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Multi-Time Scale Coordinated Optimization of Energy Systems Under Flexible Load Response

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Abstract

Since the development of society, people's demand for and use of energy have become increasingly diverse rather than remaining monotonous. Flexible load response serves as the core medium for integrating various energy sources. However, the operational performance of units within the energy system has not been ideal, and operating costs remain difficult to control. To address these challenges, this study investigates multi-time scale collaborative optimization of energy systems based on flexible load response, utilizing a combination of qualitative and quantitative methods. The research encompasses optimization architecture, optimization models, computational case studies, and validation. The results indicate that, during load response experiments, implementing an intra-day coordinated plan—specifically by further reducing thermal and electrical loads during peak hours—can significantly decrease the peak-valley difference. Additionally, in the cost comparison analysis, the operating cost was reduced by 1.47%, thereby addressing the shortcomings of traditional energy system coordination and optimization. Overall, the approach offers notable improvements both in economic performance and in system coordination and optimization, demonstrating considerable foresight.

Keywords: Flexible Load; Energy Systems; Respond; Coordinated Optimization.

1. Introduction

At present, user-side loads have gradually evolved from focusing solely on the “rigidity” of electricity to embracing the “flexibility” that comprehensively considers the complementarity of cooling, heating, and electricity [1–4]. To promote the application of flexible loads, many scholars have conducted relevant studies. For example, Sun et al. proposed an optimal scheduling model for a park-integrated energy system that incorporates flexible loads and carbon flow, aiming to explore its advantages and disadvantages under different operating conditions. This approach seeks to suppress increases in total carbon emissions, smooth load fluctuations, and enhance the coupling between energy equipment. Through simulation experiments, it was found that the bidirectional optimization of supply and demand for the source-load, including the park’s integrated energy system, can not only effectively curb carbon emissions but also further improve the overall economic benefits of the system [5].

Si et al. [6] focused on optimizing the capacity of various distributed power sources in a grid-connected integrated energy system. First, a demand-side energy management strategy termed “source-grid-load-storage” was proposed based on the scheduling characteristics of three types of flexible loads. Next, considering the economic aspects of the integrated

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energy system, an optimal scheduling model involving flexible load participation was developed. Finally, the model was solved using a particle swarm optimization algorithm, and the results confirmed the feasibility of the proposed approach.

Qiu et al. [7] aimed to reduce system carbon emissions and tap into the user-side load's ability to participate in system scheduling, proposed a day-ahead low-carbon economic scheduling model for an integrated energy system that includes P2G-CCS and flexible loads. Simulation experiments concluded that the operational strategy involving P2G-CCS and flexible loads can effectively reduce system carbon emissions, enhance the economic efficiency of system operations, and achieve low-carbon economic operation in the integrated energy system.

Esmaeili et al. [8] employed the extreme learning machine algorithm to predict wind storage power and flexible load power. From a time-based perspective, they first developed a day-ahead optimal scheduling approach. Based on real-time prediction results, they used a particle swarm optimization algorithm to perform rolling optimization on the day-ahead scheduling outcomes. Simulation results indicate that the optimal scheduling method, which considers peak load regulation, multi-objective functions, and multi-time scales of flexible loads, can effectively enhance the economic and social benefits of integrated energy systems incorporating wind and solar storage. It also increases the capacity for absorbing renewable energy and provides a valuable reference for the coordinated scheduling of peak shaving and valley filling involving source loads.

In summary, it is evident that many studies conclude at the stage of system model construction, seldom addressing the multi-time scale problem. Even when multi-time scale considerations are included, they often remain focused solely on day-ahead optimal scheduling without integrating intra-day optimization. However, there are inherent errors in day-ahead load predictions, particularly for energy systems with a significant share of renewable energy sources, where ensuring the accuracy of day-ahead coordinated optimization becomes increasingly challenging. Moreover, the flexible load response itself carries certain uncertainties. As the time scale becomes more refined, the impact of flexible load response on the operation of the energy system becomes more pronounced [9, 10]. Therefore, the multi-time scale coordinated optimization of energy systems under flexible load response deserves in-depth exploration.

This paper summarizes the concepts of flexible loads through theoretical analysis and, on this basis, establishes a coordinated optimization framework. Aiming to reduce the system's operating costs, a coordinated optimization model is developed, and its feasibility is evaluated through case analysis. The findings indicate that this approach can effectively lower operating costs and enhance the operational efficiency of the units.

1.1. Basic Concept Analysis of Flexible Load

Flexible load generally refers to the type of load that can actively participate in the operational control of an energy system through its thermal and electrical components, allowing it to interact with the system and exhibit flexible characteristics [11-13]. In essence, flexible loads are variable and possess significant coordination capabilities within energy system operations.

Based on response modes, flexible loads can be categorized into shifting loads, transfer loads, and reducible loads. The roles of these different types of flexible loads in an energy system are as follows:

(1) Shifting load: Within the coordination cycle of the energy system, the total thermal and electrical load remains constant, but the load can be flexibly adjusted across different time periods. Users can redistribute the load from one time slot to another by modifying production schedules within a certain capacity range. The key feature is that while the total load stays unchanged, the timing of the load can shift between periods.

(2) Transfer load: In energy system coordination, based on day-ahead forecasts of thermal and electrical loads, unit outputs, and system demands, the system can adjust loads during peak shaving without negatively affecting the system's overall economy or load stability.

(3) Reducible load: In an energy system, reducible load provides a certain degree of peak shaving capability in the day-ahead coordination plan. However, because the day-ahead time scale is relatively long, precise values for reducible loads are difficult to determine, and only an approximate capacity range can be estimated. Meanwhile, the thermal and electrical load capacities that can be reduced are better identified through short-term forecasts conducted over shorter intra-day time scales.

2. Construction of Multi-Time Scale Coordinated Optimization Architecture for Energy Systems

2.1. Energy System Architecture Under Flexible Load Response

The energy system generally takes heat and electricity as the main energy sources, and the system contains equipment for the production, conversion, and storage of various types of energy to meet the diverse choices of users [14, 15]. The system architecture diagram is shown in Figure 1.

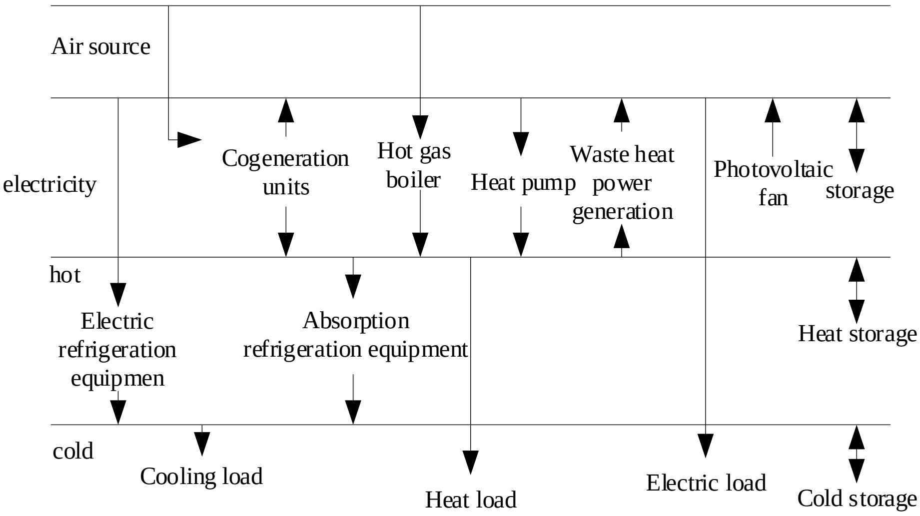


Figure 1. Specific system architecture of gas-steam combined cycle unit

2.2. Energy System Coordination and Optimization Architecture

The precision of day-ahead coordination is relatively low, and if only a day-ahead coordination optimization strategy is applied, it becomes difficult to fully leverage the benefits of flexible loads [16, 17]. At the same time, as the energy system transitions from day-ahead coordination to intraday scheduling, the accuracy of prediction curves for renewable energy generation improves. However, if the precision of day-ahead coordination cannot be effectively enhanced, the performance of day-ahead guidance for intraday operations will fall short of the required standards. Therefore, optimal scheduling of flexible loads can be better achieved through appropriate model construction. To address these challenges, this paper proposes a combined day-ahead and intraday joint optimization coordination framework, as illustrated in Figure 2.

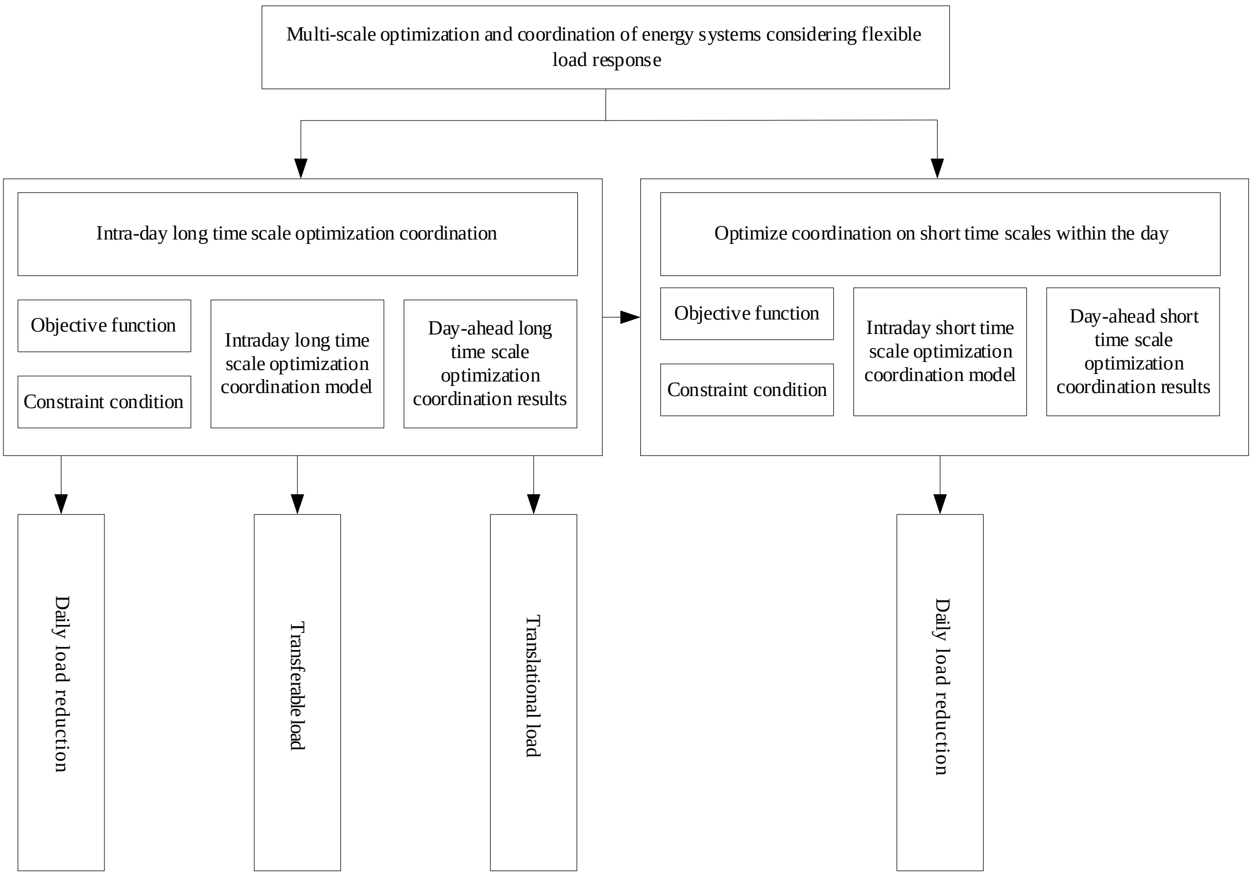


Figure 2. Day-ahead - day joint optimization coordination architecture

The time scale in this context is mainly divided into two categories: first, the day-ahead long-term time scale; and second, the intraday short-term time scale. During the coordinated optimization period, the heat load includes reducible, transferable, and translational loads; similarly, the electrical load also comprises reducible, transferable, and translational loads. In intraday short-term optimization coordination, the plan developed during the day-ahead stage is taken into account. Factors such as intraday load variations, renewable energy output, and maintaining user production without disruption are considered. The intraday secondary adjustment of the load focuses solely on reducing thermal and electrical loads to participate in the coordination process.

3. Multi-Time Scale Coordinated Optimization Strategy of Energy System Under Flexible Load Response

3.1. Coordinate the Optimization Process

Multi-time scale integrated energy optimization coordination is divided into two parts: day-ahead and intraday. Day-ahead optimization coordination first determines whether the day-ahead coordination period has been reached. If it has, the day-ahead forecast load data is input, and the day-ahead coordination model is solved to determine the day-ahead coordination plan, including the reducible, transferable, and translatable quantities [18]. Intraday optimization coordination begins by checking whether the intraday coordination cycle has been reached. If so, the intraday coordination model is solved by inputting the predicted values of the energy system, photovoltaic output, and system adjustments two hours in advance, based on the day-ahead coordination. This results in an intraday coordinated plan that includes intraday load reduction.

The steps for the coordinated optimization of multi-time scale energy systems are shown in Figure 3.

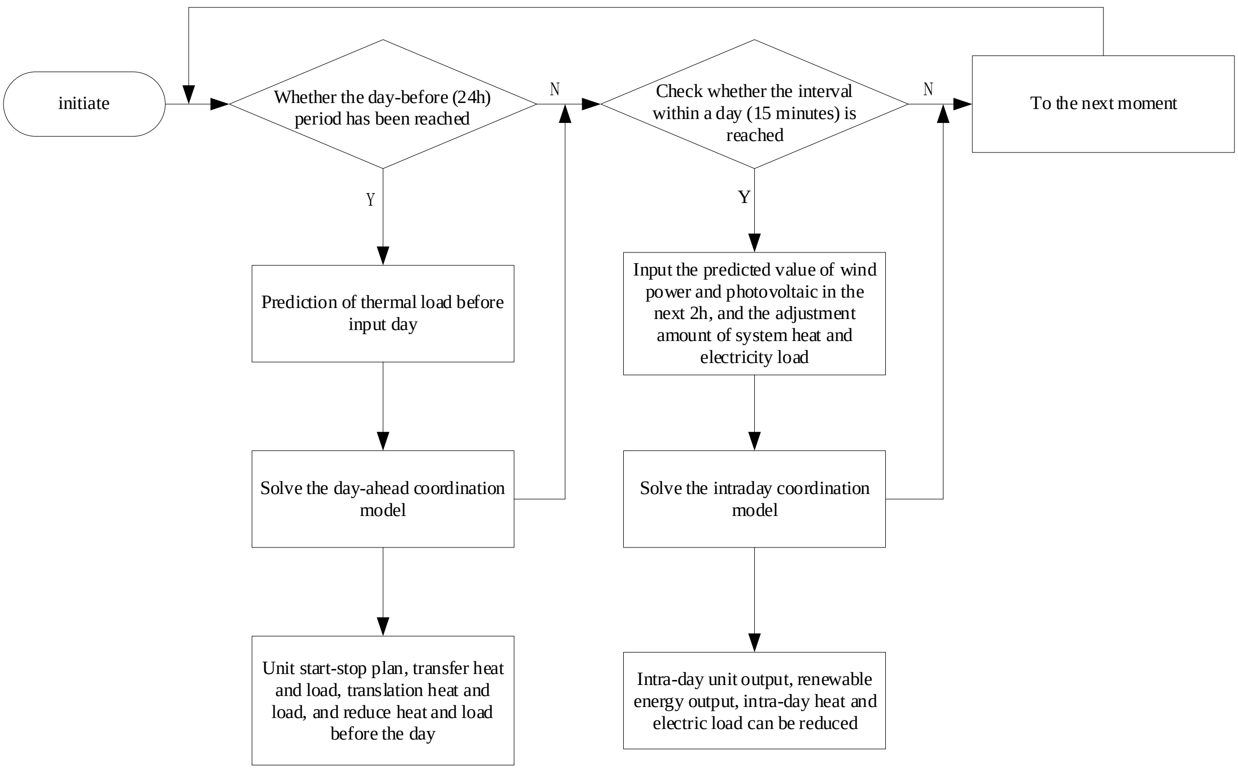


Figure 3. Multi-time scale energy system optimization coordination process

3.2. Day-Ahead Coordination Model

It is preferred to determine the day-ahead collaborative objective function [19], that is, to minimize the sum of system unit generation, start-stop cost, steam production cost, and flexible load coordination cost:

$$\mathrm{min}E=\mathrm{min}\left[\sum_{t\in T}\left(\sum_{i\in Z}C_{t,i}^{de}+\sum_{i\in Z}C_{t,i}^{OF}+E_{t,i}+O_{t,i}^{en}+C_{t,i}^{tr}+C_{fl}\right)\right] \tag{1}$$

$$C_{fl}=C_{Cut\ down}+C_{Tanslation}+C_{Transfer} \tag{2}$$

$$C_{Cut\ down}=M_{Cut\ down}\cdot P_{Cut\ down}\cdot\Delta t \tag{3}$$

$$\mathrm{C_{Tanslation}} = \mathrm{M_{Tanslation}} \cdot \mathrm{P_{Tanslation}} \cdot \mathrm{F_{on1}} \tag{4}$$

$$\mathrm{C_{Transfer}} = \mathrm{M_{Transfer}} \cdot \mathrm{P_{Transfer}} \cdot \mathrm{F_{on2}} \tag{5}$$

In the above formula, the expected total system cost is represented by E; One period of the coordination cycle is represented by t; The set of units is represented by Z; The combustion and operating costs of unit i are represented by $\mathrm{C_{t,i}^{de}}$ and $\mathrm{C_{t,i}^{OF}}$ respectively; The cost of system and large grid transactions is represented by $\mathrm{E_{t,i}}$; The revenue of steam production of the unit is represented by $\mathrm{O_{t,i}^{en}}$; The transmission cost of steam is represented by $\mathrm{C_{t,i}^{tr}}$; The flexible load coordination cost is represented by $\mathrm{C_{fl}}$. Reducible load cost is represented by $\mathrm{C_{Cut\,down}}$; The cost of shifting load is represented by $\mathrm{C_{Tanslation}}$; The cost of transferable load is represented by $\mathrm{C_{Transfer}}$; Unit capacity compensation that can reduce load is represented by $\mathrm{M_{Cut\,down}}$; The power of the unit can be reduced by $\mathrm{P_{Cut\,down}}$; The unit capacity compensation of translation load is represented by $\mathrm{M_{Tanslation}}$, and the capacity of translation load is represented by $\mathrm{P_{Tanslation}}$. The system determines that the translation instruction is represented by $\mathrm{F_{on1}}$, and there are only two states of 0 and 1. The system determines that the transfer instruction is represented by $\mathrm{F_{on2}}$, and there are only two states of 0 and 1. The constraints on power balance are as follows:

$$\sum_{t\in T}\left[\sum_{i\in Z} e_{i,s,t}^{gen} - e_{i,s,t}^{con} + e_{t,s}^{b}\right] = \sum_{t\in T} D_t^e \tag{6}$$

$$e_{t,s}^{b} = e_{t,s}^{buy} - e_{t,s}^{sell} \tag{7}$$

Among them, the electricity production of the production unit is represented by $e_{i,s,t}^{gen}$; The system power loss is represented by $e_{i,s,t}^{con}$; The change of electricity generated by large grid transactions is represented by $e_{t,s}^{b}$; Electricity obtained through purchase by $e_{t,s}^{buy}$; Electricity sold by means of sales by $e_{t,s}^{sell}$; The electrical load load of the system at time is expressed by D_t^e. Then, the thermal stationary constraints of the system are given as follows:

$$\sum_{t\in T}\left(G_{t,s} + L_{t,s} + \sum_{i\in Z} h_{i,t,s}^{gen} + G_{t,s}^{c}\right) = \sum_{t\in T} D_t^h \tag{8}$$

$$G_{t,s} = A_{t,s} + P_{t,s} \tag{9}$$

The steam output of the unit is represented by $h_{i,t,s}^{gen}$. t time, the total amount of steam stored by $G_{t,s}$; In time t, D_t^h is the thermal load; The loss of steam during transmission is represented by $L_{t,s}$; The amount of steam stored in time$t$ is represented by $A_{t,s}$; The steam storage capacity in the pipeline at time t is represented by $P_{t,s}$; The steam consumption in the system is represented by $G_{t,s}^{c}$. Unit start-stop constraints are as follows:

$$\begin{cases} \Delta z_{i,t,s} \geq z_{i,t,s} - z_{i,t-1,s} \\ \Delta z_{i,t,s} \leq 1 - z_{i,t-1,s} \\ \Delta z_{i,t,s} \leq z_{i,t-1,s} \\ \sum_{t\in T} \Delta z_{i,t.s} \leq N_{i.s} \end{cases} \tag{10}$$

Among them, the change of unit start and stop is represented by $\Delta z_{i,t,s}$; $z_{i,t,s}$ indicates the start and stop status of the device; which is divided into binary states of 0,1; The maximum number of units allowed by the system is represented by $N_{i.s}$. The flexible load constraints are as follows:

$$\begin{cases} P_{\mathrm{Transfer}}^{min} \leq P_{\mathrm{Transfer}} \leq P_{\mathrm{Transfer}}^{max} \\ \sum_{t\in T} P_{\mathrm{Transfer}}^{t}(t) \cdot \Delta t = \sum_{t\in T} P_{\mathrm{i,Transfer}}^{t}(t) \cdot \Delta t \end{cases} \tag{11}$$

Among them, the minimum power is represented by $P_{\mathrm{Transfer}}^{min}$; The maximum power is represented by $P_{\mathrm{Transfer}}^{max}$; In the new time, $P_{\mathrm{Transfer}}^{t}(t)$ represents the progress of the transfer load;In A given time, $P_{\mathrm{i,Transfer}}^{t}(t)$ represents the progress of the load transfer; When permitted, utilization can reduce the load and reduce the power loss of the system, thus achieving the purpose of reducing the economic loss of the system, the specific expression is as follows:

$$P_{\mathrm{Cut\,down}}^{min} \leq P_{\mathrm{Cut\,down}} \leq P_{\mathrm{Cut\,down}}^{max} \tag{12}$$

where, the maximum power that can be reduced within a day is represented by $P_{\mathrm{Cut\,down}}^{min}$; The minimum power that can be reduced per day is represented by $P_{\mathrm{Cut\,down}}^{max}$. The function of the translation load is that when the power consumption period is changed, it cannot respond immediately due to the influence of equipment and technology level, and can only carry out the overall translation. Constrained by time, the load after translation should be consistent with the original load, and the corresponding expression is as follows:

$$P_{\text{Tanslation}}(t) = P_{\text{Tanslation}}^{new}(t + \Delta t) \tag{13}$$

where, the original load capacity at the original time is represented by $P_{\text{Tanslation}}(t)$; The translation load capacity at the translation time is represented by $P_{\text{Tanslation}}^{new}(t + \Delta t)$. The user energy balance constraints are as follows:

$$\sum_{t\in T} h_{user} = \sum_{t\in T} D_t^h + \sum_{t\in T} P_{\text{Tanslation,h}} + \sum_{t\in T} P_{\text{Transfer,h}} + \sum_{t\in T} P_{\text{Cut down,h}} \tag{14}$$

In time t, h_{user} represents the user's demand;In t time, D_t^h represents the thermal load; The transferable load of heat load is represented by $P_{\text{Tanslation,h}}$; Heat load transferable load is represented by $P_{\text{Transfer,h}}$; The heat load can be reduced by $P_{\text{Cut down,h}}$.

3.3. Intra-Day Coordination Model

There are certain limitations of the forward coordination policy. First, the time scale is long and cannot meet the actual demand; second, the system operation and load demand changes under the day-ahead coordination strategy will have certain deviations. Therefore, we should integrate the day-before and day-before coordination strategies to improve the quality of system operation [20]. There is no conflict between the two in the choice of optimization objectives, and both aim at reducing operation to become the ultimate goal. Equation 13 is the desired objective function.

$$\text{minE} = \min\left[\sum_{\text{t}\in\text{T}}\left(\sum_{\text{i}\in\text{Z}} \text{C}_{\text{t,i}}^{\text{be}} + \sum_{\text{i}\in\text{Z}} \text{C}_{\text{t,i}}^{\text{OF}} + \text{E}_{\text{t,i}} + \text{O}_{\text{t,i}}^{\text{en}} + \text{C}_{\text{Cut down,lh}}\right)\right] \tag{15}$$

where, the expected total system cost is represented by E; The set of units is represented by Z; The cost of unit i during combustion is represented by $\text{C}_{\text{t,i}}^{\text{be}}$;The cost of unit equipment consumed during use is determined by $\text{C}_{\text{t,i}}^{\text{OF}}$; The cost of system and large grid transactions is represented by $\text{E}_{\text{t,i}}$; When the unit equipment i receives revenue, it can be represented by $\text{O}_{\text{t,i}}^{\text{en}}$; Daily load reduction cost is represented by $\text{C}_{\text{Cut down,lh}}$. The power balance constraints of the system are as follows:

$$\sum_{i\in T}\left[\sum_{i\in Z}\left(e_{i,t,s}^{gan} - e_{i,t,s}^{con}\right) + e_{t,s}^{b} + e_{t,s}^{c}\right] = \sum_{i\in T} D_t^e \tag{16}$$

Among them, the electricity production of the production unit is represented by $e_{i,t,s}^{gan}$; $e_{i,t,s}^{con}$ indicates the system energy consumption; The change of electricity generated by large grid transactions is represented by $e_{t,s}^{b}$; The change of the electric quantity of the storage equipment in the system is represented by $e_{t,s}^{c}$; D_t^e is the amount of charge in t time;The thermal balance constraints of the system are as follows:

$$\sum_{t\in T}\left(G_{t,s} + G_{t,s}^{c} + \sum_{i\in Z} h_{i,t,s}^{gen}\right) = \sum_{i\in T} D_t^h \tag{17}$$

The steam output of the unit is represented by $h_{i,t,s}^{gen}$. The total amount of steam stored in time t is represented by $G_{t,s}$; The system thermal load at time t is represented by D_t^h; The steam consumption in the system is indicated by $G_{t,s}^{c}$. Because of the long opening and closing time span of the unit equipment, the application effect of intra-day coordination optimization strategy has limitations in a short time, and it is necessary to use the day-before coordination optimization strategy to intervene. The specific constraints are shown in formula 16.

$$P_{\text{Cut down,1h}}^{min} \le P_{\text{Cut down,1h}} \le P_{\text{Cut down,1h}}^{max} \tag{18}$$

where, the maximum power that can be reduced within a day is represented by $P_{\text{Cut down,1h}}^{max}$; The minimum power that can be reduced per day is represented by $P_{\text{Cut down,1h}}^{min}$.

4. Analysis of Numerical Examples

4.1. System Overview

In order to make the coordinated preferential strategy can be applied in practice, a simulation experiment is carried out here. In the experiment, the energy system consists of a back-pressure gas-steam combined cycle device, a pumping gas-steam combined cycle device, a photovoltaic power station, and a wind turbine. The relevant parameters are shown in Table 1.

Table 1. Related parameters of system equipment

Device name	Parameter name	Parameter value
Back pressure gas steam combined cycle unit	Rated power /MW	10
	Thermoelectric ratio	0.817
	Operation and maintenance cost/(Yuan ·kWh-1)	0.01
Extraction gas steam combined cycle unit	Rated power /MW	70
	Thermoelectric ratio	0.542
	Operation and maintenance cost/(Yuan ·kWh-1)	0.05
Photovoltaic power generation	Maximum generating power /MW	20
	Operation and maintenance cost/(Yuan·kWh-1)	0.002
Wind power generation	Maximum generating power /MW	20
	Operation and maintenance cost/(Yuan ·kWh-1)	0.003

At different times, the electricity price is also different; the specific situation is shown in Table 2.

Table 2. TOU electricity price

Type	Price/(Yuan ·kWh^{-1})	Time frame
Peak price	0.971	12：00-15：00
		19：00-22：00
Ordinary price	0.675	08：00-12：00
		15：00-19：00
Valley price	0.377	22：00-08：00

In the energy system, whether for electricity or heat production, a large amount of natural gas is required. The system does not consider the coordination of natural gas, treating it as an unlimited energy supply, with a unified price of 2.66 yuan/m³ (under standard conditions).

4.2. Effect Analysis

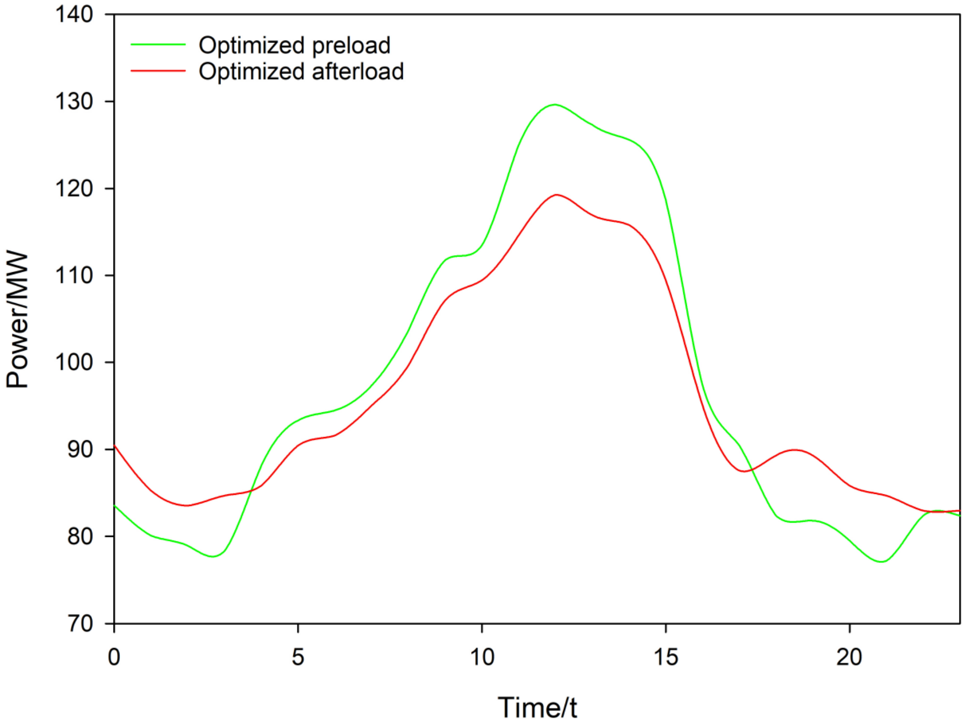
The optimization and coordination of the energy system is a mixed-integer linear programming problem involving multiple variables and multi-condition constraints.

4.2.1. Intra-Day Comparison of Heat Load Balance Output Before and After Optimization

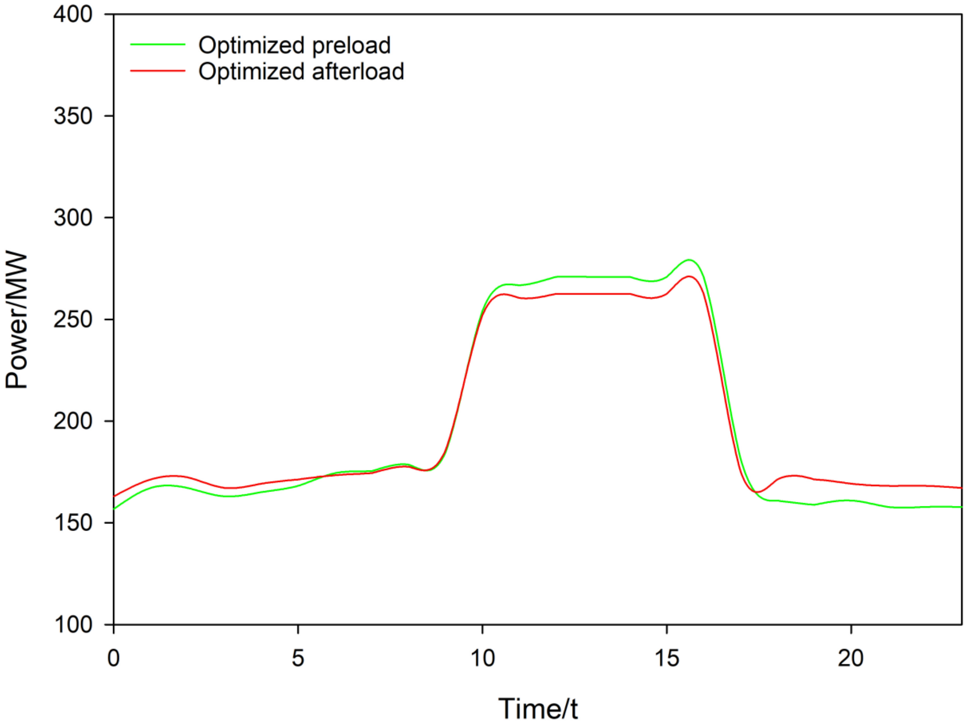
The core idea of the day-ahead collaborative optimization strategy is to control thermal and electrical output by managing the start-up and shutdown states of equipment. The load output before and after optimization obtained from the experiment is shown in Figure 4.

It is evident in Figure 4(a) that the peak-valley difference of the load before the flexible load participated in coordination was 52.428 MW. After incorporating flexible load coordination, the difference reduced to 36.29 MW, representing a decrease of 30.78%. Therefore, when flexible load coordination is considered on the day-ahead time scale, the peak-valley difference decreases.

In Figure 4(b), for day-ahead coordination of thermal load, the peak-valley difference before involving the flexible thermal load was 114.18 MW. After adding flexible thermal load coordination, the load result decreased to 99.65 MW, a reduction of 12.72%. This indicates that, even after coordinated optimization of the flexible thermal load, there remains potential for further reducing the peak-valley difference in thermal load.



a) Comparison of electrical load balance output before and after optimization

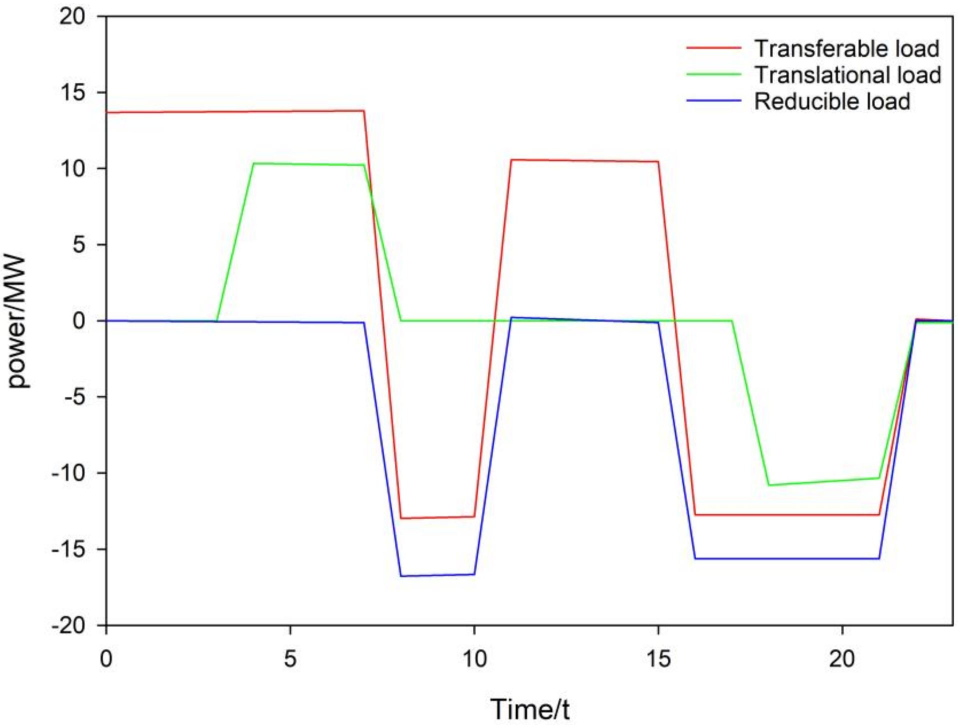


b) Comparison of average output of thermal load before and after optimization

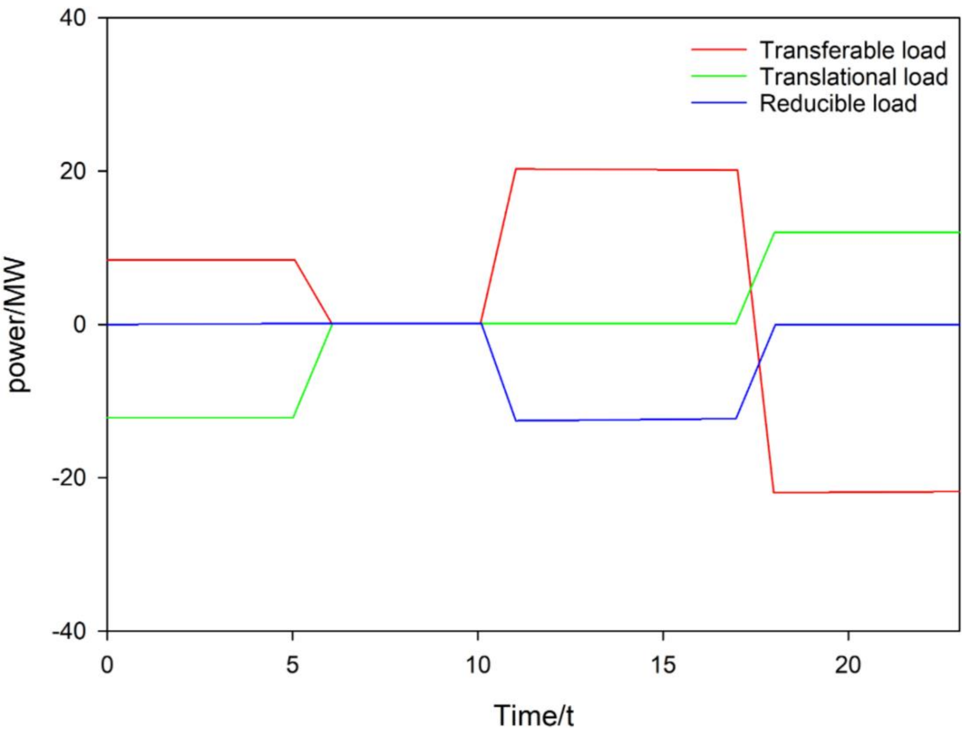
Figure 4. Comparison of average output of thermal and electrical loads of energy systems under intra-day coordination strategy

Subsequently, the flexible load response of the day-ahead coordinated energy system is illustrated in Figure 5.

It is evident that during peak periods of electricity and heat load, interventions using translational and transferable loads can help reduce the load levels. Over time, this effect becomes more pronounced, eventually bringing the load back down toward the trough period, demonstrating a significant intervention impact. However, reducing the load further can have a greater effect on users. Therefore, if the first two load adjustment methods are insufficient to meet the requirements after coordination, additional reductions in both thermal and electrical loads are implemented.



a) Before and after optimization of flexible electrical load results

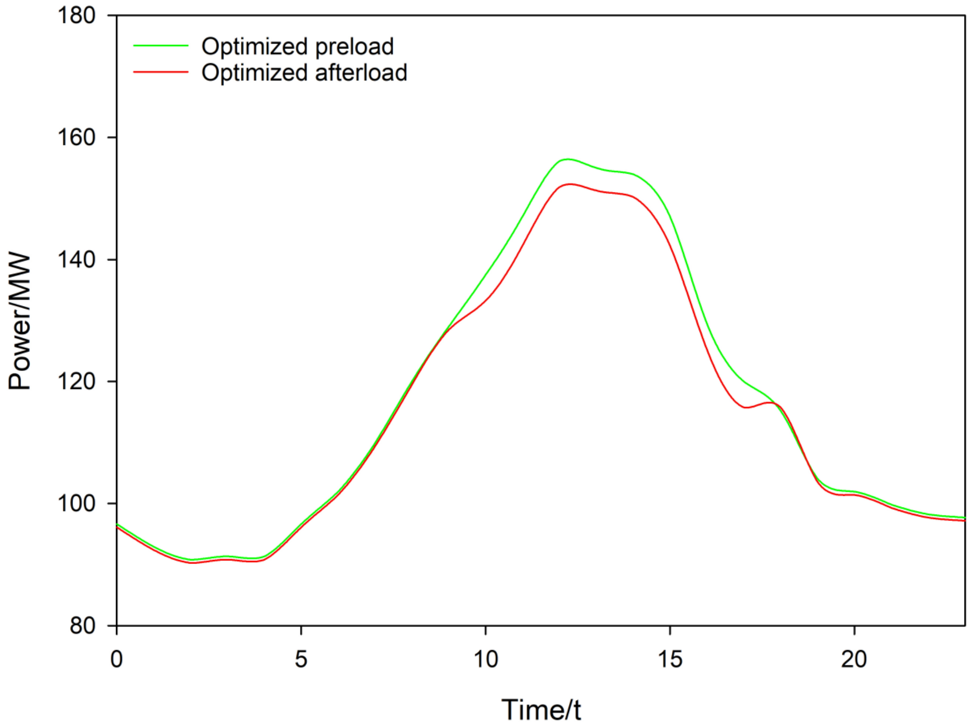


b) The flexible thermal load response results before and after optimization

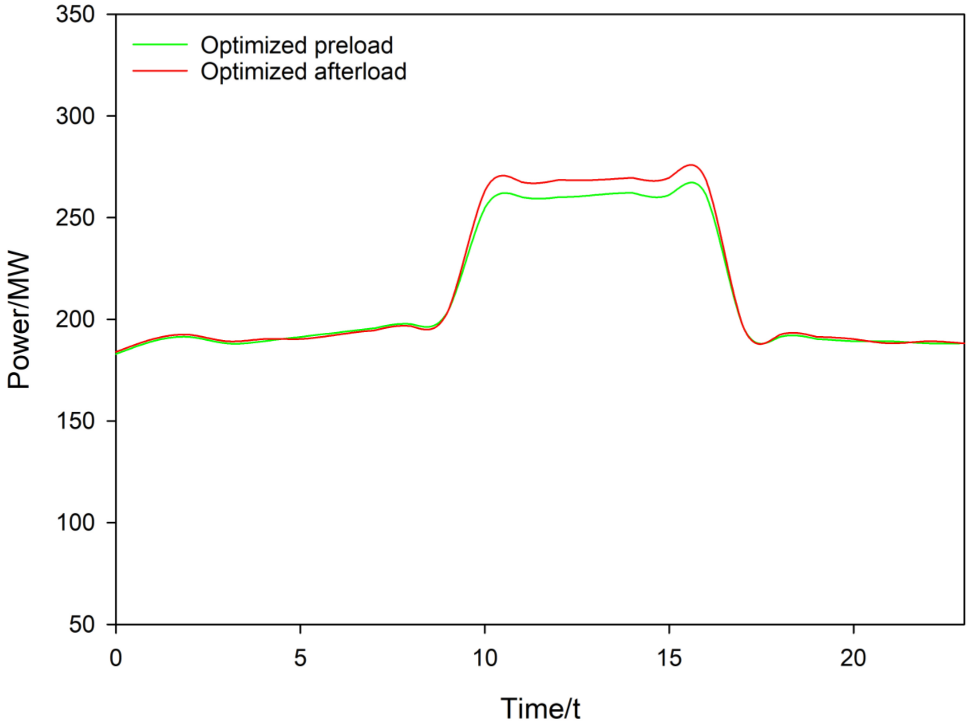
Figure 5. Results of flexible load response of energy system under pre-coordinated conditions

4.2.2. Intra-Day Comparison of Electrical Load Balance Output Before and After Optimization

Intraday optimization coordination is performed based on the day-ahead coordination, allowing for adjustments to thermal and electrical load performance through load reduction. Under the intervention of the intraday coordinated optimization strategy for the energy system, the results obtained are presented in Figure 6.



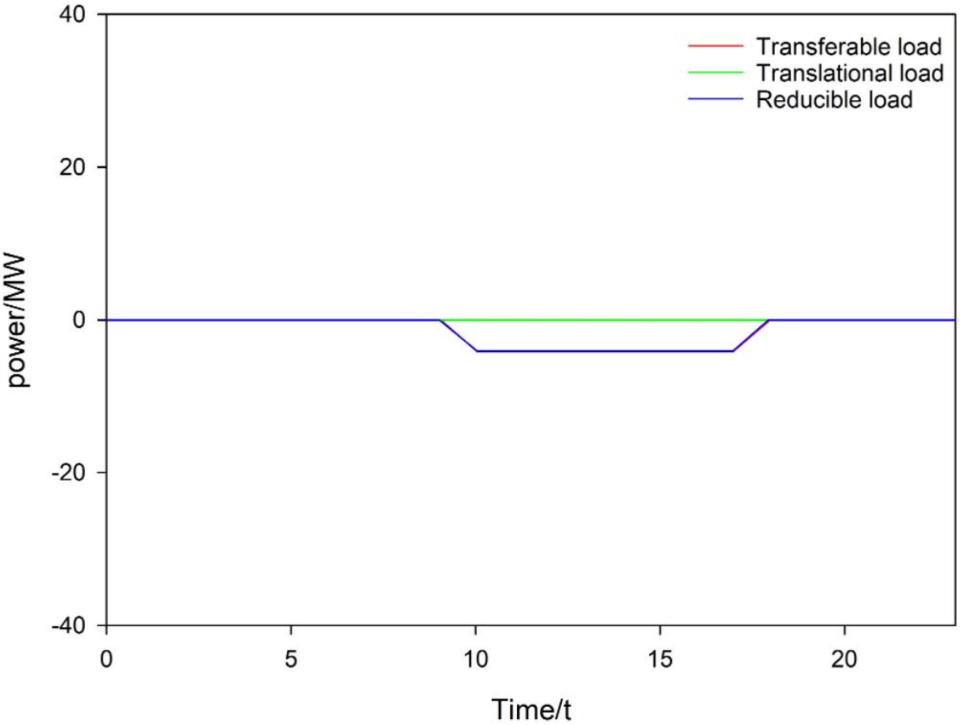
a) Comparison of electrical load balance output before and after intra-day optimization



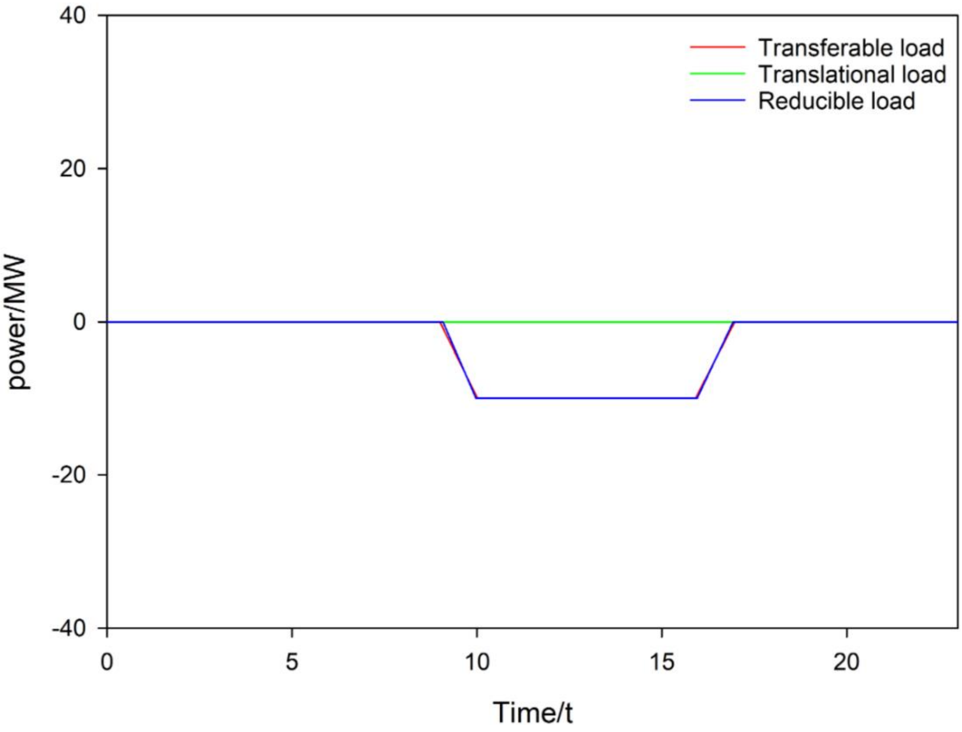
b) Comparison of thermal load balance output before and after intra-day optimization

Figure 6. Comparison of thermal and electrical load balance output of energy system under intra-day coordination strategy

As shown in Figure 6(a), during intraday load coordination, the integration of renewable energy into the system output led to an increase in the system's power load. Before intraday coordination, the peak-valley difference in the power load was 65.186 MW, which decreased to 61.593 MW after intraday coordination—a reduction of 5.5%. In the case of heat load, intraday coordination further reduced the peak heat load of the energy system. The peak-valley difference in heat load decreased from 85.65 MW before intraday coordination to 79.305 MW afterward, representing a reduction of 7.4%. These results indicate that reducing heat and electricity loads contributes significantly to improving the day-ahead coordinated plan. Compared to the day-ahead coordination, peak loads were reduced under intraday coordination. The flexible load response under intraday coordination is illustrated in Figure 7.



a) The flexible electrical load response results before and after intra-day optimization



b) The flexible thermal load response results before and after intra-day optimization

Figure 7. Results of flexible load response under intra-day coordination strategy

In Figure 7, the intraday short-term optimization coordination plan considers the pre-day coordination strategy, intraday load variations, and the need to avoid impacting user production. In this plan, the intraday secondary coordination of thermal and electrical loads focuses solely on utilizing the reducible load available during the day. Under this intraday coordination plan, electricity and heat loads during peak hours are further reduced beyond the reductions achieved in the day-ahead plan, resulting in an additional decrease in the peak-valley difference. A comparative analysis of the energy system's economic performance is presented in Table 3.

Table 3. Comparison of energy system operation costs before and after coordination

Coordination strategy	Cost classification	Cost/yuan	Total
Pre-coordinated optimization	Unit cost	204345.26	262017.86
	Operation and maintenance cost	57672.6	
After coordinated optimization	Unit cost	155110.2	258147.92
	Operation and maintenance cost	30043.55	
	Can reduce load cost	30212.22	
	Transferable load cost	11766.55	
	Operation and maintenance cost	31015.4	

It can be seen that incorporating flexible loads into the energy system effectively reduces the peak-valley difference of system load through multi-scale energy coordination, thereby lowering the system's total operating costs to some extent. For example, the unit's power generation cost decreases from 204,345.26 yuan to 155,110.20 yuan, representing a reduction of 49,235.06 yuan. Operation and maintenance costs are reduced from the original 57,672.60 yuan to 30,043.55 yuan, a decrease of 27,629.05 yuan. This demonstrates that significant cost differences exist before and after coordination optimization for these two cost categories. Overall, prior to implementing multi-scale coordination optimization with flexible load response, the daily operating cost of energy coordination stood at 262,017.86 yuan. After optimization and coordination, the operating cost was reduced to 258,147.92 yuan, achieving a reduction of 1.47%. This proves that multi-scale coordination of the energy system, considering flexible load response, can reduce operating costs and enhance the economic efficiency of the energy system to a certain extent.

5. Conclusion

Based on the analysis of flexible load characteristics, this paper integrates thermal and electrical flexible loads into the energy system and performs coordinated optimization across multiple time scales. A multi-time scale coordination model of the energy system considering thermal and electrical flexible loads is proposed, and an example analysis is conducted. The results show that, in the comparison of thermal load balance output before and after intraday optimization, the peak-valley difference was 52.428 MW before flexible load coordination, which decreased to 36.29 MW after incorporating flexible load coordination—a reduction of 30.78%. For heat load, the peak-valley difference was 114.18 MW before flexible load coordination and was reduced to 99.65 MW afterward, representing a 12.72% decrease.

In the comparison of electrical load balance output before and after intraday optimization, the peak-valley difference of the electrical load was 65.186 MW before coordination and decreased to 61.593 MW after intraday coordination, reflecting a reduction of 5.5%. During intraday coordination of thermal load, the peak-valley difference was initially 85.65 MW and decreased to 79.305 MW after coordination, a reduction of 7.4%. These findings indicate that incorporating thermal and electrical flexible loads into the energy system coordination plan effectively achieves peak shaving and valley filling.

Additionally, a comparison of the system's operational costs before and after coordination reveals that the optimized coordination reduces operational costs by 1.47%, demonstrating that the proposed research approach can lower system operating expenses and offers good economic benefits.

6. Declarations

6.1. Author Contributions

Conceptualization, J.G. and C.X.; methodology, D.G.; software, J.G.; validation, D.G, and C.X.; formal analysis, J.G.; investigation, D.G.; resources, J.G.; data curation, C.X.; writing—original draft preparation, J.G.; writing—review and editing, C.X.; visualization, C.X.; supervision, D.G.; project administration, D.G.; funding acquisition, D.G. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

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6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

7. References

[1] Zhang, J., & Liu, Z. (2024). Low carbon economic scheduling model for a park integrated energy system considering integrated demand response, ladder-type carbon trading and fine utilization of hydrogen. Energy, 290, 130311. doi:10.1016/j.energy.2024.130311.

[2] Wang, H., Lu, G., Wang, J., Lv, S., Wu, Z., & Guo, H. (2024). Low Carbon Dispatch Method for Integrated Energy System Considering Low Carbon Demand Response. 2024 4th International Conference on Energy, Power and Electrical Engineering, EPEE 2024, 1281–1288. doi:10.1109/EPEE63731.2024.10875340.

[3] Chen, Y., Ma, C., Sun, Y., & Wang, B. (2024). Low Carbon Economic Dispatch of Integrated Energy System Considering Demand Response and Carbon Capture Under Stepped Carbon Trading. Asia-Pacific Power and Energy Engineering Conference, APPEEC, 1–5. doi:10.1109/APPEEC61255.2024.10922517.

[4] Rasgianti, R. A., Nugraha, A. D., Sitanggang, R. B., Pandoe, W. W., Aprijanto, T. Y., & Santosa, M. A. (2024). System Parameters Sensitivity Analysis of Ocean Thermal Energy Conversion. Emerging Science Journal, 8, 428-448. doi:10.28991/esj-2024-08-02-04.

[5] Sun, H., Sun, X., Kou, L., Zhang, B., & Zhu, X. (2023). Optimal scheduling of park-level integrated energy system considering ladder-type carbon trading mechanism and flexible load. Energy Reports, 9, 3417–3430. doi:10.1016/j.egyr.2023.02.029.

[6] Si, D., Tang, Z., Li, L., Yao, Y., Sun, P., Hu, B., & Xie, K. (2022). Reliability Evaluation of Hybrid Energy Storage System Considering Flexible Resources of Source, Network and Load. EI2 2022 - 6th IEEE Conference on Energy Internet and Energy System Integration, EI2, 144–148. doi:10.1109/EI256261.2022.10116756.

[7] Qiu, B., Wang, X., & Wang, K. (2023). Low-Carbon Economic Dispatch of P2G-CCS Integrated Energy System Considering Wind-Solar Uncertainty. 2023 IEEE International Conference on Power Science and Technology, ICPST 2023, 663–669. doi:10.1109/ICPST56889.2023.10165079.

[8] Esmaeili, S., Anvari-Moghaddam, A., & Jadid, S. (2019). Optimal operational scheduling of reconfigurable multi-microgrids considering energy storage systems. Energies, 12(9), 1766. doi:10.3390/en12091766.

[9] Wang, Z., Wang, S., Ni, H., Wang, J., & Zhang, J. (2025). A configuration and scheduling optimization method for integrated energy systems considering massive flexible load resources. Frontiers in Energy Research, 13. doi:10.3389/fenrg.2025.1556000.

[10] Yan, Q., Zhang, G., Zhang, Y., & Yu, H. (2024). Coordinated scheduling optimization of building integrated energy system with flexible load. Energy Reports, 12, 3422–3436. doi:10.1016/j.egyr.2024.08.081.

[11] Chen, L., Xu, G., Hu, X., & Yin, Y. (2025). Research on Thermal Rectification Method and Flexible Load Regulation in RCC-PCM Enclosure Structures. Kung Cheng Je Wu Li Hsueh Pao/Journal of Engineering Thermophysics, 46(1), 201–209.

[12] Song, Q., Wang, B., Wang, Z., & Wen, L. (2024). Multi-objective capacity configuration optimization of the combined wind - Storage system considering ELCC and LCOE. Energy, 301, 131558. doi:10.1016/j.energy.2024.131558.

[13] Rinthaisong, I., & Duangtong, P. (2024). The Dynamic Capability, Innovation, Competitive Advantage, and Survival of Tech Startups. HighTech and Innovation Journal, 5(4), 977–994. doi:10.28991/HIJ-2024-05-04-08.

[14] Li, B. (2024). An integrated energy system day-ahead scheduling method based on an improved dynamic time warping algorithm. Frontiers in Energy Research, 12, 12. doi:10.3389/fenrg.2024.1354196.

[15] Mo, M., Xiong, X., Wu, Y., & Yu, Z. (2023). Deep-Reinforcement-Learning-Based Low-Carbon Economic Dispatch for Community-Integrated Energy System under Multiple Uncertainties. Energies, 16(22), 7669. doi:10.3390/en16227669.

[16] Ebrie, A. S., & Kim, Y. J. (2024). Reinforcement learning-based optimization for power scheduling in a renewable energy connected grid. Renewable Energy, 230, 120886. doi:10.1016/j.renene.2024.120886.

[17] Yang, C., Zhang, J., Jiang, W., Wang, L., Zhang, H., Yi, Z., & Lin, F. (2023). Reinforcement Learning and Stochastic Optimization with Deep Learning-Based Forecasting on Power Grid Scheduling. Processes, 11(11), 3188. doi:10.3390/pr11113188.

[18] Choi, S. (2017). Practical coordination between day-ahead and real-time optimization for economic and stable operation of distribution systems. IEEE Transactions on Power Systems, 33(4), 4475-4487. doi:10.1109/TPWRS.2017.2782806.

[19] Pratap, A., Tiwari, P., Maurya, R., & Singh, B. (2023). A Novel Hybrid Optimization Approach for Optimal Allocation of Distributed Generation and Distribution Static Compensator with Network Reconfiguration in Consideration of Electric Vehicle Charging Station. Electric Power Components and Systems, 51(13), 1302–1327. doi:10.1080/15325008.2023.2196673.

[20] Yang, Z., Yang, F., Liao, X., Wei, H., Min, H., Lei, Y., Su, L., & Shen, Y. (2022). Two stage affinely adjustable robust optimal scheduling for AC/DC hybrid distribution network based on source–grid–load–storage coordination. Energy Reports, 8, 15686–15701. doi:10.1016/j.egyr.2022.11.119.