A Framework for Several Electricity Retailers Cooperatively Implement Demand Response to Distributed Data Center

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***Abstract*—A distributed data center cluster (DDCC) consists of data centers that are geographically dispersed while managed by the same company. A DDCC is composed of several data centers in different regions, so it purchases electricity from several electricity retailers in different regions. Commonly, there is a lack of cooperation between the several electricity retailers. In this paper, a cooperation framework where several electricity retailers cooperatively implement incentive-based demand response (DR) to the same DDCC is proposed. Firstly, several electricity retailers which power for the same DDCC together publish their DR instructions to the DDCC. The DR instructions are analyzed in this paper. Then a novel DDCC energy management model is proposed for the DDCC to participate in the collaborative DR. Finally, a reasonable profit distribution mechanism is adopted for the several electricity retailers and the DDCC to allocate the entire profit of the collaborative DR. The case study verifies that the proposed cooperation framework can maximize the whole benefit of the DDCC and the several electricity retailers meanwhile ensures that the profits obtained by each member (the DDCC and the several electricity retailers) from the collaborative DR are not fewer than that of the independent operation.**

***Index Terms*—Distributed Data Centers, Several Electricity Retailer, Demand Response, Cooperation Framework.**

NOMENCLATURE

A. Abbreviations

DDCC	Distributed data center cluster
DR	Demand response

B. Indices

f	Index of DDCC's front-end servers
k	Index of electricity retailers/data centers
n	Index of members in a cooperation union
t	Index of hour

C. Parameters

a_k^+	The upper limit of the electricity increase
a_k^-	The upper limit of the electricity reduction
b_i^+	The profit change of electricity Retailer-*k* if Data centers-*k* increases unit electricity use
b_k^-	The profit change of electricity Retailer-*k* if Data centers-*k* reduces unit electricity use
cap_k	The capacity of distribution network
E_k^{base}	The estimated electricity usage of Data center-*k* if it does not participate in a DR program
F	The DDCC contains F front-end servers
K	The DDCC contains K data centers
L_k	The electricity to be brought by electricity Retailer-*k* in the day-ahead wholesale market
$\hat{L}_k$	The demand of electricity Retailer-*k*'s customer without DR
ΔL_k^+	Increase of the amount of electricity use of Data center-*k*
ΔL_k^-	Reduction in the amount of electricity use of Data center-*k*
M_k	The maximum available servers of Data center-*k*
P_k^{idle}	The idle energy consumption of a server in Data center-*k*
P_k^{peak}	The peak energy consumption of a server in Data center-*k*
PUE_k	The power usage effectiveness of Data center-*k*
r_k^+	The unit load increase fine that electricity Retailer-*k* pays for system operator
r_k^-	Increase in the unit load fine that electricity Retailer-*k* pays for system operator
TU_k	The turnover of electricity Retailer-*k* without DR

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TU_k^+	The turnover of electricity Retailer-*k* if Data center-*k* increases electricity consumption
TU_k^-	The turnover of electricity Retailer-*k* if Data center-*k* reduces electricity consumption
$t_{k,f}^d$	The transmission time of workloads from the front-end servers *f* to Data center-*k*
t_k^d	The maximum time delay of Data center-*k*' workload
v_k	The maximum permissible deviation
γ_k	Binary parameter equals to 1 if electricity Retailer-*k* has a load reducing DR contract with the system operator
ϕ_k	The retail price of electricity Retailer-*k*
π_k	The electricity prices of the day-ahead electricity market
ρ_k	The electricity price of the real-time electricity market
λ_f	The workloads in the front-end server *f*
μ_k	The service rate of Data center-*k*'s per server

D. Decision variables

X_k^-	Binary variable, is one when Data center-*k* reduces electricity consumption
X_k^+	Binary variable, is one when Data center-*k* increases electricity consumption
$\lambda_{k,f}$	The workloads that front-end server *f* distribute to Data center-*k*
$s_{k,f}$	The number of active servers in Data center-*k* which is used to process the workloads $\lambda_{k,f}$

E. Indirect variables

E_k	The electricity usage of Data center-*k*
W_k	The initial profit of electricity Retailer-*k* in the collaborative DR
W_{DDCC}	The initial profit of the DDCC in the collaborative DR
W_{uni}	The entire profits of the ED union when they together implement the collaborative DR.
$W_{DDCC}^{shapley}$	The final profits of the DDCC in the collaborative DR
$W_k^{shapley}$	The final profits of electricity Retailer-*k* in the collaborative DR
W_{DDCC}^{pool}	The money that the DDCC swaps with the fund pool.
W_k^{pool}	The money that the electricity Retailer-*k* swaps with the fund pool.
$\delta_{k,f}$	The utilization in the active servers $s_{i,f}$
e_k^s	The electricity usage of Data center-*k*'s active servers

I. Introduction

With the rapid increase of demand in information services (big data services, internet services, cloud-computing services, etc.), many data centers have been established around the world by different companies for their business processing or to provide cloud-computing services to customers [1]- [4]. For a company, if it only operates one data center, the failure of this data center will lead to this company's business shutdown and the company's important data loss. Therefore, some large companies, such as Alibaba and Amazon, will establish several data centers distributed in different regions. When one of their data centers breakdowns, their data centers in other regions can take over the computing request (workloads) of the failed data center. Their business and data will not be affected by the accident [5]. Those data centers that are geographically dispersed while managed by the same company normally called a distributed data center cluster (DDCC) [6].

A DDCC may contain thousands or even hundreds of thousands of servers, so the energy consumption of a DDCC can be very large. For instances, google company reported in 2011 that its DDCC continued to consume nearly 260 megawatts of electricity [7]. Another aspect is, in a DDCC, one data center can transfer its workloads to the DDCC's other data centers or receive the workloads from the other data centers (namely, workload space shifting). The electricity consumption of each data center in a DDCC hence can be changed flexibly [8]. Demand response (DR) [9], [10] is a program to motivate changes in electricity usage by customers through giving customers time-varying electricity prices (price-based DR) [11] or giving customers incentive payments (incentive-based DR) [12]. DDCCs are regarded as a high-quality DR resource because of their huge power consumption and flexible load regulation ability [13]-[15]. DDCCs participating in DR can reduce the electricity cost of DDCCs and improve the reliability of the power system [16]-[19].

Based on the above reasons, the topic of DDCCs participating in DR has been explored in the recent rich body of literature, which can be summarized into two types. The first type of literature concerns with DDCCs' energy management under DR programs. Qureshi et al. in [20] developed an method for DDCCs to optimize their energy consumption plans. The method takes advantage of differences in electricity prices between regions and to minimize DDCCs' energy cost. Ref. [21] designed an algorithm to deal with the optimization problem of the DDCCs' energy management. The carbon emission [22], renewable sources [23] and quality of service [24] were also considered by researchers when optimizing DDCCs' energy management under DR programs.

The second thread of literature pays attention to the interactions among electric companies/institutions and DDCCs. Wang et al. [25] studied how the electric companies actively exploit DDCCs' workloads distribution between regions to achieve the purpose of power load balance between regions. A two-stage optimization model is proposed by them to optimize electric companies' price-based DR mechanisms designed for DDCCs. Ref. [26] analyzed the interactions among multiple electricity companies and a DDCC by the Stackelberg game theory. In the Stackelberg game model of [26], each electricity company will set a real-time price to maximize its benefit in stage I. In stage II, the DDCC' operator will draw up its workload shifting plan according to the real-time price. The interactions between a cloud computing system and a smart power grid equipped with distributed photovoltaic power generation were studied by literature [27].

Our paper falls into the second thread, yet is different from other literature because we focus on how several electricity retailers cooperatively implement incentive-based DR to the same DDCC. A DDCC is composed of several data centers in different regions, so it purchases electricity from several electricity retailers in different regions. In common practice, there is a lack of cooperation between the several electricity retailers. Each of them independently issues incentive-based DR to the DDCC. However, the several electricity retailers could benefit more if they cooperatively manage the DDCC's DR behavior. For a simple example, as shown in Fig. 1, three electricity retailers in different regions (Retailer-1, Retailer-2, Retailer-3) supply electricity to a DDCC's three data centers respectively. At a timeslot, Retailer-1 wants to cut down the electricity usage of Data center-1. Meanwhile, the electricity usage increase of Data center-2 will lead to the financial loss of Retailer-2 and the electricity consumption increase of Data center-3 will cause a profit of Retailer-3. If the three electricity retailers lake of cooperation, and Retailer-1 independently issues an incentive-based DR to the DDCC which aims to cut down Data center-1's electricity usage, the DDCC operator may transfer Data center-1's workloads to Data center-2 instead of Data center-3. Retailer-2 will lose money and Retailer-3 does not have the profit. Conversely, if the three electricity retailers cooperatively manage the DR behavior of the DDCC, they can work together to guide the DDCC operator to move the workloads from Data center-1 to Data center-3, which can maximize the overall profit of the three electricity retailers and the DDCC. All in all, when several electricity retailers power for the same DDCC, the several electricity retailers cooperatively manage the DR behavior of the DDCC can maximize their overall profit because the requirements of all electricity retailers can be considered by the DDCC. If the overall profit is improved, the profit of each member can be improved through a reasonable profit distribution strategy. So far, there is few literature paying attention to the problem that several electricity retailers cooperatively manage the DR behavior of the same DDCC.

Considering the facts mentioned above, this paper proposes a cooperation framework where several electricity retailers cooperatively implement incentive-based DR to the same DDCC which can increase the profits of the several electricity retailers and the DDCC. In the proposed cooperation framework, several electricity retailers who power for the same DDCC together send their DR instructions to the DDCC. Then, the DDCC operator redistributes the workloads of each data center to maximize the entire profit of the several electricity retailers and the DDCC. After the DR event, the entire profit is allocated by the several electricity retailers and the DDCC.

The Shapley value method is often mentioned by researchers in cooperative game research. The Shapley value method could fairly allocate the entire profit of a union to each member according to the contribution of each member and ensure that the profits obtained by each member from the cooperation situation are not fewer than that of the independent operation. In this paper, the Shapley value method is used to allocate the entire profit of collaborative DR to the DDCC and the several electricity retailers fairly.

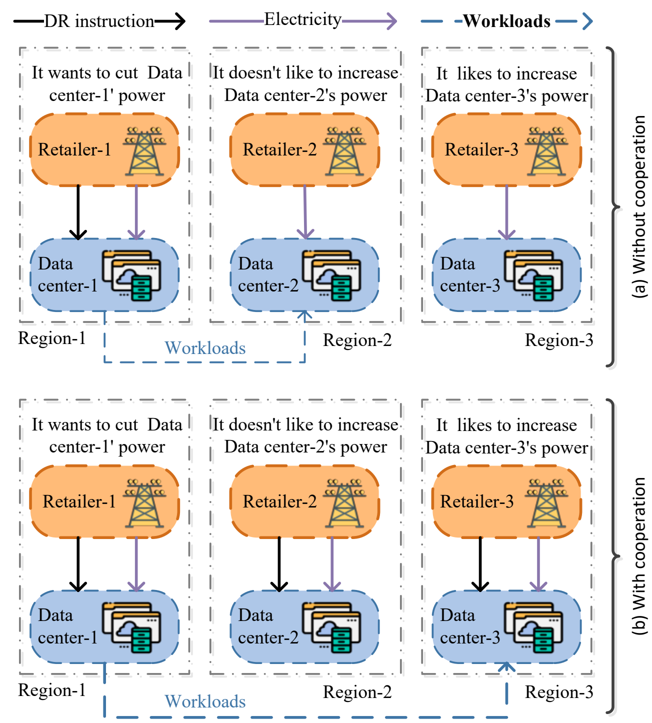

Fig. 1. Two scenarios in which electricity retailers implement incentive based DR. (a) without cooperation. (b) with cooperation.

The Shapley value method is extensively used in different scenarios and different cooperation unions for union profit allocation [28], [29]. In Ref. [28], a cooperation union which contains an electricity retailer and multiple residents was established for aiding residents to access the balance market. It should be noted that the cooperation between electricity retailers and DDCCs was researched in Ref. [29]. However, the cooperation model in [29] targets at facilitating collaboration between one electricity retailer and several DDCCs and optimizing electricity retailer's bidding plans in the day-ahead electricity market. It played a role in the scenario that several DDCCs acquire electricity from the same electricity retailer. In contrast, given that a DDCC generally purchases electricity from several electricity retailers in different regions, as such the present authors consider significantly different cases and focus on how several electricity retailers cooperatively implement incentive-based DR to the same DDCC and how the DDCC can participate in the collaborative DR to maximize the entire profit of the several electricity retailers and the DDCC. Another aspect is, the specific formulas of the Shapley value method in Ref. [29] is also different from that in this paper due to the different cooperation members, cooperation conditions, cooperation goals and cooperation profit functions in the two articles.

Besides, there has been some meaningful work on addressing the collaborative DR problem through multi-objective or multi-agent optimizations [30], [31]. The common feature of the existing literature is that the intersection between different DR aggregators/agents' customers is empty. That is to say, in the existing literature, a single electricity customer is not controlled by multiple aggregators/agents at the same time. In contrast, this paper pioneered the collaborative DR problem that multiple geographically dispersed DR aggregators cooperatively manage the DR behavior of a single electricity customer. To the best of our knowledge, no research literature is carried out to the topic that several geographically dispersed retailers (DR aggregators) cooperatively implement incentive-based DR to the identical DDCC.

Fig. 2 is the conceptual diagram of the proposed cooperation framework. In Fig. 2, different squares represent the profits of different members (electricity retailers and the DDCC). The larger the square area, the higher the profits of members. The cooperation framework can be divided into two steps. The first step is that several electricity retailers and the DDCC implement the collaborative DR together to maximize their entire profit. After the collaborative DR event, the profits obtained by some members from the collaborative DR may be fewer than that of the independent operation. (Maximizing the entire profit does not mean that the profits of each member will be increased). Therefore, in the second step, the entire profit is reallocated by the several electricity retailers and the DDCC according to the Shapley value method. By implementing the profit reallocation scheme, the profits obtained by each member from the collaborative DR are not fewer than that of the independent operation.

The contributions of this paper can be summarized as follows:

1) This paper proposes a cooperation framework where several electricity retailers cooperatively implement incentive-based DR for the same DDCC which can increase the profits of the several electricity retailers and the DDCC.

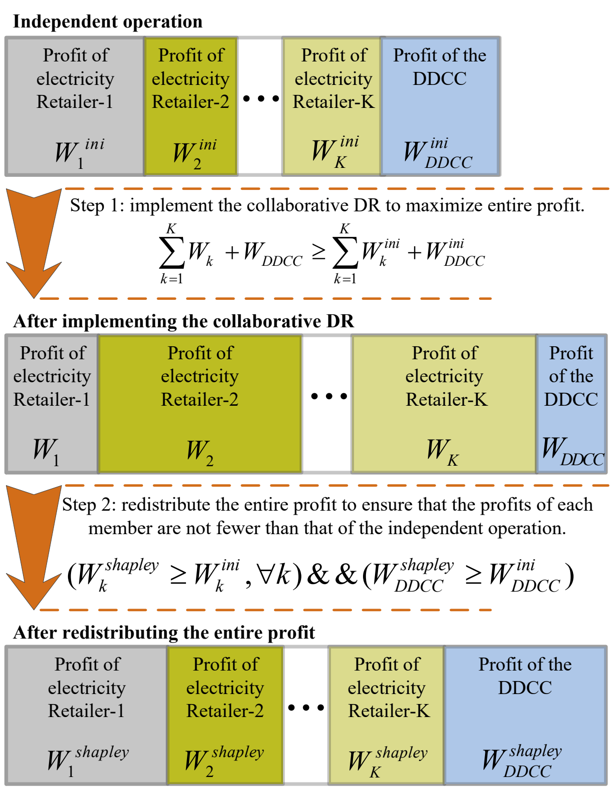

Fig. 2. The conceptual diagram of the proposed cooperation framework.

2) To achieve the proposed cooperation framework, the DR instructions of the several electricity retailers are analyzed, and a novel energy management model is proposed for the DDCC to participate in the collaborative DR. The goal of the DDCC energy management model is to maximize the entire profit of the several electricity retailers and the DDCC in the collaborative DR.

3) To achieve the proposed cooperation framework, Shapley value method is adopted to determine how the entire profit of the collaborative DR is allocated among the DDCC and the several electricity retailers. This profits allocation method could ensure that the profits obtained by each member from the collaborative DR are not fewer than that of the independent operation.

The rest of this paper is organized as follows. Section II illustrates the approach of implementing the collaborative DR which includes two stages. First, the several electricity retailers together publish DR instructions to the DDCC, and second, the DDCC participates in the collaborative DR. Section III describes the method of allocating the entire profit of the collaborative DR to the DDCC and the several electricity retailers. Case studies are presented in Section IV. Section V draws the conclusions.

II. Collaborative Demand Response Model

A. Overview of the Cooperation Framework

The system structure of this paper is illustrated in Fig. 3. There are K electricity retailers in different regions supplying power for a DDCC's K data centers respectively (other customers of these electricity retailers are beyond the research scope of this article). To obtain more profits, the K retailers cooperatively implement incentive-based DR to modify the electricity consumption of the K data centers in the DDCC. The process of the cooperation framework is as follows:

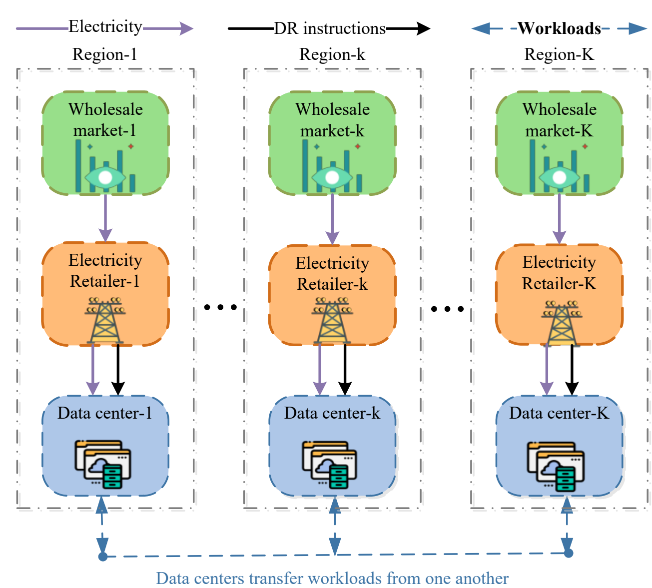

Fig. 3. The structure and mechanism of the system model.

1) The K electricity retailers and the DDCC form a union (ED union). When any electricity retailer in the ED union wants to implement a collaborative DR, it should inform the other electricity retailers in the ED union. Then, the K electricity retailers together publish their DR instructions to the DDCC. More details about the K electricity retailers' DR instructions are illustrated in Subsection B of Section II.

2) After receiving the K electricity retailers' DR instructions, the DDCC operator manages the electricity consumption of each data center by the proposed energy management model, which aims to maximize the entire profit of the ED union (entire profit of the collaborative DR). The details of this step and the proposed DDCC energy management model are given in Subsection C of Section II.

3) When the collaborative DR event is over, the K electricity retailers and the DDCC together allocate the entire profit of the collaborative DR. More on profit allocation can be found in Section III.

B. DR Instructions of Electricity Retailers

In the proposed cooperation framework, the K electricity retailers together publish DR instructions to the DDCC. Each electricity retailer's DR instructions include: the impact of the local data center's load change on electricity retailer's revenue, and the allowable range of local data center's load change.

For an electricity retailer in the ED union, electricity Retailer-*k*, it buys electricity from the day-ahead wholesale electricity market and supplies electricity to its customers [32]. If the electricity that electricity Retailer-*k* buys from the day-ahead wholesale market mismatches the demand of its customers, electricity Retailer-*k* has to buy electricity in the real-time wholesale market to maintain a balance between electricity purchasing and customer demand [33], [34]. In simple terms, the turnover of electricity Retailer-*k* in a timeslot depends on the cost of purchasing electricity from the day-ahead wholesale market and real-time wholesale market, as well as the revenue from supplying electricity to customers, as shown in (1).

$$TU_{\mathrm{k}} = \hat{L}_k \phi_k - L_k \pi_k - (\hat{L}_k - L_k)\rho_k \quad ,\forall k \tag{1}$$

where ϕ_k is the price of electricity Retailer-*k* supplying electricity to customers. π_k and ρ_k are the prices of electricity Retailer-*k* buying electricity from the day-ahead wholesale market and the real-time wholesale market. $\hat{L}_k$ denotes the electricity demand of electricity Retailer-*k*'s customers. L_k is the electricity that electricity Retailer-*k* buys from the day-ahead wholesale market. $(\hat{L}_k - L_k)$ is the electricity that electricity Retailer-*k* buys from the real-time wholesale market.

As one of the customers of electricity Retailer-*k*, if Data center-*k* reduces electricity consumption ΔL_k^- in a timeslot, the demand of electricity Retailer-*k*'s customers will change to $\hat{L}_k - \Delta L_k^-$. According to Equation (1), the turnover of electricity Retailer-*k* in this situation can be calculated as (2).

$$\begin{aligned} TU_k^- &= (\hat{L}_k - \Delta L_k^-)\phi_k - L_k\pi_k - ((\hat{L}_k - \Delta L_k^-) - L_k)\rho_k \\ &\quad + Y_k \Delta L_k^- r^- \quad ,\forall k \end{aligned} \tag{2}$$

The incentive-based DR issued by system operators is also considered in this paper. Y_k is a binary parameter. It equals to one when electricity Retailer-*k* has a load reducing DR contract with the system operator. r^- is the DR rewards that the system operator gives to electricity Retailer-*k* when electricity Retailer-*k* reducing unit load.

Similarly, if Data center-*k* increases electricity consumption ΔL_k^+ in a timeslot, the demand of electricity Retailer-*k*'s customers will change to $\hat{L}_k + \Delta L_k^+$. According to Equation (1), the turnover of electricity Retailer-*k* in this situation can be calculated as (3).

$$\begin{aligned} TU_k^+ &= (\hat{L}_k + \Delta L_k^+)\phi_k - L_k\pi_k - ((\hat{L}_k + \Delta L_k^+) - L_k)\rho_k \\ &\quad - Y_k \Delta L_k^+ r^+ \quad ,\forall k \end{aligned} \tag{3}$$

If electricity Retailer-*k* has a load reducing DR contract with the system operator. Its customers increasing electricity consumption may cause it fined by the system operator. r^+ is the fine that electricity Retailer-*k* pays for system operator due to electricity Retailer-*k*'s customers increase unit electricity consumption.

According to (1)-(3), electricity Retailer-*k* can calculate the impact of the local data center's load change on the its profit, which are specified as:

$$b_k^- = (TU_k^- - TU_k) / \Delta L_k^- = \rho_k - \phi_k + Y_k r^- \quad ,\forall k \tag{4}$$

$$b_k^+ = (TU_k^+ - TU_k) / \Delta L_k^+ = \phi_k - \rho_k - Y_k r^+ \quad ,\forall k \tag{5}$$

where b_k^- is the profit change of electricity Retailer-*k* when Data center-*k* reduces unit electricity consumption. b_k^+ is the profit change of electricity Retailer-*k* when Data center-*k* increases unit electricity consumption.

Electricity Retailer-*k* will be fined by the system operator if the deviation $\hat{L}_k - L_k$ (the deviation between the electricity consumption of electricity Retailer-*k*'s customers $\hat{L}_k$ and the electricity that electricity Retailer-*k* buys in the day-ahead wholesale market L_k) exceeds the maximum permissible deviation v_k. In this paper, how much electricity can Data centers-*k* reduce/ increase at most depends on the maximum permissible deviation v_k and the capacity of the local distribution network cap_k.

$$a_k^+ = \min[v_k - (\hat{L}_k - L_k),\ cap_k - \hat{L}_k] \quad ,\forall k \tag{6}$$

$$a_k^- = v_k - (L_k - \hat{L}_k) \quad ,\forall k \tag{7}$$

where a_k^+ and a_k^- are the electricity consumption that Data center-*k* can increase/ reduce at most allowed by electricity Retailer-*k*.

All in all, the K electricity retailers in the ED union will together publish their DR instructions to the DDCC. Each electricity retailer's DR instructions include: the impact of the local data center's load change on the its revenue (b_k^+ and b_k^-), and the range of local data center's load change allowed by it (a_k^+ and a_k^-).

C. Energy Management Model of the DDCC

This section will introduce the energy management model of the DDCC when it participates in the collaborative DR. Maximizing the entire profit of the ED union W_{uni} (including the DDCC and the K electricity retailers) is the optimization goal of the DDCC energy management model, which is shown as (8)

$$\max \quad W_{uni} = \sum_{k=1}^{K} W_k + W_{DDCC} \tag{8}$$
subject to constraints (1)-(7), (9)-(21)

where W_k is the profit of electricity Retailer-*k* when it participates in the collaborative DR, and W_{DDCC} is the profit of the DDCC participating in the collaborative DR. Let E_k^{base} denotes the estimated electricity usage of Data center-*k* if the DDCC does not participate in DR program [35]-[37], and E_k denotes the actual electricity usage of Data center-*k* when the DDCC participates in the collaborative DR program. W_k and W_{DDCC} are calculated as (9) - (13).

$$W_{DDCC} = \sum_{k=1}^{K} (E_k^{base}\phi_k - E_k\phi_k) \tag{9}$$

$$W_k = X_k^- b_k^- (E_k^{base} - E_k) + X_k^+ b_k^+ (E_k - E_k^{base}) \quad ,\forall k \tag{10}$$

$$X_k^+ + X_k^- = 1 \quad ,\forall k \tag{11}$$

$$X_k^- (E_k^{base} - E_k) \geq 0 \quad ,\forall k \tag{12}$$

$$X_k^+ (E_k - E_k^{base}) \geq 0 \quad ,\forall k \tag{13}$$

$\sum_{k=1}^{K} E_k\phi_k$ is the electricity bill of the DDCC after participating in the collaborative DR, and $\sum_{k=1}^{K} E_k^{base}\phi_k$ is the electricity bill of the DDCC if it do not participate in the collaborative DR. Where X_k^- and X_k^+ are binary variables. If Data center-*k* increases its electricity consumption ($E_k > E_k^{base}$), the X_k^+ will equal to 1, and the X_k^- equal to 0. On the contrary, If Data center-*k* decreases its electricity consumption ($E_k^{base} > E_k$), the X_k^+ will equal to 0, and X_k^- equal to 1. Increasing or decreasing electricity consumption by Data center-*k* should satisfy the constraints (14), (15).

$$E_k^{base} - E_k \leq a_k^- \quad ,\forall k \tag{14}$$

$$E_k - E_k^{base} \leq a_k^+ \quad ,\forall k \tag{15}$$

The values of W_k and W_{DDCC} depend on the actual electricity usage of each data center E_k. The DDCC energy management model will optimize the actual electricity consumption of each data center E_k so that to maximize the entire profit of the ED union. The specific approach is to optimize the distribution of workloads, the number of each data center's active servers.

For the DDCC, we assume that it contains F front-end servers and K geographically dispersed data centers. The computing requests (workloads) of the DDCC's customers will be sent to the front-end servers at first, then the front-end servers distribute the workloads to the *K* data centers. Let λ_f be the workloads that customers send to the front-end server *f*, and $\lambda_{k,f}$ be the workloads that front-end server *f* (1 <*f* < F) distributes to Data center-*k* (1 <*k* < K). Then, we have.

$$\sum_{k=1}^{K} \lambda_{k,f} = \lambda_f \quad ,\forall f \tag{16}$$

The fewer active servers a data center starts, the longer time it takes to process the workloads. However, the time taken to process the user's workloads cannot exceed the specified time. When we optimize the number of each data center's active servers, we have the time delay constraints.

$$\frac{1}{s_{k,f}\mu_k - \lambda_{k,f}} + t_{k,f}^d \leq t_k^d \quad ,\forall k, \forall f \tag{17}$$

$$s_{k,f}\mu_k \geq \lambda_{k,f} \quad ,\forall k, \forall f \tag{18}$$

where $t_{k,f}^d$ is the transmission time required for a workload to be transmitted from the front-end servers *f* to Data center-*k*. Based on the M/M/1 queuing theory [38], when Data center-*k* arranges $s_{k,f}$ active servers (service rate of per server: μ_k) to process workloads $\lambda_{k,f}$, the average delay time of a workload is $\frac{1}{s_{k,f}\mu_k - \lambda_{k,f}}$. Where t_k^d is the maximum time delay of the workloads allowed by Data center-*k*' customers. The active servers that can be started in a data center should be fewer than the servers owned by data center, M_k. We have

$$\sum_{f=1}^{F} s_{k,f} \leq M_k \quad ,\forall k \tag{19}$$

Let P_k^{idle} be the power of a single server when it is idle. P_k^{peak} denotes peak power of a single server. The power of an active server is always between P_k^{idle} and P_k^{idle} which can be calculated as $P_k^{idle} + (P_k^{peak} - P_k^{idle})\delta_{k,f}$. Where $\delta_{k,f} = \frac{\lambda_{k,f}}{\mu_k s_{k,f}}$ (0 < $\delta_{k,f}$ <1) is the utilization of this server. Considering that there are $s_{k,f}\,(f = 1...F)$ active servers in Data center-*k*, we can get the power of Data center-*k* 's active servers as follows:

$$e_k^s = \sum_{f=1}^{F} s_{k,f} [P_k^{idle} + (P_k^{peak} - P_k^{idle})\delta_{k,f}] \quad ,\forall k \tag{20}$$

The total electricity usage of Data center-*k* can be calculated as (21). PUE_k represents the ratio between Data center-*k*'s total electricity usage and Data center-*k*'s active servers electricity usage.

$$E_k = PUE_k e_k^s \quad ,\forall k \tag{21}$$

The proposed energy management model is an optimization problem that belongs to the category of mixed-integer linear programming. According to the theory of operations research, the mixed-integer linear programming can invariably be solved and get the optimal solution by many mature algorithms, such as branch and bound method and cut plane method. Therefore, the proposed energy management model can invariably be solved and obtain the optimal solution.

III. Profit Allocation Model

A. Formulating Profit Allocation Scheme

If the ED union does not redistribute the entire profit, the profit of each electricity retailer and the DDCC in the collaborative DR are W_k and W_{DDCC} which are shown as (9)-(10). Although the entire profit was maximized in the collaborative DR, this profit situation may not satisfy all members because the profits obtained by some members from the collaborative DR may fewer than that of the independent operation. From the perspective of the cooperative game theory, in order to maintain the long-term existence of the ED union, it is necessary to ensure that the profits obtained by each member (the DDCC and the several electricity retailers) from the collaborative DR are not fewer than that of the independent operation. To this end, the Shapley value method is used in this paper to determine how the entire profit of the collaborative DR is allocated among the DDCC and the K electricity retailers.

According to the Shapley value method, in a cooperation union $\boldsymbol{N}$, the Shapley value of a member *n* is presented as (22). The profit that should be allocated to a member *n* depends on the Shapley value of this member.

$$\varphi(n) = \sum_{S \subset N/\{n\}} \frac{|S|!(|N|-|S|-1)!}{|N|!} \cdot \left(V\left(S \cup \{n\}\right) - V(S)\right) \tag{22}$$

where $\varphi(n)$ is the Shapley value of the member *n* and also represents the profit that should be allocated to member *n*. S denotes all subsets of set $\boldsymbol{N}/\{n\}$. The cooperation profits of set $\boldsymbol{S}$ and set $\boldsymbol{S} \cup \{n\}$ are represented by $V(\boldsymbol{S})$ and $V(\boldsymbol{S} \cup \{n\})$ respectively. Therefore, $\left(V\left(S \cup \{n\}\right) - V(S)\right)$ can be thought of as the contribution of member *n*.

B. Implementing Profit Allocation Scheme

If the ED union does not redistribute the entire profit, the profit of each electricity retailer and the DDCC in the collaborative DR are W_k and W_{DDCC} which are shown as (9)-(10). Let $W_k^{shapley}$ represents the profit that should be allocated to electricity retailers *k* according to the Shapley value method. $W_{DDCC}^{shapley}$ represents the profit that should be allocated to DDCC according to the Shapley value method. $W_k^{shapley}$ and $W_{DDCC}^{shapley}$ can be calculated based on (22). To realize the profit allocation scheme mentioned above, that is, to change the profits of each electricity retailer/the DDCC from W_k / W_{DDCC} to $W_k^{shapley}$ / $W_{DDCC}^{shapley}$, the suggested approach is to establish a fund pool in the ED union. After the end of the collaborative DR event, all members in the ED union (the K electricity retailers and the DDCC) are required to swap a certain amount of money with the fund pool, which is presented as follows:

$$W_k^{pool} = W_k - W_k^{shapley} \quad ,\forall k \tag{23}$$

$$W_{DDCC}^{pool} = W_{DDCC} - W_{DDCC}^{shapley} \tag{24}$$

$$\sum_{k=1}^{K} W_k^{pool} + W_{DDCC}^{pool} = 0 \tag{25}$$

where W_k^{pool} and W_{DDCC}^{pool} are the money that electricity Retailer-*k* and the DDCC swap with the fund pool respectively. According to Equation (25), it can be seen that the money swap with the fund pool by each retailer and the DDCC may be positive or negative, and the total is zero. This means that some members pay money to the fund pool and some members receive money from the fund pool. W_{DDCC}^{pool} is usually negative, that is, the DDCC will obtain money from the fund pool, which is the incentive obtained by the DDCC in the collaborative DR event. After each electricity retailer swaps W_k^{pool} with the fund pool, their profits will change from W_k to $W_k^{shapley}$. The profit of the DDCC will change from W_{DDCC} to $W_{DDCC}^{shapley}$ after it swaps W_{DDCC}^{pool} with the fund pool. The entire profit of the ED union remains unchanged. By implementing the profit allocation scheme, the profits obtained by each member from the collaborative DR are not fewer than that of the independent operation.

IV. Case Study

A case study is conducted in this section for evaluating the proposed cooperation framework. There are four electricity retailers (electricity Retailer-1, electricity Retailer-2, electricity Retailer-3, electricity Retailer-4) in different regions supplying power for a DDCC's four data centers respectively (Data center-1, Data center-2, Data center-3, Data center-4). Four different scenarios are simulated in this section.

S1: The four electricity retailers and the DDCC operate independently. None of electricity retailers implement the incentive-based DR.

S2-1 to S2-4: The four electricity retailers and the DDCC operate independently. S2-1 to S2-4 represent each electricity retailer issues an incentive-based DR individually.

S3: The four electricity retailers and the DDCC form a union (ED union). Then, they together implement collaborative DR and the proposed profit allocation scheme.

S4: The four electricity retailers and the DDCC form a union (ED union). Then, they together implement collaborative DR and the traditional profit allocation scheme.

The other conditions of the four electricity retailers and the DDCC in the four scenarios are the same.

A. Simulation Data

The information of data centers' workloads is obtained from an archive of data centers [39]. We get the electricity price data from the official website of PJM company [40]. In actual operation, the electricity prices and the data centers' workloads can be predicted relatively accurately [41], [42]. TABLE I shows the parameters of the four electricity retailers, and the meaning of each parameter can be found in (1)-(7). For the DDCC, each of data centers has 100000 servers and the service rate is 1.5 requests per server. The idle power of a server is 100 watts and a server will consume 200 watts when it is in the peak mode [43]. TABLE II gives the other parameters of the four data. The optimization problem (DDCC energy management model) is constructed as a mixed-integer linear programming problem, which is solved using "Gurobi 9.0" on a Core i3 3.6 GHz CPU laptop with 8 GB of RAM. The computation time is 0.5 seconds.

TABLE I. PARAMETERS OF ELECTRICITY RETAILERS

	Electricity Retailer-1	Electricity Retailer-2	Electricity Retailer-3	Electricity Retailer-4
π_i ($/kWh)	0.038	0.061	0.021	0.028
ρ_i ($/kWh)	0.192	0.13	0.022	0.002
ϕ_i ($/kWh)	0.102	0.105	0.105	0.108
r^- ($/kWh)	0.050	0.000	0.000	0.000
r^+ ($/kWh)	0.070	0.000	0.000	0.000
b_i^- ($/kWh)	0.140	0.025	-0.083	-0.106
b_i^+ ($/kWh)	-0.160	-0.025	0.083	0.106
a_i^- (kWh)	35000	35000	35000	35000
a_i^+ (kWh)	0	35000	35000	35000

TABLE II. PARAMETERS OF THE DATA CENTERS

	Data center-1	Data center-2	Data center-3	Data center-4
t_i^d (s)	0.2	0.2	0.2	0.2
$t_{i,f=1}^d$ (s)	0.01	0.02	0.02	0.03
$t_{i,f=2}^d$ (s)	0.02	0.01	0.03	0.02
$t_{i,f=3}^d$ (s)	0.02	0.03	0.01	0.02
$t_{i,f=4}^d$ (s)	0.03	0.02	0.02	0.01

B. Results and Analysis

Fig. 4 to Fig. 6 depict the operation of the DDCC when it does not participate in the DR, participates in the traditional DR issued by a single electricity retailer and participates in the collaborative DR. The workloads of the DDCC's four data centers are shown in Fig. 4. In Scenario S1, none of the electricity retailers implements an incentive-based DR. The DDCC operator will distribute more workloads to data centers that can purchase electricity with low prices. Due to Data center-4 purchases electricity from electricity Retailer-4 and electricity Retailer-4 sells electricity at higher prices compared with the other three electricity retailers, the DDCC operator distributes few workloads to Data center-4.

In Scenario S2-1, electricity Retailer-1 implements an incentive-based DR independently to induce Data center-1 reducing electricity consumption. For achieving the goal of reducing Data center-1's electricity consumption, the DDCC transfers the workloads of Data center-1 to Data center-2, Data center-3 and Data center-4, so that the workloads of Data center-2, Data center-3 and Data center-4 increase compared with Scenario S1.

In Scenario S3, the four electricity retailers together implement the collaborative DR. The optimization goal of the DDCC energy management model is maximizing the overall profit of the four electricity retailers and the DDCC. According to TABLE I, we know that reducing the electricity consumption of Data center-1 and Data center-2 can benefit electricity Retailer-1 and electricity Retailer-2. Electricity retailers-3 and electricity retailers-4 can benefit from increased electricity consumption in Data center-3 and Data center-4. Therefore, the DDCC operator transfers the workloads of Data center-1 and Data center-2 to Data center-3 and Data center-4. So that the workloads of Data center-1 and Data center-2 decrease compared with Scenario S1. Data center-3's workloads and Data center-4's workload increase compared with Scenario S1. The entire profit of the four electricity retailers and the DDCC can be maximized.

The active server number of the DDCC's four data centers is shown in Fig. 5. Meanwhile, the electricity usage of the DDCC's four data centers is shown in Fig. 6. The active server number and the electricity usage of the data centers depend on their workloads, so that Figs. 5 and 6 are similar to Fig. 4.

The four electricity retailers supply power for the four data centers respectively. Therefore, changes in the electricity usage of the four data centers will cause changes in electricity sales and profits of the four electricity retailers. To further explain the significance of the proposed cooperation framework, we show the changes in electricity sales and profits of the four electricity retailers in Scenario S2-1 and Scenario S3 in TABLE III and TABLE IV respectively.

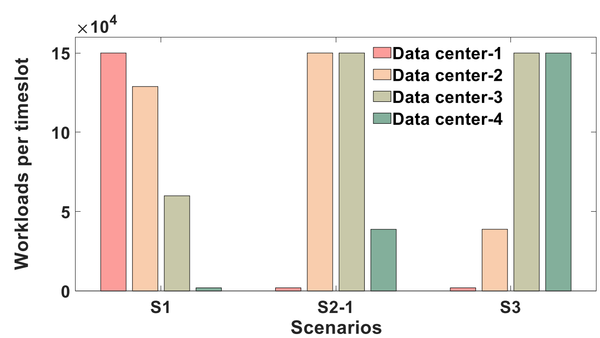

Fig. 4 The workload of the DDCC's four data centers in the three scenarios.

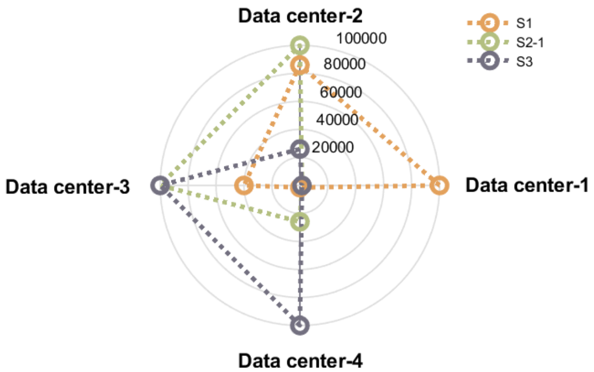

Fig. 5 The active server number of the DDCC's four data centers in the three scenarios.

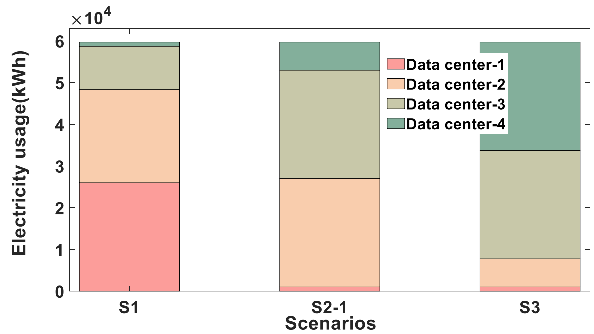

Fig. 6 The electricity consumption of the DDCC's four data centers in the three scenarios.

When only electricity Retailer-1 issues the DR instruction to induce Data center-1 reducing electricity consumption (Scenario S2), the DDCC operator does not know the situations of the other electricity retailers. For achieving the goal of reducing Data center-1's electricity consumption, the DDCC operator transfers the workloads of Data center-1 to Data center-2, Data center-3 and Data center-4, so that the electricity consumptions of Data center-2, Data center-3, Data center-4 increase. This will cause the electricity sales of electricity Retailer-2, electricity Retailer-3 and electricity Retailer-4 increase which are shown in TABLE III. The increase in electricity sales of electricity Retailer-2 will cause damage to its profit (the b_2^+ = -0.025 means that the profit of electricity Retailer-2 increasing unit electricity sales is minus 0.025$). Therefore, electricity Retailer-1 implements the incentive-based DR has harmed the profit of electricity Retailer-2 inadvertently.

When the four electricity retailers together implement the collaborative DR program, the DDCC operator can get the requirements of all electricity retailers. The DDCC operator reduces the electricity usage of Data center-1, Data center-2 and increases the electricity usage of Data center-3, Data center-4. This will cause the electricity sale of electricity Retailer-1, electricity Retailer-2 reducing and the profits of Retailer-1, electricity Retailer-2 increasing, which are shown in TABLE IV. This also leads to the increase in electricity sales of electricity Retailer-3, electricity Retailer-4 and the increase in profits of electricity Retailer-3, electricity Retailer-4. The results explain why the proposed cooperation framework can increase the overall profit of the ED union. It is worth mentioning that the electricity retailers' profits shown in TABLE 3 and TABLE 4 refer to the DR profits of the four electricity retailers before redistributing the entire profit.

TABLE III. THE ELECTRICITY SALE CHANGE AND PROFIT CHANGE OF THE FOUR ELECTRICITY RETAILERS IN S2-1

	Changes of electricity sale (kWh)	Profit of reducing/ increasing unit electricity sale ($/kWh)	Changes of profit ($)
Electricity Retailer-1	-25996	$b_1^- = 0.14$ $b_1^+ = -0.16$	3639
Electricity Retailer-2	3661	$b_2^- = 0.025$ $b_2^+ = -0.025$	-92
Electricity Retailer-3	15598	$b_3^- = -0.083$ $b_3^+ = 0.083$	1295
Electricity Retailer-4	6739	$b_4^- = -0.106$ $b_4^+ = 0.106$	714

TABLE IV. THE ELECTRICITY SALE CHANGE AND PROFIT CHANGE OF THE FOUR ELECTRICITY RETAILERS IN S3

	Changes of electricity sales (kWh)	Profit of reducing/ increasing unit electricity sale ($/kWh)	Changes of profit ($)
Electricity Retailer-1	-25996	$b_1^- = 0.14$ $b_1^+ = -0.16$	3639
Electricity Retailer-2	-15592	$b_2^- = 0.025$ $b_2^+ = -0.025$	390
Electricity Retailer-3	15597	$b_3^- = -0.083$ $b_3^+ = 0.083$	1295
Electricity Retailer-4	25995	$b_4^- = -0.106$ $b_4^+ = 0.106$	2756

After redistributing the entire profit, the final DR profits of the four electricity retailers and the DDCC in Scenarios S2-1 to S2-4 and S3 are shown in Fig. 7. It can be seen that the entire profit of the four electricity retailers and the DDCC in Scenario S3 is bigger than that in Scenarios S2-1 to S2-4. This is because the optimization goal of the proposed collaborative DR model is to maximize the entire profit of the four electricity retailers and the DDCC, while the goal of the traditional DR model is to maximize the profit of the DDCC. Meanwhile, each electricity retailer's profit under Scenario S3 is greater than its profit under Scenarios S2-1 to S2-4. The profit of the DDCC under Scenario S3 is also greater than its profit under Scenarios S2-1 to S2-4. The results prove that the proposed cooperation framework can benefit all participants. In other words, the profits obtained by each member from the collaborative DR (Scenario S3) are not fewer than that of the independent operation (Scenarios S2-1 to S2-4).

To further demonstrate the advantage of the proposed profit distribution mechanism, we compare the final DR profits of the four electricity retailers and the DDCC in Scenarios S3 and S4 and the comparison results are shown in Fig. 8. What Scenario S3 and Scenario S4 have in common is that the four retailers and the DDCC together implement collaborative DR. The difference lies in the profit allocation strategy. In Scenario S3, the four retailers and the DDCC carry out the profit allocation scheme proposed in this paper, that is, calculate the financial incentives paid by each retailer to the local data center based on the Shapley value method. In Scenario S4, the four retailers and the DDCC perform the traditional profit allocation method, that is, each retailer provides financial incentives to the local data center according to the load reduction of the local data center.

As seen from Fig. 8, the overall profit of the four retailers and the DDCC is the same in the two scenarios, but the profit of each member is different in the two scenarios due to different allocation strategies.

In Scenario S4, considering that the increase of electricity consumption of Data center-3 can increase the profit of Retailer-3, the DDCC transfers the workloads of Data center-2 to Data center-3 through workload spatial migration technology, which reduces the electricity consumption of Data center-2 and increases the electricity consumption of Data center-3. That is to say, the Retailer-3 is the biggest beneficiary in this workload spatial migration. Retailer-2 is not the biggest gainer but needs to provide financial incentives to Data center-2 because Data center-2 has reduced electricity consumption. This is unfair to Retailer-2, and also makes the income of Retailer-2 negative.

Therefore, the traditional profit allocation method (that is, each retailer provides financial incentives to the local data center according to the load reduction of the local data center) is inapplicable in the collaborative DR. Because the load reduction in a data center may not benefit the local electricity retailer under the collaborative DR, it is unreasonable for the local electricity retailer to reward it. On the contrary, the proposed profit allocation method can ensure profits for all participants which can be seen from the results of Scenario S3.

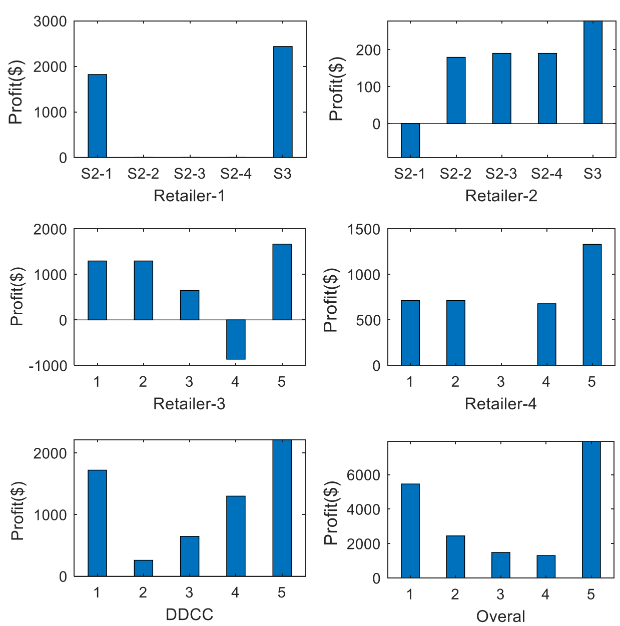

Fig. 7 The final profits of the four electricity retailers and the DDCC in S2-1 to S2-4 and S3.

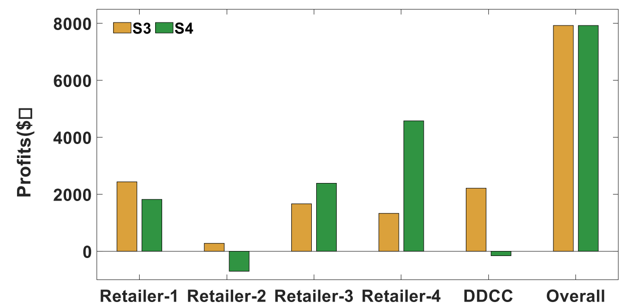

Fig. 8 The final profits of the four electricity retailers and the DDCC in S3 and S4.

All in all, this paper proposes a cooperation framework, which includes a collaborative DR model (Section II) and a profit allocation model (Section III). Four electricity retailers and a DDCC are selected to verify the effect of the collaborative DR model and the profit allocation model. The simulation results show that the proposed collaborative DR model could maximize the entire profit of the four retailers and the DDCC. Meanwhile, the simulation results demonstrate that the proposed profit allocation model can fairly allocate the maximized entire profit to each member and ensure that the profits obtained by each member from the cooperation situation are not fewer than that of the independent operation.

V. Conclusion

In this paper, a cooperation framework where several electricity retailers cooperatively implement incentive-based DR to the same DDCC is proposed. Specifically, several electricity retailers which power for the same DDCC together publish their DR instructions to the DDCC. Then the DDCC operator manages the electricity usage of each data center to maximize the entire profit of the several electricity retailers and the DDCC. After the collaborative DR event, the entire profit is allocated by the several electricity retailers and the DDCC according to the Shapley value theory. The simulation results show that the proposed cooperation framework can maximize the whole benefit of the DDCC and the several electricity retailers and ensure that the profits obtained by each member (the DDCC and the several electricity retailers) from the collaborative DR are not fewer than that of the independent operation. In the future, the processing time shift of the DDCC's workloads will be considered in the cooperation framework. Moreover, the cooperation framework should be further improved to accommodate more scenarios. For example, the DDCC purchases electricity from the wholesale markets rather than electricity retailers or the DDCC equips with renewable energy generations.

Appendix

In the proposed cooperation game model, the union consists of a DDCC and K electricity retailers and is denoted by set $\boldsymbol{N}$. In order to show that the cooperation game model is superadditive, we need to proof the following inequality.

$$V(S_1 \cup S_2) \geq V(S_1) + V(S_2) \quad S_1 \cap S_2 = \varnothing \tag{26}$$

While $\boldsymbol{S_1}$ and $\boldsymbol{S_2}$ are the subsets of set $\boldsymbol{N}$. The cooperation profits of union $\boldsymbol{S_1}$, $\boldsymbol{S_2}$ and union $\boldsymbol{S_1 \cup S_2}$ are represented by V($\boldsymbol{S_1}$), V($\boldsymbol{S_2}$) and V($\boldsymbol{S_1 \cup S_2}$) respectively. We will prove the Inequality (26) in the following three cases.

(1) Case 1: the DDCC is contained in the union $\boldsymbol{S_1}$

Because the DDCC is contained in the union $\boldsymbol{S_1}$, the collaborative DR program is unable to be executed by the union $\boldsymbol{S_2}$ due to the absence of the DDCC. Therefore, the cooperation profit of union $\boldsymbol{S_2}$ is 0. We have V($\boldsymbol{S_2}$) = 0. Conversely, the collaborative DR program can be executed by the union $\boldsymbol{S_1}$ because the DDCC is contained in this union. The cooperation profit of union $\boldsymbol{S_1}$ is generated by the collaborative DR program and can be calculated by the optimization model (8)-(21). We have:

$$V(S_1) = Max\left\{\sum_{k\in S_1/\{DDCC\}} W_k + W_{DDCC}\right\} = Max\left\{\begin{array}{l}\sum_{k\in S_1/\{DDCC\}} X_k^- b_k^- (E_k^{base} - E_k) \\ + \sum_{k\in S_1/\{DDCC\}} X_k^+ b_k^+ (E_k - E_k^{base}) \\ + \sum_{k\in S_1/\{DDCC\}} (E_k^{base}\phi_k - E_k\phi_k)\end{array}\right\} \tag{27}$$

Analogously, the cooperation profit of union $\boldsymbol{S_1 \cup S_2}$ is generated by the collaborative DR program and can be calculated by the optimization model (8)-(21). We have:

$$\begin{aligned} &V(S_1 \cup S_2) \\ &= Max\left\{\sum_{k\in S_2} W_k + \sum_{k\in S_1/\{DDCC\}} W_k + W_{DDCC}\right\} \\ &= Max\left\{\begin{array}{l}\sum_{k\in S_2} X_k^- b_k^- (E_k^{base} - E_k) \\ + \sum_{k\in S_2} X_k^+ b_k^+ (E_k - E_k^{base}) \\ + \sum_{k\in S_1/\{DDCC\}} X_k^- b_k^- (E_k^{base} - E_k) \\ + \sum_{k\in S_1/\{DDCC\}} X_k^+ b_k^+ (E_k - E_k^{base}) \\ + \sum_{k\in S_2} (E_k^{base}\phi_k - E_k\phi_k) \\ + \sum_{k\in S_1/\{DDCC\}} (E_k^{base}\phi_k - E_k\phi_k)\end{array}\right\}\end{aligned} \tag{28}$$

In Equations (27)-(28), the variables are the E_k. Given that the intersection of sets $\boldsymbol{S_1}$ and $\boldsymbol{S_2}$ is an empty set ($S_1 \cap S_2 = \varnothing$), we can get that the intersection of variable sets $\{E_k \mid k \in S_2\}$ and $\{E_k \mid k \in S_1 / \{DDCC\}\}$ is an empty set ($\{E_k \mid k \in S_2\} \cap \{E_k \mid k \in S_1 / \{DDCC\}\} = \varnothing$). Therefore, we can apply the following transformation to Equation (28).

$$\begin{aligned} &V(S_1 \cup S_2) \\ &= Max\left\{\begin{array}{l}\sum_{k\in S_2} X_k^- b_k^- (E_k^{base} - E_k) \\ + \sum_{k\in S_2} X_k^+ b_k^+ (E_k - E_k^{base}) \\ + \sum_{k\in S_2} (E_k^{base}\phi_k - E_k\phi_k)\end{array}\right\} \\ &+ Max\left\{\begin{array}{l}\sum_{k\in S_1/\{DDCC\}} X_k^- b_k^- (E_k^{base} - E_k) \\ + \sum_{k\in S_1/\{DDCC\}} X_k^+ b_k^+ (E_k - E_k^{base}) \\ + \sum_{k\in S_1/\{DDCC\}} (E_k^{base}\phi_k - E_k\phi_k)\end{array}\right\} \\ &= \text{Max } f(E_k, k \in S_2) + V(S_1)\end{aligned} \tag{29}$$

$$f(E_k, k \in S_2) = \left\{\begin{array}{l}\sum_{k\in S_2} X_k^- b_k^- (E_k^{base} - E_k) \\ + \sum_{k\in S_2} X_k^+ b_k^+ (E_k - E_k^{base}) \\ + \sum_{k\in S_2} (E_k^{base}\phi_k - E_k\phi_k)\end{array}\right\} \tag{30}$$

The function $f(E_k, k \in S_2)$ is equal to 0 when its variables $E_k, k \in S_2$ are equal to $E_k^{base}, k \in S_2$, which is shown as follows:

$$\begin{aligned} &f(E_k, k \in S_2)\big|_{E_k = E_k^{base}, k\in S_2} = \\ &\left\{\begin{array}{l}\sum_{k\in S_2} X_k^- b_k^- (E_k^{base} - E_k^{base}) + X_k^+ b_k^+ (E_k^{base} - E_k^{base}) \\ + \sum_{k\in S_2} (E_k^{base}\phi_k - E_k^{base}\phi_k)\end{array}\right\} \\ &= 0\end{aligned} \tag{31}$$

Given that V($\boldsymbol{S_2}$) is equal to 0 and $Max\ f(E_k, k \in S_2)$ is not less than $f(E_k, k \in S_2)\big|_{E_k = E_k^{base}, k\in S_2}$, we can obtain:

$$\begin{aligned} V(S_1 \cup S_2) &= \text{Max } f(E_k, k \in S_2) + V(S_1) \\ &\geq f(E_k, k \in S_2)\big|_{E_k = E_k^{base}, k\in S_2} + V(S_1) \\ &= 0 + V(S_1) = V(S_2) + V(S_1)\end{aligned} \tag{32}$$

Therefore, Inequality (35) is true in Case 1.

(2) Case 2: the DDCC is contained in the union $\boldsymbol{S_2}$

The analysis process of Case 2 is similar to Case 1. Because the DDCC is contained in the union $\boldsymbol{S_2}$, the collaborative DR program is unable to be executed by the union $\boldsymbol{S_1}$ because the absence of the DDCC. Therefore, the cooperation profit of union $\boldsymbol{S_1}$ is 0. We have V($\boldsymbol{S_1}$) = 0. Conversely, the collaborative DR program can be executed by the union $\boldsymbol{S_2}$ due to the DDCC is contained in this union. The cooperation profit of union $\boldsymbol{S_2}$ is generated by the collaborative DR program and can be calculated by the optimization model (8)-(21). We have:

$$V(S_2)=Max\left\{\sum_{k\in S_2/\{DDCC\}} W_k + W_{DDCC}\right\}$$

$$=Max\left\{\begin{array}{l}\sum_{k\in S_2/\{DDCC\}} X_k^- b_k^- (E_k^{base}-E_k)\\ +\sum_{k\in S_2/\{DDCC\}} X_k^+ b_k^+ (E_k-E_k^{base})\\ +\sum_{k\in S_2/\{DDCC\}} (E_k^{base}\phi_k - E_k\phi_k)\end{array}\right\} \quad (33)$$

Analogously, the cooperation profit of union $S_1 \cup S_2$ is generated by the collaborative DR program and can be calculated by the optimization model (8)-(21). We have:

$$V(S_1\cup S_2)=Max\left\{\sum_{k\in S_1} W_k + \sum_{k\in S_2/\{DDCC\}} W_k + W_{DDCC}\right\}$$

$$=Max\left\{\begin{array}{l}\sum_{k\in S_1} X_k^- b_k^- (E_k^{base}-E_k) + \sum_{k\in S_1} X_k^+ b_k^+ (E_k-E_k^{base})\\ +\sum_{k\in S_2/\{DDCC\}} X_k^- b_k^- (E_k^{base}-E_k)\\ +\sum_{k\in S_2/\{DDCC\}} X_k^+ b_k^+ (E_k-E_k^{base})\\ +\sum_{k\in S_1} (E_k^{base}\phi_k - E_k\phi_k)\\ +\sum_{k\in S_2/\{DDCC\}} (E_k^{base}\phi_k - E_k\phi_k)\end{array}\right\} \quad (34)$$

In Equations (33)-(34), the variables are the E_k. Given that the intersection of sets S_1 and S_2 is an empty set ($S_1 \cap S_2 = \varnothing$), we can get that the intersection of variable sets $\{E_k \mid k\in S_1\}$ and $\{E_k \mid k\in S_2/\{DDCC\}\}$ is an empty set ($\{E_k \mid k\in S_1\}\cap\{E_k \mid k\in S_2/\{DDCC\}\}=\varnothing$). Therefore, we can apply the following transformation to Equation (34).

$$V(S_1\cup S_2)$$
$$=Max\left\{\begin{array}{l}\sum_{k\in S_1} X_k^- b_k^- (E_k^{base}-E_k)\\ +\sum_{k\in S_1} X_k^+ b_k^+ (E_k-E_k^{base})\\ +\sum_{k\in S_1} (E_k^{base}\phi_k - E_k\phi_k)\end{array}\right\}$$
$$+Max\left\{\begin{array}{l}\sum_{k\in S_2/\{DDCC\}} X_k^- b_k^- (E_k^{base}-E_k)\\ +\sum_{k\in S_2/\{DDCC\}} X_k^+ b_k^+ (E_k-E_k^{base})\\ +\sum_{k\in S_2/\{DDCC\}} (E_k^{base}\phi_k - E_k\phi_k)\end{array}\right\} \quad (35)$$
$$=\text{Max } f(E_k, k\in S_1)+V(S_2)$$

$$f(E_k, k\in S_1)=\left\{\begin{array}{l}\sum_{k\in S_1} X_k^- b_k^- (E_k^{base}-E_k)\\ +\sum_{k\in S_1} X_k^+ b_k^+ (E_k-E_k^{base})\\ +\sum_{k\in S_1} (E_k^{base}\phi_k - E_k\phi_k)\end{array}\right\} \quad (36)$$

The function $f(E_k, k\in S_1)$ is equal to 0 when its variables $E_k, k\in S_1$ are equal to $E_k^{base}, k\in S_1$, which is shown as follows:

$$f(E_k, k\in S_1)\big|_{E_k=E_k^{base}, k\in S_1}=$$
$$\left\{\begin{array}{l}\sum_{k\in S_1} X_k^- b_k^- (E_k^{base}-E_k^{base}) + X_k^+ b_k^+ (E_k^{base}-E_k^{base})\\ +\sum_{k\in S_1} (E_k^{base}\phi_k - E_k^{base}\phi_k)\end{array}\right\} \quad (37)$$
$$=0$$

Given that V(S_1) is equal to 0 and $Max\ f(E_k, k\in S_1)$ is not less than $f(E_k, k\in S_1)\big|_{E_k=E_k^{base}, k\in S_1}$, we can obtain:

$$\begin{aligned}V(S_1\cup S_2) &= \text{Max } f(E_k, k\in S_1)+V(S_2)\\ &\geq f(E_k, k\in S_1)\big|_{E_k=E_k^{base}, k\in S_1} + V(S_2)\\ &= 0+V(S_2)=V(S_1)+V(S_2)\end{aligned} \quad (38)$$

Therefore, Inequality (35) is true in Case 2.

(3) Case 3: the DDCC belongs to neither union S_1 nor union S_2.

In this case, the collaborative DR program is unable to be executed by the union S_1, union S_2 and union $S_1 \cup S_2$ because none of the three unions contain the DDCC. Therefore, the cooperation profit of each union is 0. We have:

$$V(S_1\cup S_2)=0=V(S_1)+V(S_2) \quad (39)$$

To sum up, for any two union S_1 and S_2 ($S_1 \cap S_2 = \varnothing$), the V($S_1 \cup S_2$) is greater than or equal to the sum of V(S_1) and V(S_2). That is to say, the cooperative game model in this paper is superadditive.

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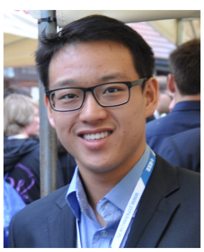

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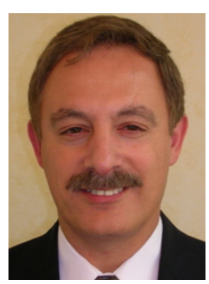

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