Joint Workload Scheduling Method in Geo-Distributed Data Centers Considering UPS Loss

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***Abstract*—The rapidly growing energy consumption of modern data centers has drawn widespread attention and extensive research. Among all of the current researches, reducing the electricity cost in geo-distributed internet data center (IDC) is a hot spot. In this paper, electricity price, power output of photovoltaic and energy storage system (ESS) in geo-distributed IDC are optimized in combine with the computational tasks scheduling, while considering the power loss of uninterruptible power supply (UPS). Case studies are simulated and provided, whose results have demonstrated the effectiveness of this proposed method.**

Keywords*—Geo-distributed internet data center, uninterruptible power supply, workload scheduling, electricity bill.

I. Nomanclature

A. Indices and Sets

T Set of all time slots, index by t

I Set of geo-distributed data centers, index by i

J Set of UPS, index by j

A Total number of batch workloads, index by a

G Set of conventional units, index by g

B. System Paramenters

$\lambda_{i,j,t}$ Amount of total workloads allocated to data center i UPS node j at time t

$\mu_{total,a}^{batch}$ Total batch workloads of the batch workload a

ζ_t^{inter} Total interactive workload should be served at time t

D_a^{batch} Maximum service delay of the batch workload a

t_a^{batch} The time slot when the batch workload a arrive

$Cap_{i,j}$ IT capacity limitation of servers in data center i UPS node j

$P_{peak,i,j}^{server}$ Peak power of servers in data center i UPS node j

$P_{idle,i,j}^{server}$ Idle power of servers in data center i UPS node j

$M_{i,j}$ Total number of servers in data center i UPS node j

$P_{i,j,t}^{servers}$ Power of servers in data center i UPS node j at time t

$P_{rated,i,j}^{UPS}$ Rated power of the UPS j in data center i

$P_{i,j,t}^{Loss\_UPS}$ Power loss of the UPS j in data center i at time t

$P_{i,j,t}^{UPS}$ Total input power of UPS j in data center i

$ES_{i,t}$ Energy storage condition of ESS in data center i at the beginning of time slot t

$ES_{\max,i}$ Maximum energy storage of battery in data center i

$ES_{\min,i}$ Minimum energy storage of battery in data center i

$P_{\max,i}^{char}$ Maximum charging power of ESS in data center i

$P_{\max,i}^{dischar}$ Maximum discharging power of ESS in data center i

η_i^{char} Charging efficiency of ESS in data center i

$\eta_i^{dischar}$ Discharging efficiency of ESS in data center i

$P_{i,t}^{PV}$ Solar power output in data center i at time t

$P_{i,t}^{grid}$ Power purchased from grid in data center i at time t

$P_{\max,i,l}^{unit}$ Minimum power output for generator l in data center i

$P_{\min,i,l}^{unit}$ Minimum power output for generator l in data center i

$MU_{i,l}^{unit}$ Minimum-up time for generator l in data center i

$MD_{i,l}^{unit}$ Minimum-down time for generator l in data center i

$UR_{i,l}^{unit}$ Ramp-up rate limit of generator l in data center i

$DR_{i,l}^{unit}$ Ramp-down rate limit of generator l in data center i

$CU_{i,l}^{unit}$ Start-up cost of generator l in data center i

$CD_{i,l}^{unit}$ Shut-down cost of generator l in data center i

$CO_{i,l}^{unit}$ No load cost of generator l in data center i

$CM_{i,l}^{unit}$ Marginal cost of generator l in data center i

$C_{i,t}^{grid}$ Power procurement cost of data center i at time t

$\pi_{i,t}^{grid}$ Electricity price of data center i at time t

C. Decision Variables

$\mu_{a,i,j,t}^{batch}$ Amount of batch workloads a allocated on the servers in data center i and powered by UPS j at time t

$\zeta_{i,j,t}^{inter}$ Allocated interactive workloads on the servers in data center i and powered by UPS j at time t

$P_{i,t}^{char}$ Charging power of ESS in data center i at time t

$P_{i,t}^{dischar}$ Discharging power of ESS in data center i at time t

$Z_{i,t}^{char}$ Binary variable to indicate if ESS in data center i is charging at time t

$Z_{i,t}^{dischar}$ Binary variable to indicate if ESS in data center i is discharging at time t

$P_{i,t}^{grid}$ Amount of electricity buying from utility grid by data center i at time t

$P_{i,l,t}^{unit}$ Output of conventional unit l in data center i at time t

$o_{i,l,t}^{unit}$ Binary variable to indicate if conventional generator l in data center i is on at time t

$u_{i,l,t}^{unit}$ Binary variable to indicate if conventional generator l in data center i is started up at time t

$v_{i,l,t}^{unit}$ Binary variable to indicate if conventional generator l in data center i is shut down at time t

II. INTRODUCTION

Data center energy consumption issue becomes increasingly prominent as the number of data centers increases. In 2018, there were 436,000 data centers and 4.899 million server racks in the world, and the number is still rising steadily. Recent data shows that the energy consumed by data centers in the U.S. is roughly 78 billion kWh in 2017, and it accounts for about 2.9% of the total energy consumed in the U.S [1].

Therefore, reducing the energy consumption cost of data centers has become the focus of many researchers. The first way is to reduce electricity consumption of servers and data center infrastructure. High efficiency UPSs and power supply units are designed to reduce the energy loss in power transmission [2-4]. And computational workload allocation is optimized to reduce idle power of servers[5-8]. By combining the workload allocation with UPS efficiency, Zhang *et al.* proposed a computational workload allocation strategy considering AC UPS efficiency [9]. Al-Hazemi *et al.* proposed a dynamic power delivery path allocation strategy[10]. This strategy has reduced energy consumption of servers and data center power supply units, but the energy storage devices and renewable energy are not effectively utilized.

To further reduce electricity cost of data centers, another way is to optimize the operation of data center micro grid. Solar power, wind power, energy storage and heat recovery are scheduled and optimized in cooperate with computational workload allocation [11-12]. And the differential electricity fee in a day is taken into account to reduce the electricity bills. Reference [13] [14] proposed micro grid resource planning schemes considering ESS, and reduced the energy cost and carbon emission. Yu *et al*. proposed a real-time and distributed algorithm for the micro grid optimal operation problem based on Lyapunov optimization technique [15]. Reference [16] proposed a UPS node based workload management strategy, and reduced the electricity charge. However, these researches only focus on one data center micro grid.

Computational task scheduling in geo-distributed provided another method to the electricity cost reduction. Reference [17] developed an workload scheduling method considering variability of nodal price and quality of service. By dispatching workloads into data center with lower electricity price, the total electricity bill is cut down. Shao *et al.* proposed an energy and workload management strategy considering electricity price and network delay [18]. Yuan *et al.* proposed several algorithm to solve the spatiotemporal task scheduling problem [19-20]. However, power supply efficiency in data centers is ignored.

Basing on the formal research, this paper proposed a hybrid optimization method for geo-distributed data center electricity cost reduction by jointly considering workload scheduling, nodal real-time electricity price, micro grid operation status and UPS power loss. By limiting the nonlinear growth of UPS power loss and increasing the degree of freedom in computational workload scheduling, the system operational cost can be reduced. Case studies are built on the CPLEX platform, whose result has proved the effectiveness of the proposed method.

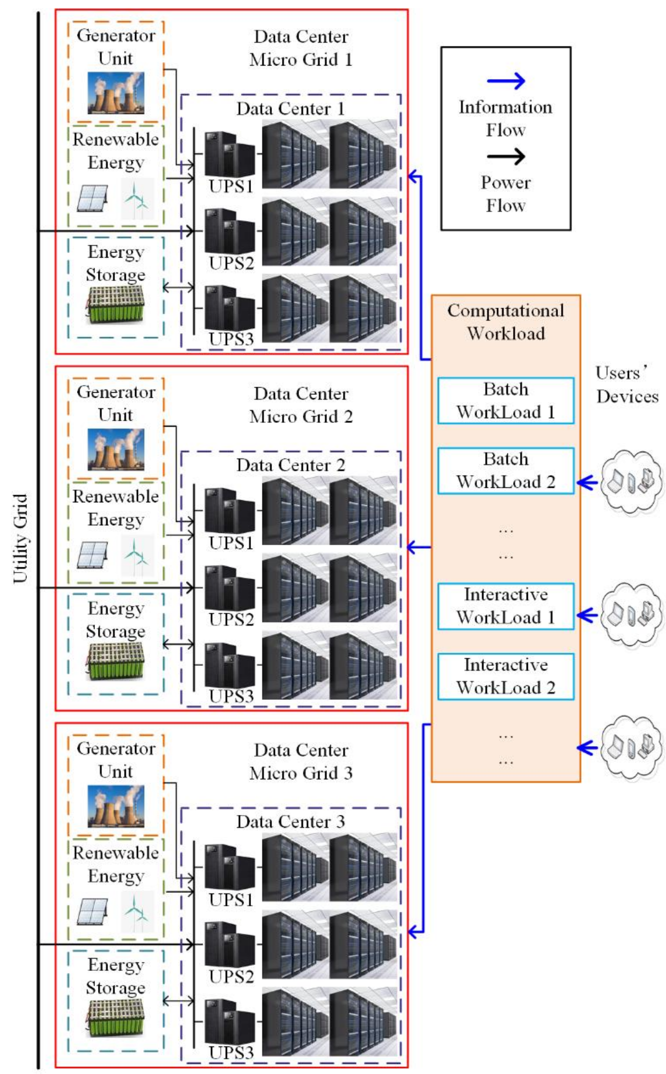

Fig. 1. Architecture of the geo-distributed IDC system.

This paper is organized as follows. In section 3, the problem is modeled and analyzed. In section 4, three cases are built and simulated, and the result is analyzed.

III. SYETEM MODEL AND MATHEMATICAL FORMULATION

The system model and mathematical model of the optimization problem is provided in this section. A typical system architecture of geo-distributed data centers is shown in Fig. 1, and each data center is running in a micro grid, where renewable power, conventional generator units and energy storage devices are deployed. Each data center contains multiple UPS nodes, which corresponds one set of UPS device and large number of servers. The system is modeled as a discrete time system with equal length time slots. Each time slot is 1 hour.

The system is categorized as power demand side and power supply side. On the power demand side, we built the model of workloads and UPS, and illustrated the correspondence between computational workloads and data center power consumption. On the power supply side, we built the model of energy storage and conventional generator units, and power balance is implemented in this part. Finally, the optimization problem is built in this part, which aims to minimize the operational costs and electricity bills of the total system.

A. Power Demand Side

1) Workload Allocation Model

Computational workloads of a data center can be briefly divided into two categories according to its responds time requirement: interactive workloads and batch workloads [21]. The interactive workloads should be served immediately, while the batch workloads are allowed to be served after a service delay of several hours. Both types of the workloads are considered in this paper.

In the system, the computational workloads come from users' devices, and then get allocated into servers in geo-distributed data centers. Assume the batch workload a arrive at time slot t_a^{batch} and should be served before a time delay D_a^{batch}. For each time slot t, the total amount of interactive workloads and batch workloads on every UPS node should not exceed the maximum CPU capacity, and the total power of servers on the node should not exceed the rated power of its corresponding UPS, as is defined as follows:

$$\lambda_{i,j,t} = \zeta_{i,j,t}^{inter} + \sum_{a}^{A} \mu_{a,i,j,t}^{batch} \, (\forall i,j,t) \tag{1}$$

$$0 \le \lambda_{i,j,t} \le Cap_{i,j} \, (\forall i,j,t) \tag{2}$$

$$\sum_{t_a^{batch}}^{D_a^{batch}} \mu_{a,i,j,t}^{batch} = \mu_{total,a}^{batch} \, (\forall a \in A) \tag{3}$$

$$P_{i,j,t}^{servers} \le P_{rated\,i,j}^{UPS} \, (\forall i,j,t) \tag{4}$$

In addition, for every time slot, the total real-time power in data center i, node j is:

$$P_{i,j,t}^{servers} = M_{i,j} \times \left(\varphi_{i,j}^{server} \times \lambda_{i,j,t} + P_{i,j}^{idle} \right) (\forall i,j,t) \tag{5}$$

where
$$\varphi_{i,j}^{server} = P_{i,j}^{peak} - P_{i,j}^{idle} \tag{6}$$

2) UPS Power Loss Model

UPS power loss nonlinearly varies depending on the load rate, which can be expressed as follows:

$$P_{i,j,t}^{Loss\_UPS} = P_{rated,i,j}^{UPS} \times \left[a_0 + a_1 \times \frac{P_{i,j,t}^{servers}}{P_{rated,i,j}^{UPS}} + a_2 \times \left(\frac{P_{i,j,t}^{servers}}{P_{rated,i,j}^{UPS}} \right)^2 \right] (\forall i,j,t) \tag{7}$$

where a_0, a_1 and a_2 are constants decided by UPS type.

So the UPS input power is as follows:

$$P_{i,j,t}^{UPS} = P_{i,j,t}^{Loss\_UPS} + P_{i,j,t}^{servers} \, (\forall i,j,t) \tag{8}$$

B. Power Supply Side

In each micro grid, the servers and UPSs are powered by solar power, wind power, conventional generator unit and utility grid. Energy storage devices are also deployed to cut down the volatility of renewable energy and reduce the electricity cost by making use of the daily electricity price difference.

1) Conventional Generator Unit Model

Conventional generator unit commitment decision model can be described as follows [22]:

$$P_{\min,i,l}^{unit} \cdot o_{i,l,t}^{unit} \le P_{i,l,t}^{unit} \le P_{\max,i,l}^{unit} \cdot o_{i,l,t}^{unit} \, (\forall i,j,t) \tag{9}$$

$$\begin{gathered} -o_{i,l,t-1}^{unit} + o_{i,l,t}^{unit} - o_{i,l,k}^{unit} \le 0 \\ 2 \le k-(t-1) \le MU_{i,l}^{unit} \, (\forall i,j,t) \end{gathered} \tag{10}$$

$$\begin{gathered} o_{i,l,t-1}^{unit} - o_{i,l,t}^{unit} + o_{i,l,k}^{unit} \le 1 \\ 2 \le k-(t-1) \le MD_{i,l}^{unit} \, (\forall i,j,t) \end{gathered} \tag{11}$$

$$-o_{i,l,t-1}^{unit} + o_{i,l,t}^{unit} - u_{i,l,t}^{unit} \le 0 (\forall i,j,t) \tag{12}$$

$$o_{i,l,t-1}^{unit} - o_{i,l,t}^{unit} + v_{i,l,t}^{unit} \le 0 (\forall i,j,t) \tag{13}$$

$$\begin{aligned} & P_{i,l,t}^{unit} - P_{i,l,t-1}^{unit} \le (2 - o_{i,l,t-1}^{unit} - o_{i,l,t}^{unit}) \cdot P_{\min,i,l}^{unit} \\ & + (1 + o_{i,l,t-1}^{unit} - o_{i,l,t}^{unit}) \cdot UR_{i,l}^{unit} \, (\forall i,j,t) \end{aligned} \tag{14}$$

$$\begin{aligned} & P_{i,l,t-1}^{unit} - P_{i,l,t}^{unit} \le (2 - o_{i,l,t-1}^{unit} - o_{i,l,t}^{unit}) \cdot P_{\min,i,l}^{unit} \\ & + (1 - o_{i,l,t-1}^{unit} + o_{i,l,t}^{unit}) \cdot DR_{i,l}^{unit} \, (\forall i,j,t) \end{aligned} \tag{15}$$

$$o_{i,l,t}^{unit}, u_{i,l,t}^{unit}, v_{i,l,t}^{unit} \in \{0,1\} (\forall i,j,t) \tag{16}$$

In the above equations, (9) describes the generators capacity constraint, (10)-(11) describe unit minimum-up/down time constraints, (12)-(13) describe unit start-up and shut-down constraints, and (14)-(15) describe unit ramping up/down constraints.

2) Energy Storage Device Model

The ESS can be described by the following equations:

$$ES_{i,t+1} = ES_{i,t} + \eta_i^{char} \cdot P_{i,t}^{char} - \eta_i^{dischar} \cdot P_{i,t}^{dischar} \, (\forall i,t) \tag{17}$$

$$ES_{\min,i} \le ES_{i,t} \le ES_{\max,i} \, (\forall i,t) \tag{18}$$

$$Z_{i,t}^{char}, Z_{i,t}^{dischar} \in \{0,1\} (\forall i,t) \tag{19}$$

$$Z_{i,t}^{char} + Z_{i,t}^{dischar} \le 1 (\forall i,t) \tag{20}$$

$$0 \le P_{i,t}^{char} \le P_{\max,i}^{char} \cdot Z_{i,t}^{char} \, (\forall i,t) \tag{21}$$

$$0 \le P_{i,t}^{dischar} \le P_{\max,i}^{dischar} \cdot Z_{i,t}^{dischar} \left(\forall i,t\right) \tag{22}$$

In the above equations, (17) describes the energy storage condition of every time slot, which is decided by the charging and discharging operation. Since there is conversion loss in the process of power charging and discharging, the energy conversion efficiency is considered in (17). Also, the state of charge should be within the maximum and minimum energy storage, so it should satisfy equation (18). (19)-(20) describe the charge/discharge constraints, and (21)-(22) describe maximum charging/discharging power constraints.

3) System Power Balance

Combining the supply side and demand side together, the power balance constraints can be obtained as follows:

$$\begin{aligned} P_{i,t}^{grid} &= \sum_{j}^{J} P_{i,j,t}^{UPS} + \eta_i^{char} \cdot P_{i,t}^{char} \\ &-\eta_i^{dischar} \cdot P_{i,t}^{dischar} - \sum_{l}^{L} P_{i,l,t}^{unit} - P_{i,t}^{PV} \left(\forall i,t\right) \end{aligned} \tag{23}$$

Since the electricity varies in different geographical location and time slots, the power procurement cost in each micro grid can be expressed by:

$$C_{i,t}^{grid} = P_{i,t}^{grid} \cdot \pi_{i,t}^{grid} \left(\forall i,t\right) \tag{24}$$

C. Minimization Problem

To reduce the operational cost of the geo-distributed data centers, the operational cost of conventional units and electricity purchasing cost should be comprehensively considered. And the computational workloads, ESS and conventional unit should be skillfully managed to realize optimal operation of the system.

So, the optimization problem is formulated as follows:

$$\min \sum_{i=1}^{I} \sum_{t=1}^{T} \left(C_{i,t}^{grid} + C_{i,t}^{unit} \right) \tag{25}$$

where

$$\begin{aligned} C_{i,t}^{unit} &= \sum_{l=1}^{L} (CU_{i,l}^{unit} \cdot u_{i,l,t}^{unit} + CD_{i,l}^{unit} \cdot v_{i,l,t}^{unit} \\ &+ CO_{i,l}^{unit} \cdot o_{i,l,t}^{unit} + CM_{i,l}^{unit} \cdot P_{i,l,t}^{unit}) \left(\forall i,t\right) \end{aligned} \tag{26}$$

s.t.

$$\lambda_{i,j,t} = \zeta_{i,j,t}^{inter} + \sum_{a}^{A} \mu_{a,i,j,t}^{batch} (\forall i,j,t) \tag{27}$$

$$0 \le \lambda_{i,j,t} \le Cap_{i,j} (\forall i,j,t) \tag{28}$$

$$\sum_{t_a^{batch}}^{D_a^{batch}} \mu_{a,i,j,t}^{batch} = \mu_{total,a}^{batch} (\forall a \in A) \tag{29}$$

$$P_{i,j,t}^{servers} \le P_{rated,i,j}^{UPS} (\forall i,j,t) \tag{30}$$

$$P_{\min,i,l}^{unit} \cdot o_{i,l,t}^{unit} \le P_{i,l,t}^{unit} \le P_{\max,i,l}^{unit} \cdot o_{i,l,t}^{unit} \left(\forall i,j,t\right) \tag{31}$$

$$\begin{aligned} &-o_{i,l,t-1}^{unit} + o_{i,l,t}^{unit} - o_{i,l,k}^{unit} \le 0 \\ &2 \le k-(t-1) \le MU_{i,l}^{unit} \left(\forall i,j,t\right) \end{aligned} \tag{32}$$

$$\begin{aligned} &o_{i,l,t-1}^{unit} - o_{i,l,t}^{unit} + o_{i,l,k}^{unit} \le 1 \\ &2 \le k-(t-1) \le MD_{i,l}^{unit} \left(\forall i,j,t\right) \end{aligned} \tag{33}$$

$$-o_{i,l,t-1}^{unit} + o_{i,l,t}^{unit} - u_{i,l,t}^{unit} \le 0\left(\forall i,j,t\right) \tag{34}$$

$$o_{i,l,t-1}^{unit} - o_{i,l,t}^{unit} + v_{i,l,t}^{unit} \le 0\left(\forall i,j,t\right) \tag{35}$$

$$\begin{aligned} &P_{i,l,t}^{unit} - P_{i,l,t-1}^{unit} \le (2 - o_{i,l,t-1}^{unit} - o_{i,l,t}^{unit}) \cdot P_{\min,i,l}^{unit} \\ &+(1 + o_{i,l,t-1}^{unit} - o_{i,l,t}^{unit}) \cdot UR_{i,l}^{unit} \left(\forall i,j,t\right) \end{aligned} \tag{36}$$

$$\begin{aligned} &P_{i,l,t-1}^{unit} - P_{i,l,t}^{unit} \le (2 - o_{i,l,t-1}^{unit} - o_{i,l,t}^{unit}) \cdot P_{\min,i,l}^{unit} \\ &+(1 - o_{i,l,t-1}^{unit} + o_{i,l,t}^{unit}) \cdot DR_{i,l}^{unit} \left(\forall i,j,t\right) \end{aligned} \tag{37}$$

$$Z_{i,t}^{char} + Z_{i,t}^{dischar} \le 1\left(\forall i,t\right) \tag{38}$$

$$0 \le P_{i,t}^{char} \le P_{\max,i}^{char} \cdot Z_{i,t}^{char} \left(\forall i,t\right) \tag{39}$$

$$0 \le P_{i,t}^{dischar} \le P_{\max,i}^{dischar} \cdot Z_{i,t}^{dischar} \left(\forall i,t\right) \tag{40}$$

$$\begin{aligned} P_{i,t}^{grid} &= \sum_{j}^{J} P_{i,j,t}^{UPS} + \eta_i^{char} \cdot P_{i,t}^{char} \\ &-\eta_i^{dischar} \cdot P_{i,t}^{dischar} - \sum_{l}^{L} P_{i,l,t}^{unit} - P_{i,t}^{PV} \left(\forall i,t\right) \end{aligned} \tag{41}$$

$$o_{i,l,t}^{unit}, u_{i,l,t}^{unit}, v_{i,l,t}^{unit}, Z_{i,t}^{char}, Z_{i,t}^{dischar} \in \{0,1\} \left(\forall i,j,t\right) \tag{42}$$

As is shown above, the optimization goal is to minimize the operational cost of the system, which is composed of electricity cost and conventional unit operational cost. The conventional unit operational cost consists no load cost, marginal cost, start-up and shut-down cost, which is defined in equation (26). (27)-(30) are the constraints in the power demand side, and (31)-(41) are the constraints which ensure the running of power supply side. The decision variables for the optimal problem include the allocation of interactive and batch workloads, the operation schedule of ESS and conventional generator units. The proposed resource planning model is formulated as a mixed-integer linear programming (MILP) problem.

IV. Case Studies

In this section, a sample of geo-distributed data center micro grid system is established to examine the proposed method in this paper. All the system modeling and solving algorithms are coded in CPLEX platform [23], which is commonly used to solve linear programming or mixed integer programming problem. The simulations are conducted on a desktop computer with Intel Core i5-8400 CPU @ 2.80GHz and 8 GB memory.

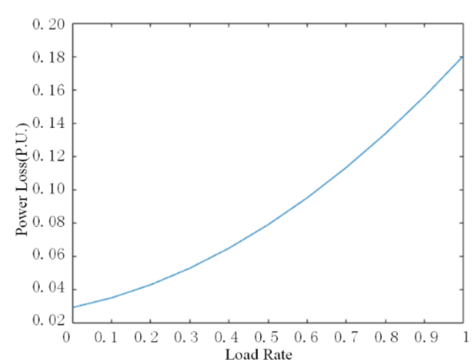

Fig. 2. UPS power loss curve.

A. *Simulation Setup*

In this paper, three geo-distributed data center micro grids are simulated. In each micro grid, two conventional generators (one is coal based and another is gas based), distributed solar and wind generations and energy storage system are deployed. The micro grids are connected to the utility grid, and each provides power for one data center. In each data center, there are three UPS nodes, which contain the same number of servers. Three types of UPSs are simulated, and for the sake of simplicity, the deployment of three data centers is the same, which means there are one of each types of UPS in the data center. Parameters of the system are listed in Table I-V.

TABLE I. PARAMETERS OF DATA CENTERS

UPS Node	Maximum Capacity(MW)	Number of Servers	UPS Type
Node 1	15	$6*10^4$	1
Node 2	15	$6*10^4$	2
Node 3	15	$6*10^4$	3

TABLE II. UPS PARAMENTERS

UPS Types	Power Loss Equation Parameters		
	a_0	a_1	a_2
1	0.0086	0.0241	-0.0027
2	0.0241	0.0353	0.0617
3	0.0518	0.1787	0.0947

TABLE III. PARAMENTERS OF CONVENTIONAL GENERATOR UNITS

Unit	Fuel Type	High/Low Sustainable Limit (MW)	Ramp Up/Down Rate (MW/h)	Minimum Up/Down Time (h)
Unit 1	Gas	15/5	4/4	4/4
Unit 2	Coal	20/9	6/6	3/3

TABLE IV. PARAMENTERS OF CONVENTIONAL GENERATOR UNITS

Unit	Initial State	Initial Power(MW)	Start-up/Shut-down Cost($)	No Load Cost($)	Marginal Cost($/MWh)
Unit 1	On	10	50	40	18
Unit 2	On	14	40	30	16

TABLE V. PARAMENTERS OF ENERGY STORAGE SYSTEM

Maximum/Minimum State (MWh)	Initial/Final State (MWh)	Maximum Charging/Discharging Rate (MW/h)	Charging/ Discharging Efficiency
30/5	5	5	0.8

The characteristics of conventional generation units and energy storage system are scaled from ERCOT scheduling data [14]. The workload data is based on the information in [14] and [24]. Assume the three data centers are located in Texas, New York and California, data of real-time electricity price, solar and wind power output are collected from ERCOT [25], CAISO [26] and NYISO [27] respectively and plotted in Fig. 3, Fig. 4 and Fig. 5.

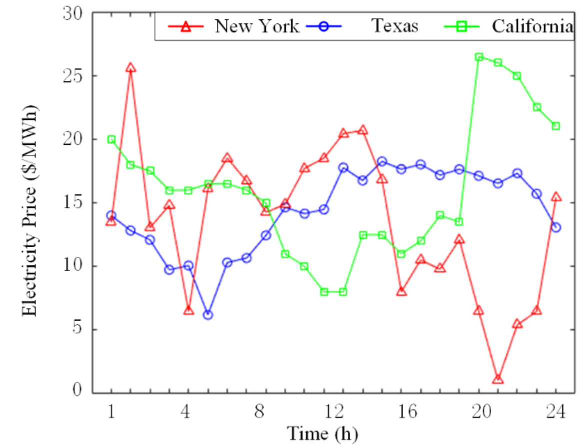

Fig. 3. Real-time electricity price in three city.

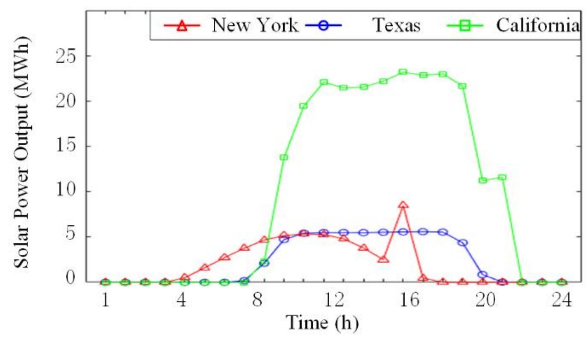

Fig. 4. Solar power output in three data centers.

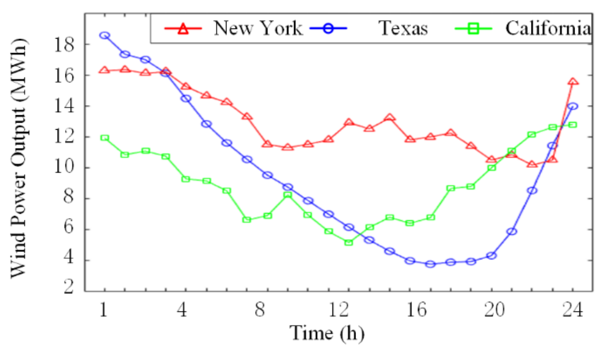

Fig. 5. Wind power output in three data centers.

B. *Cases and Comparision*

In the proposed optimal method, the workload allocation and micro grid management of three IDC micro grids are jointly optimized. To verify its effectiveness, three cases are simulated and compared:

Case I: Workload distribution in three IDC are optimized considering local electricity price, but then the workloads are evenly allocated on three UPS nodes inside the data center.

Case II: Workload distribution in three IDC are optimized considering local electricity price in the first step, and its distribution on UPS nodes are optimized in the second step.

Case III: Workload distribution in IDC and UPS nodes are jointly optimized considering local electricity price, micro grid operation and UPS power loss.

The existing research has studied the workload scheduling in geo-distributed data centers and workload scheduling in UPS nodes separately. Being differently, in case II and case III we combined the workload scheduling in data centers with the workload scheduling in UPS nodes. By comparing operational cost in these three cases, effectiveness of the joint optimization can be proved.

C. *Results and Analysis*

Total operational cost of the system in three cases are listed in Table VI. By comparing operational cost in case I with the operational cost in case II and case III, it can be found that operational cost has been cut down by 0.43% and 1.23%. This has proved that combing geo-distributed data center workload scheduling with UPS node workload scheduling can achieve remarkable improvement in cutting down the operational cost of the system. Compared to case II, the operational cost in case III is reduced by 0.8%, which has verified the effectiveness of the proposed joint optimization method.

To show the improvement in reducing energy consumption, the total electricity consumption of the three data centers in three cases are listed in Table VII. And the reduction of electricity consumption is calculated. Compared to case I and case II, the total electricity consumption in case III is reduced by 3.54% and 0.76%, which has proved the superiority of the proposed method.

To provide a detailed comparison of the electricity consumption in three cases, hourly electricity consumption inside the IDC is plotted in Fig. 6. In this figure, three lines refer to hourly total electricity of servers and UPSs in three cases. It is obvious that case III performs better in reducing the total energy consumption in data centers.

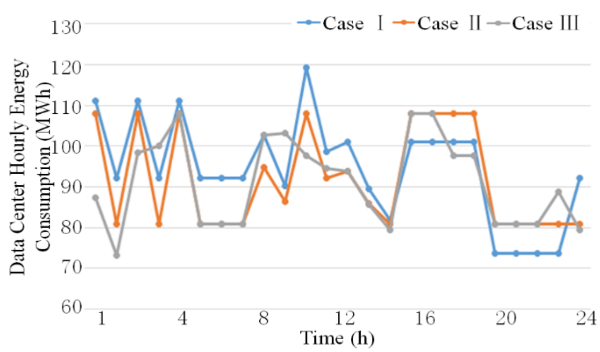

Fig. 6. Data center hourly energy consumption in three cases.

TABLE VI. OPERATIONAL COST

Case	Case I	Case II	Case III
Operational Cost ($)	14546.71	14483.72	14367.30

TABLE VII. ELECTRICITY CONSUMPTION

Case	Case I	Case II	Case III
Electricity Consumption (MWh)	2268.6	2205.1	2188.3

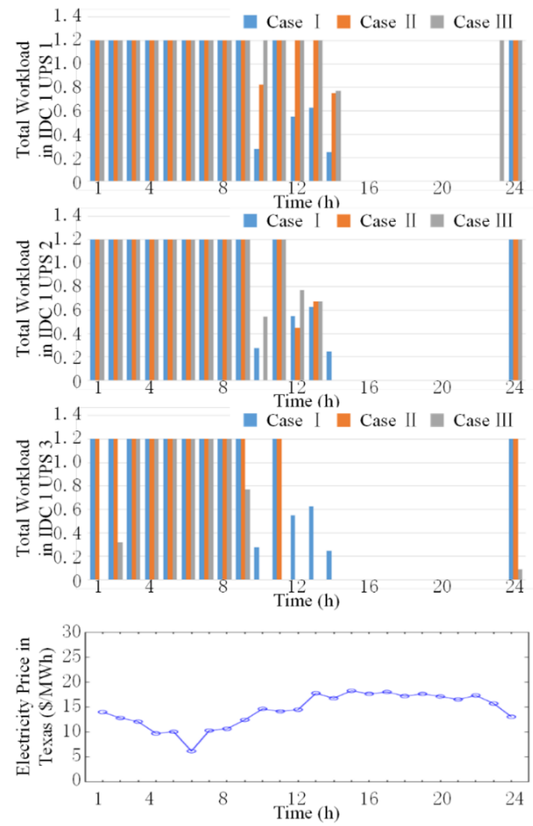

Fig. 7. Workload Distribution in IDC 1

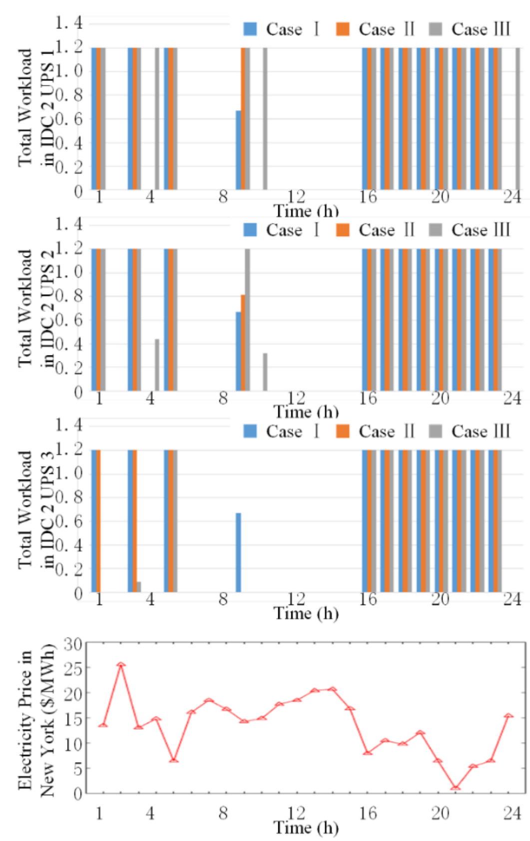

Fig. 8. Workload Distribution in IDC 2.

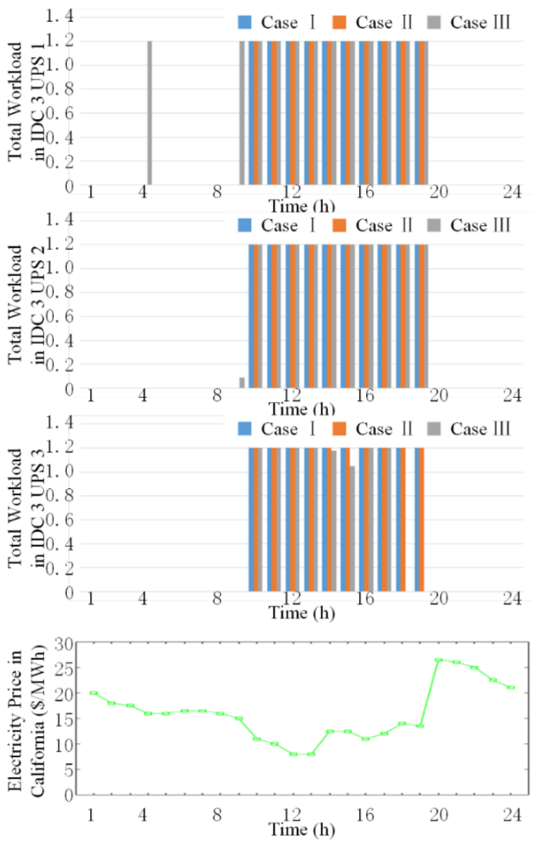

Fig. 9. Workload Distribution in IDC 3.

To further analyze the difference of workload distribution, total workloads on each UPS node in case I, case II and case III are plotted in Fig. 7, Fig. 8 and Fig. 9 with different color. By comparing workload distribution in three cases, it can be figured out that the workloads are allocated in the UPS nodes powered by UPSs with lower power loss and higher energy conversion efficiency. However, in case I and case II, since the workload distribution in each time slot is decided in the first step, it can't be freely scheduled in different time slots and UPS nodes, which accounts for the difference in operational cost.

The charge and discharge operation of the ESS in case III is plotted in Fig. 10, Fig. 11 and Fig. 12. As the chart shows, the battery is charged when local market price is high, and discharged when price is low, which has helped to reduce the electricity bill.

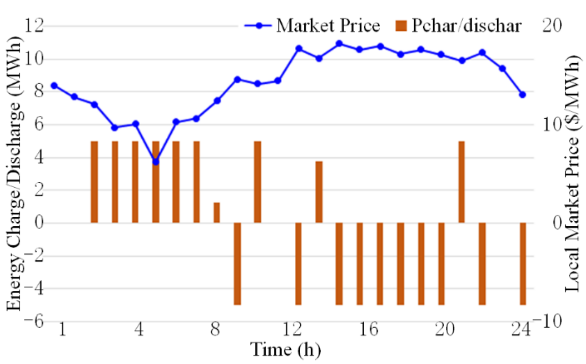

Fig. 10. Charge and discharge operation of ESS in IDC 1.

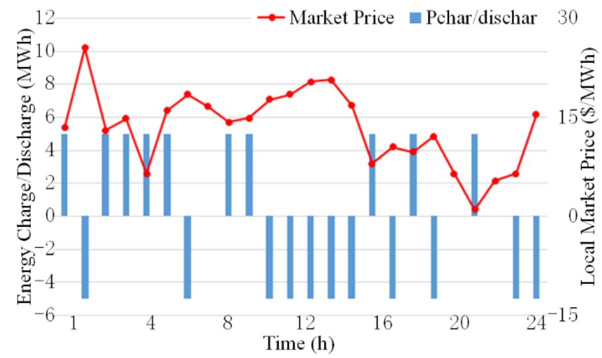

Fig. 11. Charge and discharge operation of ESS in IDC 2.

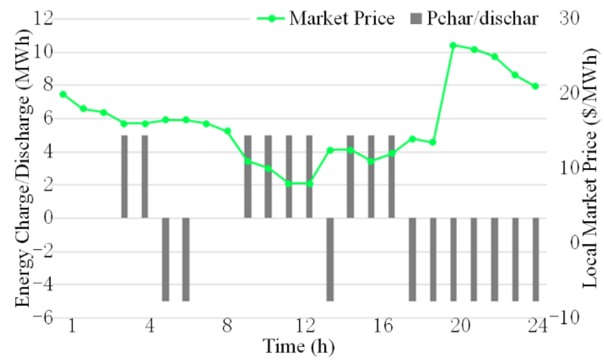

Fig. 12. Charge and discharge operation of ESS in IDC 3.

V. Conclusion

This paper proposes a joint optimized operation method for geo-distributed IDC. By fully considering the UPS power loss and the operation of data center micro grids, the computational workload distribution and operational status of micro grids are further optimized, thus lead to reduction of system operational cost and total energy consumption. A simulation is built on CPLEX platform, and three different cases are simulated and analyzed, whose results verified the superiority of the proposed method in comparison with other popular methods.

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