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## EDITED BY

Yue Zhou,  
Cardiff University, United Kingdom

## REVIEWED BY

Chun Chen,  
Changsha University of Science and  
Technology, China  
Lv Chaoxian,  
China University of Mining and Technology,  
China

## \*CORRESPONDENCE

Xinhao Lin,  
✉ linxh2@csg.cn

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# Operation optimization considering multiple uncertainties for the multi-energy system of data center parks based on information gap decision theory

Zhuoyue Wang<sup>1</sup>, Xinhao Lin<sup>2\*</sup>, Hengrong Zhang<sup>1</sup>, Lei Yu<sup>2</sup>,  
Song Pan<sup>1</sup>, Tong Liu<sup>2</sup>, Peng Wu<sup>1</sup> and Tianqi Wang<sup>2</sup>

<sup>1</sup>Electric Power Research Institute of Guizhou Power Grid Co. Ltd, Guangzhou, China, <sup>2</sup>Electrical Power Research Institute, China Southern Power Grid (CSG), Guangzhou, China

With the rapid growth of the digital economy, data centers have emerged as significant consumers of electricity. This presents challenges due to their high energy demand but also brings opportunities for utilizing waste heat. This paper introduces an operation optimization method for multi-energy systems with data centers, leveraging the information gap decision theory (IGDT) to consider various uncertainties from data requests and the environment. First, a model is established for the operation of a multi-energy system within data centers, considering the integration of server waste heat recovery technology. Second, IGDT is employed to address uncertainties of photovoltaic output and data load requests, thereby formulating an optimal energy management strategy for the data center park. Case studies demonstrate that the electricity purchase cost increased by 5.3%, but the total cost decreased by 30.4%, amounting to 5.17 thousand USD after optimization. It indicates that the operational strategy effectively ensures both efficient and cost-effective power supply for the data center and the park. Moreover, it successfully mitigates the risks associated with fluctuations in data load, thus minimizing the possibility of data load abandonment during uncertain periods.

## KEYWORDS

data center, multi-energy, waste heat recovery, operation optimization, information gap

## 1 Introduction

With the rapid development of digital technology, data has emerged as a critical production resource. Data centers, serving as core facilities for data processing and computing, have become significant consumers of electricity (Hao et al., 2024). The power demand of global data centers in 2022 ranged from 240 to 340 TWh, accounting for approximately 1%–1.3% of global power consumption (International Energy Agency, 2022). Given this substantial energy consumption, implementing advanced energy management practices in data centers to enhance energy utilization efficiency and reduce energy costs holds significant practical importance.

The electricity consumption of data centers mainly consists of three parts: information technology (IT) devices, cooling devices, and auxiliary devices (Zhang et al., 2021). Among

these, IT devices account for approximately 50% of a typical data center's energy consumption, with almost all consumed electrical energy eventually transformed into heat. Cooling devices account for about 40% of all power consumption in data centers, expelling the heat generated by IT devices to the outside of the room (He et al., 2021). IT equipment and cooling equipment generates a significant quantity of waste heat. Leveraging and recovering the waste heat. For example, through conversion into electricity, thermal energy, or cooling output, offers a chance to improve the energy utilization efficiency of data centers even more.

The coordinated optimization of power consumption between cooling systems and IT devices has been discussed in (Li et al., 2012), using the metric of power usage effectiveness (PUE), with excess heat being directly expelled outdoors. Reference (Chen et al., 2021) considers cooling devices designed to cool the data center, while excess heat is efficiently expelled outdoors. To convert the waste heat generated by data centers into thermal resources, it has been proposed in (Wan et al., 2021) to utilize absorption chillers to collect waste heat expelled from server racks and reuse it, thereby improving the energy efficiency of the data center. Moreover, it has been suggested in (Davies et al., 2016) to elevate the temperature of waste heat from data centers using heat pumps to enhance the quality of waste heat resources and supply heat to district heating networks. In (He et al., 2018), heat pumps are employed to capture and reuse the waste heat generated by data centers equipped with distributed cooling devices, consequently improving the energy utilization efficiency of the data center park.

In a data center park, there are various forms of energy demand, including the cooling and electricity needs of data centers, as well as the heating requirements of residential areas. The integration of waste heat recovery technology into data centers helps establish a multi-energy distribution system that provides stable heating services for the living areas within the park. Moreover, it promotes the incorporation of distributed energy resources, such as photovoltaic (PV) power generation, thus fostering the utilization of renewable energy. It is of great significance for promoting the sustainable development and energy structure optimization of data center parks. However, within the multi-energy distribution system that integrates waste heat recovery technology and PV power generation, significant uncertainty arises regarding both PV output and data load requests. This uncertainty presents challenges for data centers in effectively scheduling and managing the operational status of various devices within the park, impacting not only the lifespan of IT and cooling devices but also potentially leading to consequences such as inadequate cooling supply and data load abandonment.

Thus, in researching operation optimization methods for data centers, it is essential to consider uncertainty factors and develop operational strategies that account for uncertainties in both PV output and data load requests. Various methods can be employed to address these uncertainties in operation. In (Chen et al., 2014), the Monte Carlo simulation method is utilized to generate random scenarios, and stochastic optimization is applied to evaluate power demand response management in distributed large-scale data centers. The objective is to minimize total power costs under uncertain conditions by considering various types of data load tasks. Reference (Yu et al., 2018) proposes a real-time distributed optimization scheduling method for data centers, addressing

uncertainties related to electricity prices, distributed power generation, and data loads. This method fully considers the flexible transfer of different types of data loads in time and space, aiming to reduce the operating costs of data center microgrids. A robust planning model is established for data center parks with uncertainties to balance the operational economy, reliability, and planning conservatism in (Wang et al., 2024). Additionally, reference (Lian et al., 2023) presents a flexible robust multi-objective optimization strategy, considering uncertainty in wind power output and data load. The strategy aims to minimize wind power curtailment, data load abandonment, and the operating costs of data center microgrids.

However, in practical applications, stochastic optimization often involves significant computational complexity. Moreover, the challenge of obtaining accurate probability distribution models leads to less precise models and scenarios that may not adequately represent practical conditions. On the other hand, robust optimization tends to yield conservative solutions with high operating costs (Wu et al., 2022). At the level of the data center park, the uncertainty of PV output and data load requests is significant. For newly built data center parks, the information provided by historical data is limited, making it difficult to obtain accurate scenario probability distributions. Additionally, the demand for data load can fluctuate significantly due to user needs, unexpected events, and other factors. Consequently, schedulers may struggle to obtain accurate and complete future data load request information. Therefore, traditional uncertainty methods may not be effective in optimizing the operations of multi-energy distribution systems that integrate data centers.

Information gap decision theory (IGDT) is a decision-making method designed to handle severe uncertainty. It does not require the probability distribution of uncertain quantities but instead optimizes the error of uncertain quantities under predefined objectives, thus determining the potential impacts of uncertain quantities on the system (Yeganehkia et al., 2023). During the solving process, uncertain factors are described as interval variables. It aims to maximize the range of uncertainty variables while ensuring the minimum expected target value, thereby maximizing the ability to mitigate the impact of uncertainty on the solution results. In the context of wind power generation and load demand uncertainty, IGDT has been applied in scenarios where wind power and electric vehicles operate jointly to guarantee the safe and stable operation of the generator units, as discussed in (Ahmadi et al., 2020). To mitigate the risks posed by the uncertainty of electricity prices, thermal energy production, and demand response in virtual power plants, reference (Zhao et al., 2019) proposed strategies based on IGDT, aiming to maximize profits while effectively managing and mitigating risks.

Overall, current research primarily focuses on enhancing the operational flexibility of data center cooling systems to elevate energy efficiency levels, often overlooking the potential utilization of waste heat generated by data center operations. Moreover, existing studies commonly rely on traditional stochastic optimization or robust optimization methods to devise operational strategies for uncertain environments, which may fall short of effectively addressing fluctuations in uncertainty. There is a pressing need to develop an operation optimization method that considers waste heat recovery and uncertainties. It would facilitate the formulation of operational strategies for the multi-energy system in the data center park to maximize both

economic and energy efficiency while striking a balance between economic viability and reliability.

In this paper, we propose an operation optimization method for a multi-energy distribution system in a data center park, which is based on the IGDT theory and considers waste heat recovery for heating. Firstly, a model of the waste heat recovery system and thermal segment in the data center park is established. Subsequently, the IGDT theory was adopted to handle the uncertainty in PV output and data load requests to establish an operation optimization method for data center parks in uncertain scenarios. Finally, the optimization of data center park operation under uncertain scenarios was achieved, reducing operating cost under fluctuating conditions. The main contributions of this paper are as follows:

- 1) An operation model for data centers equipped with a waste heat recovery system is established considering the dynamic thermal behaviors of data servers. This model provides a basis for energy management and operation optimization of the multi-energy distribution system in the data center park.
- 2) An operation optimization method based on IGDT is proposed for the data center park, addressing uncertainties of distributed generation and computational requests. The robustness of the obtained operational strategy can be significantly enhanced without compromising economic and efficiency performance.
- 3) The effectiveness of the proposed method is validated using a typical multi-energy system in a data center park. Through the coordinated operation of IT devices and cooling/heating devices, a synergistic supply of electricity and heat within the park can be achieved, resulting in a reduction in operating costs by 30.44%.

The organization of this paper is introduced as follows. Section 2 establishes the waste heat recovery model and the thermal segment model, in which the space thermal inertia is considered. Section 3 describes the operation optimization method for the data center park. Case studies based on the modified practical network and the specifications for data center design are conducted in Section 4. Finally, conclusions are drawn in Section 5.

## 2 Models of the multi-energy distribution system in the data center park

In this section, the waste heat recovery system model and the thermal segment model of the multi-energy distribution system in the data center park were established. The waste heat recovery system model encompasses operating models for the heat pump, electric boiler, thermal storage tank, and heat exchanger. Based on the law of energy conservation, the thermal segment model encompasses two parts: the thermal inertia model of the data center room and the living area.

### 2.1 Waste heat recovery system model for the data center park

A typical data center park is chosen as the primary research subject. To investigate the process of utilizing waste heat from the

data center, this paper primarily focuses on the heating season for operational scheduling. Further, heating for the living area of the data center park is provided based on the strategy. The energy supply structure is depicted in Figure 1. The system is connected to the grid and supplemented by a PV system to meet electricity demands. It includes heat exchanger equipment, a heat pump unit, an electric boiler, and a thermal storage tank. During the heating season, waste heat recovery and heating are realized. The system operates without considering the start-stop cycles of various energy conversion equipment, and all equipment is operated continuously.

During the heating season in the data center park, the electricity demand of the park is met by both the external power grid and the PV system. The heat pump unit and electric boiler convert electricity into heat for thermal supply, while the thermal storage tank regulates the peak and off-peak energy of the park. During operation, a substantial quantity of electrical energy consumed by the multitude of IT devices deployed in the data center room is converted into heat energy. This heat energy is collected through the waste heat recovery system and transferred through heat exchangers to collect the heat. The collected heat is then sent to the heat pump unit, where low-grade heat energy is converted into high-grade heat energy, as shown in Figure 2. The park is equipped with an electric boiler, which supplements the heat energy based on the utilization of the recovered waste heat to fulfill the heating requirements of the living area within the data center park (Ding et al., 2019). Any excess heat is discharged outdoors.

Based on the above process, the total energy consumption of the data center can be summarized by Eq. 1, where the energy consumption of auxiliary devices can be indicated by a function of  $P_t^{IT}$ .

$$P_t^{DC} = P_t^{IT} + P_t^{CO} + P_t^L \quad (1)$$

$$P_t^L = P_0^L + \chi P_t^{IT} \quad (2)$$

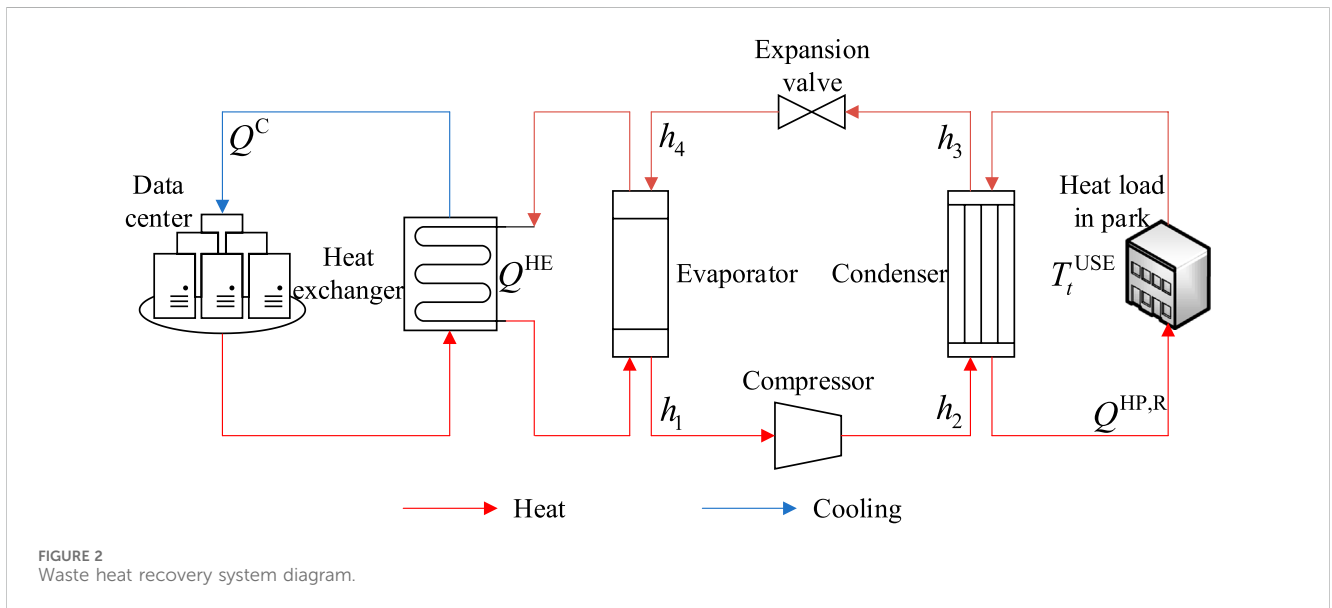
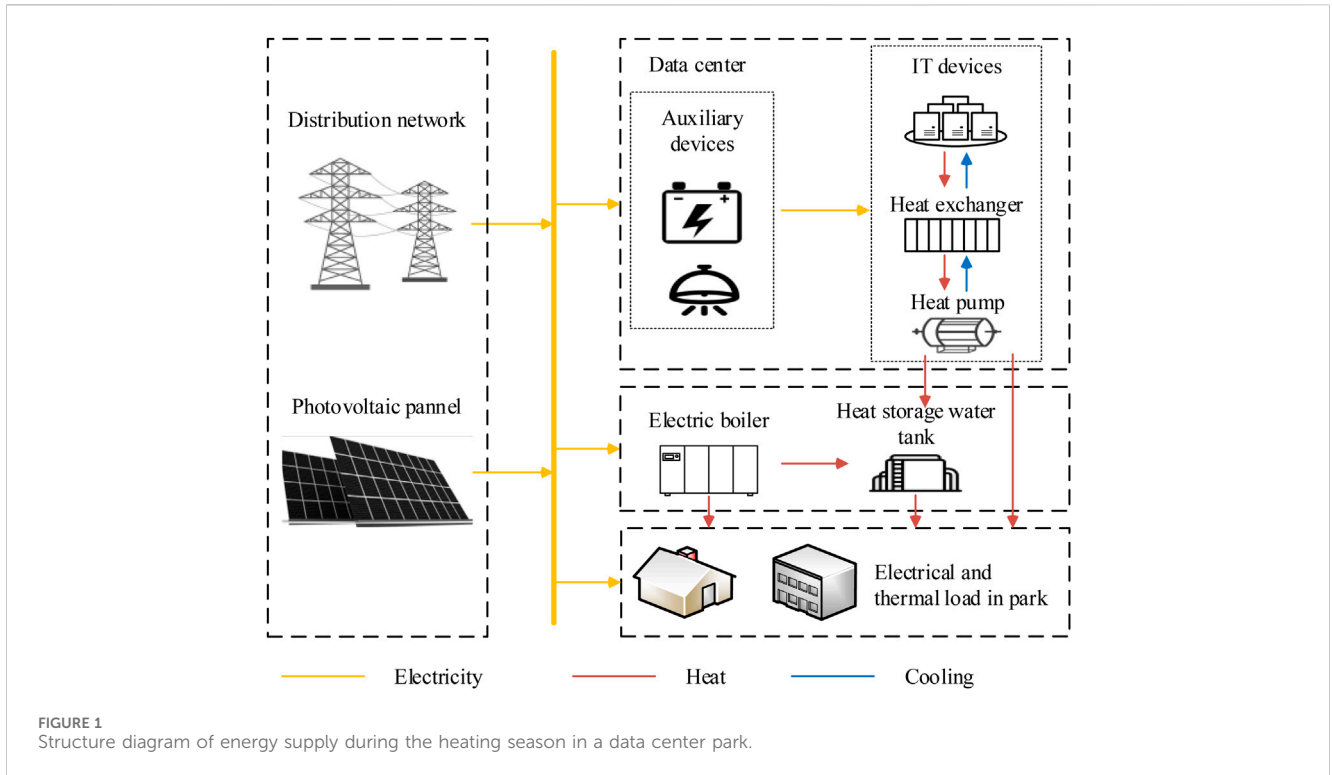
where  $P_t^{DC}$  represents the total power consumption of the data center during period  $t$ ,  $P_t^{IT}$  denotes the power consumption of IT devices during period  $t$ ,  $P_t^{CO}$  represents the power consumption of cooling devices during period  $t$ ,  $P_t^L$  denotes the power consumption of auxiliary devices during period  $t$ ,  $P_0^L$  is the fixed part of auxiliary device consumption, and  $\chi$  is the coefficient representing the ratio between the power consumption of auxiliary devices and IT devices. The operational structure of the data center park with waste heat recovery is illustrated in Figure 3.

The total power consumption  $P_t^{IT}$  of various IT equipment that can be deployed within a data center can be indicated as (Jian et al., 2024):

$$P_t^{IT} = \sum_{k=1}^{N_k} M_k^{ser} P_{k,t}^{ser} \quad (3)$$

$$P_{k,t}^{ser} = P_k^{fixed} + P_{k,t}^{CPU} \quad (4)$$

where  $M_k^{ser}$  is the total number of type  $k$  servers running in the data center,  $N_k$  is the total number of server types in the data center,  $P_{k,t}^{ser}$  is the active power consumption per type  $k$  server during period  $t$ ,  $P_k^{fixed}$  is the fixed power consumption per type  $k$  server in the data center,  $P_{k,t}^{CPU}$  is the active power consumption of the CPU per type  $k$  server during period  $t$ .



Based on dynamic voltage and frequency scaling technology, the linearized description of CPU energy consumption can be represented using auxiliary variables as follows (Zhu et al., 2023):

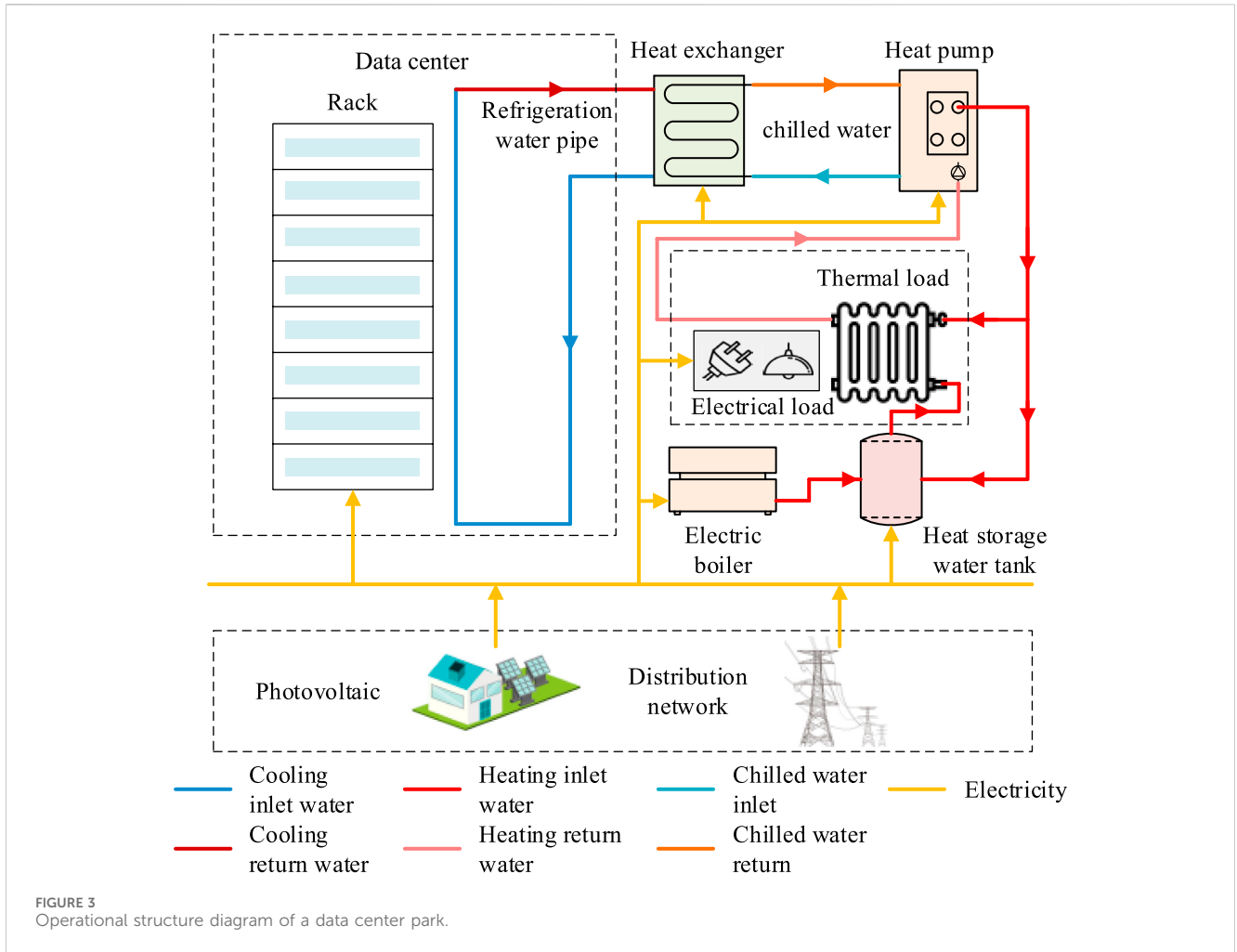
$$P_{k,t}^{CPU} = C^{CPU} \sum_{s=1}^{N_s} b_{k,t,s} (f_{k,s}^{CPU})^2 \quad (5)$$

where  $C^{CPU}$  is CPU power consumption coefficient,  $f_{k,s}^{CPU}$  is CPU's operating frequency of type  $k$  servers in the data center,  $b_{k,t,s}$  is an auxiliary variable associated with the data load processed by type  $k$  servers in period  $t$  and frequency  $s$ .

The power consumption of the cooling devices ( $P_t^{CO}$ ) is mainly composed of four parts: the heat pump, electric boiler, thermal storage tank, and heat exchanger, shown as follows:

$$P_t^{CO} = P_t^{HP} + P_t^B + P_t^{WT} + P_t^{HE} \quad (6)$$

where  $P_t^{HP}$  is the power consumption of the heat pump during period  $t$ ,  $P_t^B$  is the power consumption of the electric boiler during period  $t$ ,  $P_t^{WT}$  is the power consumption of the thermal storage tank during period  $t$ , and  $P_t^{HE}$  is the power consumption of the heat



exchanger during period  $t$ , which is assumed to be constant in this paper.

### 1) Heat pump operating model

Based on the principles of the reverse Carnot cycle, a model for the power consumption of the heat pump equipment is established. According to the first law of thermodynamics, the heat output of the heat pump is as follows:

$$Q_t^{HP} = Q_t^{HE} / P_t^{HP} \quad (7)$$

where  $Q_t^{HP}$  is the heat released by the refrigerant in the condenser during period  $t$ , which is the heat output of the heat pump.  $Q_t^{HE}$  is the heat absorbed by the refrigerant in the evaporator during period  $t$ , which is the heat extracted from the environment.

In the theoretical cycle of a heat pump system, the coefficient of performance (COP) of the heat pump can be expressed as follows:

$$\gamma^{HP} = Q_t^{HP} / P_t^{HP} \quad (8)$$

where  $\gamma^{HP}$  is COP of the heat pump.

The COP of the heat pump can be further expressed as:

$$\gamma^{HP} = (Q_t^{HE} + P_t^{HP}) / P_t^{HP} \quad (9)$$

This gives the electrical power consumed by the heat pump which can be expressed as:

$$P_t^{HP} = Q_t^{HE} / (\gamma^{HP} - 1) \quad (10)$$

A portion of the heat generated by the heat pump gets stored in the thermal storage tank, while another portion is directly supplied to the park to meet the heat demand. Eq. 11 constrains the heat output of the heat pump, ensuring it does not surpass the upper limit of the heating power:

$$Q_t^{HP} = Q_t^{HP,S} + Q_t^{HP,R} \quad (11)$$

$$0 \leq Q_t^{HP} \leq \bar{Q}^{HP} \quad (12)$$

where  $Q_t^{HP,S}$  is the thermal storage power of the heat pump during period  $t$ ,  $Q_t^{HP,R}$  is the heat power directly supplied to the park by the heat pump during period  $t$ , and  $\bar{Q}^{HP}$  is the upper limit of the heating power of the heat pump.

### 2) Electric boiler operating model

The relationship between the heating power and the power consumption of the electric boiler satisfies:



$$P_t^B = Q_t^B / \eta^B + P_t^{B,WP} \quad (13)$$

where  $Q_t^B$  is the heating power of the electric boiler during period  $t$ ,  $\eta^B$  is the energy efficiency of the electric boiler, and  $P_t^{B,WP}$  is the rated power consumption of the electric boiler's circulating water pump during period  $t$ .

A portion of the heat produced by the electric boiler is stored in the thermal storage tank, while another portion is directly supplied to the park to meet the heat demand. Eq. 15 limits the heating power of the electric boiler, ensuring it does not exceed the upper limit of the heating power:

$$Q_t^B = Q_t^{B,S} + Q_t^{B,R} \quad (14)$$

$$0 \leq Q_t^B \leq \bar{Q}^B \quad (15)$$

where  $Q_t^{B,S}$  is the thermal storage power of the electric boiler during period  $t$ ,  $Q_t^{B,R}$  is the heat power directly supplied to the park by the electric boiler during period  $t$ , and  $\bar{Q}^B$  is the upper limit of the heating power of the electric boiler.

### 3) Thermal storage tank operating model

The thermal storage tank reduces system operating energy consumption and saves operating costs by storing and releasing heat at different periods. Considering self-loss phenomena, the energy storage model of the thermal storage tank can be illustrated as:

$$W_t^H = (1 - \varepsilon^H)W_{t-1}^H + Q_t^{H,S} \alpha^H \Delta t - Q_t^{H,R} \beta^H \Delta t \quad (16)$$

where  $W_t^H$  is the thermal storage capacity of the tank during period  $t$ ,  $\varepsilon^H$  is the energy loss rate of the tank,  $Q_t^{H,S}$  and  $Q_t^{H,R}$  respectively represent the thermal storage and heat release power during period  $t$ ,  $\alpha^H$  and  $\beta^H$  respectively represent the energy storage and release efficiency.

Equations 17 and (18) impose constraints on the storage of thermal energy in the tank:

$$0 \leq W_t^H \leq \bar{W}^H \quad (17)$$

$$W_{t_0}^H = W_T^H \quad (18)$$

where  $\bar{W}^H$  is the capacity of the thermal storage tank,  $t_0$  is the initial period of operation, and  $T$  represents the final period of operation.

The thermal storage tank cannot simultaneously store and release heat. The constraints on its storage and release states can be demonstrated as:

$$0 \leq Q_t^{H,S} \leq U_t^{H,S} \bar{Q}^{H,S} \quad (19)$$

$$0 \leq Q_t^{H,R} \leq U_t^{H,R} \bar{Q}^{H,R} \quad (20)$$

$$U_t^{H,S} + U_t^{H,R} = 1 \quad (21)$$

where  $U_t^{H,S}$  and  $U_t^{H,R}$  respectively represent the storage and release states of the thermal storage tank during period  $t$ , while  $\bar{Q}^{H,S}$  and  $\bar{Q}^{H,R}$  respectively represent the upper limits of the storage and release power.

The power consumption of the thermal storage tank in the storage state is indicated as follows:

$$P_t^{WT} = U_t^{WT} P^{WT,rated} \quad (22)$$

where  $U_t^{WT}$  is the operating state of the thermal storage tank during period  $t$ ,  $P^{WT,rated}$  is the rated electrical power of the thermal storage tank.

### 4) Heat exchanger operating model

Considering a certain heat recovery efficiency, the heat power extracted by the heat exchanger during period  $t$  is as follows:

$$Q_t^{HE} = \alpha^{eff} Q_t^C \quad (23)$$

where  $\alpha^{eff}$  is the heat recovery efficiency of the data center room, and  $Q_t^C$  is the heat power reduced when the hot air flows through the evaporator located at the back of the server rack during period  $t$ .

## 2.2 Thermal segment model of the multi-energy distribution system in the data center

Most existing data centers are predominantly air-cooled, employing raised floor designs to optimize airflow arrangement and improve cooling efficiency. In data centers, both recirculated air and chilled water can serve as waste heat resources. However, data center rooms typically house multiple air conditioning units, and utilizing hot return air as a waste heat resource would significantly increase system complexity. Considering both system complexity and efficiency factors, this paper assumes that the data center rooms adopt liquid cooling technology, thereby facilitating waste heat recovery using chilled water as a resource. The energy balance relationship of the thermal segment of the data center multi-energy distribution system is illustrated in Figure 4.

### 1) Thermal inertia model of data center room

Based on the law of conservation of energy, the total heat generation power of servers in the data center room is as follows:

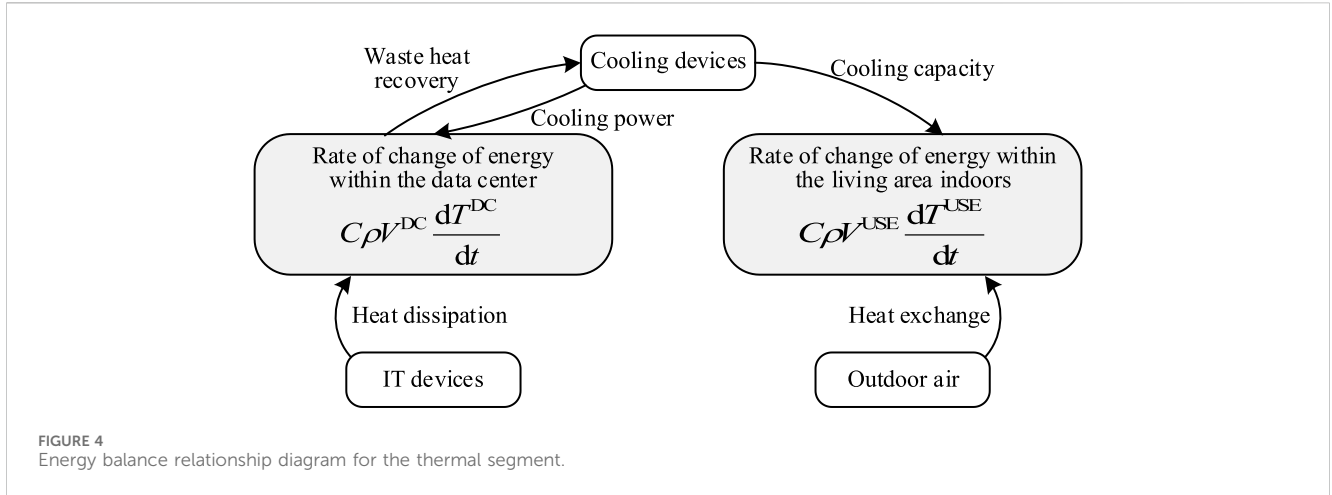
$$Q_t^H = \sum_{k=1}^{N_k} M_k^{ser} P_{k,t}^{ser} \quad (24)$$

where  $M_k^{ser}$  is the total number of type- $k$  servers running in the data center,  $P_{k,t}^{ser}$  is the active power consumption per type- $k$  server in the data center during period  $t$ .

When servers are running, the heat they emit will heat the air flowing through them. Cooling modules are installed at the rear of each rack to cool the hot air flowing through the servers. The entrance temperature of the server is approximately the same as the exit temperature, so there is no traditional cold or hot aisle. Therefore, the thermal balance equation for the data center room can be illustrated as (Zhang et al., 2024):

$$C\rho V^{DC} \frac{dT^{DC}}{dt} = Q^H - Q^C \quad (25)$$

where  $C$  is the specific heat capacity of air,  $\rho$  is the air density,  $V^{DC}$  is the volume of air flowing through the server per unit time,  $T^{DC}$  is the temperature at the exit and entrance of the server,  $Q^H$  is the heat dissipated by the server,  $Q^C$  is the heat power reduced when the hot air flows through the evaporator located at the back of the server rack.



Assuming the rate of change of internal energy of air in the data center remains constant in each time interval, Eq. 24 can be discretized into the following difference equation:

$$C\rho V^{\text{DC}} \Delta T_t^{\text{DC}} = Q_t^{\text{H}} - Q_t^{\text{C}} \quad (26)$$

$$T_{t+1}^{\text{DC}} = T_t^{\text{DC}} + \Delta T_t^{\text{DC}} \quad (27)$$

where  $T_t^{\text{DC}}$  is the temperature of the server outlet and inlet during period  $t$ , while  $\Delta T_t^{\text{DC}}$  represents the temperature change of the server outlet and inlet during period  $t$ .

The temperature at the server outlet and inlet in the data center must fluctuate within an acceptable range. The constraint is as follows:

$$T_{\text{min}}^{\text{DC}} \leq T_t^{\text{DC}} \leq T_{\text{max}}^{\text{DC}} \quad (28)$$

where  $T_{\text{max}}^{\text{DC}}$  and  $T_{\text{min}}^{\text{DC}}$  represent the upper and lower limits of the temperature at the outlet and inlet of the data center servers, respectively.

To ensure the normal operation of the servers, the rate of change of temperature at the outlet and inlet of the data center servers is also constrained within a certain range. The relevant constraints are as follows:

$$R_{\text{min}}^{\text{DC}} \leq \Delta T_t^{\text{DC}} \leq R_{\text{max}}^{\text{DC}} \quad (29)$$

where  $R_{\text{max}}^{\text{DC}}$  and  $R_{\text{min}}^{\text{DC}}$  respectively represent the upper and lower limits of the temperature change at the outlet and inlet of the data center servers.

## 2) Heating thermal inertia model of the living area

The thermal balance equation for the indoor area of the living area is as follows:

$$C\rho V^{\text{USE}} \frac{dT^{\text{USE}}}{dt} = \frac{T^{\text{USE}} - T^{\text{OUT}}}{R^{\text{USE}}} + Q^{\text{U,H}} \quad (30)$$

where  $V^{\text{USE}}$  is the volume of heating air in the living area,  $T^{\text{USE}}$  is the indoor temperature,  $T^{\text{OUT}}$  is the outdoor temperature,  $R^{\text{USE}}$  is the thermal resistance between the indoor and outdoor environments, and  $Q^{\text{U,H}}$  is the heating power.

Similarly, Eq. 30 can be discretized into a different equation as follows:

$$C\rho V^{\text{USE}} \Delta T_t^{\text{USE}} = (T_t^{\text{USE}} - T_t^{\text{OUT}})/R^{\text{USE}} + Q_t^{\text{U,H}} \quad (31)$$

$$T_{t+1}^{\text{USE}} = T_t^{\text{USE}} + \Delta T_t^{\text{USE}} \quad (32)$$

where  $T_t^{\text{USE}}$  is the indoor temperature during period  $t$ ,  $\Delta T_t^{\text{USE}}$  is the change in indoor temperature during period  $t$ .

Constraints related to the acceptable fluctuation range of indoor temperature in the living area are as follows:

$$T_{\text{min}}^{\text{USE}} \leq T_t^{\text{USE}} \leq T_{\text{max}}^{\text{USE}} \quad (33)$$

where  $T_{\text{max}}^{\text{USE}}$  and  $T_{\text{min}}^{\text{USE}}$  represent the upper and lower limits of indoor temperature, respectively.

To ensure the comfort level of indoor temperature, its rate of change is also constrained within a certain range. The relevant constraint is as follows:

$$R_{\text{min}}^{\text{USE}} \leq \Delta T_t^{\text{USE}} \leq R_{\text{max}}^{\text{USE}} \quad (34)$$

where  $R_{\text{max}}^{\text{USE}}$  and  $R_{\text{min}}^{\text{USE}}$  represent the upper and lower limits of the rate of change of indoor temperature, respectively.

## 3 Operation optimization method for the data center park

In this section, the operational regulation with the data center park is formulated, in which the waste heat recovery system and the space thermal inertia are considered. Besides, the PV output and data load requests have obvious fluctuations in temporal distribution, which may influence the efficiency of IT devices and cooling devices. It has the potential to result in inadequate cooling within data centers, data loss, reduced lifespan of IT devices, financial losses for data users, and inadequate heating in residential areas. Information gap decision theory, as a decision-making approach that does not require probability information to address uncertainties, can effectively deal with uncertainties in the data center park, where uncertainties are severe and it is difficult to form precise probability density functions for uncertain variables to enhance the operation reliability of the data center park.

### 3.1 Optimization of the multi-energy distribution system in the data center

Based on the above analysis, integrating waste heat recovery technology and the flexibility of the system's thermal process can enhance the energy utilization efficiency of the data center park, thereby reducing operating costs.

Assuming that the power supply of the data center can be provided by both the external grid and local PVs, the objective function of the optimization scheduling model can be formulated as follows:

$$\min f = f_E + f_D \quad (35)$$

$$f_E = \sum_{t=1}^{N_T} c_t P_t^{TL} \quad (36)$$

$$f_D = c^D \sum_{\rho=1}^{N_\rho} \lambda_\rho^{\text{dis}} \quad (37)$$

where  $f$  represents the total operating cost and the cost of discarding data loads within one scheduling period,  $f_E$  denotes the electricity cost incurred by the data center within one scheduling period,  $f_D$  is the cost of discarding data loads,  $N_T$  is the total number of scheduling intervals within one scheduling period,  $c_t$  represents the electricity price during period  $t$ ,  $c^D$  is the penalty cost per unit of discarded data load,  $N_\rho$  represents the total number of data load types, and  $\lambda_\rho^{\text{dis}}$  denotes the amount of discarded data load for data load type  $\rho$  during period  $t$ .

$P_t^{TL}$  represents the cost of purchasing electricity for the data center during period  $t$ , which is related to the total power consumption of the data center:

$$P_t^{\text{DC}} = P_t^{\text{PV}} + P_t^{\text{TL}} \quad (38)$$

where  $P_t^{\text{PV}}$  is the PV output during period  $t$ .

In actual operation, the heat storage power of the thermal storage tank is the sum of the heat storage power of the electric boiler and the heat pump. The total heating power of the thermal load supplied to the park is the sum of the heat release power of the thermal storage tank, the heat supplied directly by the electric boiler, and the heat supplied directly by the heat pump. The relevant constraints are as follows:

$$Q_t^{\text{H,S}} = Q_t^{\text{B,S}} + Q_t^{\text{HP,S}} \quad (39)$$

$$Q_t^{\text{U,H}} = Q_t^{\text{H,R}} + Q_t^{\text{B,R}} + Q_t^{\text{HP,R}} \quad (40)$$

where  $Q_t^{\text{U,H}}$  is the total heating power supplied to the park during period  $t$ .

In conclusion, the deterministic operational model of the data center park considering waste heat recovery can be illustrated as follows:

$$\min f = f_E + f_D \quad (41)$$

$$\text{s.t. (1) - (6), (10) - (24), (26) - (29), (31) - (34), (38) - (40)} \quad (42)$$

In this operational model, it is assumed that the predictions of PV output and data load requests are accurate, and the corresponding predicted values of PV output and data load requests are treated as actual values for optimization. However, in the actual optimization scenario of data center parks, the PV output and data load requests exhibit significant uncertainty during

operation (Zhao et al., 2023). Therefore, it is necessary to consider the uncertainty of PV and data load in the park and develop optimization strategies for the operation of data center parks.

### 3.2 Operation optimization method for data center parks based on IGDT

IGDT deals with the uncertainty problem without the requirement of probability information, representing the uncertainties as interval variables. It aims to maximize the range of uncertainty variables while ensuring the minimum expected target value, thereby maximizing the ability to mitigate the impact of uncertainty on the solution results. To effectively address the significant uncertainty within the park, where precise probability density functions are difficult to formulate, this section applies IGDT to incorporate the uncertainty of PV output and data load requests in the data center park.

#### 1) Modeling uncertainty of PV output and data load requests

The fluctuation range of uncertainty in PV output can be indicated using IGDT as follows:

$$U(\alpha^{\text{DG}}, \tilde{P}_t^{\text{DG}}) = \left\{ P_t^{\text{DG},r} : |P_t^{\text{DG},r} - \tilde{P}_t^{\text{DG}}| \leq \alpha^{\text{DG}} \tilde{P}_t^{\text{DG}} \right\} \quad (43)$$

where  $\alpha^{\text{DG}}$  is the uncertainty radius of the PV output, its magnitude is correlated with the prediction error of the PV output,  $\tilde{P}_t^{\text{DG}}$  is the predicted value of the PV output during period  $t$ ,  $P_t^{\text{DG},r}$  is the actual value of the PV output during period  $t$ .

The uncertainty range of data load requests can be indicated as follows:

$$U(\alpha^\lambda, \tilde{\lambda}_{\rho,t}) = \left\{ \lambda_{\rho,t}^r : |\lambda_{\rho,t}^r - \tilde{\lambda}_{\rho,t}| \leq \alpha^\lambda \tilde{\lambda}_{\rho,t} \right\} \quad (44)$$

where  $\alpha^\lambda$  is the uncertainty radius of data load requests, which is related to the prediction error,  $\tilde{\lambda}_{\rho,t}$  is the predicted data load requests during period  $t$ ,  $\lambda_{\rho,t}^r$  is the actual data load requests during period  $t$ .

#### 2) Model construction and transformation based on IGDT

Based on the objective function and constraints outlined in Section 3, the deterministic optimization model to be solved can be illustrated as follows:

$$\min f = F(\mathbf{s}, \mathbf{w}) \quad (45)$$

$$\text{s.t. } \begin{cases} \mathbf{G}(\mathbf{s}, \mathbf{w}) = 0 \\ \mathbf{K}(\mathbf{s}, \mathbf{w}) \leq 0 \end{cases} \quad (46)$$

where  $F(\mathbf{s}, \mathbf{w})$  is the objective function,  $\mathbf{s}$  is the decision variable set,  $\mathbf{w}$  is the uncertainty variable set,  $\mathbf{G}(\mathbf{s}, \mathbf{w})$  is the system equality constraints, and  $\mathbf{K}(\mathbf{s}, \mathbf{w})$  is the system inequality constraints.

The limitations of historical scenario information make it difficult to obtain accurate scenario probability distributions. Therefore, IGDT without probabilistic information is utilized in this paper to analyze the uncertainty of PV outputs and front-end server data load requests. Decision makers can be categorized into pessimistic and optimistic types based on their differences in risk



perception and behavioral habits, and they adopt opposing value propositions in facing risks. This paper aims to mitigate the impact of uncertainty in PV output and data load requests on the operational results of the data center parks. Therefore, a risk aversion strategy is employed in this paper to construct the IGDT robust optimization model. The general form of the IGDT robust model is as follows:

$$\begin{aligned} \min f &= \varphi & (47) \\ \text{s.t.} \begin{cases} \max F(\mathbf{s}, \mathbf{w}) \leq F_C \\ F_C = (1 + \beta)F_0 \\ \mathbf{G}(\mathbf{s}, \mathbf{w}) = 0 \\ \mathbf{K}(\mathbf{s}, \mathbf{w}) \leq 0 \\ \mathbf{U}(\varphi, \tilde{\mathbf{w}}) = \{\mathbf{w}: |\mathbf{w} - \tilde{\mathbf{w}}| \leq \varphi \tilde{\mathbf{w}}\} \end{cases} & (48) \end{aligned}$$

where  $\varphi$  is the uncertainty radius, indicating the magnitude of fluctuations in uncertain variables,  $\mathbf{w}$  is the actual values of uncertain variables,  $\tilde{\mathbf{w}}$  represents the predicted values of uncertain variables,  $F_C$  is the maximum expected target value acceptable to the decision-maker,  $\beta$  is the cost deviation factor, indicating the extent of the deviation between the maximum expected target value of IGDT and the optimal target value of the deterministic model,  $F_0$  is the optimal target value of the deterministic model,  $\mathbf{U}(\varphi, \tilde{\mathbf{w}})$  is the range of fluctuations in uncertain variables. During the model-solving process, the upper-level model seeks the maximum value of uncertainty when the target is set, while the lower-level model seeks the maximum value of the objective function when solving the fluctuation of uncertain variables.

Equations 47 and (48) establish a two-level optimization problem: the upper model seeks to maximize the uncertainty and the lower model to maximize the objective function. In the lower layer model, the purchased power of the system will increase as the PV output decreases, which leads to an increase in the operating cost. When the PV output reaches its minimum value, the lower-level objective function value achieves its maximal value. Meanwhile, as the data load requirement increases, the power consumption of the system increases, resulting in an operating cost increase. From another perspective, the lower-level objective function value reaches the maximum when the data load request reaches the maximum value. Combining these two influencing factors, the maximum value of the lower-level model occurs when the PV output is minimum and the data load request is maximum. In this case, the two-level optimization model can be equivalently converted to a single-level optimization model as follows:

$$\begin{aligned} \min f &= \varphi & (49) \\ \text{s.t.} \begin{cases} F(\mathbf{s}, \mathbf{w}) \leq F_C \\ F_C = (1 + \beta)F_0 \\ \mathbf{G}(\mathbf{s}, \mathbf{w}) = 0 \\ \mathbf{K}(\mathbf{s}, \mathbf{w}) \leq 0 \\ \varphi = \varepsilon^{\text{DG}} \alpha^{\text{DG}} + \varepsilon^\lambda \alpha^\lambda \\ P_t^{\text{DG},r} = (1 - \alpha^{\text{DG}}) \tilde{P}_t^{\text{DG}} \\ \lambda_{\rho,t}^r = (1 + \alpha^\lambda) \tilde{\lambda}_{\rho,t} \end{cases} & (50) \end{aligned}$$

where  $\varphi$  is the comprehensive uncertainty radius, while  $\varepsilon^{\text{DG}}$  and  $\varepsilon^\lambda$  are the weighting coefficients for the uncertainties of PV output and data load requests, respectively. They satisfy:

$$\varepsilon^{\text{DG}} + \varepsilon^\lambda = 1 \tag{51}$$

Based on IGDT, the robust optimization model for the data center park ultimately transforms into a single-layer optimization model. The process for solving the model is illustrated in Figure 5, and the detailed steps for solving it are as follows:

Step 1: Input deterministic model data of the data center park, including information on the composition and parameters of the devices in the data center, the composition of data loads and tolerance times, the thermal inertia parameter information of the data center and living areas within the park, outdoor temperature information, basic parameters for time-of-use electricity prices, PV output curve, and data load request curve, etc.

Step 2: Solve the deterministic model of the data center park considering waste heat recovery to minimize operating costs. Obtain the optimal value  $F_0$  of the deterministic model's objective function and set it as the benchmark value.

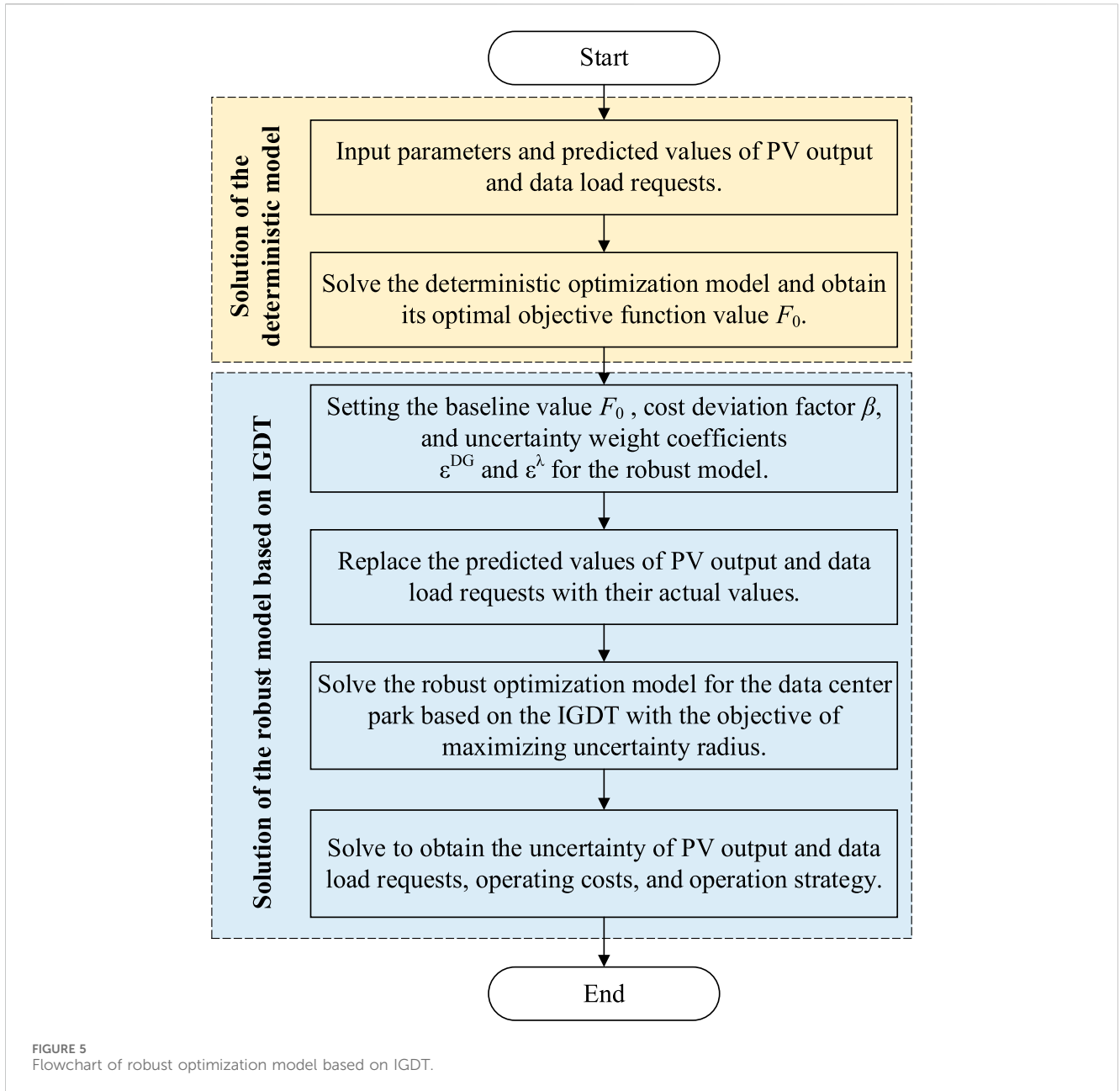
Step 3: Set the cost deviation factor  $\beta$  for the IGDT, the acceptable expected target value  $(1 + \beta)F_0$  of the IGDT model, and define the empirical weighting coefficients for the uncertainty radius of PV output and data load requests. Replace the predicted values with the actual values of PV output and data load requests.

Step 4: Optimize the robust optimization model for the data center park based on the IGDT to maximize uncertainty. Obtain the uncertainty radius of PV output and data load requests, the operating cost of the data center park, and the unit output plan.

## 4 Case study

In this paper, the case in (Ji et al., 2022) is adopted to verify the effectiveness of the proposed method. The time is set during the winter heating season and the other parameters are set according to the specifications for data center design.

The data center contains a total of 12,000 servers divided into two types (Ji et al., 2022). The parameters of the cooling and heating equipment as well as the thermal inertia are shown in Table 1 and 2, respectively. The variation curve of the outdoor temperature is shown in Figure 6. The curves of data load requests and PV output are illustrated in Figure 7. In Figure 7A, the solid blue line represents the number of data load requests under a deterministic scenario. The dark blue portion indicates the numerical range of the number of data load requests under a cost deviation factor of 0.05. The light blue and dark blue portions collectively represent the number of data load requests under a cost deviation factor of 0.1. Similarly, in Figure 7B, the solid green line represents the PV output curve under a deterministic scenario. The dark green portion indicates the numerical range of PV output in the park under a cost deviation factor of 0.05. The light green and dark green portions collectively represent the numerical range of PV output in the park under a cost deviation factor of 0.1. The time-of-use pricing is adopted and the peak, off-peak, and shoulder electricity prices are USD 0.187/kWh, USD 0.125/kWh, and USD 0.064/kWh, respectively, as shown in Figure 8. The residential area's electricity load is not considered due to its non-controllable nature. In addition, electric boilers serve as supplementary heating equipment in the park, which could



provide heating to the residential area when the heat recovery from the data center is insufficient.

#### 4.1 Analysis of optimization results

This section begins by analyzing the robust optimization results of the IGDT considering only the uncertainty of PV output and only considering the uncertainty of data load requests. Subsequently, the analysis extends to the robust optimization results of the data center park when simultaneously considering the uncertainties of both PV output and data load requests.

##### 1) Considering only the uncertainty of PV output

When considering only the uncertainty in PV output without considering the uncertainty of data load requests, robust optimization based on IGDT is conducted. Corresponding to different cost deviation factors, which refer to the difference or deviation between the actual cost and the expected cost during the decision-making process, the variation of PV output uncertainty radius is presented in [Table 3](#).

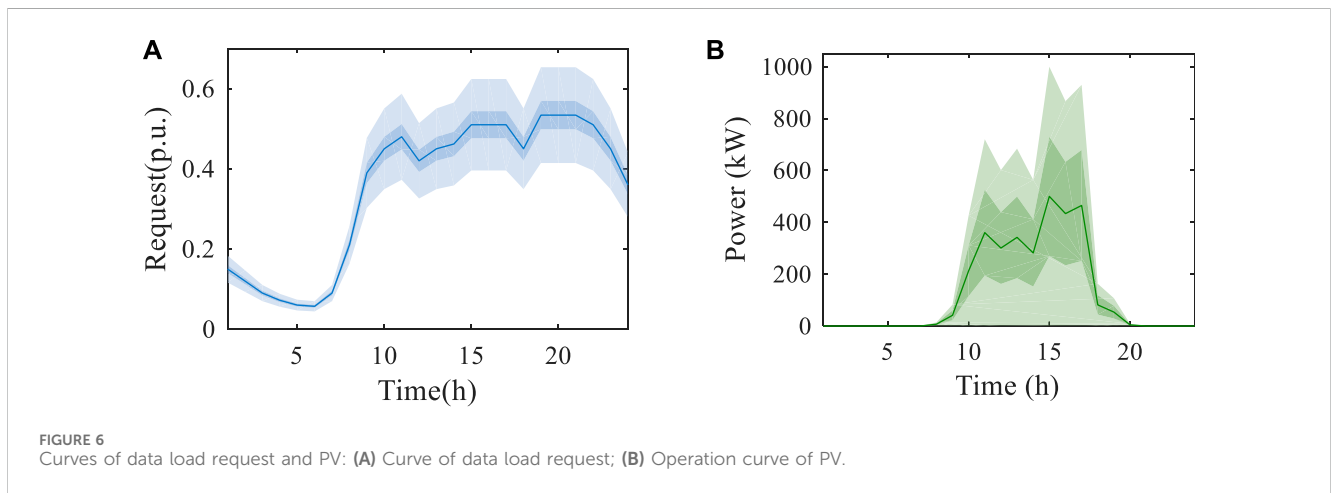
From [Table 3](#), it can be observed that a cost reserve within 0.5% cannot meet the operational requirements of the system in an uncertain environment, and the operation of the park cannot accept the prediction deviation of the PV output. However, as the cost deviation factor gradually increases, the data center park can gradually accept higher prediction deviations of the PV output. Moreover, as the set cost deviation factor  $\beta$  increases, the expected operating cost of the park increases accordingly,

TABLE 1 Parameters of the cooling and heating equipment in the park.

Equipment	Parameter	Value
Heat pump	Rated capacity/kW	3300
	Rated COP	1.5
Electric boiler	Rated capacity/kW	2000
	COP	0.99
	Rated power consumption of the cascade circulating water pump	10
Thermal storage tank	Rated capacity/kWh	2000
	Thermal loss rate	1.5
	Thermal storage efficiency/%	99.9
	Heat release efficiency/%	99.9
	Maximum heat storage/release power/kW	2000
	Rated power consumption/kW	10
Heat exchanger	Rated power consumption	5

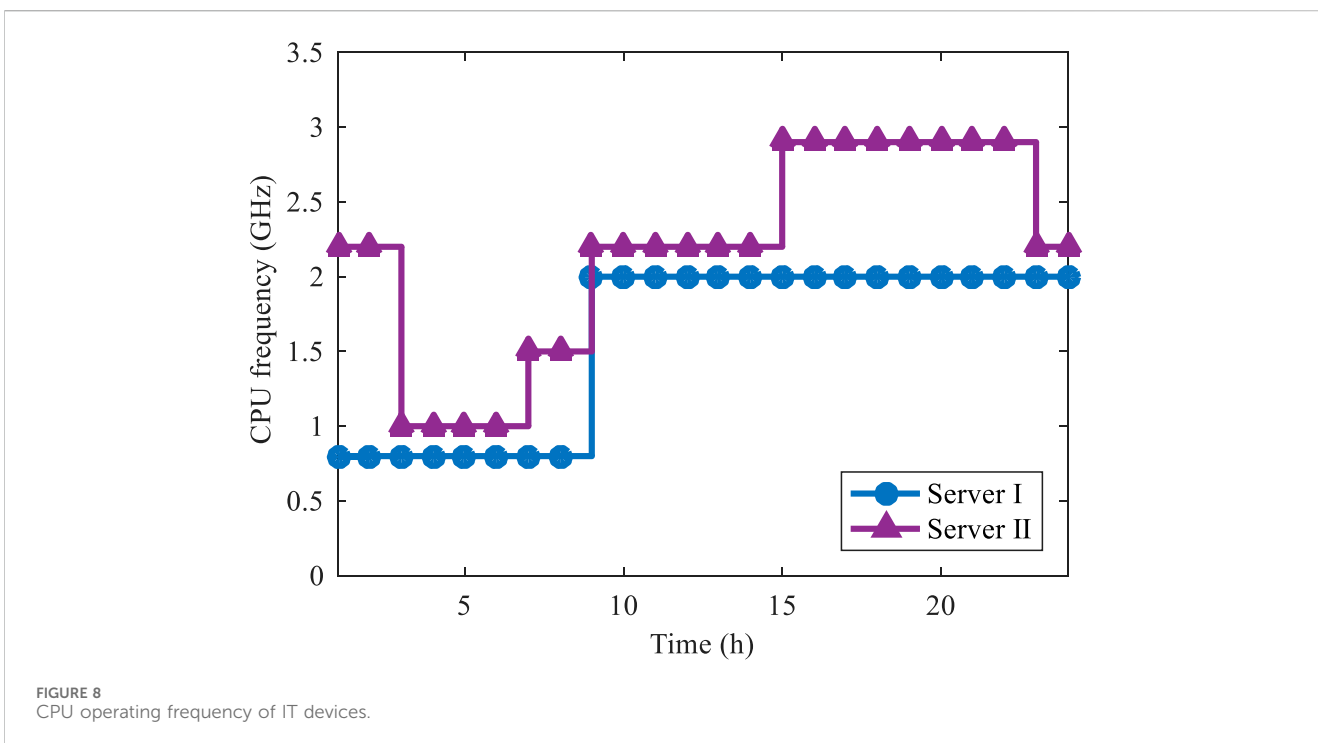
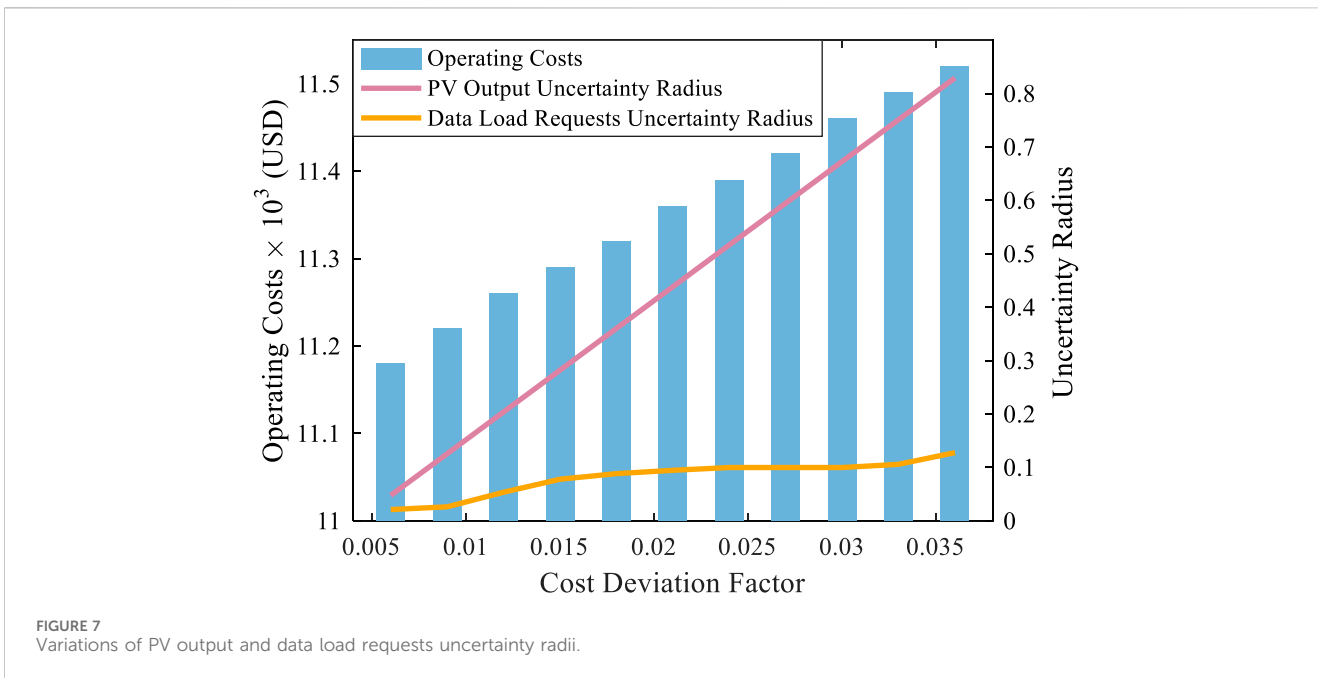
TABLE 2 Parameters of thermal inertia in the park.

Parameter	Data center	Park living area
Volume/m <sup>3</sup>	240	4,000
Initial temperature/°C	25	20
Lower temperature limit/°C	25	18
Upper temperature limit/°C	33	26
Temperature variation upper and lower limits/°C/h	±2	±3
Heat dissipation coefficient	-	0.004



along with an increase in the PV output uncertainty. The actual operating cost of the park increases numerically to the same value as the expected operating cost of the park until it reaches its maximum robustness. It is because, in the robust model of the IGDT, the uncertainty factors harm the reduction of the target

value: the larger the uncertainty radius of the PV output, the higher the operating cost of the park. Additionally, when the PV output varies within the interval  $[(1 - \alpha^{DG})\tilde{P}_t^{DG}, (1 + \alpha^{DG})\tilde{P}_t^{DG}]$ , the operating cost of the park will be lower than the expected operating cost  $(1 + \beta)F_0$ .



2) Considering only the uncertainty of data load requests

Without factoring in the uncertainty of PV output, only the prediction of data load requests is inaccurate. The variation of uncertainty radius in data load requests for different cost deviation factors is shown in Table 4.

From Table 4, it can be observed that the reserved cost within 0.5% cannot meet the operational requirements under uncertain conditions. Similarly, due to the negative impact of uncertainty

factors on the target value in the robust model of IGDT, the larger the uncertainty radius of data load requests, the higher the operating cost of the park. Therefore, as the decision maker sets a larger cost deviation factor  $\beta$ , the uncertainty radius of data load requests increases, leading to an increase in operating costs until the robustness is maximized. When the data load requests vary within the specified interval  $[(1 - \alpha^\lambda)\tilde{\lambda}_{p,t}, (1 + \alpha^\lambda)\tilde{\lambda}_{p,t}]$ , the operating costs of the park will be lower than the expected operating cost  $(1 + \beta)F_0$ .

TABLE 3 Variation of PV output uncertainty radius.

Cost deviation factor $\beta$	Operating costs/thousand USD	PV output uncertainty radius $\alpha^{DG}$
<0.005	-	-
0.005	11.18	0.0215
0.006	11.18	0.0476
0.009	11.22	0.1257
0.012	11.26	0.2039
0.015	11.29	0.2821
0.018	11.32	0.3603
0.021	11.36	0.4384
0.024	11.39	0.5166
0.027	11.42	0.5948
0.030	11.46	0.6729

TABLE 4 Variation of data load requests uncertainty radius.

Cost deviation factor $\beta$	Operating costs/thousand USD	Data load requests uncertainty radius $\alpha^{\lambda}$
<0.005	-	-
0.005	11.18	0.0099
0.006	11.18	0.0212
0.009	11.22	0.0263
0.012	11.26	0.0536
0.015	11.29	0.0780
0.018	11.32	0.0884
0.021	11.36	0.0947
0.024	11.39	0.0999
0.027	11.42	0.0999
0.030	11.46	0.0999
0.033	11.49	0.1059
0.036	11.52	0.1278

Furthermore, when the cost deviation factor  $\beta$  is in the range of 0.024–0.030, the uncertainty radius of data load requests remains constant at 0.999. It is due to the limitation of the central processing unit (CPU) frequency levels of the servers in the data center, where the reserved cost at that moment cannot allow the servers to operate at higher frequency levels to handle more data loads, rather than the uncertainty radius of data load requests reaching the upper limit. When the cost deviation factor  $\beta$  exceeds 0.33, the uncertainty radius of data load requests continues to increase.

Figure 9 illustrates the fluctuations in operating cost as the cost deviation factor varies, and its corresponding variations in PV power, and data load uncertainty radius. As the cost deviation factor increases, the operating cost and the uncertainty radius associated with the PV power and data loads increase

simultaneously. Among them, the PV uncertainty radius experiences the most rapid variation, whereas conversely, the data load uncertainty radius undergoes a more gradual change. This difference arises from the fact that the power consumption of IT devices in data centers is significantly larger than the installed capacity of PV power generation, making the fluctuation radius of PV output larger for a given cost deviation factor. Meanwhile, the nonlinear relationship between the power consumption of IT devices and their data load requests introduces the growth rate fluctuations during the data load uncertainty radius increase. In summary, variations in the uncertainty radius of PV output and data load requests exhibit different response characteristics to cost deviation factor fluctuations. These factors collectively contribute to a significant impact on operating costs, making it necessary to



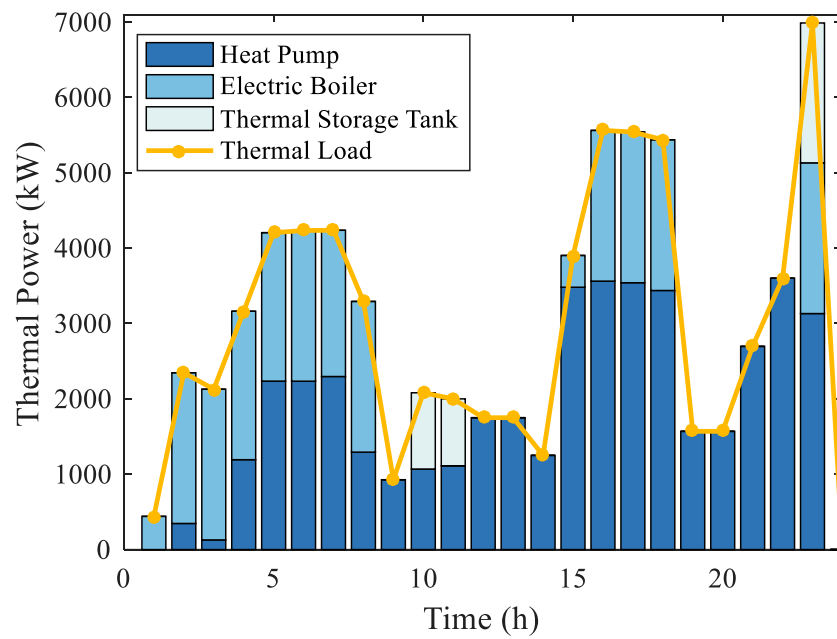


FIGURE 9 Heat power distribution chart.

TABLE 5 Variation of comprehensive uncertainty radius.

Cost deviation factor $\beta$	Expected operating cost/ thousand USD	Operating costs/ thousand USD	PV output uncertainty radius $\alpha^{DG}$	Data load requests uncertainty radius $\alpha^\lambda$	Comprehensive uncertainty radius $\varphi$
<0.005	<11.18	-	-	-	-
0.005	11.18	11.18	0.0215	0	0.0108
0.010	11.24	11.24	0.1518	0	0.0759
0.015	11.29	11.29	0.2821	0	0.1410
0.020	11.35	11.35	0.4124	0	0.2062
0.025	11.40	11.40	0.5427	0	0.2713
0.030	11.46	11.46	0.6729	0	0.3365
0.035	11.51	11.51	0.8032	0	0.4016
0.040	11.57	11.57	0.9335	0	0.4667
0.045	11.62	11.62	1	0.0217	0.5108
0.050	11.68	11.68	1	0.0479	0.5240
0.055	11.74	11.74	1	0.0855	0.5428
0.060	11.79	11.79	1	0.0999	0.5500

simultaneously consider their impact on data center operations optimization.

- 3) Considering both the uncertainty of PV output and data load simultaneously

The uncertainty of PV output and data load requests is assumed to have the same weighting coefficients. The variation of the

comprehensive uncertainty radius corresponding to different cost deviation factors is shown in Table 5.

From Table 5, it can be observed that, like the optimization results considering only PV or data load uncertainties, a cost reserve of 0.5% cannot meet the operational requirements under uncertain conditions. Due to the negative impact of uncertainty factors on the reduction of target value operating costs, the uncertainty radius of uncertain quantities increases with the increase of the cost deviation factor  $\beta$ .

TABLE 6 Variation of comprehensive uncertainty radius after adjusting the coefficients.

Cost deviation factor $\beta$	Expected operating cost/ thousand USD	Operating costs/ thousand USD	PV output uncertainty radius $\alpha^{DG}$	Data load requests uncertainty radius $\alpha^\lambda$	Comprehensive uncertainty radius $\varphi$
<0.005	<11.18	-	-	-	-
0.005	11.18	11.18	0	0.0099	0.0070
0.010	11.24	11.24	0.1032	0.0217	0.0453
0.020	11.35	11.35	0.3637	0.0217	0.1209
0.030	11.46	11.46	0.6243	0.0217	0.1964
0.040	11.57	11.57	0.8849	0.0217	0.2720
0.050	11.68	11.68	0.9604	0.0663	0.3256
0.060	11.79	11.79	1	0.0999	0.3610
0.070	11.90	11.90	1	0.0999	0.3610
0.080	12.01	12.01	1	0.1517	0.3977
0.090	12.13	12.13	1	0.1613	0.4045
0.100	12.24	12.22	1	0.2237	0.4488

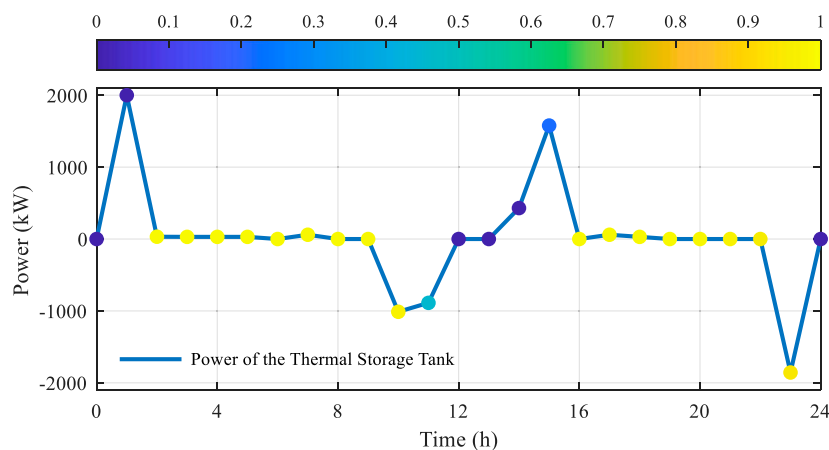


FIGURE 10 Power and state of thermal storage in thermal storage tanks.

When the cost deviation factor is less than 0.045, only the uncertainty radius of PV output increases with the deviation factor, while the uncertainty radius of data load requests remains constant at zero. When the cost deviation factor exceeds 0.045, the uncertainty radius of data load requests gradually increases. It is attributed to the relatively low penetration level of PV systems in the system, resulting in a low proportion of PV output in the total power consumption. Consequently, the uncertainty radius of PV output is more sensitive to changes in the cost deviation factor.

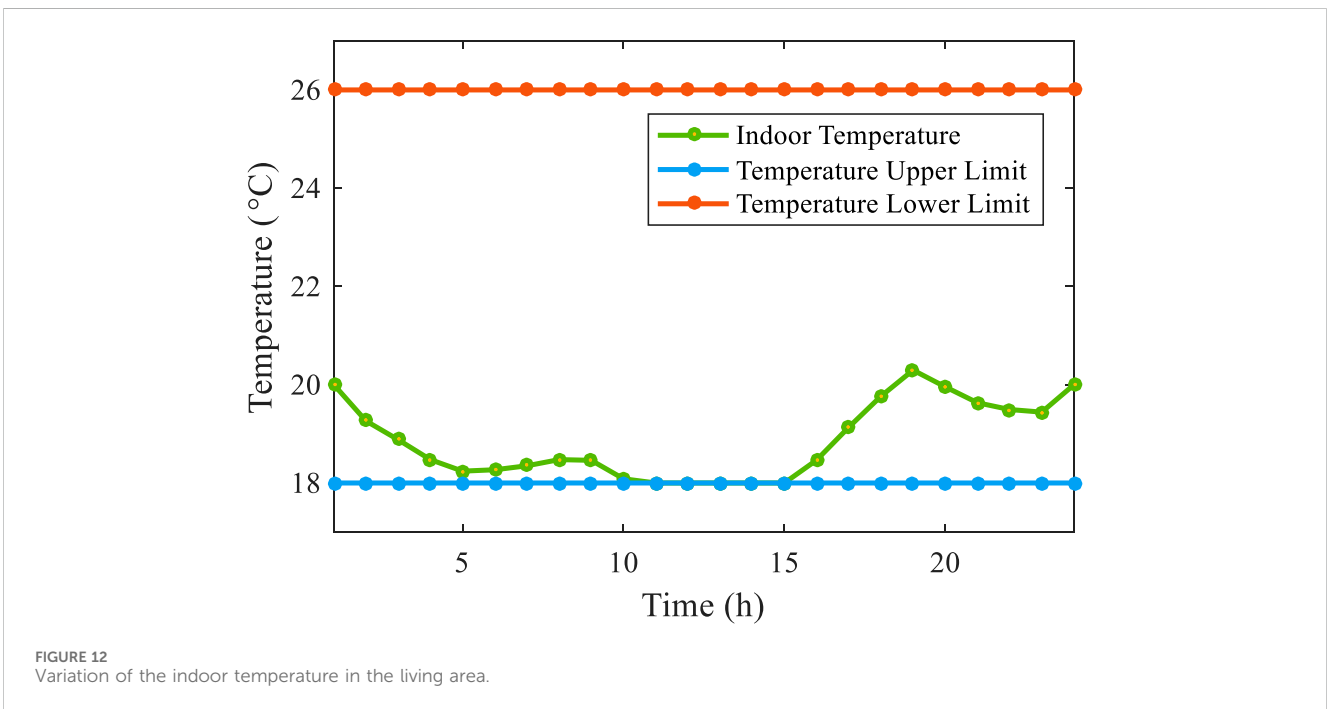
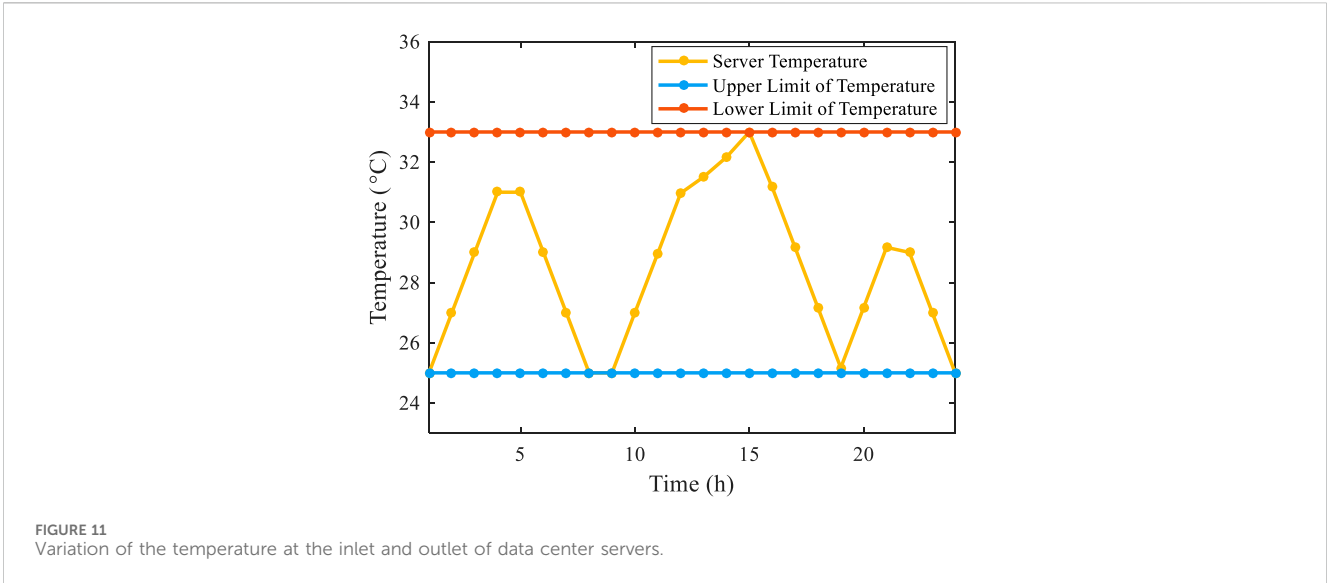
Therefore, considering the maximum values of PV output and IT devices' power consumption as the reference values, the uncertainty weighting coefficients for PV output and data load requests are redefined. In the deterministic optimization of the park, the maximum values of PV output and IT device power consumption are 500 kW and 1227 kW, respectively, with a ratio of 1:2.454. Hence, the uncertainty weighting coefficients for PV

output and data load requests, denoted as  $\epsilon^{DG}$  and  $\epsilon^\lambda$  respectively, are set to 0.29 and 0.71.

After adjusting the uncertainty weighting coefficients for PV output and data load requests, a re-analysis of the robust optimization is conducted. The comprehensive uncertainty variations corresponding to different cost deviation factors are shown in Table 6.

From Table 6, it is evident that a 0.5% cost reserve cannot meet the operational requirements of the system under uncertain conditions. As the cost deviation factor  $\beta$  increases, the expected operating cost of the park increases, and the uncertainty radius increases accordingly, leading to an increase in the operating cost of the park until it reaches maximum robustness.

Furthermore, when the cost deviation factor is set to 0.100, the actual operating cost of the park is slightly lower than the expected operating cost. It is due to the constraints imposed by



the temperature and temperature variation rate of the data center, limiting the fluctuation range of uncertain factors and preventing the operating cost from reaching the expected value. When the cost deviation factors are set to the same value, the uncertainty radius of the PV output is generally greater than that of the data load request, and it reaches 1 when the deviation factor is set to 0.6. This is because the uncertainty radius of the PV output is more pronounced compared to the IT devices' power consumption, as the PV output values are relatively low. The comprehensive uncertainty radius is numerically close to the uncertainty radius of the data load request, indicating that

the overall park is mainly affected by the uncertainty of the data load request.

#### 4.2 Analysis of the system operating strategy

To validate the effectiveness of the above methods, 100 scenarios were randomly selected with cost deviation factors less than 0.1, indicating a PV output uncertainty radius less than 1, and a data load request uncertainty radius less than 0.2237. Three comparison schemes were set up as follows:

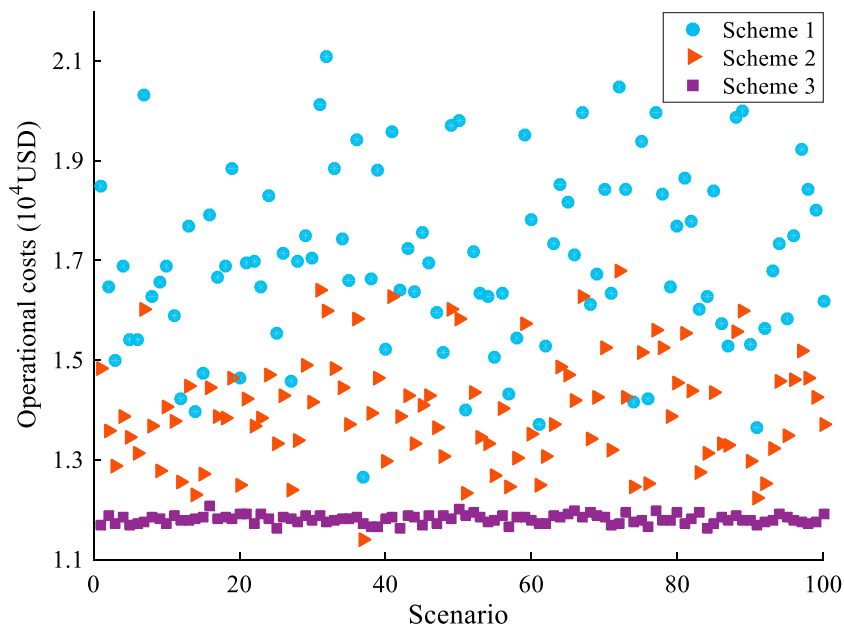


FIGURE 13 Total operating costs of the data center park.

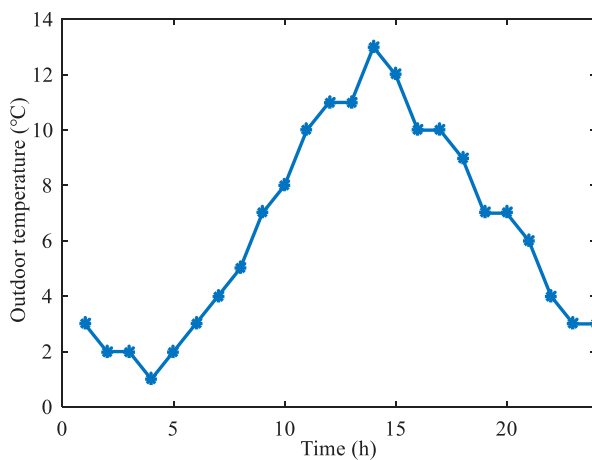


FIGURE 14 Outdoor temperature.

Scheme 1: Disregarding the influence of uncertainty factors, with a cost deviation factor set to 0, deterministic optimization scheduling is conducted for the data center using the predicted values of PV output and data load requests.

Scheme 2: Considering the influence of uncertainty factors including PV output and data load requests, with a cost deviation factor set to 0.05, optimization scheduling is conducted for the data center.

Scheme 3: Considering the influence of uncertainty factors including PV output and data load requests, with a cost deviation factor set to 0.1, optimization scheduling is conducted for the data center.

### 1) Analysis of the operational strategies

Figure 10 depicts the variation in CPU frequency of the data center's IT devices for Scheme 1. It is evident from the graph that CPU frequency is closely associated with the volume of data load processing. As the data load processing increases, the CPU frequency also rises. Additionally, it can be observed that under this strategy, the variation in server CPU frequency is relatively stable, without frequent fluctuations. This stability ensures the smooth operation of IT devices, thereby guaranteeing stable performance.

TABLE 7 Comparison of operating costs in three scenarios for data center park.

Operating costs	Scheme 1		Scheme 2		Scheme 3	
	Mean	Maximum	Mean	Maximum	Mean	Maximum
Electricity cost of IT devices/USD	2991.17	3031.41	3045.64	3097.70	3483.53	3577.39
Electricity cost of heat pump/USD	4098.53	4098.53	4320.05	4320.05	5062.15	5062.15
Total electricity cost/USD	11073.96	11330.64	11139.32	11402.81	11664.78	11957.75
Cost of data load abandonment/USD	5864.54	10042.01	2805.08	5683.76	0	0
Cost of heat load supplementation/USD	51.34	76.00	72.32	102.48	145.94	208.41
Total cost/thousand USD	16.99	21.08	14.02	16.80	11.82	12.07

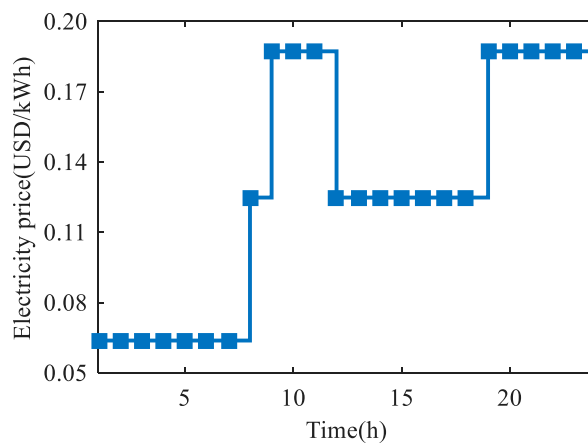


FIGURE 15 Electricity price.

Figure 11 illustrates the distribution of heat power in the living area under Scheme 3. From the graph, it can be observed that within the scheduling cycle, due to the low economic cost of waste heat recovery, the heat pump becomes the main heating method, ensuring the basic heating demand of the park. However, when the waste heat from the computer room alone cannot meet the heating demand, electric boilers will undertake part of the heating tasks to ensure that the heating load always receives sufficient heat supply.

Figure 12 illustrates the fluctuation of the power supplied by the thermal storage tank and the corresponding heat storage state during the day. During the early morning hours with lower electricity prices, heat is stored in the thermal storage tanks. Conversely, during the morning peak hours with a higher electricity price, the stored heat is released, contributing to the reduction of the operating costs of the data center park. In addition, during the peak heat load demand in the evening, the heat storage tanks are utilized in combination with heat pumps and electric boilers to effectively meet the required thermal load. This operational strategy ensures a stable supply of heating demand in the park while fully leveraging the economic advantages of waste heat recovery, thereby achieving efficient energy utilization.

2) Analysis of the operation effectiveness

Figure 13 depicts the variation of the temperatures at the inlet and outlet of data center servers for Scheme 3. It is evident from the graph that temperatures at the inlet and outlet of servers fluctuate between 25°C and 33°C. Moreover, due to the optimization method proposed in this paper, which limits the rate of temperature change of the servers within a certain range, the temperature variation of the servers shown in the graph remains relatively stable, without significant fluctuations. This stability avoids the occurrence of temperature exceedance in the server room, thereby guaranteeing stable performance.

Figure 14 depicts the variation of indoor temperatures in the living area for Scheme 3. From the graph, it is evident that the indoor temperatures in the living area remain within a comfortable range for humans, fluctuating between 18°C and 21°C. Additionally, it can be observed that under this strategy, the indoor temperatures in the living area exhibit relative stability, with minimal fluctuations. This stability ensures the comfort of individuals within the rooms, thereby guaranteeing the suitability of temperature for daily living activities.

Table 7 shows the comparison of operating costs for the three schemes in the data center park. In this study, the penalty cost for abandoning each request is set to 0.069 USD, and the shortfall in heat load is supplemented by electric boilers. From the operation results, upon accounting for the uncertainty of both PV output and data load requests, the IT devices in the data center operate at a higher frequency to accommodate the fluctuation in data load. It leads to an increase in electricity costs for IT devices and an increase in the power of heat



recovery. Additionally, the electricity costs for heat pumps also rise. Due to the low penetration rate of PV, the total electricity purchasing costs still increase under the fluctuation of PV output. Moreover, considering the uncertainty of data load results in improved computational capacity, significantly reducing the amount of discarded data load and consequently lowering the cost associated with data load abandonment. In Scheme 3, all data load requests can be processed, thus avoiding data abandonment.

However, when considering the uncertainty of data load, the power consumption of IT devices in the data center increases, and the expected power of heat recovery also increases. When the actual data load processing quantity is less than the expected value, due to the higher CPU operating frequency, the reduction in heat recovery power is more significant compared to Scheme 1. Consequently, the cost of supplementing heat load also increases. Additionally, if heat recovery is not considered and heat pumps are replaced with electric boilers for heating, the heating costs for the three schemes would increase by 899.45 USD, 946.44 USD, and 1103.86 USD, respectively. It indicates that heat recovery can effectively reduce the operating costs of data centers. Ultimately, Scheme 3 exhibits the lowest total operating cost for the data center park, demonstrating that optimizing the operation of data center parks considering uncertainty can reduce the cost of data load abandonment and make data centers operate more reliably and economically.

Figure 15 depicts the scatter plot comparing the operating costs of the data center park under three schemes across 100 randomly selected scenarios. The blue dots correspond to the deterministic operational scheme, while the orange and purple dots represent schemes considering uncertainty with cost deviation factors of 0.05 and 0.1, respectively. It can be observed from the graph that the operating costs are significantly influenced by uncertainty. When uncertainty is high, the operating costs of Scheme 1 are considerably elevated, whereas Scenario 3 demonstrates greater economic efficiency. These results underscore the importance of considering uncertainty factors in the management of data center park operations to derive the optimal operational strategy.

## 5 Conclusion

Waste heat recycling in data centers can provide energy to the living quarters of the data center park, resulting in a significant improvement in energy efficiency. This paper proposes an IGDT-based operation optimization method for multi-energy distribution systems in integrated data centers, considering the uncertainties of PV output and data load requests. Firstly, a deterministic model has been developed to capture the detailed thermal characteristics of the data center and the waste heat recovery system. Subsequently, IGDT is employed to handle the uncertainties in the PV output and data load requests. The case studies demonstrate that despite a 5.3% increase in electricity purchase costs, the total expenses decreased by 30.4%, amounting to 5.17 thousand USD. This indicates that the proposed method can significantly reduce the operating cost and data task abandonment under fluctuating conditions.

Several directions remain to be investigated in future works. First, considering the spatial and temporal regulation potential of data centers, the peak load shifting can be realized to save electricity purchase cost and improve energy utilization. Additionally, the efficiency of cooling systems is intricately linked to the placement of IT devices. Therefore, it is imperative to consider the impact of IT device placement in the optimization process.

## Data availability statement

The original contributions presented in the study are included in the article/Supplementary material. Further inquiries can be directed to the corresponding author.

## Author contributions

ZW: Conceptualization, Writing–review and editing. XL: Methodology, Validation, Writing–review and editing. HZ: Methodology, Validation, Writing–review and editing. YL: Resources, Software, Writing–review and editing. SP: Resources, Software, Writing–review and editing. TL: Data curation, Writing–review and editing. PW: Data curation, Writing–review and editing. TW: Writing–original draft, Writing–review and editing.

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## Conflict of interest

Authors ZW, HZ, SP, and PW were employed by Electric Power Research Institute of Guizhou Power Grid Co. Ltd. Authors XL, LY, TL, and TW were employed by China Southern Power Grid (CSG).

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