have, to some extent, similar external characteristics. In order to maximize the benefits of each cluster in the game process for itself while optimizing the benefits of multiple clusters as a whole, the potential function is considered to be constructed as the sum of the benefits of each insider, which can be expressed as:

$$G(y^n, y^{-n}) = \sum_{n=1}^{\mathrm{N}} \sum_{t=1}^{\mathrm{T}} (W_{n,t} + r_{n,t}^{\mathrm{se}}) c_{n,t} \tag{11}$$

In addition, the gaming process of clusters should be predicated on meeting the requirements of the power grid, as shown in the following equation.

$$F_{pun}(y^n, y^{-n}) = R_t^{\mathrm{se}} - \sum_{n=1}^{\mathrm{N}} r_{n,t}^{\mathrm{se}} = 0 \tag{12}$$

In this paper, a penalty function approach is used to consider the power balance constraint, and the deviation of the optimization result is set to characterize the degree of satisfaction of the constraint. The penalty function term is constructed through the deviation of the optimization result and added to the insiders' benefit function and potential function, so that each insider takes meeting the grid optimization requirements as a necessary factor in their decision making. Then, the insiders' benefit function and potential function are modified as follows.

$$U(y^n, y^{-n}) = \sum_{t=1}^{\mathrm{T}} (W_{n,t} + r_{n,t}^{\mathrm{se}}) c_{n,t} - \alpha F_{pun}(y^n, y^{-n}) \tag{13}$$

$$G(y^n, y^{-n}) = \sum_{n=1}^{\mathrm{N}} \sum_{t=1}^{\mathrm{T}} (W_{n,t} + r_{n,t}^{\mathrm{se}}) c_{n,t} - \alpha F_{pun}(y^n, y^{-n}) \tag{14}$$

where α is the penalty factor. From Equation (15), it can be seen that the potential game model based on the optimal allocation of cluster benefits satisfies the definition of a full potential game and has all the properties of a potential game, and the model satisfying the form of a potential game must have a purely strategic Nash equilibrium solution [24].

$$U(y^n, y^{-n}) - U(y^{n'}, y^{-n}) = G(y^n, y^{-n}) - G(y^{n'}, y^{-n}) = (r_{n,t}^{\mathrm{se}} - r_{n',t}^{\mathrm{se}}) c_{n,t}^{\mathrm{se}} - \alpha [F_{pun}(y^n, y^{-n}) - F_{pun}(y^{n'}, y^{-n})] \tag{15}$$

Considering the matching between the penalty factor and the iteration speed during the iteration of the game, and avoiding that the large penalty factor leading to poor convergence or even non-convergence, the penalty factor of each iteration is set as:

$$\alpha_m = 2\lg(1 + m) \tag{16}$$

where m represents the number of iterations elapsed until the current game.

4. Intra-Day Scale Optimization Model

With the goal of minimizing the correction ratio of cluster optimization results and considering the flexibility and economic efficiency of each cluster, an intra-day timescale rolling optimization model is established. Through this method, the total output of the clusters can be stabilized without significant adjustment of each cluster.

4.1. Objective Function

1. Minimal correction ratio for cluster optimization results

$$\min \sum_{h=1}^{\mathrm{H}} \sum_{n=1}^{\mathrm{N}} \frac{\left|\Delta r_{n,h}^{\mathrm{se}}\right|}{W_{n,h} + r_{n,h}^{\mathrm{se}}} \tag{17}$$

where H represents the time dimension of intra-day optimization, with 15 min as the time interval; $\Delta r_{n,h}^{\mathrm{se}}$ represents the correction amount of cluster n in time slot h relative to its intra-day aggregated predicted output in the same time slot optimization result; $W_{n,h} + r_{n,h}^{\mathrm{se}}$ represents the day-ahead optimization output of cluster n in time slot h, which can be obtained from the day-ahead optimization result.

4.2. Constraints

1. Adjustable margin constraint for each time period

Considering that the randomness of renewable energy may lead to significant differences between the day-ahead aggregation volume and the intra-day aggregation volume in some clusters, and the intra-day aggregation curve may be beyond the day-ahead adjustable range, the regulable margin constraint for each time period shall be slackened.

$$W_{n,h} + R_{n,h}^{\mathrm{se,up}} \geq W_{n,h}^{\mathrm{rn}} + \Delta r_{n,h}^{\mathrm{se}} - \Delta r_{n,h}^{\mathrm{k}} \geq W_{n,h} + R_{n,h}^{\mathrm{se,dn}} \tag{18}$$

$$\Delta r_{i,h}^{se} \times \Delta r_{j,h}^{se} \geq 0, \forall i, j \in \mathrm{N} \tag{19}$$

$$\Delta r_{n,h}^{k} = \begin{cases} W_{n,h}^{\mathrm{rn}} - (W_{n,h} + R_{n,h}^{\mathrm{se,up}}), W_{n,h}^{\mathrm{rn}} > W_{n,h} + R_{n,h}^{\mathrm{se,up}} \\ W_{n,h}^{\mathrm{rn}} - (W_{n,h} + R_{n,h}^{\mathrm{se,dn}}), W_{n,h} + R_{n,h}^{\mathrm{se,dn}} > W_{n,h}^{\mathrm{rn}} \\ 0, W_{n,h} + R_{n,h}^{\mathrm{se,up}} \geq W_{n,h}^{\mathrm{rn}} \geq W_{n,h} + R_{n,h}^{\mathrm{se,dn}} \end{cases} \tag{20}$$

where $W_{n,h}^{\mathrm{rn}}$ represents the intra-day aggregated power of cluster n in time period t, and $\Delta r_{n,h}^{\mathrm{k}}$ represents the power of the over-range part of intra-day aggregation; clusters with excessive deviation of intra-day aggregation from day-ahead aggregation are not considered to have power re-regulation capability, so when $\Delta r_{n,h}^{\mathrm{k}} \neq 0$, $\Delta r_{n,h}^{se} = 0$. The direction of flexibility usage should be the same for all clusters in order to protect the interest of the clusters.

2. Cluster power balance

$$\sum_{n=1}^{\mathrm{N}} (W_{n,t}^{\mathrm{rn}} + \Delta r_{n,h}^{\mathrm{se}}) = W_{\mathrm{goal},h} \tag{21}$$

where $W_{\mathrm{goal},h}$ represents the external power interaction instruction from the grid to the system at time t.

5. Algorithm Solving Process

The proposed multi-timescale optimization process of clusters is shown in Figure 3. The day-ahead optimization considers system external stability, maximum utilization of cluster resources and optimal economy, and makes preliminary coordination for clusters in the region. The intra-day rolling optimization considers the correction of instructions for each cluster under the satisfaction of external interaction power instructions to guarantee the stability of the system and the execution of instructions. The model is solved by calling the GUROBI solver through MATLAB software.

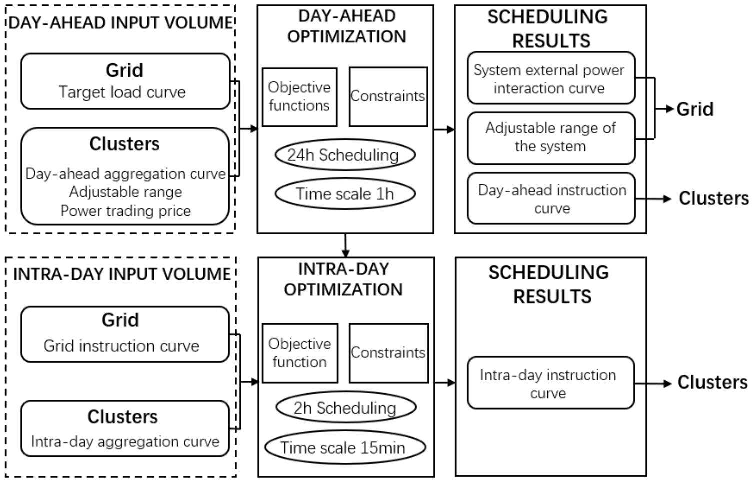

Figure 3. Flow chart of multi-timescale optimization method of clusters.

The specific processes of the day-ahead optimization phase are as follows.

Step 1: Enter the day-ahead aggregation curve, adjustable range and power trading price of each cluster, and enter the target load curve of the grid.

Step 2: Set the objective of best fit to the target load curve, solve the day-ahead optimization model and obtain the first-level single-objective optimal value $f_1^* = \min f_1(R_t^{\mathrm{se}})$.

Step 3: Add the first level single objective equal to the optimal value to the constraints, solve the day-ahead optimization model with the objective of maximizing the utilization of cluster resources, and obtain the second level single objective optimal value $f_2^* = \min f_2(R_t^{\mathrm{se}})$ and the pareto optimal solution $\{R_t^{\mathrm{se}}\}$.

Step 4: Add the Pareto optimal solution obtained in step 3 to the strategy space of the insiders. Considering the economic optimization of the power grid, the insider with the lowest electricity trading price starts the game process.

Step 5: The insider determines the deviation of the current optimization result by asking the other insiders about the power output in the order of increasing power trading price in sequence by means of broadcasting and selects the strategy that maximizes the gain function, determines the optimal power output $\left\{r_{n,t}^{\mathrm{se}}\right\}$ and updates the strategy.

Step 6: The grid judges whether the deviation of the result satisfies the given accuracy, and if it does, it turns to step 7; if not, it turns to step 4 and starts a new round of gaming.

Step 7: End the game, the insiders adjust their output according to the results of the game. The day-ahead optimization phase ends.

The specific processes of the intra-day optimization phase are as follows.

Step 1: Enter the grid instruction curve, the day-ahead optimization results, the cluster adjustable range and the intra-day aggregation curve.

Step 2: The grid solves the intra-day optimization model with the objective of minimizing the correction ratio for cluster optimization results and obtains the amount of optimization correction $\left\{\Delta r_{n,h}^{\mathrm{se}}\right\}$ for clusters.

6. Simulation and Experimentation

In order to verify the effectiveness of the multi-timescale optimization model and algorithm considering flexibility margin, a day-ahead and intra-day optimization model is established for three clusters participating in grid optimization in a certain region of Guangdong province. The optimal outgoing power optimal results day-ahead and intra-day are obtained for clusters.

6.1. Day-Ahead Optimizition

6.1.1. Scene and Parameter Setting

The system contains three clusters, numbered as cluster 1, cluster 2, and cluster 3, whose day-ahead aggregation curves and adjustable margin ranges are shown in Figure 4 and the target curves issued by the grid to the system are shown in Figure 5. Cluster 1 is mainly composed of distributed photovoltaic but also includes a small amount of distributed wind turbines, distributed energy storage and load. Cluster 2 is mainly composed of distributed wind turbines but also includes a small amount of distributed energy storage and load. Cluster 3 is a load zone with the distributed wind turbines, distributed photovoltaic and distributed energy storage used to achieve the self-supply of energy to a certain. To simplify the calculation, it is assumed that each cluster has a fixed daily power trading price with the grid, As shown in Table 1. Set the iteration termination condition of the potential game to $|\sum_{t=1}^{T}(R_t^{se} - \sum_{n=1}^{N} r_{n,t}^{se})| \le 0.5$.

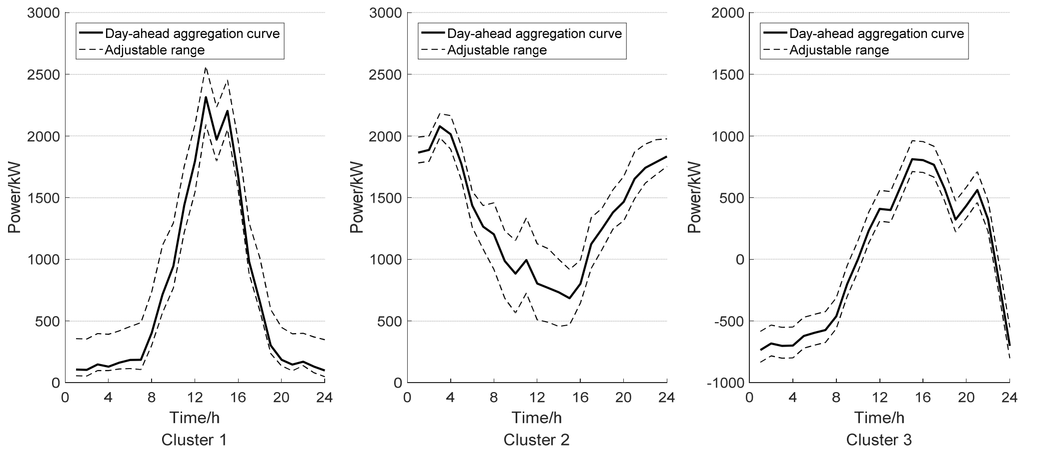

Figure 4. Day−ahead aggregation curve and adjustable range of each cluster.

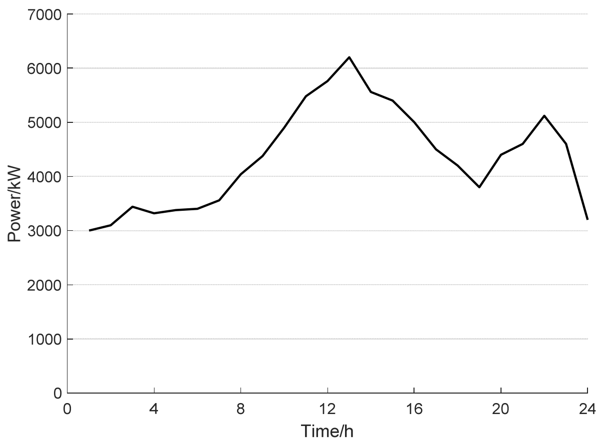

Figure 5. Target load curve.

Table 1. Electricity trading prices of each cluster.

	Cluster 1	Cluster 2	Cluster 3
Power trading price/(kW/yuan)	0.32	0.41	0.36

6.1.2. Analysis of Day-Ahead Optimization Results

In order to verify the efficiency of the method in the paper, the results before and after optimization are compared and analyzed. The fitting effect of the total power output of the clusters to the target curve for each time period before and after optimization is shown in Figure 6, and the system external power interaction curve (the difference between the target load curve and the total power output of the clusters) is shown in Figure 7. After optimization, the day-ahead instructions to each cluster are shown in Figure 8, and the power transaction cost of the grid through the clusters is shown in Table 2.

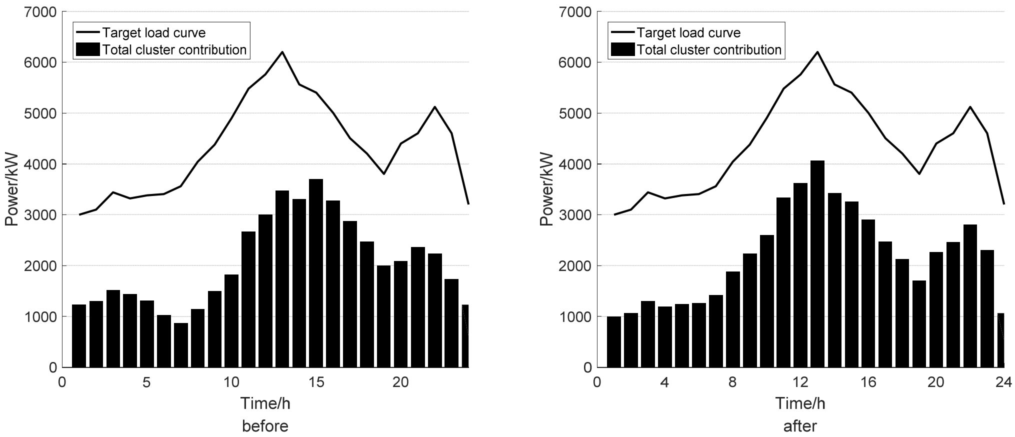

Figure 6. Total cluster output on target load curve fitting effect.

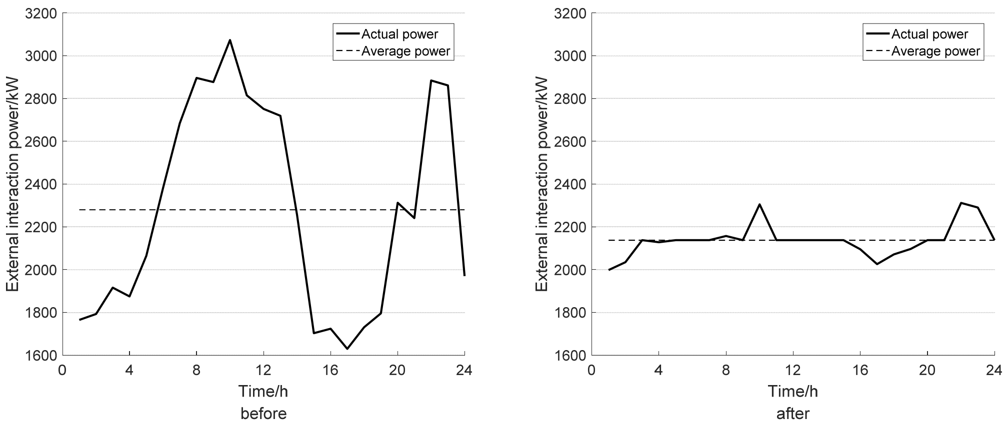

Figure 7. External power interaction curve of the system.

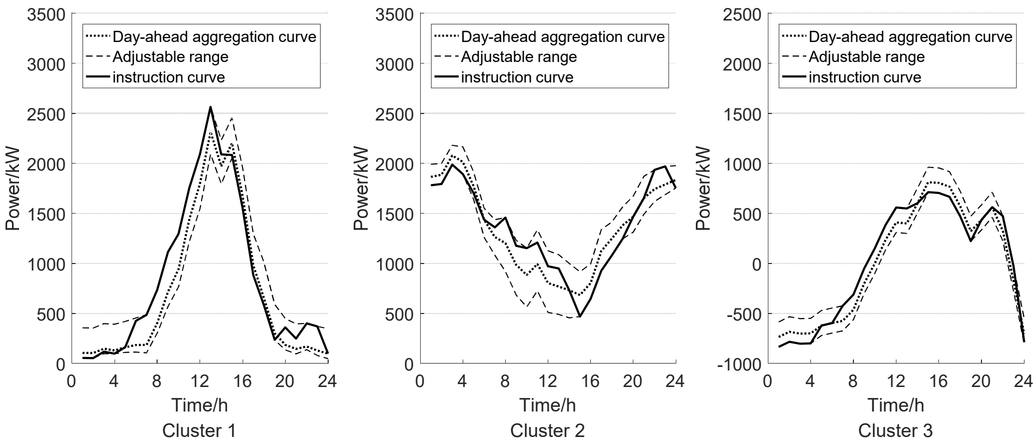

Figure 8. Day-ahead instruction curve of each cluster.

Table 2. Electricity trading cost.

	Cluster 1	Cluster 2	Cluster 3	Total Cost
Power trading cost/(yuan)	6304.9	13,500.9	148.0	19,953.8

After the day-ahead optimization, the total cluster power output better fits the target curve, and the average value of system external power interaction is reduced from 2279.9 kW to 2137.6 kW. This is a 6.2% reduction and represents an increment of the utilization of cluster resources. In addition, the maximum value of external power interaction is reduced from 3073 kW to 1630 kW and the minimum value is increased from 1630 kW to 1998 kW. The fluctuation of external power interaction curve is reduced from 1443 kW before optimization to 314 kW after optimization, which indicates a good suppressing effect on the target curve, effectively reduces the peak-to-valley difference of load and reduces the optimization pressure of the grid.

From Figure 7 and Table 2, the power allocation of each cluster basically follows the principle of "within the adjustable margin, the lower price has priority", which ensures the economy of grid optimization. It is not allowed to ask another cluster to reduce its output while one cluster's output increases, guaranteeing the basic interests of individual clusters. In addition, the instruction curve for clusters essentially reaches the upper limit of their adjustable margin during the peak hours of the target load curve, which can objectively guide clusters to increase the amount of flexibility margin reserved during the peak hours. It is conducive to maintaining the external stability and internal coordination of the system during the peak hours of the load. The revenue obtained by a cluster through the grid is related to the target load curve, the power output available from individual clusters and the power trading price, etc. The more the power output from individual clusters, the better their power output curve fits the target load curve, and the lower the power trading price, the higher the revenue they can obtain by participating in optimization.

6.2. Intra-Day Optimizition

6.2.1. Scene and Parameter Setting

Based on the parameters and results of day-ahead optimization, the scenarios and parameters of intra-day optimization are set. To reflect the typicality, the 2 h period from 12:00–2:00 is taken as an example for the simulation analysis of intraday optimization arithmetic. The instruction curve of the grid to the system is shown in Figure 9, and the instruction curve should not exceed the adjustable margin of the system. The intra-day aggregated power curve of each cluster in this 2 h period is shown in Figure 10.

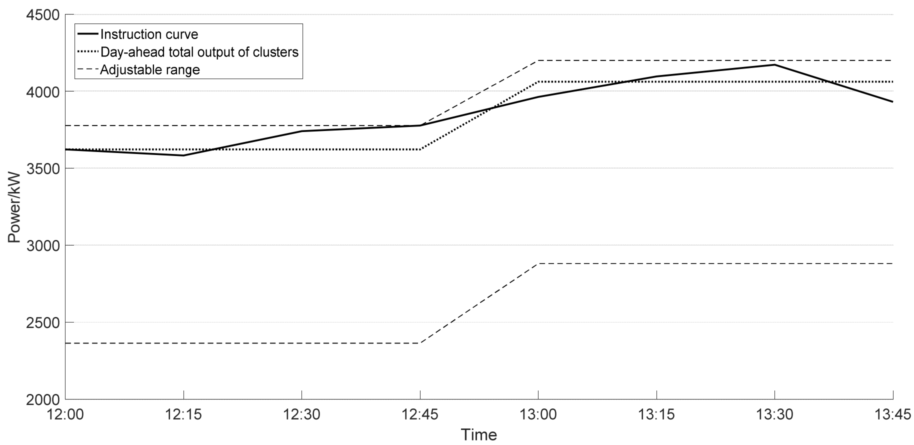

Figure 9. Grid-to-system instruction curve.

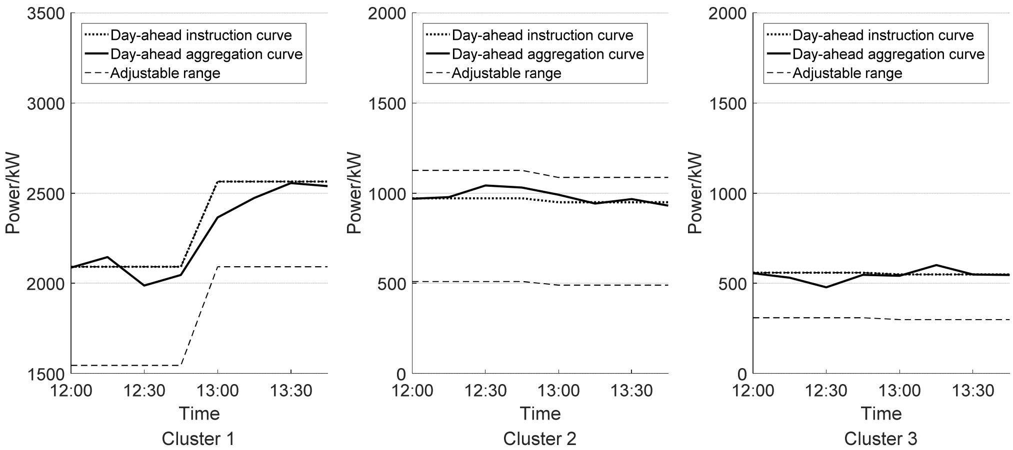

Figure 10. Intra-day aggregation curve of each cluster.

In the day-ahead optimization results, both Cluster 1 and Cluster 3 have reached the upper limit of their margin range. During intra-day aggregation, Cluster 1 has an aggregation curve that exceeds the upper limit of its margin range at 12:15, and Cluster 3 has an aggregation curve that exceeds the upper limit of its margin range at 13:15. It is thus considered that the adjustable capacity of these two clusters in the corresponding time period is insufficient and they do not have the capacity for further regulation.

6.2.2. Analysis of Intra-Day Optimization Results

To verify the effectiveness of the method in the paper, the results before and after optimization are compared and analyzed. The intra-day instruction curves for the clusters are shown in Figure 11.

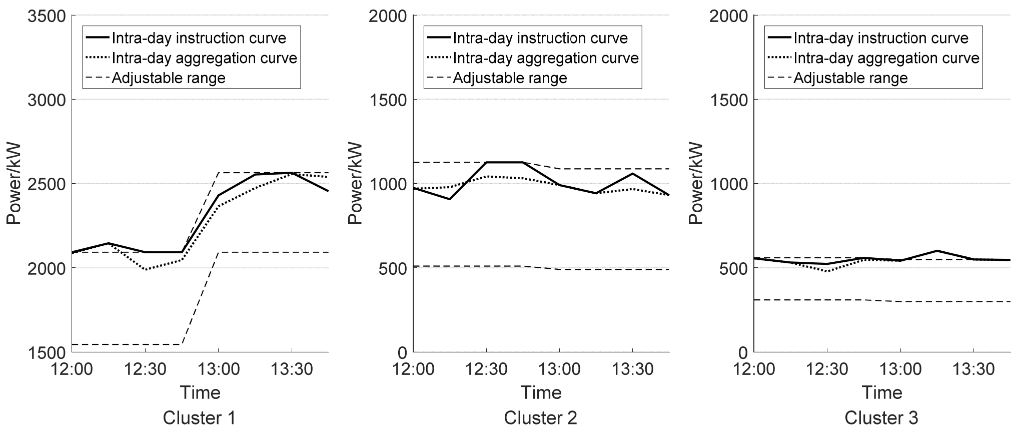

Figure 11. Intra-day instruction curve of each cluster.

The intra-day instruction curves of the three clusters are all corrected to different degrees compared to their intra-day aggregation curves. Cluster 2, which does not reach its adjustable margin range limit at the day-ahead optimization, plays a better regulating role at the intra-day optimization. In this time period, the maximum correction percentages of the three clusters are 4.97%, 9.78% and 8.05%, respectively, which are less than 10%, so that the optimization demand can be reasonably shared. The clusters are not optimized when the intra-day aggregation curve is out of range, which is conducive to the execution of optimization orders by the clusters. As in the case of day-ahead optimization, intra-day optimization also does not require another cluster to reduce its capacity while one cluster's capacity increases, which protects the basic interests of clusters.

7. Conclusions

For massive DERs access to the power grid, this paper proposes a multi-timescale optimization method of "day-ahead planning—intra-day rolling optimization" based on the cluster characteristics formed by the aggregation of DERs and combined with China's power grid architecture and optimization requirements. The main work of this paper includes: The day-ahead optimization takes into account the overall external stability of the system, the maximum utilization of cluster resources and economy to achieve the initial day-ahead allocation of optimization tasks. The intra-day rolling optimization takes into account the minimum correction ratio of cluster optimize results to ensure the executability of optimization instructions while satisfying the grid optimization instructions. The proposed model and method are proved to be effective through the analysis of calculation cases.

The simulation shows that: (1) The concept of cluster is introduced to coordinate the local DERs and form an external characteristic for power grid to take part in power grid optimization. Through the cluster collaborative optimization method, the effective interaction between DERs and power grid is realized. (2) Based on the potential game architecture, taking full account of the flexibility and uncertainty of the cluster itself, a collaborative optimization method with multiple timescales of "day-ahead—intra-day" is proposed. Specifically, the day-ahead optimization considers the overall external stability of the system, the maximum utilization of cluster resources and the economy of optimization to achieve the initial day ahead allocation of optimization tasks. The intra-day rolling optimization satisfies the optimization instructions of the power grid and takes into account the minimum correction rate of the cluster optimization results to ensure the enforceability of the optimization instructions. Finally, taking the peak shaving and valley filling scenario as an example, the simulation proves that the proposed model and method can give full play to the complementary characteristics of DERs, and the cluster shows the "external stability" characteristics. While ensuring the enforceability of optimization instructions, it ensures the basic benefits of each cluster, assists in peak clipping and valley filling and proves the effectiveness of the method.

The proposed model and method can achieve the orderly participation of clusters in grid optimization under the premise of ensuring grid stability. However, we have not considered the reliability of the information that the clusters provided to the grid. The issue of the evaluation of the cluster and how the reliability of the cluster information can be considered in the optimization structure will be discussed in the further research.

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