Scheduling IDC-Based Virtual Power Plants Considering Backup Power

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***Abstract*—The virtual power plant (VPP) can aggregate massive distributed resources to participate in power system operation. Different types of resources have been investigated to construct VPPs. Internet data centers (IDCs) are regarded as flexible power consumers that can potentially cooperate with power systems. This paper exhibits the insight for constructing VPPs based on IDCs while comprehensively considering the operational flexibility of the workloads and power supply devices. On the workloads, this paper models the temporal and spatial flexibility of workloads in detail. On the power supply devices, this paper explores their spare capacity with respect to the power supply reliability requirement. Then, a day-ahead scheduling method of the IDC-based VPPs is established based on the operational flexibility modeling. Case studies validate the proposed approach. Moreover, because of the coupling of workload dispatch and power supply device operation, the synergy effect does not equal the sum of its parts.**

***Index Terms*—Virtual Power Plant, Internet Data Center, Day-ahead Scheduling, Backup Power**

I. Introduction

A. Motivation & Literature Review

The virtual power plant (VPP) is an effective solution to aggregate massive distributed flexible resources from the demand side and the generation side [1]. With the development of renewable energy integration, power systems need more flexibility to guarantee operational security and efficiency [2]. Hence, VPP is regarded as a promising way to enrich power system flexibility by dispatching distributed resources. Methodologies for integrating electric vehicles [3], flexible power loads [4], distributed generation [5], and other resources into the VPP framework have been studied in the literature.

Internet data centers (IDCs) have the potential to construct VPPs. First, along with the rapid development of information and communication technology (ICT), the amount of IDCs increased quickly. From 2010 to 2018, the global data center workloads increased more than sixfold [6]. Moreover, because of the success of large language models (LLM) and other artificial intelligence (AI) techniques, the need for computation services will grow explosively, leading to a steep increase in IDCs [7]. Second, IDCs have operational flexibility so that the power consumption of IDCs can be dispatched.

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Scheduling and dispatching computation workloads of IDCs have been widely investigated as a solution to explore flexibility. Compared with other types of data centers, some of IDCs' workloads are delayable, such as data compaction, machine learning, simulation, and data processing pipelines. This feature enables the scheduling of workloads to different time slots and different IDCs. The temporal and spatial dispatch potential of computation workloads is discussed [8]. Also, mappings from computation workloads to power consumptions in IDCs are studied [9]. Hence, IDCs can participate in the demand-side operation of power systems by dispatching computation workloads. Researchers have studied the workload dispatch on different time scales towards respective targets [10]. Deng *et al.* [11] proposed a mechanism of IDC online power management and load scheduling with environmental considerations. Dong *et al.* [12] minimized the total power consumption by optimizing the number of activated servers. Gupta *et al.* [13] proposed a method to co-optimize the workloads and cooling infrastructures of IDCs. Liu *et al.* [14] studied the online scheduling of workloads in IDCs considering the information and energy coupling. Yuan *et al.* [15] proposed a framework to schedule the delayable workloads temporally. Zheng *et al.* [16] reduced the load curtailment and carbon emissions through workload dispatch among different IDCs.

The workload dispatch has also been applied to the industry. Companies build their own scheduling structures to improve workload management. Typical examples include Borg [17] for Google, Yarn [18] for Microsoft, Fuxi [19] for Alibaba, and Mesos [20] for Twitter. These applications are roughly real-time workload scheduling. Recently, some higher-level applications have been proposed. Aiming at dispatching computation workloads at the day scale, Google has developed an in-production system (named the Carbon-Intelligent Compute Management (CICM) system) [10], which enables interactions with power systems and reduces carbon emissions.

Moreover, IDCs need uninterruptible power supply (UPS) services. Thus, energy storage devices are deployed as backup power. The backup power is designed to provide emergency electricity during power supply network failures. While providing UPS services, energy storage devices still have spare capacity that can be flexibly scheduled [21]. If properly utilized, the energy storage devices can further enrich the operational flexibility of IDCs. Wang *et al.* [22] proposed a framework to dispatch the energy storage in an IDC based on the model predictive control.

Another trend is the development of the green IDC concept. Some IDCs are equipped with distributed renewable energy (such as solar panels) so that part of the power consumption can be supplied by local renewable energy. Kwon *et al.* [23] proposed the method to operate IDCs with the consideration of renewable energy utilization. Huang *et al.* [24] discussed the role of IDCs in local renewable energy integration.

Although the operational flexibility of IDCs has been widely discussed, existing literature has the following drawbacks. First, IDCs are still studied as flexible power consumers, but there lie difficulties for IDCs to directly participate in the power system operation. The VPP is regarded as an effective methodology for demand-side resource integration, so IDC-based VPPs should be further investigated. Second, the operational flexibility of IDCs has yet to be comprehensively studied, especially from the power supply side. By combining the operation of backup power devices and the workload dispatch, the feasible region of IDC-based VPP scheduling can be enlarged.

B. Contributions

In this regard, this paper exhibits the insight for constructing VPPs based on IDCs considering the flexibility of workloads and backup power. Then, for IDC-based VPPs cooperating with power systems in the day-ahead horizon, this paper establishes the scheduling framework for IDC-based VPPs to develop operation schemes and participate in the day-ahead market. The main contributions of this paper compared with existing literature are listed as follows:

1) A framework is established to quantify the potential flexibility of backup power to participate in the operation of IDC-based VPPs while guaranteeing the power supply reliability requirement.
2) The coordination between the backup power operation and computation workload dispatch in IDCs is realized to further enhance flexibility.
3) A novel day-ahead scheduling framework is proposed for IDC-based VPPs combining the power and computation dispatch.

C. Paper Organization

The remainder of this paper is organized as follows. Section II states the proposed framework and methodology. Section III investigates the operational modeling of IDCs in detail. Then, Section IV proposes the formulation of the day-ahead scheduling problem of the IDC-based VPPs. Further, we conduct case studies in Section V to validate the effectiveness of the proposed framework. Finally, Section VI draws the conclusions.

II. Framework and Methodology

In this section, we first discuss the framework of IDC-based VPPs. Then, we introduce the roadmap to model the operational flexibility of different parts of IDCs. Based on this, the scheduling approach for IDC-based VPPs is stated.

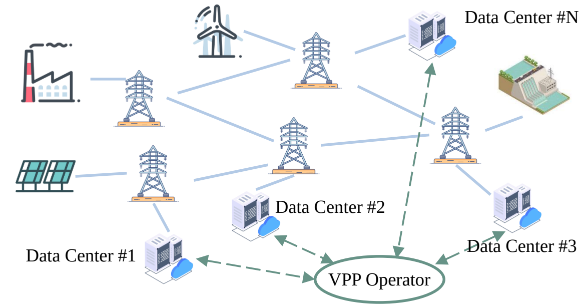


Fig. 1: The framework of IDC-based VPPs

As shown in Fig. 1, IDCs are deployed at different nodes in power systems. The VPP operator plays the role of coordinator between power systems and IDCs. It is essential for the VPP operator to conduct day-ahead scheduling so that the VPP operator can obtain the operation schemes for the next day and participate in the day-ahead market. Several steps are needed to fulfill the day-ahead scheduling of IDC-based VPPs. First, each IDC first forecasts the workloads of the next day. Reference [10] provides a practical method for workload forecasting. Based on the forecasting results, the operational boundaries of IDCs can be quantified and sent to the VPP operator. Then, the VPP operator conducts the day-ahead scheduling and bids in the day-ahead market. After the market clearing process, the VPP operator allocates the planned schemes to each IDC for the operation of the next day.

Aiming at fully utilizing the operational flexibility of IDCs to enlarge the feasible operation region of IDC-based VPPs and improve the cooperation with power systems, we propose the following methodology for IDC-based VPP scheduling.

First, the operational flexibility of IDCs is comprehensively modeled. In this paper, we classify the flexibility sources of IDCs into two categories. One is from the power consumption of IDCs; the other is from the power supply equipment. For the power consumption, we establish the temporal-spatial dispatch model of computation workloads and build the relationship between computation workloads and power consumption. For the power supply equipment, we adopt a framework to estimate the spare capacity of backup power devices with respect to the reliability requirement. According to the spare capacity estimation, we propose the operation model of backup power devices. The details are introduced in Section III.

Remark 1: Other types of flexible power consumers are also equipped with energy storage to provide UPS services, such as cellular base stations [21]. However, the power consumptions of cellular base stations are determined by the communication demands of wireless network users. The communication demands are usually real-time. On the contrary, some of IDCs' workloads have temporal and/or spatial flexibility. The scheduling of workloads will also influence the energy reserve requirement of backup power devices. As a result, the spare capacity of backup power devices changes. Therefore, IDCs need to conduct coupled scheduling of workload and backup

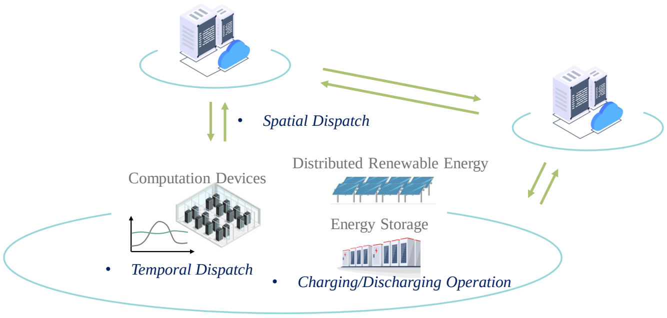


Fig. 2: The operational flexibility of IDC clusters

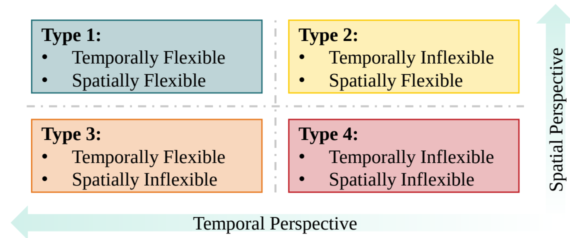


Fig. 3: The classification of IDC workloads

power devices.

Then, based on the comprehensive modeling of the operational flexibility of IDCs, we establish a day-ahead scheduling model for the IDC-based VPP. In the framework, both computational workloads and backup power devices of IDCs in the VPP are dispatched. Specifically, flexible computational workloads are apportioned spatially and temporally, while the behaviors of backup power devices and renewable energy are also optimized. Therefore, with an optimized power consumption scheme, the IDC-based VPP can improve its bidding strategy in the day-ahead market. The details are presented in Section IV.

Scheduling IDC-based VPPs would benefit both power systems and IDCs. For IDCs, operational flexibility is explored to optimize the power consumption behaviors and reduce cost. For power systems, the dispatch potential of the demand side is extended. With appropriate price signals, IDC-based VPPs can contribute to power system applications like peak shaving and congestion management. Moreover, compared with existing works that only optimize computational workloads, dispatching backup power devices enriches operational flexibility and further improves the scheduling results.

III. Operational Modeling of IDCs

This section discusses the operational flexibility of IDCs and establishes the corresponding modeling approach. As shown in Fig. 2, the operational flexibility of IDCs comes from multiple sources. The local flexibility comes from the temporal dispatch of the computation workloads and the operation of backup power devices. Moreover, the dispatch of workloads among different IDCs provides spatial flexibility for the VPP scheduling.

A. Operational Flexibility from Computation Workloads

Though parts of the computation tasks of an IDC should be responded to on the clock without delay tolerance (such as searching, mapping, and video streaming), other tasks that can be delayed provide temporal flexibility. Typical delayable tasks are data compaction, machine learning, simulation, and data processing pipelines. It is acceptable as long as these tasks are completed within a given period (e.g., 24 hours) [10]. Moreover, some of the compaction tasks can be transferred among IDCs [16]. Hence, these tasks are spatially flexible and can be arranged to different IDCs.

Also, it should be mentioned that although tasks of IDCs are allocated by the computing resource management system in real-time [17], [18], scheduling workloads day-ahead is practicable using some higher-level mechanisms. Reference [10] provides a mechanism named virtual capacity curve (VCC) to realize the day-ahead workload scheduling. This mechanism determines the maximum capacity that can be used for an IDC at each time slot. Then, in real-time operation, the computing resource management system allocates tasks according to the virtual capacity instead of the physically available capacity.

In this paper, we categorize the computation workloads of IDCs into four parts from the temporal and spatial perspectives, as shown in Fig. 3. Type 1 refers to workloads that are both temporally and spatially flexible. Type 2 refers to workloads that are temporally inflexible but spatially flexible. Type 3 refers to workloads that are temporally flexible but spatially inflexible. Type 4 refers to workloads that are both temporally and spatially inflexible. Therefore, workloads of Type 1 and Type 2 can be dispatched among different IDCs, while workloads of Type 1 and Type 3 can be scheduled to different time slots of a day.

The total workload capacity is the sum of the four types of workloads. Moreover, according to the empirical results in [10], the relationship between the power consumption of an IDC and its computation workload can be approximated by a linear expression:

$$P^{\mathrm{IT}}(n,t) = \alpha_n + \beta_n \cdot L^{\mathrm{IDC}}(n,t) \tag{1}$$

where $P^{\mathrm{IT}}(n,t)$ is the power consumption of IDC n at time t, $L^{\mathrm{IDC}}(n,t)$ is the workloads, and α_n and β_n are the coefficients, respectively.

B. Operational Flexibility from Backup Power

Energy storage devices are deployed for IDCs to play the role of backup power. When power supply network failures happen, the power supply of computation devices of an IDC can be switched from the power grid to energy storage devices. In [21], we have extensively discussed the spare capacity of energy storage devices that work as backup power. In this paper, we also establish the procedure to quantify the operational flexibility of backup energy storage according to [21]. The backup energy storage should first reserve enough

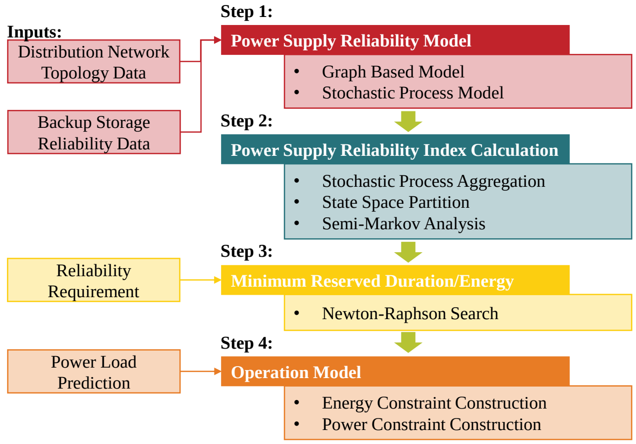


Fig. 4: The procedure to establish the energy storage operation model

energy to guarantee the power supply reliability and then use the spare capacity to provide flexibility. Therefore, before the day-ahead scheduling, it is necessary to determine the operational boundaries of energy storage with the prerequisites of power supply reliability. The procedure can be summarized as four steps, as shown in Fig. 4. First, we construct the power supply reliability model. Then, we provide the analytical approach to calculate the power supply reliability index. Based on the analytical equations, we further evaluate the minimum reserved duration and energy of the backup energy storage to satisfy the reliability requirement. According to the evaluation results, the operation model of backup energy storage can be established.

1) Step 1: The power supply reliability modeling consists of two parts: the topology modeling and the uncertainty modeling. The topology modeling considers the configuration of the studied distribution network. In order to fully capture the influence of potential failures on the studied IDC, we adopt the graph model proposed in [25], which comprehensively considers the topology of distribution networks and the operation characteristics of protection devices. Then, we use the Markov repairable model to represent the uncertainty of each component in the studied distribution network. The Markov repairable model is a two-state homogeneous stochastic process with a failure rate λ and a repair rate μ. It is widely applied in power system reliability analysis [26].

2) Step 2: The power supply reliability of an IDC is determined by some components of the studied distribution network instead of all. Hence, we apply the depth-first search (DFS) algorithm on the graph model to acquire all the components that potentially influence the power supply of the IDC. Then, we utilize the corresponding Markov repairable models of the acquired components to construct the aggregated Markov model. We partition the state space of the aggregated Markov model into four groups and introduce a semi-Markov analysis method to obtain the analytical power supply reliability index calculation equation. Because of the page limit, the deduction details can be referred to in [25].

3) Step 3: The analytical equation can be regarded as a mapping from the reserved duration of energy storage and the distribution network parameters to the power supply reliability index:

$$I_n = f(D_n, \Phi_n) \tag{2}$$

where I_n is the reliability index, D_n is the reserved duration of energy storage, and Φ_n represents the distribution network parameters. With the distribution network parameters fixed, the power supply reliability index is only determined by the reserved duration. Therefore, the minimum reserved duration $D_n^{\min}$ to satisfy the power supply reliability requirement I_n^{req} can be evaluated using the Newton-Raphson search based on the analytical expression of Eq. (2).

4) Step 4: Once the minimum reserved duration $D_n^{\min}$ is acquired, the minimum reserved energy $R^{\min}(n,t)$ can be calculated as follows:

$$R^{\min}(n,t) = \int_{\tau=t}^{t+D_n^{\min}} P^{\mathrm{IT}}(n,\tau)d\tau \tag{3}$$

Then, the state of charge (SoC) of the energy storage should always be scheduled above $R^{\min}(n,t)$. Moreover, the charging and discharging power should also be constrained.

Remark 2: Eq. (3) contains the integral operation, which cannot be directly incorporated into an optimization model. Therefore, we can discrete Eq. (3) according to the time step of the scheduling problem and use the discrete form in optimization.

Remark 3: Compared with our previous research, the power consumption $P^{\mathrm{IT}}(n,t)$ can be dispatched. Hence, the minimum reserved energy $R^{\min}(n,t)$ is also adjustable in the optimization model, enlarging the feasible operation region.

IV. Scheduling Problem Formulation

In this section, we propose the scheduling model for the IDC-based VPPs. The model follows the assumptions of [27], [28], [29] that VPPs are treated as price takers. By applying this model, the IDC-based VPPs can conduct the day-ahead self-scheduling to build offering curves for the day-ahead market based on the prediction of market clearing prices and load demands [28].

Remark 4: We present a deterministic scheduling model in this section. This is because this paper mainly focuses on establishing the operational models to explore the flexibility of IDCs comprehensively and constructing IDC-based VPPs. Nevertheless, more sophisticated optimization techniques, such as stochastic optimization, robust optimization, adaptive robust optimization, and other methods, can be easily applied to our framework with minor modifications.

A. Optimization Target

It is assumed that the scheduling model has K time slots in total. Then, the optimization target is to minimize the total operational cost of the VPP:

$$\min C = \sum_{k=1}^{K} \hat{\pi}(k) \cdot \sum_{n=1}^{N} P^{\mathrm{NET}}(n,k) + \sum_{k=1}^{K}\sum_{n=1}^{N} P^{\mathrm{DEG}}(n,k) \tag{4}$$

where $\hat{\pi}(k)$ is the predicted price at time slot k, $P^{\mathrm{NET}}(n,k)$ is the net power consumption of IDC n, and $P^{\mathrm{DEG}}(n,k)$ is the battery degradation cost of IDC n caused by the charging and discharging operation. The net power consumption of IDC n is calculated as follows:

$$P^{\mathrm{NET}}(n,k) = P^{\mathrm{IT}}(n,k) + (P^{c}(n,k) - P^{d}(n,k)) - P^{\mathrm{RE}}(n,k) \tag{5}$$

where the first term $P^{\mathrm{IT}}(n,k)$ is the power consumption of the computation devices in the IDC, the second term $P^{c}(n,k) - P^{d}(n,k)$ is the net output of the energy storage, and the third term $P^{\mathrm{RE}}(n,k)$ is the scheduled renewable energy. $P^{\mathrm{DEG}}(n,k)$ is the battery degradation cost.In this paper, we adopt the degradation cost model proposed in [30]. This model uses the charging and discharging mileage to allocate the investment cost of the energy storage into the whole lifecycle:

$$P^{\mathrm{DEG}}(n,k) = \lambda_n \cdot (P^{c}(n,k) + P^{d}(n,k)) \tag{6}$$

where λ_n is the unit degradation cost coefficient.

B. Energy Storage Operation

The operational constraints of the energy storage of IDC n is stated as follows:

$$SoC(n,k+1) = SoC(n,k) + \eta_n^c \cdot P^c(n,k) - \frac{1}{\eta_n^d} \cdot P^d(n,k) \tag{7}$$

$$0 \le P^c(n,k) \le P^{c,\max}(n,k) \cdot x^c(n,k) \tag{8}$$

$$0 \le P^d(n,k) \le P^{d,\max}(n,k) \cdot x^d(n,k) \tag{9}$$

$$SoC^{\min}(n,k) \le SoC(n,k) \le SoC^{\max}(n,k) \tag{10}$$

$$x^c(n,k) + x^d(n,k) \le 1 \tag{11}$$

where $SoC(n,k)$ is the SoC of storage of IDC n, η_n^c and η_n^d are the charging and discharging efficiency, $P^c(n,k)$ and $P^d(n,k)$ are the charging and discharging power, respectively. Hence, Eq. (7) is the energy conservation equation of the storage. Eq. (8), (9), and (10) depict the feasible region of the energy storage, where $P^{c,\max}(n,k)$, $P^{d,\max}(n,k)$, $SoC^{\min}(n,k)$, and $SoC^{\max}(n,k)$ are the operational boundaries quantified using the method presented in Section III-B. Scheduling the energy storage within the feasible region satisfies both the physical constraints and the reliability requirement. Moreover, $x^c(n,k)$ and $x^d(n,k)$ are binary variables representing the operation status of the energy storage. Eq. (11) avoids the energy storage charging and discharging simultaneously.

C. Workload Dispatch

According to Section III-A, the power consumption of the computation devices is approximated linearly with the corresponding workload:

$$P^{\mathrm{IT}}(n,k) = \alpha_n + \beta_n \cdot L^{\mathrm{IDC}}(n,k) \tag{12}$$

where α_n and β_n are coefficients, and $L^{\mathrm{IDC}}(n,k)$ is the scheduled workload. The scheduled workload is composed of four parts, as discussed in Section III-A:

$$\begin{aligned} L^{\mathrm{IDC}}(n,k) =& L^{\mathrm{IDC},1}(n,k) + L^{\mathrm{IDC},2}(n,k) \\ &+ L^{\mathrm{IDC},3}(n,k) + L^{\mathrm{IDC},4}(n,k) \end{aligned} \tag{13}$$

where $L^{\mathrm{IDC},1}(n,k)$, $L^{\mathrm{IDC},2}(n,k)$, $L^{\mathrm{IDC},3}(n,k)$, and $L^{\mathrm{IDC},4}(n,k)$ are the Type 1, 2, 3, and 4 workloads discussed in Section III-A, respectively. Then, different kinds of workloads should satisfy the following constraints:

$$\sum_{n=1}^{N}\sum_{k=1}^{K} L^{\mathrm{IDC},1}(n,k) = \hat{L}^{\mathrm{IDC},1} \tag{14}$$

$$\sum_{n=1}^{N} L^{\mathrm{IDC},2}(n,k) = \hat{L}^{\mathrm{IDC},2}(k) \tag{15}$$

$$\sum_{k=1}^{K} L^{\mathrm{IDC},3}(n,k) = \hat{L}^{\mathrm{IDC},3}(n) \tag{16}$$

$$L^{\mathrm{IDC},4}(n,k) = \hat{L}^{\mathrm{IDC},4}(n,k) \tag{17}$$

where $\hat{L}^{\mathrm{IDC},1}$ is the predicted Type 1 workload of the whole VPP among the whole scheduling period, $\hat{L}^{\mathrm{IDC},2}(k)$ is the predicted Type 2 workload of the whole VPP at time slot k, $\hat{L}^{\mathrm{IDC},3}(n)$ is the predicted Type 3 workload of IDC n among the whole scheduling period, and $\hat{L}^{\mathrm{IDC},4}(n,k)$ is the predicted Type 4 workload of IDC n at time slot k.

In addition, the scheduled workloads of IDC n should not exceed its capacity, and all types of workloads should be non-negative:

$$0 \le L^{\mathrm{IDC}}(n,k) \le L^{\mathrm{IDC},\max}(n,k) \tag{18}$$

$$L^{\mathrm{IDC},i}(n,k) \ge 0 \quad i = 1,2,3,4 \tag{19}$$

D. Renewable Energy Scheduling

The scheduled power of renewable energy of IDC n is no greater than the predicted power:

$$P^{\mathrm{RE}}(n,k) \le \bar{P}^{\mathrm{RE}}(n,k) \tag{20}$$

Mathematically, this model is a mixed-integer linear programming (MILP) problem, which academic or commercial solvers can efficiently solve.

V. Case Studies

This section conducts case studies on three test systems to validate the proposed framework. First, the proposed flexibility modeling and scheduling framework is illustrated on a single IDC. Then, the coordination among IDCs is explored using a dual IDCs case. Finally, the benefits of scheduling IDC-based VPPs are studied.

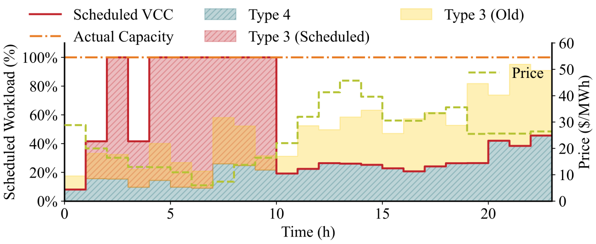
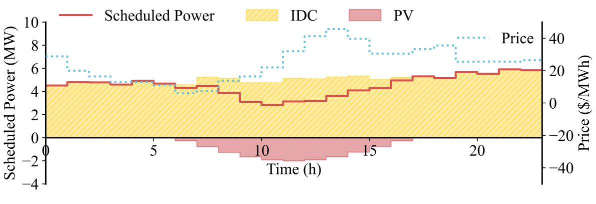
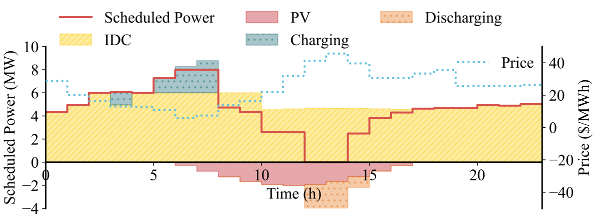


Fig. 5: The scheduled workloads of an IDC



(a) Without optimization



(b) With optimization

Fig. 6: The scheduled power of an IDC

A. Single IDC Case

We investigate the cooperation of the workload dispatch and power supply device operation in a single IDC. The basic settings of this case are established as follows. The rated power of the IDC is set as 6000kW, with coefficients α_n and β_n of Eq. (1) estimated according to [10]. The studied IDC is deployed with 6000kW backup energy storage. The energy capacity is three hours, and the changing/discharging efficiencies are both 95%. The installed capacity of the photovoltaic panels is set as 2000kW. The workloads of the studied IDC are constructed based on the Google cluster-data.The electricity price curve is obtained from the locational marginal price (LMP) of the South Power Pool (SPP).

According to Section III-A and Section III-B, the operational flexibility of workloads and backup power is quantified first. Then, the scheduling model in Section IV is applied. The scheduled workloads of the studied day are shown in Fig. 5. The spatial flexibility cannot be considered for a single IDC, so workloads of Type 3 and Type 4 are studied in this case. The workloads with and without the proposed scheduling method are both exhibited in Fig. 5. Comparing the two results, we can find that the flexible workloads are scheduled to time slots with relatively low prices. Correspondingly, the scheduled power of the studied IDC is presented in Fig. 6. Here, Fig. 6a shows the power consumption without optimization, while Fig. 6b shows the power consumption with optimization. Since the workloads

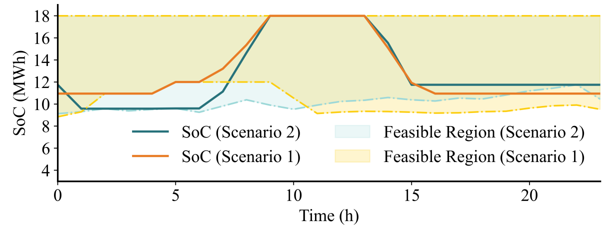


Fig. 7: The SoC of the backup energy storage

of the studied IDC are scheduled, the power consumption of the computation devices is reshaped. In addition, the spare capacity of the backup energy storage is also utilized to charge at time slots with low prices and discharge at time slots with high prices. Therefore, the net power consumption can be optimized from the curve in Fig. 6a to that in Fig. 6b. The original operational cost without any optimization is 2648.8$. By considering the workload scheduling, the operational cost is reduced to 2482.9$. Then, the charging and discharging of backup energy storage further reduce the cost to 2379.4$. As a result, the operational cost of the studied day is reduced by 10.2%.

Moreover, the SoC of the backup energy storage is shown in Fig. 7 to illustrate the coupling of the workload dispatch and power supply device operation. Here, two scenarios are discussed. In Scenario 1, the backup energy storage is optimized coordinately with the workloads. In Scenario 2, only the operation of the backup energy storage is optimized. Because the scheduled workloads would determine the power consumption of the computation devices and further influence the minimum reserved capacity (as in Eq. (3)), the spare capacity changes. Therefore, the feasible operation region of the energy storage varies. Accordingly, the SoC curves of Scenario 1 and Scenario 2 are also different. In addition, the operation of the backup energy storage makes the SoC changes with time. Compared with keeping the SoC at the highest level for all time, the power supply reliability index decreases. However, because the spare capacity is evaluated according to the predefined reliability requirement, the operation of backup energy storage could still keep the reliability level above the requirement.

B. Dual IDCs Cooperation Case

The spatial coordination of workload dispatch can further improve the scheduling. In this case, two IDCs are considered, and the basic settings are similar to Section V-A. By applying the proposed framework, the workloads can be scheduled, and the corresponding operational cost is shown in Table I. The operational costs of IDC 1, IDC 2, and the total cost are presented in the table, respectively. Note that this case mainly aims at illustrating the effectiveness of temporal-spatial dispatch of workloads, so the backup power scheduling is not considered. In Table I, the benchmark cost refers to the results without any workload scheduling. When the workloads are scheduled temporally, which means the two

IDCs optimize their workloads separately, the operational cost of both IDCs reduces, and the total cost decreases. Moreover, if we further consider the spatial coordination of IDCs, although the operational cost of IDC 1 increases, the operational cost of IDC 2 has a greater decrease, and the total cost is improved correspondingly. This is because the workloads can be transferred when spatial coordination is enabled. Therefore, the scheduling scheme can be optimized in a larger space.

TABLE I: The operational cost of the dual IDCs case with workload scheduling

	Benchmark	Temporal Dispatch		Temporal-Spatial Dispatch	
	Cost	Cost	Reduce Rate	Cost	Reduce Rate
IDC1	2648.83	2482.94	6.26%	2722.74	-2.79%
IDC2	3806.44	3745.10	1.61%	3408.45	10.46%
Total	6455.27	6228.04	3.52%	6131.19	5.02%

C. Multiple IDCs Case

In this case, we study the scheduling of the IDC-based VPPs. We consider a VPP constructed by ten IDCs. The basic parameters are set as in Section V-A. We adopt the LMP of a whole year from the South Power Pool to conduct the scheduling based on the proposed framework. In Table II, we present the scheduling results of three typical days and the average cost of the whole year. Here, we adopt the operation results without any scheduling as the benchmark, and the workload dispatch, backup power scheduling, and combined optimization are realized, respectively. Scenario 1 represents a day with normal prices. The workload dispatch and the backup power scheduling can both reduce the operational cost. Moreover, because of the coupling discussed in Section V-A, the synergy effect of workload dispatch and backup power scheduling does not equal the sum of its parts. Scenario 2 represents a day with plain prices. Because the price difference within the day is slight, the benefits of operating energy storage are less than the degradation cost. Hence, the backup power is not dispatched in Scenario 2. Scenario 3 represents a day with congestion periods. During congestion periods, the prices are exceptionally high, so scheduling the backup energy storage to discharge and minimize the net power consumption can significantly reduce the cost. On a yearly average, the scheduling of IDC-based VPPs can reduce the operational cost by 11.84% under this case's settings.

VI. Conclusion and Future Works

IDCs are potential flexibility resources for power systems. Constructing VPPs based on IDCs enables the cooperation between power and information systems. This paper provides a novel method to schedule IDC-based VPPs while comprehensively considering the operational flexibility of the workloads and the power supply devices. The workload dispatch can exploit the temporal and spatial flexibility of computational workloads of an IDC group. The backup power scheduling can take advantage of the spare capacity of the backup energy storage devices. They both benefit the operation of IDC-based VPPs. In addition, because of the coupling of the two flexibility resources, the synergy effect does not equal the sum of its parts. More scenarios will be studied to further validate the proposed framework. Future works include incorporating uncertainties into the scheduling model, considering strategic bidding of IDC-based VPPs, constructing the corresponding market mechanisms, and implementing the scheduling framework to IDCs' daily operation.

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TABLE II: The operational cost of the IDC-based VPP with different scheduling methods

		Day 10	Day 177	Day 3	Average
Benchmark	Cost	25281.6	33029.8	73887.7	37777.3
Workload	Cost	23882.1	32484.6	69486.5	36075.0
	Reduce Rate	-5.54%	-1.65%	-5.96%	-4.51%
Backup Power	Cost	24159.9	33029.8	56655.7	35082.3
	Reduce Rate	-4.44%	0.00%	-23.32%	-7.13%
Workload + Backup Power	Cost	22890.0	32484.6	50422.1	33303.4
	Reduce Rate	-9.46%	-1.65%	-31.76%	-11.84%

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