Optimal Scheduling of MGT-IES Considering Heat Load Uncertainty and Heating Characteristics

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Abstract. Considering the thermal and electricity needs of users in the integrated energy system, in recent years, combined heat and power systems with micro gas turbines as the core have been widely used in integrated energy systems. How to coordinate and schedule heating and power supply in an integrated energy system is very important. In this paper, we take a micro gas turbine-integrated energy system (MGT-IES) as the research object, aiming at the uncertainty of heat load, we adopt a multi-scenario random planning method, while combining user heating comfort, the degree of ambiguity and the thermal inertia of the heating system are considered. The indoor thermal comfort index is used to convert the heat load demand from the traditional curve to the interval, so that the heat load is elastic at each point in time, and finally it is established to be more in line with the actual optimal scheduling model. The case analysis shows that after comprehensively considering the uncertainty of the heat load side and the thermal characteristics of the heating system, MGT-IES can effectively reduce the operation cost of the optimized dispatching while meeting the user's heat load demand.

1. Introduction

With the increasingly serious energy and environmental problems, in order to improve the overall energy efficiency and renewable energy consumption capacity, the need for multi-type energy interconnection integration and complementary integration is urgent [1]. At the same time, with the development of various energy conversion equipment technologies, the coupling effect of various forms of energy in production, transmission, consumption and other links has become stronger and stronger [2]. Therefore, the optimal scheduling of integrated energy systems (IES) including multiple energy carriers and networks has gradually become a research hotspot.

Compared with the traditional optimal scheduling problem, the optimal scheduling of the integrated energy system is a more complex problem with high uncertainty and multiple time scales. The various types of load demand in the integrated energy system are different from person to person, and are determined by user behaviours and energy preferences in production and life [3], which results in a reduction in the accuracy of the system's load demand prediction. In addition, the randomness of the load is also obvious, and the fluctuation of the load demand makes the system a whole subject with great uncertainty. Zhang et al [4] focused on the wind power uncertainty and establish a two-stage distributed robust optimization model to solve the scheduling problem. Wang et al [5] considered the uncertainty of renewable energy power generation and load, proposed a multi-scenario stochastic programming combined with model predictive control, and built a multi-time scale coordinated optimization model of the combined cooling heating and power system. Niknam, et al [6] adopted a chance-constrained programming based on joint distributed random variable method to solve the...
multi-objective stochastic optimization model of integrated energy system, and considered the uncertainty of multiple renewable energy generation and load in the optimization. Liu et al [7] proposed a multi-stage mixed integer stochastic programming model based on scenario tree to study the optimal operation of building energy-saving systems, and the uncertainty of electrical load was considered in this system.

Most of the above literatures consider the impact of the uncertainty of renewable energy power generation on dispatching. Their research of the uncertain impact on the load side is mostly concentrated on the electric load side, while the research of the uncertain impact on the heat load side is rarely considered. Moreover, none of the above-mentioned literatures considers the thermal load uncertainty by introducing thermal inertia and user comfort.

This paper takes the micro gas turbine-integrated energy system (MGT-IES) as the research object. It firstly establishes the basic equipment characteristic model of the MGT-IES, and then explores the impact of heat load side uncertainty on the day-ahead scheduling plan. On the one hand, considering the influence of the ambiguity of the user's heating comfort on the demand for heat load, a thermal sensory average scale (PMV, the predicted mean vote) index for evaluating indoor thermal comfort is introduced. The heat load curve is converted into the demand interval through PMV. On the other hand, the thermal inertia of the heating system is considered. By combining the two characteristics with the uncertainty of thermal load, an optimal scheduling model of MGT-IES is proposed, and the model is verified by an example.

2. Thermal load characteristics

2.1. User's thermal comfort PMV index

The PMV index is widely applied to represent the average value of hot and cold feelings of most people in the same environment. A PMV of 0 corresponds to the best thermal comfort of the indoor thermal environment. PMV is +1, +2, +3 means slightly warm, warm and hot respectively, while PMV of -1, -2, -3 indicates slightly cool, cool and cold [8].

The PMV value can be obtained by the following formula (1) [8].

\[
\begin{align*}
\text{PMV} &= \left(0.303 e^{-0.028 t_a} + 0.028\right) \left(M W - 3.05 \times 10^3 \times [5733 - 6.99(M W - P_a)] \right. \\
& \quad - 0.42[(M W - 58.15)] - 1.7 \times 10^{-3} M (5867 - P_a) - 0.0014 M (34 - t_o) \\
& \quad - 3.96 \times 10^{-1} \left[ f_{cl}(t_a + 273)^{0.6} - (t_o + 273)^{0.6} \right] - f_{cl}(t_a - t_o) \\
\end{align*}
\]

Where \( M \) is the energy metabolism rate of the human body; \( W \) is the mechanical power of the human body; \( f_{cl} \) is the ratio of the area covered by the human body to the bare area; \( h_c \) is the surface heat transfer coefficient; \( P_a \) is the partial pressure of water vapor in the air around the human body; \( t_a, t_r, t_{cl} \) are the temperature of the air around the human body, the average radiation temperature, and the temperature of the outer surface of the clothing, respectively. This article focuses on heat supply, and temperature is the most intuitive perception of the comfort of the indoor environment, so it is assumed that all parameters are given values except the temperature \( t_a \) of the air around the human body.

This paper applies the user comfort PMV index to set the user comfort to an acceptable range, thereby objectively setting the appropriate temperature value.

2.2. Thermal inertia of heating system

The heating system consists of a heat source and a heating network so on. The heating network and the heating building both have a large thermal inertia [8]. The temperature dynamic characteristics of the heating system can be obtained through statistical/data mining or physical models [9]. In this paper, the heating system temperature auto-regressive moving average (ARMA) model is used to show the coupling relationship between the temperature parameters in multiple time periods.

This paper uses the model in [10], assuming the relationships between the heating network water supply temperature \( T_{w,o} \), the heating network backflow water temperature \( T_{h,o} \), the indoor temperature \( T_{w,o} \), of the building, and the outdoor temperature \( T_{w,o} \), are as follows:
\begin{align*}
T_e &= \sum_{j=0}^{J} \alpha T_{e,j} + \sum_{j=0}^{J} \beta T_{e,j-1} + \sum_{j=0}^{J} \gamma T_{e,j-2} \\
T_a &= \sum_{j=0}^{J} \theta T_{a,j} + \sum_{j=0}^{J} \phi T_{a,j-1} + \sum_{j=0}^{J} \omega T_{a,j-2}
\end{align*}
(2.1)

In this ARMA time series model, the order \(J\) reflects the size of the thermal inertia of the heating system, \(\alpha\), \(\beta\), \(\gamma\), \(\theta\), \(\phi\), \(\omega\) are the physical parameters of the thermal inertia of the heating system, which can be obtained by parameter identification through measured data [10]. In the PMV index, the temperature \(t_a\) of the air around the human body is considered to be equal to the indoor temperature \(T_n\) of the heating building, namely, \(t_a = T_n\).

2.3. Description of heat load uncertainty

Due to the user's uncertain behaviour and inaccurate prediction, there is uncertainty in the size of the heat load. In this article, the scenario analysis method includes scene generation and scene reduction is applied to express the uncertainty of the heat load [11].

(1) Initial Scene Generation
The prediction error of thermal load is determined to conform to the standard normal distribution and the Monte Carlo simulation method is used to generate a large number of initial thermal load scenarios. Firstly, \(N\) sets of random vectors (each vector contains \(M\) random numbers) are generated to form the initial scene set of heat load, which is a matrix of \(R^{N \times M}\). While there is no difference in the importance between these initially generated scene vectors, the probability of setting the initial scene vectors for each group of heat loads is equal to \(1/N\). It is worth noting that \(N\) is required to be large enough to ensure that the initial set of heat loads cover all possible scenarios.

(2) Scene Reduction
Most of the scenarios in the random initial scene set has some similarities. The similar scenes in them provide similar amounts of information, and these similar scenes cannot be accurately resolved. And these similar scenarios will seriously affect the computing efficiency of the scheduling model. Therefore, it is necessary to merge most of the scenes that cannot be accurately distinguished to form a typical scene set with a small proportion of unequal probabilities.

This paper uses a heuristic-based simultaneous back-ward reduction method to reduce the generated scenes. The basic idea of scene reduction is to minimize the probability distance between the set of scenes before reduction and the subset of scenes that are ultimately retained. The specific steps are described in [12].

3. MGT-IES scheduling model

3.1. Basic model of MGT-IES
Generally, the MGT-IES mainly uses solar energy, wind energy, natural gas and other energy as the energy input. Through energy production, conversion and transmission, it can meet the load demand of users such as electricity, heat and cooling. In this paper, an MGT-IES including cogeneration system, photovoltaic power generation system (PV), wind power generation system (PW), energy storage system (ESS) and heat pump (HP) is established, and its structure diagram is shown in Figure1. Among them, cogeneration system uses a MGT as power generation and heat generation equipment, and an HP is chosen as auxiliary heating equipment. For the ESS, lead-carbon battery is used for the storage and auxiliary supply of electric energy. The whole system is in off grid state.
3.2. Mathematical model

Both thermal load and renewable energy generation are characteristics with uncertainties. This article focuses on the impact of thermal load uncertainty on optimal scheduling. When obtaining the day-ahead forecast data, the scenario analysis method is used only for thermal load forecasting. The scenario analysis method is widely used because it can clearly describe the uncertainty and the calculation of the optimization model is convenient. The difference from considering the uncertainty of the electrical load is that when considering the uncertainty of the thermal load, the thermal energy does not need to meet the equilibrium in real time, but only needs to meet a certain range. Therefore, after generating a random model, it is planned to consider another decision. Filter out the curve beyond the set range, and finally get the scheduling plan for the next 24 hours according to the optimized scheduling model.

3.2.1 Objective function. In terms of the optimal scheduling model, the objective function of the day-ahead optimal scheduling model that takes the uncertainty of the heat load into account is generally the minimum value of cost expectations. Assuming that there are S heat load typical scenes after many scenes are reduced. The probability of each typical scene s is \( p_s \), and the sum of the scene probabilities is 1. Time interval \( \Delta T = 1h \). The objective function is shown in formula (3).

\[
\min E[C_{IES}] = \sum_{s=1}^{S} p_s \left[ C_{PV} + C_{PW} + C_{MGT,s} + C_{ESS,s} + C_{HP,s} \right]
\]  

Where \( C_{PV} \) is the operation and maintenance cost of photovoltaic power generation; \( C_{PW} \) is the operation and maintenance cost of wind power generation; \( C_{MGT,s} \) is the fuel cost and operation and maintenance cost of the cogeneration unit in scenario s; \( C_{ESS,s} \) is the battery operation and maintenance cost in scenario s; \( C_{HP,s} \) is the heat pump operation and maintenance cost in scenario s. The calculation method of each income is shown in Equation (4) and Equation (5):

(1) In the above objective function, the cost of PV, PW, ESS and HP is mainly the operation and maintenance cost, which is composed of equipment operation loss, labor maintenance cost and labor inspection cost, and is related to equipment selection, actual operation power and operation frequency. The calculation formula for the operation and maintenance costs of the above equipment is as follows:

\[
C_{PV/PW/HP/ESS} = \sum_{t=1}^{24} C_{om_{PV/PW/HP/ESS}} P_{PV/PW/HP/ESS}^{t-1}
\]  

Where \( C_{om_{PV/PW/HP/ESS}} \) is the unit operation and maintenance cost of PV, PW, HP or ESS; \( P_{PV/PW/HP/ESS}^{t-1} \) is the actual operation power of the corresponding equipment in the \( t \)-th period of the day.

(2) The calculation the cost of MGT in the objective function is divided into two parts, the first part
is the fuel cost of MGT, and the second part is the operation and maintenance cost of MGT. The calculation formula is as follows:

\[ C_{\text{MGT}} = \sum_{i=1}^{24} C_{\text{om,MGT}} \cdot P_{\text{MGT}}^i + \sum_{i=1}^{24} \frac{P_{\text{MGT}}^i}{\eta_{\text{MGT}}} \cdot C_{\text{fuel}} \]  

(5)

Where \( C_{\text{om,MGT}} \) is the unit operation and maintenance cost of MGT; \( P_{\text{MGT}}^i \) is the actual operation power of the MGT in the \( t \)-th period of the day. \( \eta_{\text{MGT}} \) is the power generation efficiency of the MGT, and in order to solve it, \( \eta_{\text{MGT}} \) in this paper uses constant efficiency.; \( Q_{\text{net, gas}} \) is net calorific value per unit volume of natural gas; \( C_{\text{fuel}} \) is the purchase cost per unit volume of natural gas.

3.2.2 Constraint condition. For the MGT-IES with multi-energy coupling, its operation process should meet the demand of multi-energy load. At the same time, in order to ensure the safe operation of the system, each equipment should also meet the corresponding operating characteristics and power limiting. Therefore, in the system constraints, there are mainly three kinds of constraints: the electric energy balance constraints, the thermal energy balance constraints and the operation characteristics constraints of the equipment.

1) Electric energy balance constraints

As the system is in off grid operation state, for power supply, the sum of generation power of the MGT, PV, PW and charge / discharge power of the ESS should be equal to the sum of system electrical load demand and HP consumption power, namely:

\[ P_{\text{PV}} + P_{\text{PW}} + P_{\text{ESS,dis}} \cdot z_{\text{ESS,dis}} \cdot z_{\text{ESS,chg}} = P_{\text{load}} + P_{\text{HP}} \]  

(6)

Where \( P_{\text{MGT}} \), \( P_{\text{PV}} \), \( P_{\text{PW}} \), \( P_{\text{ESD},d} \), \( P_{\text{ESD},c} \), \( P_{\text{ESD},b} \), and \( P_{\text{ESD},e} \) are respectively the electric power of the MGT, PV, PW and the discharge/charge power of the ESS under the scenarios; \( z_{\text{ESD},d} \) and \( z_{\text{ESD},b} \) are 0-1 variables, respectively expressed as the discharge state and charging state of the ESS; \( P_{\text{load}} \) is the electric load demand of the system; \( P_{\text{HP}} \) is the amount of electrical power consumed by the HP.

2) Thermal energy balance constraints

In the heat load supply stage, the heat balance mainly includes the waste heat utilization power of MGT and the heat power of the HP to meet the heat load demand of the whole system, namely:

\[ Q_{\text{MGT},d} + Q_{\text{HP},c} = \kappa (T_{\text{h,s}} - T_{\text{bs}}) \]  

(7)

\[ T_{\text{bs}} \leq T_{\text{h,s}} \leq T_{\text{max}} \]  

(8)

\[ -\sigma \leq \lambda_{\text{PMV}} \leq +\sigma \]  

(9)

Where \( Q_{\text{MGT},d} \) and \( Q_{\text{HP},c} \) are respectively the waste heat utilization power of the MGT and the thermal power of the HP under the scenario \( s \); \( \kappa \) is the relationship coefficient between the heat supply of the system and the temperature difference between the water supply and backflow water of the heating network, which is related to the water flow of the heating network.; \( T_{\text{bs}} \) and \( T_{\text{h,s}} \) are respectively the heating network water supply temperature and the heating network return water temperature in scenario \( s \); \( T_{\text{max}} \) is the maximum water supply temperature of the heating network; \( \sigma \) is the value range of the PMV index; \( \lambda_{\text{PMV}} \) is the PMV index of the time period \( t \) in the scenario \( s \). Equation (7) is the relationship between the heat supply of the system and the temperature of the heating network. Together with equations (2.1) and (2.2), it describes the thermal inertia between the heat energy consumed by the heating system and the temperature in the building.

3) Operation characteristics constraints of equipment

In order to ensure the safe operation of the system, the equipment shall be required to operate within the specified working conditions. In addition, the operation of the equipment shall also meet its own operation characteristics.

When MGT is running, its power input should be within the constraints, and the constraints are as
follows:

\[ Q_{\text{MGT}} = P_{\text{MGT}} \frac{(1 - \eta_{\text{MGT}}) \eta_{\text{rec}}}{\eta_{\text{MGT}}} \]  \hfill (10) 

\[ P_{\text{MGT}}^{\text{min}} \leq P_{\text{MGT}} \leq P_{\text{MGT}}^{\text{max}} \]  \hfill (11)

Where \( \eta_{\text{MGT}}, \eta_{\text{rec}} \) are the power generation efficiency of the MGT and the waste heat recovery rate of the MGT, respectively; \( P_{\text{MGT}}^{\text{min}} \) is the lowest electric output power of the MGT; \( P_{\text{MGT}}^{\text{max}} \) is the highest electric output power of the MGT.

When considering the real-time charge and discharge power, the storage capacity of the ESS should also meet the capacity constraints of the ESS itself. It can be seen from the objective function that the ESS equipment also has the decision-making variable of charge and discharge state, so it should be ensured that charge process and discharge process won’t happen at the same time during the operation of the ESS. The ESS constraints can be obtained:

\[ E_{\text{ESS}}^{\text{sch}} + P_{\text{ESS}}^{\text{dis}} \cdot z_{\text{ESS,dis}} + P_{\text{ESS}}^{\text{sch}} \cdot z_{\text{ESS,sch}} \leq E_{\text{ESS}}^{\text{cap}} \leq 0.2 \cdot P_{\text{ESS}}^{\text{cap}} \]  \hfill (12)

\[ 0 \leq z_{\text{ESS,sch}}^{\text{sch}} + z_{\text{ESS,dis}}^{\text{dis}} \leq 1 \]  \hfill (13)

Where \( E_{\text{ESS}}^{\text{sch}}, E_{\text{ESS}}^{\text{dis}} \) are respectively the storage capacity of the ESS, and \( P_{\text{ESS}}^{\text{max}} \) are the maximum storage capacity of the ESS. \( z_{\text{ESS,sch}}^{\text{sch}}, z_{\text{ESS,dis}}^{\text{dis}} \) is the auxiliary running state variable, and both are 0/1 variables.

The HP is an energy conversion device that converts electric energy into heat energy. Therefore, considering the restriction of heat output power of the HP, it should also meet the restriction of energy conversion efficiency. The restriction conditions are as follows:

\[ Q_{\text{HP}} = \text{COP}_{\text{HP}} \cdot P_{\text{HP}} \]  \hfill (15)

\[ Q_{\text{HP}}^{\text{min}} \leq Q_{\text{HP}} \leq Q_{\text{HP}}^{\text{max}} \]  \hfill (16)

Where \( \text{COP}_{\text{HP}} \) is the coefficients of performance (COP) of the HP; \( Q_{\text{HP}}^{\text{min}} \) is the lowest heat output power of the HP; \( Q_{\text{HP}}^{\text{max}} \) is the highest heat output power of the HP.

4. Case study

4.1. Research objective

In this paper, a hotel in Nanjing, China is taken as the research object. The system adopts Capstone30(C30) micro-gas turbine, with a power of 30kw, a photovoltaic power of 7.5kw and a wind power of 10kw. Other basic data are shown in Table 1[13].

| \( P_{\text{MGT}}^{\text{max}} \) (kW) | \( P_{\text{MGT}}^{\text{min}} \) (kW) | \( P_{\text{cap,ESS}} \) (kW) | \( T_{g_{\text{max}}} \) (℃) | \( Q_{\text{HP}}^{\text{min}} \) (kW) |
|---|---|---|---|---|
| 30.0 | 0.0 | 10.0 | 120.0 | 0.0 |

| \( Q_{\text{HP}}^{\text{max}} \) (kW) | \( Q_{\text{net, gas}} \) (kWh/m³) | \( k \) (kW/℃) | \( \eta_{\text{rec}} \) | \( \eta_{\text{MGT}} \) |
|---|---|---|---|---|
| 27.0 | 9.7 | 0.63 | 0.90 | 0.26 |

| \( \text{COP} \) | \( C_{\text{fuel}} \) (¥/m³) | \( C_{\text{com, p}} \) (¥/kW) | \( C_{\text{com, pW}} \) (¥/kW) | \( C_{\text{com, MGT}} \) (¥/kW) |
|---|---|---|---|---|
| 3.0 | 2.5 | 0.03 | 0.05 | 0.08 |

| \( C_{\text{com, ESS}} \) (¥/kW) | \( C_{\text{com, HP}} \) (¥/kW) |
|---|---|
| 0.49 | 0.001 |

The parameters of the PMV equation and the given parameters of the ARMA time series model of the heating system are shown in Tables 2 and 3, respectively, where the PMV value is between ± 1 and the thermal inertia coefficient \( J = 2 \).
Table 2. Parameters of PMV equation [8]

| Parameter | $M$ ($W/m^2$) | $W$ ($W/m^2$) | $P_a$ (Pa) | $t_r$ ($^\circ C$) |
|-----------|---------------|---------------|------------|-----------------|
|           | 70.0          | 0.0           | 2000.0     | 29.7            |
| $t_c$ ($^\circ C$) | 32.0          |               |            |                 |
| $f_{cl}$ |               |               |            |                 |
| $h_c$ ($W/(m^2 K)$) | 1.15          | 4.7           |            |                 |

Table 3. ARMA Model Coefficients of Heating System [14] ($J=2$)

| $j$ | $\alpha_j$ | $\beta_j$ | $\gamma_j$ | $\theta_j$ | $\varphi_j$ | $\omega_j$ |
|-----|-------------|------------|------------|------------|-------------|------------|
| 0   | 0.0000      | 0.2112     | 0.3317     | 0.0000     | 0.0000      | 0.0000     |
| 1   | 0.5721      | -0.0243    | -0.3169    | 0.6991     | 0.1011      | 0.1998     |
| 2   | 0.0607      | -0.0104    | 0.1741     | 0.0000     | 0.0000      | 0.0000     |

The initial running values of MGT-IES are shown in Table 4.

Table 4. Initial operation values of MGT-IES

| $T_{g,0}$ ($^\circ C$) | $T_{g,1}$ ($^\circ C$) | $T_{a,0}$ ($^\circ C$) | $T_{a,1}$ ($^\circ C$) | $T_{w,0}$ ($^\circ C$) | $T_{w,1}$ ($^\circ C$) |
|------------------------|------------------------|------------------------|------------------------|------------------------|------------------------|
| 75                     | 75                     | 25                     | 25                     | 0                      | 0                      |

The data of daily power, thermal forecast load curve and electrical forecast load curve are shown in Figure 2 [15]. The output power of photovoltaic and wind is shown in Figure 3 [15].

Figure 2. Electrical and heat load curves

Figure 3. Output power curves of photovoltaic and wind power

Based on the previous heat load prediction data, when considering the uncertainty of the heat load, the prediction error is set 20%. Scene generation and reduction are performed using Monte Carlo method and synchronous backup reduction method is applied to generate 500 random scenes and reduce them to 5 typical scenes. The five typical scenarios are shown in Figure 4, and their corresponding probabilities are shown in Table 5.

Table 5. Probability of each scene

| $P_{Scene 1}$ | $P_{Scene 2}$ | $P_{Scene 3}$ | $P_{Scene 4}$ | $P_{Scene 5}$ |
|---------------|---------------|---------------|---------------|---------------|
| 0.240         | 0.255         | 0.195         | 0.245         | 0.065         |
In this section, in order to illustrate the impact of PMV, heating characteristics and heat load uncertainty on MGT-IES scheduling in advance, two cases are simulated.

Case 1: Only consider the impact of the uncertainty of the heat load on the MGT-IES system.

Case 2: On the basis of Case 1, namely, when considering the uncertainty of heat load, PMV index and the influence of thermal inertia are introduced into the scheduling calculation.

The model established in this paper is a mixed integer quadratic programming model, which is solved using CPLEX 12.8. The simulation results obtained by solving the above optimal scheduling model are shown in Figure 5 to Figure 8.

4.2. Simulation results

When considering case 2, on the basis of considering the heat load uncertainty in case 1, further consider the impact of adding PMV index and thermal inertia of heating on scheduling. Because the PMV index converts the heat load curve into a demand interval, the uncertain typical scenario of heat load does not need to be adjusted in the demand interval, only the heat load beyond the range of the interval needs to be adjusted. The simulation results are shown in Figure 6 and Figure 8.

Both Figure 5 and Figure 6 show that the electrical load has reached equilibrium. The sufficiency of electricity that exceeds the consumer’s electricity load is converted into thermal energy and used in subsequent periods. Wind power and photovoltaic generation are all absorbed, and the output of micro gas turbines is relatively stable during the entire dispatching process.
Figure 7. Thermal energy balance of Case1

Figure 8. Thermal energy balance of Case2

Figure 7 and Figure 8 show the heat load balance in cases1 and case2, respectively. In case 1, the scheduling scheme is the result of comprehensive consideration of typical scenarios. Because the influence of the PMV index is not considered, the heat supply in the system needs to meet the requirements of the thermal load as much as possible, and the system must meet the requirements of the electrical load, which makes the scheduling flexibility of the system low.

In case 2, after comprehensively considering the typical scenarios, the scheduling scheme takes the inertia of into account. The heat supply only needs to reach the set range, and it does not have to meet the demand of the thermal load, which is great. Improved system scheduling flexibility. As it is not necessary to meet the demand for a fixed heat load, it can be obtained from Figure 8 that the heat supply is much less than that in Case 1, which reduces the output of the micro gas turbine and heat pump, thereby reducing the operating cost of the entire system. Table 6 is the cost comparison of the two cases. It can be seen that the main cost difference is in the operating cost of the micro gas turbine. The reasons have been analysed above.

The state of charge (SOC) of the battery during dispatch in both cases is shown in Figure 9, and both meet the capacity constraints. This paper considers the scheduling of the energy storage system the next day during the scheduling process, so that the SOC returns to its original position after the scheduling is completed.

Figure 9. Comparison of battery SOC in two cases

|       | Cost_PW | Cost_PV | Cost_Pt  | Cost_HP | Cost_ESS | Total Cost |
|-------|---------|---------|----------|---------|----------|------------|
| Case1 | 4.885   | 1.155   | 277.072  | 0.526   | 4.224    | 287.863    |
| Case2 | 4.885   | 1.155   | 243.164  | 0.248   | 10.224   | 259.677    |
Figure 10 shows the indoor temperature change in both cases. The black dotted line in the figure is the indoor temperature range obtained from the PMV index. When the temperature exceeds the black dotted line, people will obviously feel cold or hot. In case 1, because the influence of thermal characteristics is not considered, although the heating can meet the demand of the heat load, the indoor temperature fluctuates greatly. As can be seen from Figure 10, the indoor temperature often drops below the PMV index, which greatly affects people's comfort. This situation is impractical and the operation cost of the entire system is high.

In case 2, the effects of thermal inertia and PMV index are considered in the scheduling process. It can be seen from the figure that the indoor temperature fluctuations are small and almost within the comfort range. Therefore, the scheduling plan of Case 2 not only has low operation cost, but also can satisfy people's comfort requirements.

5. Conclusions
On the basis of considering the uncertainty of heat load, this paper further considers the characteristics of users' ambiguity about heating comfort and the thermal inertia of heating systems, which makes the optimization scheduling process more in line with the actual situation.

Through the analysis of the case, it can be obtained that it is necessary to further consider the heating inertia and the user comfort index based on the uncertainty of the heat load. It can not only consider the uncertainty of the heat load in the scheduling process, making the scheduling result more practical, but also reduce the running cost in the scheduling process by combining the thermal characteristics.

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