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Dual-drive coordinated operation strategy for internet data centers by exploiting spatiotemporal flexibility

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ABSTRACT

With the rapid expansion of computational infrastructure, the electricity consumption of geographically dispersed Internet Data Centers (IDCs) has imposed a substantial influence on the power grid. Geographically distributed IDCs, which present a versatile electricity demand with significant operational flexibility, hold potential for mitigating cost issues and balancing regional supply and load demand. To exploit this flexibility, this paper has developed a dual-drive coordinated operational strategy, which integrates locational electricity prices and unit carbon emission costs based on the dynamic carbon emission intensity (DCEI) of various regions as interaction signals to improve coordination effectiveness. The upper-level determines the consumption behaviour of IDCs, the lower-level provides feedback on dual-drive signals factoring in IDCs' involvement in grid operation, whilst an iterative algorithm is suggested to solve the bi-level model. Case studies based on real-world datasets demonstrate that the proposed operation strategy can achieve arbitrage through multi-regional carbon-electricity markets, significantly reduce operating costs, and support the rapid development of IDCs. Additionally, this strategy facilitates optimal matching of power load in IDCs with renewable energy sources, thereby mitigating imbalances in regional renewable energy supply and demand.

1. Introduction

The rapid advancement in global digital technology is attributed to the development of key technologies such as 5G, cloud computing, and the increasingly popular ChatGPT (Xu et al., 2023). The internet data center (IDC), integral to the future digital industry's information foundation, has undergone substantial expansion in construction scale. However, the rapid expansion of IDCs has resulted in significant electricity expenses and subsequent carbon emissions. In China, IDC operators may annually expend tens of millions of yuan on electricity consumption, posing a significant industry-wide concern (Liang et al., 2022). Moreover, renewable generation sites are often located far from data centers around the world and therefore rely on bulk transmission grid to meet their power demand. However, the increasing proportion of renewable energy has highlighted the issue of inefficiency of transmission lines (Andrianesis et al., 2020). This, combined with the significant energy consumption of the IDC, will worsen the regional imbalance between power supply and demand. Despite the challenges posed by IDC development, there is potential for flexibility in IDCs. This potential can effectively address these issues by leveraging the transferable characteristics of workloads in spatial and temporal dimensions.

Specifically, in terms of temporal dimension, an IDC can objectively perceive the various electricity prices across different times and locations. This information is used to efficiently schedule the workload, ultimately leading to a reduction in electricity tariffs (Li et al., 2015). Additionally, this can also impact electricity spot prices by altering the balance of power supply and demand across different zones (Guo et al., 2022). In terms of spatial dimension, the workload distribution is facilitated through the information network, which allows for a modification in the electric load distribution among IDCs located throughout various regions (Chen et al., 2014). That is, the IDC load is a distinctive one that can achieve immediate electric load transfer without relying on the power grid. This process circumvents the physical transmission limitations of the electrical network, thereby reducing transmission congestion and the investment in transmission pipeline construction (Wu et al., 2023). Moreover, as the electricity consumption of the IDC rises, this spatial and temporal flexibility will significantly ease the

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Abbreviations

ACEI	Average carbon emission intensity
DCEI	Dynamic carbon emission intensity
IDC	Internet data center
TIAC	Thermal inertia of air conditioning
BWS	Batch workload scheduling
GWB	Geographical workload balancing
LMP	Locational marginal price

NomenclatureA. Sets

N^I	Number of IDCs
N^h	Number of thermal power units
T	Set of time slots
N^w	Number of wind power units
N^s	Number of solar power units
K	Set of thermal power unit output stages

B. Parameters

p_{dy}	Electricity consumption of one workload migration
σ^{ce}	Price of carbon emission credit
a_i	Thermal power generation cost coefficient
P^{th}_{min}	Thermal power generation minimum output
$P^{s,p}_{i,t}$	Forecasted solar power output
e^{pe}_i	Electricity consumption of one server at peak state
u_i	Average workload service rate of servers
ε	Computing redundancy coefficient
P^{co}_{min}	Minimum of cooling system electricity consumption
α_i	Coefficients of performance of air conditioning
O^{in}_{min}	Minimum of indoor temperature
$\lambda^{org}_{i,t}$	Original delay-sensitive workload
P_b	Basic electricity consumption of the backbone optical switching equipment
R^{ce}	Carbon emission credit of each IDC
σ^{re}	Renewable energy curtailment penalty cost coefficient
$P^{w,p}_{i,t}$	Forecasted wind power output
$O^{out}_{i,t}$	Outdoor temperature
e^{de}_i	Electricity consumption of one server at idle state
ν	Delay tolerance of delay-sensitive work-load
H_i	Maximum number of available servers
P^{co}_{max}	Maximum of cooling system electricity consumption
τ	Delay tolerance of delay-tolerant workload
O^{in}_{max}	Maximum of indoor temperature
$\chi^{org}_{i,t}$	Original delay-tolerant workload

C. Variables

C^{pro}	Electricity procurement expenses
C^{ce}	Costs associated with cap-and-trade
$\gamma_{i,t}$	Locational marginal price
$\chi_{i,t}$	Delay-tolerant workload after migration
C^{th}	Thermal generation operation cost
$P^{th}_{i,t}$	Output of thermal generation
$x^{th}_{i,t}$	State of thermal generation
$P^{w}_{i,t}$	Wind power accommodation
$P^{wor}_{i,t}$	Electricity consumption of workload processing
$P^{au}_{i,t}$	Electricity consumption of other auxiliary facilities
$m^{w\chi}_{i,t}$	Number of servers processing tolerant workload
$P^{fac}_{i,t}$	Cooling system capacity
C^{mig}	Extra costs for workload migration
$P^{IDC}_{i,t}$	Electricity consumption of IDC
$\lambda_{i,t}$	Delay-sensitive workload after migration
$\delta_{i,t}$	Dynamic carbon emission intensity
C^{re}	Renewable energy curtailment penalty
$Q^{re}_{i,t}$	Renewable energy curtailment
$P^{th}_{k,i,t}$	Thermal generation output at k stage
$P^{s}_{i,t}$	Solar power accommodation
$P^{co}_{i,t}$	Electricity consumption of cooling system
$m^{w\lambda}_{i,t}$	Number of servers processing delay-sensitive workload
$m^{wor}_{i,t}$	Number of all servers processing workload
$\beta_{i,t}$	Coefficient Of Performance

disparity between resource reserves and regional development. China has recently proposed the 'Channel Computing Resources from the East to the West' strategy. This involves guiding data resources from the eastern region of the country, which is rich in data, to the western region, which has abundant natural resources. The objective of this strategy is to address the issue of unbalanced renewable energy generation and demand between the two regions.

The IDC is responsible for substantial indirect carbon emissions as a result of its extensive use of electric energy. Even though carbon emissions stem primarily from electricity production, the demand-side should strive to promote the use of low carbon electricity (Cheng et al., 2020; Kang et al., 2015). The significant reliance of IDCs on electrical energy calls for greater responsibility in reducing carbon emissions. In Beijing, China, IDCs have been included in carbon trading markets (Li et al., 2023; Tian et al., 2024), thus providing economic incentives beyond electricity prices to encourage IDCs to reduce their carbon emissions. For carbon trading, a cap-and-trade carbon market is implemented for IDCs, including carbon emission credit (CEC) allocation, CEC trading and settlement. A mandatory cap on the total carbon emissions of IDCs is regulated by government. The IDCs can purchase the CEC inadequacy from the market, and sell the surplus CEC back. Based on this method, the IDCs then plan to transfer the load of electric energy to regions or times with more renewable energy. This enables them to reduce carbon emissions indirectly, as they can sell more excess CEC and profit economically. So, there are two driving forces, from electricity market and carbon market, respectively, for the IDCs reducing the whole operation cost.

1.1. Literature survey

Many researches have proposed methods for optimizing costs in the face of IDC huge power consumption. Researches in this field primarily concentrates on energy management solutions for IDCs. This includes optimizing the data task processing strategies (Kwon et al., 2018), scheduling server working modes (Hogade et al., 2018), and regulating cooling equipment in server rooms (Cupelli et al., 2018). The literature (Wong, 2016) addresses the problem of inefficient energy utilization by heterogeneous servers and discusses the problem of cluster scheduling of energy-proportional servers, where business scheduling is performed based on the peak efficiency of each server, rather than distributing the workload evenly across each server. This reduces the overall energy consumption of the servers and achieves cost optimization. The literature (Chen et al., 2021b) shows that the thermal delay effect in the thermal system can be utilized to treat the IDC as heat storage equipment. By making reasonable adjustments to the cooling system air temperature, it is possible to optimize cooling energy consumption. The literature (Wang

Table 1
Existing literatures about flexibility of IDCs.

Literature	Energy-save	Market mechanism	Temporal flexibility	Spatial flexibility	ACEI	DCEI
This Paper	✓	✓	✓	✓	×	✓
Kwon et al. (2018)	✓	×	✓	✓	×	×
Hogade et al. (2018)	✓	×	×	×	×	×
Cupelli et al. (2018)	✓	×	×	×	×	×
Wong (2016)	✓	×	×	×	×	×
Chen et al. (2021b)	✓	×	✓	✓	×	×
Xiao et al. (2023)	×	✓	✓	✓	✓	×
(Chen et al., 2021a)	×	✓	✓	×	×	×
Chung et al. (2022)	×	×	✓	✓	×	×
Tao et al. (2023)	✓	×	✓	✓	×	×
Zhang et al. (2022)	×	✓	✓	✓	×	×
Zhang et al. (2023)	×	×	✓	✓	×	×
Li et al. (2023)	×	✓	✓	✓	✓	×

et al., 2013) have demonstrated that increasing the cooling system air temperature by 1 °C can reduce the demand for electricity by 4.3 %–9.8 %. However, with the development of the electricity market, IDCs no longer solely reduce lower energy consumption to optimize costs, instead, they aim to seek both cross-spatiotemporal and cross-market arbitrages through their spatiotemporal flexibility. The literature (Xiao et al., 2023) proposes to adjust IDC operational strategies, including workload scheduling, server control, and storage system operation, to cater to predicted electricity prices. These adjustments enable the IDC to decrease power consumption during peak tariff hours and increase power consumption during low tariff hours.

Many researches have explored the beneficial role that spatiotemporal flexibility of IDCs plays in the operation of power grids. The literature (Chen et al., 2021a) proposes a two-stage generation and transmission expansion model considering the spatial and chronological load regulation for demand response. The simulation results show that IDC can play a role equivalent to power lines and generators in the system planning. The literature (Chung et al., 2022) suggests using an energy management system to integrate and control all energy resources within an IDC, which participates in the power grid operation as the primary regulating resource of the virtual power plant. The modelling results demonstrate that the operational framework can alleviate grid transmission congestion. The literature (Tao et al., 2023) proposes a novel co-optimization model for integrated electricity-gas-heat urban energy systems to improve resilience during extreme events, and models and analyses the optimal operation, workload redistribution and waste heat reuse of IDCs. The literature (Zhang et al., 2022) provides a detailed demonstration of how IDC spatiotemporal flexibility can improve the accommodation of renewable energy. It is highlighted that IDCs can be guided to transfer their workloads to areas where renewable energy is more available, and electricity prices are relatively low due to output of renewable energy. In (Zhang et al., 2023), a novel multi-level coordinated planning model for multiple energy hubs, considering the spatiotemporal flexibility of IDCs, is proposed to jointly optimize the structures and capacities of geographically dispersed energy hubs and their interconnection lines and pipelines.

Furthermore, in order to achieve China's '3060 carbon target', the carbon market has emerged as a critical policy tool in China. The carbon market utilizes incentives rather than punishments to encourage energy-consuming entities to adopt low-carbon practices. Currently, available literature shows that energy-consuming companies can participate in both the electricity and carbon markets simultaneously, with clear feasibility and benefits (Jiang et al., 2023; Yan et al., 2023; Cheng et al., 2020). However, limited research has explored the viability of IDCs, which represent one of the fastest-growing energy consumption entities. Pilot studies have been conducted in some cities to address this issue. For instance, IDCs are allowed to trade into carbon market in Beijing (Li et al., 2023). However, the current trading mechanism has a significant flaw: it uses a fixed "average carbon emission intensity (ACEI)" to represent the carbon dioxide emitted by the unit electricity consumption of IDCs (Chen et al., 2024). As a result, IDCs that prefer low-carbon renewable energy are not suitably incentivized, and the flexibility of IDCs to match spatiotemporal differences in multi-regional carbon intensities is not reflected. The dynamic carbon emission intensity (DCEI) calculated by carbon emission flow (Kang et al., 2015) offers a precise approach for identifying carbon emission responsibility. This method has the ability to trace carbon flow and detect changes in electricity consumption brought about by workload migration across multiple IDCs. Accurate carbon accounting is beneficial for IDCs to achieve more benefits from the carbon market.

As mentioned above, many studies have focused on the spatiotemporal flexibility of IDCs, as summarized in Table 1. Nevertheless, to the best of our knowledge, there has been little research on modelling the interactive gaming process between IDCs and the grid, and none have examined the impact of spatiotemporal flexibility on market clearing outcomes. Furthermore, there is limited research on how IDC flexibility benefits the grid by reducing imbalances between regional power supply and demand within the context of the existing 'Channel Computing Resources from the East to the West' strategy. Moreover, previous researches on IDCs' involvement in carbon markets have neglected the influence of their flexibility on carbon emission intensities, and have not integrated carbon market mechanisms to enhance operational flexibility. It is important to consider the impact of IDC flexibility on emissions, further to incorporate carbon market mechanisms for improving operational flexibility.

1.2. Research question and contributions

IDCs can actively schedule their power loads spatiotemporally, which may lead to cross-time and cross-market arbitrage behaviors under different market mechanisms. This spatiotemporal flexibility not only reduces high electricity procurement tariff but also enhances the operational flexibility of the power grid through proper demand response. However, as the proportion of IDC power loads penetrating the grid increases, the trading of IDCs in the market may affect other market participants and market outcomes, such as locational marginal prices (LMPs). Therefore, it is critical to design the way in which IDCs interact with the grid in a coordinated manner to achieve maximum advantages of spatiotemporal flexibility. Moreover, this interaction suggests that traditional market decision-making models that rely on price followers are no longer applicable. Describing the unique spatiotemporal adaptability of IDCs can aid grid decision-makers in formulating more rational electricity market criteria and operational decisions. This is crucial for achieving coordinated interactions between IDCs and the grid. Furthermore, in the context of "dual carbon target", the carbon market is a vital policy tool for China to decrease carbon emissions. Energy-intensive enterprises, such as IDCs, have a significant responsibility to fully integrate into the carbon market for low-carbon purposes. It is crucial to analyze the impact of this inclusion on the spatiotemporal flexibility of operational decisions.

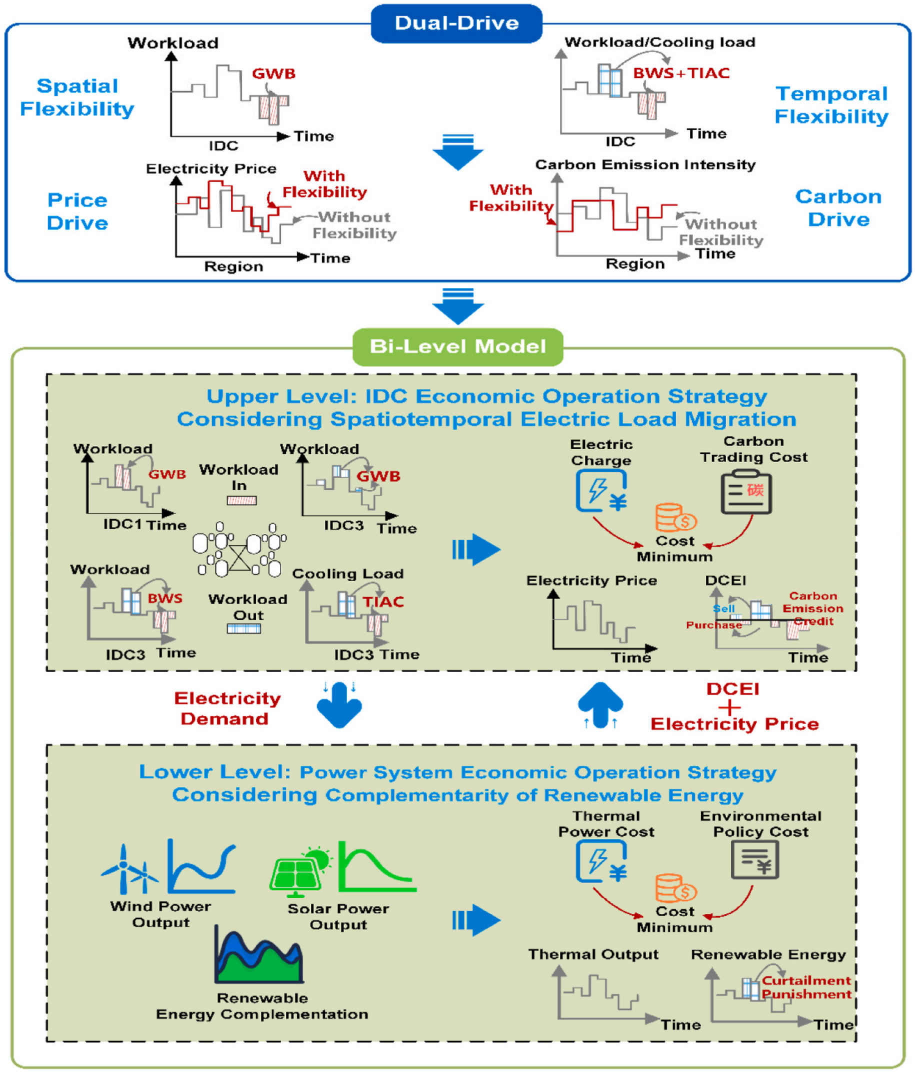


Fig. 1. Dual-drive coordination framework.

The above discussions motivate us to answer the following key questions in this paper.

1) How to portray the spatiotemporal flexibility of the IDC and their impact on participation in market transactions.
2) How can the mutually independent game interaction between IDCs and power grids be reflected in market transactions, including electricity markets and carbon markets?

The paper presents a novel power consumption model for IDC that considers various scheduling methods to demonstrate IDC flexibility and provide a basis for investigating its participation in market transactions. Then, the paper proposes a coordinated bi-level optimization model. The upper-level determines the consumption behavior of IDCs, while the lower-level simulates the electricity market clearing, and provides spot price feedback as interaction signals, taking into account IDCs' involvement in grid operation. The model illustrates the interaction between the IDC and the grid as a mutually independent game through the transfer of decision-making signals between the upper and lower levels. The iterative solution algorithm of the model enables the upper model to modify its operation strategy based on price signals, including electricity prices and unit carbon emission costs. Similarly, the lower model can adjust its power supply structure based on the upper model's electricity demand, creating a new price signal and iterating with each other. This approach considers the impact of IDC market trading on market outcomes and maximizes operational flexibility through game interactions.

On the premise of the proposed coordinated optimization operation strategy considering the flexibility of IDCs, some important conclusions are drawn: the flexible power consumption of IDCs will affect the electricity market clearing, and IDCs are not only a "price taker" but more like a "price maker"; the price difference of the interregional electricity market will encourage IDCs to schedule their power consumption to exploit a new point of cost reduction; and the participation of the carbon market further improves the operational flexibility of IDCs.

The main contributions of this paper are listed as follows.

1) A bi-level coordination framework is designed that aims to optimize the utilization of spatiotemporal flexibility in geographically distributed IDCs by integrating complementary renewable energy sources from multiple regions. To address the coordination challenges between computing and power, this paper proposes a dual-drive incentive mechanism that combines locational electricity prices and unit carbon emission costs. The designed framework regards the dynamic carbon emission intensity of various regions as interaction signals to enhance coordination incentives.

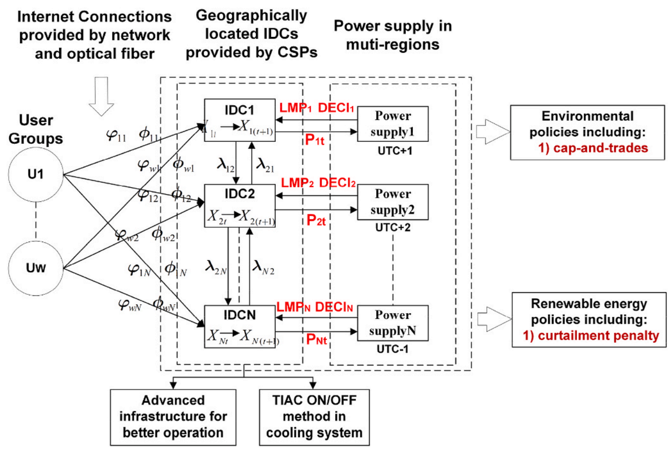


Fig. 2. Proposed bi-level optimization model framework.

2) To accurately depict the interconnection between IDCs' operations and their contribution to power system flexibility, this paper introduces a novel IDC loading model that encompasses multiple electrical components and interconnected scheduling methods. This model facilitates a precise synchronization of workloads across multiple IDCs with the renewable energy outputs from various regions. Moreover, it incorporates a real-time cooling system management based on TIAC to bolster the flexibility of geographically distributed IDCs while maintaining workload reliability.
3) To address the limitations of the current carbon market mechanism for IDC participants, this paper employs the DCEI approach, which relies on carbon emission flow tracing to determine the actual carbon responsibilities. In contrast to the fixed ACEI, DCEI enables geographically distributed IDCs to optimize their electricity consumption scheduling by capitalizing on the spatiotemporal variations in carbon emissions, which leads to increased benefits from the carbon market.

2. Dual-drive coordination framework

The IDC serves as a physical bridge facilitating the deep integration of computing and electric power. The IDC promotes the digital transformation of the power system, while the power system supplies efficient and low-carbon renewable energy for the IDC. Fig. 1 illustrates the dual-drive coordination framework in which the spatiotemporal flexibility of geo-distributed IDCs is exploited.

Firstly, in order to overcome any interaction barriers between two industries, this paper has developed a dual-drive incentive mechanism which is based on marginal electricity prices and unit carbon emission cost based on DCEI. The growing electricity consumption of IDCs across various spatial and temporal dimensions has significant implications for regional market clearing outcomes and carbon emissions. IDCs are no longer passive recipients of electricity prices and carbon emission intensities; they are now active, as they are able to make a difference in these domains. Therefore, a bi-level model based on iterative solution is built for the considering the impact between IDCs and power system. Secondly, three scheduling methods (GWB, BWS and TIAC) are implemented in the upper level controlling IDCs' operation. With the help of these scheduling methods, a single IDC can reasonably optimize its workload processing strategies through coupled scheduling methods to get benefits from the difference of regional markets for cost reduction. Thirdly, the complementarity of spatiotemporal distribution of renewable energy in multiple regions is considered in the lower-level power system operation. With the help of this complementarity, the efficiency of renewable energy accommodation has been improved, thus promoting the economy of system operation. Furthermore, some policy constraints attach to the operation of power system for further increasing the accommodation of renewable energy, thereby providing lower LMPs and DECIs for activating IDCs to change in electricity consumption along the spatial and temporal dimensions. Therefore, the coordination framework fully reflects the advantage of spatiotemporal flexibility for IDCs distributed across geographic regions.

3. The dual-drive coordination model

To present the coordinated operation between computing power and electric power, this paper proposes a bi-level optimization coordination model considering two driving forces: electricity prices, and unit carbon emission costs based on DCEI as shown in Fig. 2.

As shown in Fig. 2, the objective of this model is to depict how the spatiotemporal flexibility of IDCs contributes to achieving the optimal operation of both IDCs and the power system. The upper-level model receives the real carbon emission intensity signals and electricity price signals from the lower-level model, to schedule the time slot and location of workload processing, that is, to adjust the electric demand, realizing the minimum operational cost under the premise of quality of service. Similarly, the lower-level model receives the electric demand signals transmitted by the upper-level model, to schedule the outputs of generating units, that is, to adjust the electric supply. Both upper and lower levels are solved iteratively in this model.

3.1. Upper-level model

The upper-level model is to minimize the total operating cost of the IDCs during one day, including the electricity procurement expenses, the extra costs for workload migration in geo-distributed IDCs, and the costs associated with cap-and-trade carbon market, which is formalized by (1):

$$\min \; C^{pro} + C^{mig} + C^{ce} \tag{1a}$$

Subject to:

$$C^{pro} = \sum_{i=1}^{N^I} \sum_{t=1}^{T} P_{i,t}^{IDC} \gamma_{i,t} \tag{1b}$$

$$C^{mig} = \sum_{i \in N^I} \sum_{t \in T} \gamma_{i,t} \left\{ p_{dy} \left(\left| \lambda_{i,t} - \lambda_{i,t}^{org} \right| + \left| \chi_{i,t} - \chi_{i,t}^{org} \right| \right) + P_b \right\} \tag{1c}$$

$$C^{ce} = \sum_{i=1}^{N^I} \sum_{t=1}^{T} \sigma^{ce} \left(\delta_{i,t} P_{i,t}^{IDC} - R^{ce} \right) \tag{1d}$$

$$\mathbb{F}\left(\lambda_{i,t}, \chi_{i,t} \right) \tag{1e}$$

Constraint (1b) represents the cost of electricity procurement which is the product of electricity consumption and electricity price. Constraint (1c) represents the cost of workload migration mainly coming from the extra electricity consumption of the core switching equipment. Constraint (1d) describes the costs associated with carbon emission. $\delta_{i,t}$ is the dynamic carbon emission intensity in region where IDC i is located, and it is obtained by the lower-level model, where the detailed derivation process is shown in **APPENDIX**. $\delta_{i,t} P_{i,t}^{IDC} - R^{ce} > 0$ indicates that the IDC i purchases the carbon allowance, and $\delta_{i,t} P_{i,t}^{IDC} - R^{ce} < 0$ means the carbon allowance is sold. Constraint (1e) describes the IDC loading model (decision variable $\lambda_{i,t}$ and $\chi_{i,t}$) which is shown in **Section 3.3**.

3.2. Lower-level model

The lower-level model is to minimize the thermal generation operation cost, considering renewable energy curtailment penalty shown in (2).

$$\min \; C^{th} + C^{re} \tag{2a}$$

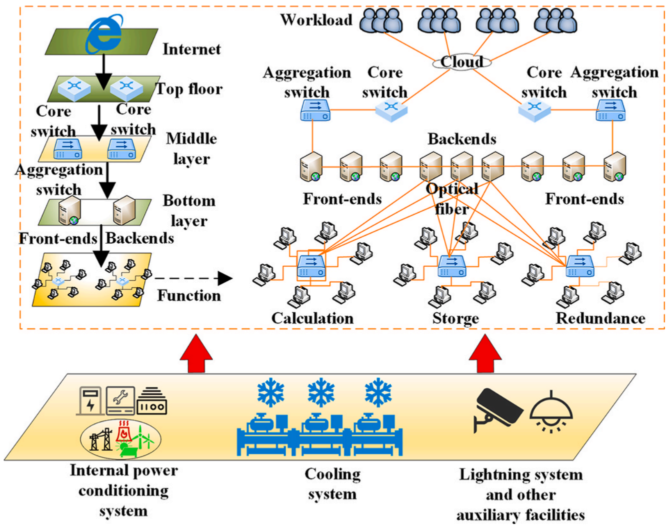


Fig. 3. IDC operation when the workloads arrive.

Subject to:

$$C^{th} = \sum_{t=1}^{T} \sum_{i=1}^{N^I} \left[a_1 \left(P^{th}_{i,t} \right)^2 + a_2 P^{th}_{i,t} + a_3 \right] \tag{2b}$$

$$C^{re} = \sum_{t=1}^{T} \sum_{i=1}^{N^I} \boldsymbol{\sigma}^{re} Q^{re}_{i,t} \tag{2c}$$

$$P^{th}_{i,t} = P^{th}_{\min} x^{th}_{i,t} + \sum_{k=1}^{K} P^{th}_{k,i,t} \tag{2d}$$

$$P^{w,p}_{i,t} + P^{s,p}_{i,t} = P^{w}_{i,t} + P^{s}_{i,t} + Q^{re}_{i,t} \tag{2e}$$

$$\sum_{k\in\Omega_x^K} P^{th}_{k,t} + \sum_{m\in\Omega_x^M} P^{w}_{m,t} + \sum_{f\in\Omega_x^F} P^{s}_{f,t} - \sum_{x\in\Omega_x} P^{l}_{xy,t} = \sum_{i\in\Omega_x^I} P^{IDC}_{i,t} + D_t : [\boldsymbol{\gamma}_{\mathbf{i,t}}] \tag{2f}$$

Constraints (2b) represents the operating costs of thermal units. In constraint (2c), renewable energy curtailment is punished for promoting more accommodation. Constraints (2d) represents the piecewise linearization of thermal power units, but the flexibility transformation constraints (such as ramping, back up and so on) will not be described in this section due to space limitations (Wu et al., 2023). Constraint (2e) represents the relationship between renewable energy accommodation and curtailment. Constraints (2f) represents the balance between electricity demand and supply in regional x. Ω_x^k, Ω_x^M, Ω_x^F, Ω_x^i Ω_x are the set of thermal power units, renewable energy units, data centers, and nodes connected to node x, respectively. $P^l_{xy,t}$ is the power flow from node x to node y, D_t is the common electric load without flexibility. According to the definition of the LMP, the dual variable of constraint (2f) is $\gamma_{i,t}$ in constraint (1b).

3.3. IDC loading model considering three scheduling methods

In traditional operation mode, IDC operators focus primarily on electricity consumption and cost, while power system operators consider both the electric load curve of the IDC and its flexibility in electricity consumption to effectively manage this flexible resource. Therefore, it is imperative to conduct a comprehensive analysis and assessment of the flexibility in coordination with the power grid.

It is necessary to comprehend the effects of the IDC's behavioral decisions under diverse scheduling methods. Accordingly, an IDC loading model considering three scheduling methods serves as a foundation to examine the coordination and interaction between the IDC and the power system. Fig. 3 shows the IDC operation when the workloads arrive. The electricity consumption of each IDC can be characterized by four parts when the workloads are processed, including basic IT equipment, the redundant system, the cooling system, and other auxiliary facilities. Additionally, this paper implements three scheduling methods including GWB, BWS and TIAC in this modeling. Moreover, the workloads are divided into delay-sensitive workloads and delay-tolerant workloads based on delay sensitivity. The load electricity consumption model of IDC i is formulated in (3).

$$P^{IDC}_{i,t} = P^{wor}_{i,t} + P^{co}_{i,t} + P^{au}_{i,t} \tag{3a}$$

3.3.1. Modelling basic IT equipment

The electricity consumption of IT equipment is the most important component of IDCs, accounting for approximately 45 % of their total electricity consumption. The model is shown as follows:

$$P^{wor}_{i,t} = m^{wor}_{i,t} e^{de}_i + \left(e^{pe}_i - e^{de}_i\right)\left(\lambda_{i,t} + \chi_{i,t}\right) \Big/ u_i \tag{3b}$$

$$m^{w\lambda}_{i,t} = \lambda_{i,t} \Big/ \left(u_i - 1/\nu\right) \tag{3c}$$

$$m^{w\chi}_{i,t} = \chi_{i,t} / u_i \tag{3d}$$

$$m^{w\lambda}_{i,t} + m^{w\chi}_{i,t} = m^{wor}_{i,t} \tag{3e}$$

$$\sum_{t=1}^{T} m^{wor}_{i,t} \le (1-\varepsilon) H_i \tag{3f}$$

Constraints (3b) describe the electricity consumption of basic IT equipment when workloads are processed. Constraint (3b) is a typical regression model showing the correlation between the electricity consumption and the computing utilization (Wu et al., 2021). Constraints (3c) - (3e) describe the power relationship between active servers and workloads. Constraints (3f) describes the number of servers used for workload processing cannot exceed the number of servers available in the IDC i..

3.3.2. Modelling cooling system

The electricity consumption of the cooling load is the second most important component of IDCs, accounting for approximately 43 % of the total electricity consumption. Therefore, it is vitally important to accurately depict the expression. The model is shown as follows:

$$P^{co}_{i,t} = \beta_{i,t} P^{fac}_{i,t} + P^{co}_{\min} \tag{3g}$$

$$\beta_{i,t} = 1 \Big/ \left(\alpha_1 \left(O^{out}_{i,t} \right)^2 + \alpha_2 O^{out}_{i,t} + \alpha_3 \right) \tag{3h}$$

$$P^{co}_{\min} \le P^{co}_{i,t} \le P^{co}_{\max} \tag{3i}$$

Constraints (3g) - (3h) describe the relationship between the electricity consumption of the cooling system and the cooling power facility outputs, where $\beta_{i,t}$ represents the coefficient of performance of air conditioning derived from repeated experiments. Constraints (3i) specifies the upper and lower limits of cooling power.

3.3.3. Modelling three scheduling methods

The diversity in delay tolerance of workloads endows the multiple geo-distributed IDCs with the spatial and temporal flexibilities in electricity consumption. Moreover, the electricity usage of the cooling system can be dynamically scheduled in response to heat inertia. Three scheduling methods are implemented to characterize above spatiotemporal flexibility, modeled as follows:

$$\sum_{i=1}^{N^I} \lambda_{i,t} = \sum_{i=1}^{N^I} \lambda^{org}_{i,t} \tag{3j}$$

$$\sum_{i=1}^{N^I}\sum_{t=1}^{t}\chi_{i,t} \leq \sum_{i=1}^{N^I}\sum_{t=1}^{t}\chi_{i,t}^{org} \quad \forall t \in T \tag{3k}$$

$$\sum_{i=1}^{N^I}\sum_{t=1}^{t+\tau}\chi_{i,t} \geq \sum_{i=1}^{N^I}\sum_{t=1}^{t}\chi_{i,t}^{org} \quad \forall t \in [1, T-\tau] \tag{3l}$$

$$\Phi\frac{dO_{i,t}^{in}}{dt} + \frac{1}{\theta}O_{i,t}^{in} - \left[O_{i,t}^{out} - \Lambda\left(P_{i,t}^{fac} - P_{i,t}^{wor} - P_{i,t}^{oth}\right)\right] = 0 \tag{3m}$$

$$O_{i,t}^{in} = e^{-\frac{\Delta t}{\Phi\theta}}O_{i,t-1}^{in} + \theta\left(1 - e^{-\frac{\Delta t}{\Phi\theta}}\right)\left[O_{i,t}^{out} - \Lambda\left(P_{i,t}^{fac} - P_{i,t}^{wor} - P_{i,t}^{oth}\right)\right] \tag{3n}$$

$$O_{\min}^{in} \leq O_{i,t}^{in} \leq O_{\max}^{in} \tag{3o}$$

Constraint (3j) represents GWB scheduling method, where workloads with spatial migration are same with the initial workloads. Constraints (3k) - (3l) represent BWS scheduling method, where workloads can be migrated in maximum delay tolerance τ. Constraints (3m) - (3o) represent TIAC scheduling method, where cooling facilities can schedule their outputs based on thermal inertia effect. Φ, θ and Λ are parameters according to the individual characteristics of the IDC, which are associated with the heat transfer coefficient, total area and so on (Sun et al., 2019; Chen et al., 2021b). Δt represents the duration of time slot. Moreover, the constraints (3m) - (3n) indicate that there exists a coupling relationship among three scheduling methods, because the outputs of cooling facilities are affected by two kinds of workload migration. Constraint (3o) specifies the upper and lower limits of indoor temperature.

3.4. Solution algorithm

The solution algorithm is fully detailed in Algorithm 1. First, input the initial parameters for both upper and lower models. Second, initiate the solution algorithm including the number of iterations to zero (s = 0), the convergence criterion (C(s+1)-C(s) < 0.001) and the decision variables ($\lambda_{i,t}$, $\chi_{i,t}$, $x_{i,t}^{th}$, $P_{i,t}^{wor}$, $P_{i,t}^{co}$ and $P_{i,t}^{th}$). Then, start the iteration for addressing the bi-level optimization problem: update its decision variables $\lambda_{i,t}$ and $\chi_{i,t}$ for the upper model, and convert the decision variables $P_{i,t}^{wor}$ and $P_{i,t}^{co}$ according to (3b) and (3g); Once the upper model has updated its decision variables, the lower model will likewise update its decision variable $x_{i,t}^{th}$ and converts the decision variable $P_{i,t}^{th}$ based on (2d); Following that, $\gamma_{i,t}$ (LMP) and $\delta_{i,t}$ (DCEI) should be computed applying duality theory and carbon emission flow, correspondingly. Finally, if the difference between two iterations of the upper model objective function is less than 0.001$ (C(s+1)-C(s) < 0.001), the convergence criterion is met. The iterative solution will be terminated, and the decision variables of IDCs will become outputs. If not, the LMP and DCEI will be fed back to the upper model, and the iterative process will continue until the convergence criterion is satisfied.

Algorithm 1. Solution algorithm for addressing the bi-level optimization problem

Input: System parameters, server parameters and workload parameters of each IDC
Initialize: s=0; decision variables $\lambda_{i,t}$, $\chi_{i,t}$, and $x_{i,t}^{th}$; converted decision variables $P_{i,t}^{wor}$, $P_{i,t}^{co}$ and $P_{i,t}^{th}$
while (C(s+1)-C(s)<0.001)
  for upper-level model **do**
    Update $\lambda_{i,t}^{s+1}$, $\chi_{i,t}^{s+1}$, $P_{i,t}^{wor,s+1}$ and $P_{i,t}^{co,s+1}$ according to (3b) and (3g)
  end
  Update $x_{i,t}^{th,s+1}$ and $P_{i,t}^{th,s+1}$ according to (2d)
  Calculate $\gamma_{i,t}^{s+1}$ according to duality theory
  Calculate $\delta_{i,t}^{s+1}$ according to carbon flow
  s=s+1
end
Output: LMP, DCEI, operation strategy of each IDC

4. Case study

Based on the strategic deployment of "Channel Computing Resources from the East to the West", three IDCs geographically dispersed across three time zones are selected: the GMT+8, GMT+7 and GMT+6, which are numbered IDC 1, IDC 2 and IDC 3, respectively. In addition, real-world data are adopted in this case study whereby each IDC uses renewable energy generated locally, based on the output data from the same typical day as that of the location. One hour is chosen as a time slot in this paper. The other key parameters are set in Table 2.

Table 2
Parameter setting.

Parameter	Unit	Value
Basic Parameter of IDC's Servers (Gu et al., 2015; Yuan et al., 2022; Chen et al., 2021b)		
e_i^{pe}, e_i^{de}	MW	0.00072/0.00032
p_{dy}	MW/Mbit	0.00128
p_b	MW	0.00172
u_i	Mbit	20
v	s	0.1
τ	h	7
Basic Parameter of IDC's Cooling System (Sun et al., 2019; Chen et al., 2021b)		
α_1, α_2, α_3	/	0.0068/0.0008/0.458
β_2	MW	2
O_{min}^{in}, O_{max}^{in}	°C	25/15
Φ	MW/°C	1/1.4
θ	°C/MW	1.4
Λ	°C/MW	1.01
Basic Parameter of Environmental Policy (Chen et al., 2018)		
σ^{ce}	$/MW	6
σ^{re}	$/MW	10

Table 3
Cost result under three scenarios.

Scenario	Electricity cost ($)	Migration cost ($)	Carbon cost ($)
S 1	17618.0	0.0	1443.0
S 2	13294.8	1930.4	1345.8
S 3	13064.7	2171.6	−1011.3

To demonstrate the advantage of the dual-drive coordination model, three scenarios are designed for comparison as follows.

1) S 1 is a benchmark, in which the spatiotemporal flexibility is not activated, and indirect carbon emission is calculated by average carbon emission intensity (ACEI) provided by the authority;
2) S 2 refers to a comparative scenario, in which spatiotemporal flexibility is activated, and indirect carbon emission is calculated by average carbon emission intensity (ACEI);
3) S 3 is the proposed coordinated operation considering the three coupled scheduling method, which includes the workload migration and cooling system spatiotemporal flexibility of IDCs, and indirect carbon emission is calculated by DCEI according to carbon emission flow tracing.

4.1. Effect of spatiotemporal flexibility on IDC costs

To evaluate the value of the spatiotemporal flexibility activated by the dual-drive coordination, S 1 is chosen as the benchmark and compare it with the remaining scenarios one by one. The cost results are shown in Table 3, which is composed of electricity cost, migration cost and carbon emission cost.

4.1.1. Electricity cost

The IDC's spatiotemporal flexibility allows transfer of delay-sensitive or delay-tolerant workloads among geographically separated IDCs and during off-peak periods. This also enables managing the cooling system through ambient temperature to conserve electricity, ultimately reducing costs for the dispersed IDCs. The variation of electricity cost under three scenarios is shown in Fig. 4, which is composed of 9 sub-charts, each of which represents the electricity cost variation of different IDCs. The circle represents the amount of the processed workloads in the current scenario. The color of the circle represents the electricity consumption of the cooling system, in which warm colors represent high electricity consumption and cool colors represent low electricity consumption. Fig. 5 shows the variation of the electricity consumption for cooling system under three scenarios.

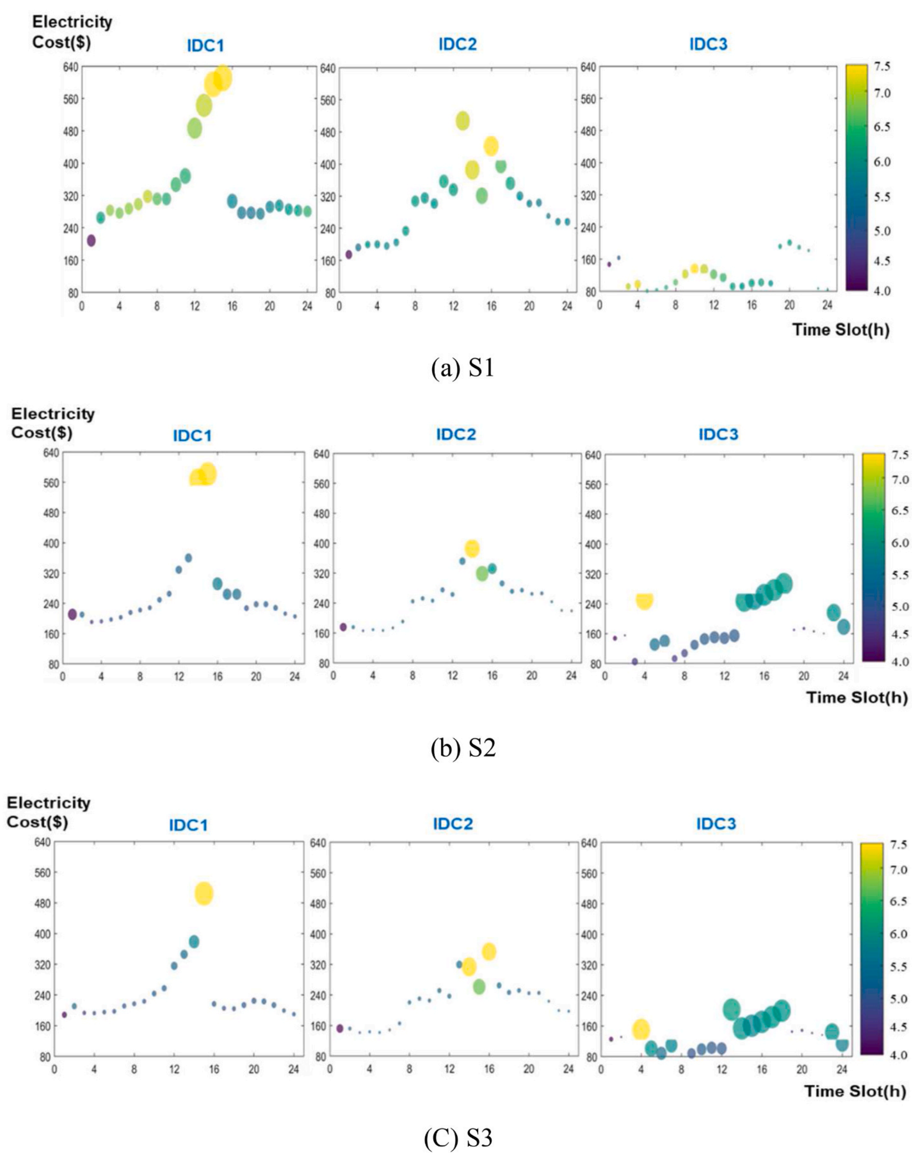


Fig. 4. The variation of electricity cost under three scenarios. (a) S 1, (b)S 2, (c)S 3.

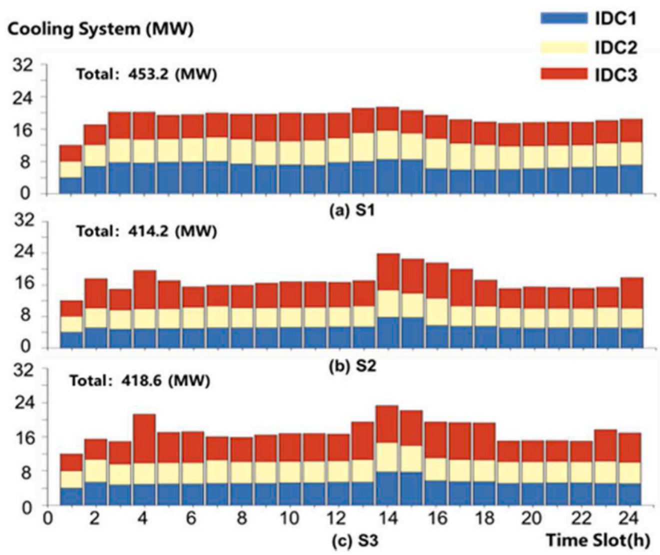


Fig. 5. The variation of cooling system electricity consumption. (a)S 1, (b)S 2, (c)S 3.

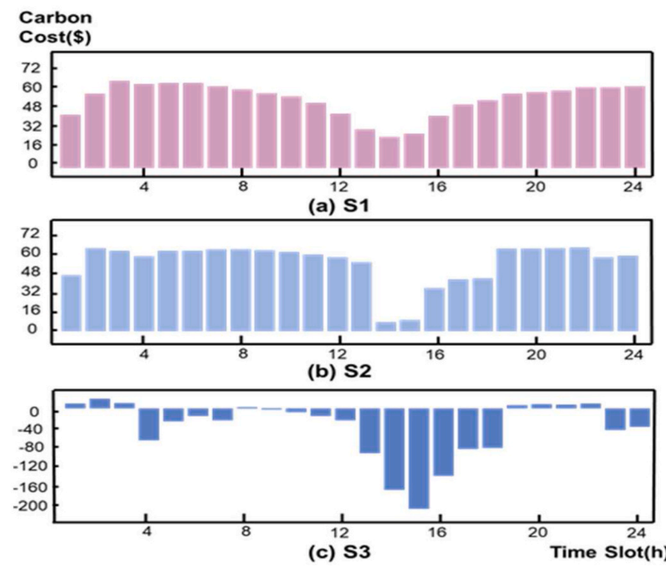


Fig. 6. The variation of carbon emission costs under three scenarios. (a)S 1, (b) S 2, (c)S 3.

Table 4
Workload migration under three scenarios.

Scenario	Delay-sensitive workload (Mbit)	Delay-tolerant workload (Mbit)
S1	0	0
S2	16786	81460
S3	16786	95081

As shown in Figs. 4 and 5, there are three points worth of discussion: Firstly, by comparing (a) and (b) in Fig. 4, a significant transfer of workloads from IDC 1 or IDC 2 to IDC 3 is observed. This can be attributed to the cost of the marginal unit, known as LMP, and the abundance of renewable energy available at no cost in the IDC 3 node, which drastically reduces the LMP in comparison to other IDC nodes. This finding highlights the effectiveness of spatiotemporal flexibility in IDCs, allowing for optimal utilization of renewable energy distribution and cost savings. Secondly, by comparing (b) and (c) in Fig. 4, It is discovered that the cost of electricity in S 2 is greater than that of S 3 at the majority of time slots, particularly in IDC 3. Furthermore, the size of the circle in IDC 3 of S 3 is larger than that of S 2, indicating that more workloads are transferred into IDC 3, enhancing its spatiotemporal flexibility. This result verifies that participation in the DCEI leads to the activation of greater spatiotemporal flexibility in IDCs. Thirdly, by comparing (b) and (c) in Fig. 5, it is found that as the workload migrated to IDC 3, heat dissipation increased, resulting in a need for the cooling system to increase its output to maintain a reasonable temperature range. As a result, electricity consumption (c) is higher than electricity consumption (b). However, considering the reduction in electricity cost, this increase is deemed acceptable. Furthermore, upon comparing (a) or (b) with (c), the TIAC proved effective in optimizing the electricity consumption of the cooling system.

4.1.2. Migration cost caused by workload migration

The analysis above shows that with the continuous enhancement of the spatiotemporal flexibility of IDCs under S 1-S 3, the electricity cost reduction of IDCs also increases. However, it is worth noting that the workload migration among geo-distributed IDCs may inevitably increase the electricity consumption of the core switches affiliated to the backbone network (Yuan et al., 2022). As a result, the flexibility also comes with some extra costs. The results are shown in Table 4. It is found that the more delay-tolerant workloads are migrated in the dual-drive coordination, which also represents more flexibility is activated. Thus, the dual-drive coordination is beneficial for taking advantage in utilizing flexibility of IDCs.

4.1.3. Carbon emission cost

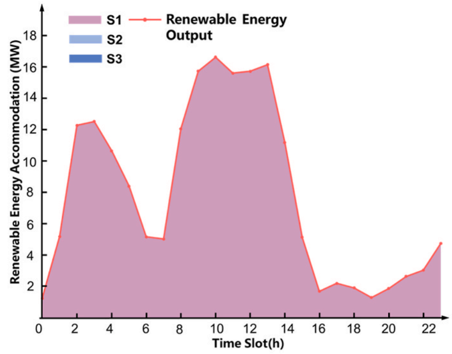
The renewable energy generation in the region where IDC is located cannot meet the electricity demand in 24 time slots, which means that thermal power needs to be purchased from the grid to compensate for the shortage, which also leads to a large amount of indirect carbon emissions. As shown in Table 4, from S 1 to S 3, carbon emission cost is decreasing, due to different accounting methods for indirect carbon emissions of IDCs. In S 1 and S 2, $\delta_{i,t}$ in Eq.(1f) is the ACEI, which is the constant equal to 0.5703 MW/t provided by authority, but in S 3, $\delta_{i,t}$ in Eq.(1f) is the DCEI, which is the variable provided by the carbon emission flow. Fig. 6 shows the variation of carbon emission cost under three scenarios. As described in the cap-and-trade carbon market above, the IDC has a certain carbon emission allowance. If the carbon emissions are greater than the carbon emission allowance, the IDC needs to buy extra allowances in the carbon market; otherwise, the IDC needs to sell its carbon emission allowance in the carbon market. The results show that the carbon emission cost of IDCs in S 3 is negative at the most time slots, while the other 2 scenarios are opposite. This confirms that the indirect carbon emission calculated by DCEI is much beneficial than that by ACEI in economic perspective.

In short, the primary incentive for IDC coordination is cost reduction. The suggested dual-drive coordinated operation strategy enhances the spatiotemporal flexibility of IDCs, thereby augmenting the effectiveness of electricity cost reduction and increasing benefits from the carbon market. However, it is unavoidable to incur some acceptable transmission costs due to workload migration.

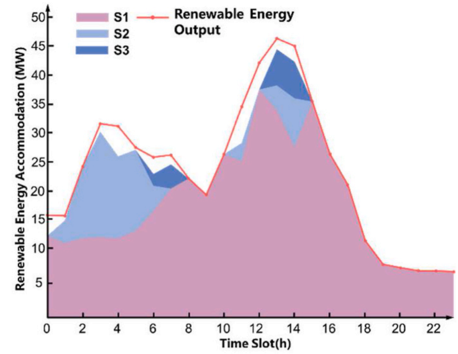
4.2. Spatiotemporal flexibility effect on renewable energy accommodation

With the further development of social economy, the contradiction of energy endowment between regions has become increasingly prominent, and the renewable energy curtailment is increasingly anabatic. This paper analyzes the degree of matching between the 24-h electricity consumption and renewable energy generation across multiple regions.

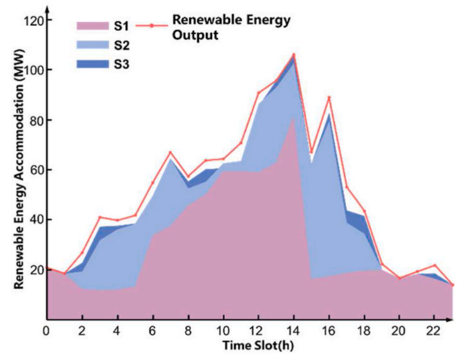
As shown in Fig. 7, the renewable energy outputs display notable volatility across various regions situated within an IDC. As a result, during certain time periods (such as all time slots of IDC 1), the



(a) GMT+8



(b) GMT+7



(c) GMT+6

Fig. 7. The degree of matching between the 24-h electricity consumption and renewable energy generation across multiple regions. (a)GMT+8, (b)GMT+7, (c)GMT+7.

renewable energy power supply falls short of meeting the power demand of the GMT+8 region where IDC 1 is located. Conversely, in other hours (such as most hours in IDC 3), a considerable surplus of renewable energy is produced, leading to wastage of resources. To address the mismatch between regional renewable energy generation and load demand, this paper proposes spatial flexibility as a solution. By migrating workloads among geographically distributed IDCs, renewable energy can be fully absorbed. Additionally, this paper proposes temporal flexibility as a further provision to track output fluctuations of renewable energy, increasing the matching degree between renewable energy generation and load demand. Finally, activating spatiotemporal flexibility in S 3 results in an increase of 2.24 % and 1.22 % in the degree of matching of the regions connected by IDC 2 and IDC 3, respectively, in comparison with the results obtained in S 2. These findings confirm that the proposed dual-drive coordinated operation strategy effectively utilizes the spatiotemporal flexibility of geo-distributed IDCs to increase renewable energy accommodation and reduce regional imbalances between renewable energy generation and load demand.

5. Conclusions and discussions

The IDC plays a vital role in providing computing system infrastructure, ensuring the stable operation of the entire digital network. A well-defined operational strategy is essential for IDCs. This paper proposes a dual-drive coordinated operation strategy for IDCs by exploiting spatiotemporal flexibility. There are several advantages that distinguish this paper from alternative approaches. Firstly, a detailed loading model is formulated to depict the spatiotemporal flexibility of the electrical loads of the IDC. Secondly, the conventional model for the electricity market decision-making, which was based on price followers, has been replaced by a bi-level model that considers the game interactions of multiple subjects. By exchanging decision-making information between the upper and lower levels of the model, IDCs and power grids can achieve a mutually beneficial outcome. Thirdly, the costs of carbon emissions per unit are integrated as interaction signals based on the DCEI of different regions to enhance coordination effectiveness.

Dual-drive coordination can enhance the flexibility of IDCs in terms of cost reduction and matching renewable energy generation supply with demand. In the case studies, three cases are compared, which demonstrates following.

1) The issue of high operational costs in IDCs has garnered significant attention from the academic community. Without economic incentives, the cost of power procurement and the added operational costs related to flexibility have dissuaded many IDC operators, leading to a waste of resources in terms of the potential for spatiotemporal IDCs. The coordination strategy proposed in this paper enables geo-distributed IDCs to successfully activate their spatiotemporal flexibility. This results in lower operating costs by tracking diversity in electricity prices and seeking benefits from market mechanisms.
2) In practice, the balance between regional resource reserves and development has been a central focus of China's electricity industry. The implementation of trans-regional transmission, which transmits excess electricity from resource-rich areas to electricity-intensive regions with lower resources via transmission lines, has been established. Yet, in recent years, as China's economy has entered a new development stage, the demand for electricity has diminished, rendering a disparity between the renewable energy supply and electricity demand. The spatiotemporal flexibility of geo-distributed IDCs plays an important role in alleviating renewable energy curtailment by transferring electric loads from areas with rich data resources to areas with rich renewable resources.

3) In the context of “dual carbon target”, China’s carbon market serves as a crucial policy instrument to reduce carbon emissions. Currently, the main purpose of China’s carbon market is to trade the difference between recorded carbon emissions and granted carbon allowances for free. IDCs have the ability to shift their electric loads to regions with abundant renewable energy sources to reduce their dependence on thermal power. This approach can utilize the low-carbon benefits of renewable energy to reduce indirect carbon emissions and gain greater trading ad-vantages in the carbon market. The inclusion of the carbon drive further enhances the benefits of the spatiotemporal flexibility of IDCs in terms of operational costs and accommodating renewable energy in the region where the IDC is located. Compared to when only the electricity price is taken into account, the total operational cost is reduced by 14.16 %. Furthermore, the regional renewable accommodation is increased by 2.24 % and 1.22 %.

6. Limitations and future works

The proposed dual-drive coordinated operation strategy has limitations that require consideration in future works to produce more universal outcomes. The paper omits any consideration of the impact of multi-source uncertainty on the coordinated results. Additionally, there are no information barriers between the IDC and the grid, and decision-making information can be exchanged directly. Finally, power loads for IDCs are typically scheduled spatially at the same level of the grid and using the same market trading mechanism by default.

For future work, three issues deserve an in-depth study: 1) When designing the coordinated operation strategy between the IDC and the grid, it is important to consider the uncertainties surrounding cloud demand, renewable energy output, and electricity prices. To address these uncertainties, it is necessary to study robust optimization algorithms. 2) Information barriers between industries can hinder IDCs and power grids from exchanging decision-making information in coordinated operation. To address this issue, an interaction model that considers industry privacy should be proposed. 3) When considering the spatial flexibility of the IDC, power grids in different regions will be affected simultaneously. Therefore, it is necessary to establish a coordinated optimization operation method for multi-level grids that takes into account spatial constraints. This will be a continuation of the research work in this paper.

CRediT authorship contribution statement

Shibo Zhou: Methodology, Investigation, Formal analysis. **Ming Zhou:** Writing – review & editing, Supervision, Funding acquisition. **Zhaoyuan Wu:** Methodology, Conceptualization. **Yuyang Wang:** Software. **Gengyin Li:** Visualization, Data curation. **Shuai Wang:** Writing – review & editing, Validation.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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Appendix

A. The Derivation of DCEI Based on Carbon Emission Flow Theory

The physical meaning of equation (A.1) is that the DCEI of region i is determined by the carbon emission flow generated by the generator affiliated to this region and from other regions. The detailed calculation process of all DECIs in a whole power topology is shown as follows:

$$\delta_{i,t} = \frac{\sum P_{s,t}^{B}\vartheta_{s}^{B} + P_{i,t}^{G}\varpi_{i}^{G}}{\sum P_{s,t}^{B} + P_{i,t}^{G}} \tag{A.1}$$

(a) According to the carbon emission flow, the carbon flow density of branch ϑ_s^B can be replaced by the DCEI of the node at the beginning of the branch, so equation (A.1) can be replaced in matrix form as follows:

$$\delta_i = \frac{\mathbf{\eta}_N^{(i)}\left(\mathbf{P}_B^{\mathrm{T}}\mathbf{E}_N + \mathbf{P}_G^{\mathrm{T}}\mathbf{E}_G\right)}{\sum\limits_{g\in N^G} P_{Ggi} + \sum\limits_{j\in N^J} P_{Bji}} \tag{A.2}$$

$\boldsymbol{\eta}_N^i$ represents a N-dimensional unit row vector where the element i is 1; $\boldsymbol{P}_B$ and $\boldsymbol{P}_G$ are branch power flow distribution matrix and power injection distribution matrix; $\boldsymbol{E}_N$ and $\boldsymbol{E}_G$ are the vector of dynamic carbon emission intensity of node i and the vector of carbon emission factor of generator; P_{Ggi} and P_{Bji} are power injection from generator g to node i and branch power flow from node j to node i.

(b) The nodal active power flux is defined as follows:

$$P_{Nii} = \sum_{s\in I^+} p_{Bs} + p_{Gi} \tag{A.3}$$

p_{Bs} represents all active power of branch s; I^+ represents the set of all active power flowing into node i; p_{Gi} represents the output of generator connected by node i.

(c) The matrix of nodal active flux is defined as follows:

$$\begin{aligned}\mathbf{P}_N &= diag(\xi_{N+K}\mathbf{P}_Z)\\ \mathbf{P}_Z &= [\mathbf{P}_B\ \ \mathbf{P}_G]^{\mathrm{T}}\end{aligned} \tag{A.4}$$

ξ_{N+K} represents a N + K-dimensional unit row vector where all the element is 1.

(d) According to equations (A.3) and (A.4), we can define the active power of node i as follows:

$$\sum_{g\in N^G} P_{Ggi} + \sum_{j\in N^J} P_{Bji} = \boldsymbol{\eta}_N^{(i)}\mathbf{P}_N\left(\boldsymbol{\eta}_N^{(i)}\right)^{\mathrm{T}} \tag{A.5}$$

(e) When we combine equations (A.2) and (A.5), we can conclude the new equation as follows:

$$\boldsymbol{\eta}_N^{(i)}\mathbf{P}_N\left(\boldsymbol{\eta}_N^{(i)}\right)^{\mathrm{T}}\delta_i = \boldsymbol{\eta}_N^{(i)}\left(\mathbf{P}_B^{\mathrm{T}}\mathbf{E}_N + \mathbf{P}_G^{\mathrm{T}}\mathbf{E}_G\right) \tag{A.6}$$

(f) Since $\boldsymbol{P}_N$ is a diagonal matrix, we extend equation (A.6) to the whole power topology, the new equation is shown as follows:

$$\mathbf{P}_N\mathbf{E}_N = \mathbf{P}_B^{\mathrm{T}}\mathbf{E}_N + \mathbf{P}_G^{\mathrm{T}}\mathbf{E}_G \tag{A.7}$$

(g) Finally, after the above series of derivations, we can conclude the formula of DCEI of all nodes in the power topology, which is shown as follows:

$$\mathbf{E}_N = \left(\mathbf{P}_N - \mathbf{P}_B^{\mathrm{T}}\right)^{-1}\mathbf{P}_G^{\mathrm{T}}\mathbf{E}_G \tag{A.8}$$

This can prove that the DCEI δ_i is calculated based on carbon emission flow theory.

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