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On Data Center Demand Response: A Cloud Federation Approach

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ABSTRACT The significantly high energy consumption of data centers constitutes a major load on the smart power grid. Data center demand response is a promising solution to incentivize the cloud providers to adapt their consumption to the power grid conditions. These policies not only mitigate the operational stability issues of the smart grid but also potentially decrease the electricity bills of cloud providers. Cloud providers can improve their contribution and reduce their energy cost by collaboratively managing their workload. Through cooperation in the form of cloud federations, providers can spatially migrate their workload to better utilize the benefits provided by demand response schemes over multiple locations. To this end, this work considers an interaction system between the independent cloud providers and the corresponding smart grid utilities in the context of a demand response program. Leveraging the cooperative game theory, this paper presents a federation formation among the cloud providers in the presence of a location-dependent demand response program. A distributed algorithm that is coupled with an optimal workload allocation problem is applied. The effect of the federation's formation on the clouds' profits and on the smart grid performance is analyzed through simulation. Simulation results show that cooperation increases the clouds' profits as well as the smart grid performance compared to the noncooperative case.

INDEX TERMS Cloud federation, coalitional game, demand response, smart grid.

I. INTRODUCTION

The use of cloud-based services has significantly increased in recent years due to their various advantages. To accommodate this growing trend, cloud providers (CPs) are incentivized to build large-scale data centers (DCs). Each data center includes hundreds to thousands of servers, storage equipment, cooling facilities, and power supplies, yielding a substantial energy consumption [1].

The significant energy consumption of data centers presents two key challenges. First, this amount of energy consumption leads to considerable cost for cloud providers. As energy cost is a major part of the operating cost of each cloud provider, it is necessary and important to minimize its electricity bill. Second, data centers as electricity customers have a major impact on the smart power grid (SG) as they significantly increase the grid load at their locations [2].

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Nonetheless, data centers are large, but flexible energy load profiles, considered as a good target for smart grid demand response (DR) [3]. Demand response which is an important feature of the smart grid, refers to programs that seek to provide suitable incentives to induce dynamic demand management of customers' load in response to power grid conditions [4], [5]. Data center demand response not only improves the smart grid sustainability, but also leads to lower electricity bill for the cloud providers [3].

Given the significant power consumption of cloud providers, another promising solution in the cloud side is emerging: *cloud federation*. Cloud federation refers to a set of cloud providers agrees to use their resources in a cooperative manner. Although the idea of using federated clouds was initially introduced to overcome the limitation of isolated clouds to fulfill all characteristics of the cloud computing paradigm [6], recent researches discovered potential opportunities of this paradigm toward energy cost saving and energy sustainability in the cloud computing environment [7].

Federation enables the cloud providers to reduce the cost of energy by using more flexible energy management strategies while leveraging the spatial variation of electricity prices and location-dependent demand response policies [8].

Given the potential opportunities and challenges of data centers' energy cost reduction through demand response programs and cloud federation, several previous work have recently appeared [8]–[18] that can be divided into two groups. The first group in [9]–[13] focuses on how to elicit the flexibility of geo-distributed data centers, and seeks to design appropriate demand response mechanisms for them. The second group [8], [12], [14]–[18] addresses the problem of cloud federation formation for the purpose of electricity cost reduction.

Most of literatures in the first group have studied demand response of one cloud, and they did not consider the interaction of multiple clouds with smart grid utilities. Meanwhile, most existing studies in the second group have focused on energy cost minimization via cloud federation formation, while failing to exploit the benefits that demand response schemes provide for cloud providers, over multiple locations. This motivate us to investigate the cooperative workload management of cloud providers in the context of smart grid demand response. In this way, we tend to assess how the cooperatively workload management of cloud providers through spacial workload migration can mitigate their cost by exploiting the location-dependent electricity pricing, and what is the influence of this cooperation on the smart grid performance.

In this way, and different from the prior art [8]–[18], the main contribution of this paper is to analyze situations in which various *independent cloud providers* deal with *smart grid demand response programs*. Our goals are two-fold: a) finding how stable federations should be formed among cloud providers such that it maximizes the cloud providers' profits /reduce their energy cost in demand response programs and b) analyzing how the smart grids' performance is affected by clouds cooperation.

To approach the first goal, we model and analyze a demand response-aware federation formation among the cloud providers by leveraging the coalition formation game. The proposed distributed hedonic coalition formation algorithm enables cloud providers to make selfish decisions on the cooperation. For the second goal, we conduct some simulations to show the effectiveness of the proposed approach on the cloud providers' profits as well as to investigate the effect of this cooperation on the smart grids' performance. Simulation results show that the cooperation would increase the clouds' profits as well as the performance of the involved smart grids.

The rest of this paper is organized as follows. In Section II, we provide a brief overview on the cloud federation and data center demand response. In Section III, we review related work and, in Section IV, we introduce our system model. In Section V, we present a cooperative game-theoretic model of the system under study, and show stability conditions and profit allocation strategies. Simulation results are presented in Section VI, and Section VII draws conclusions.

II. BACKGROUND

In this section we present as background the cloud federation concept and the opportunities and challenges of this paradigm for the cloud providers' energy management. Moreover, we also describe demand response concept, and how it could be leveraged for data center cost reduction.

A. CLOUD FEDERATION

Cloud computing as a computing paradigm aimed to provide on demand elasticity to their customers. However, in reality, the elasticity of a single cloud provider is limited by the amount of its resources and cannot satisfy the ever-increasing user demand. One of the new emerging solution introduced to overcome this limitation is *cloud federation* [19], [20].

Cloud federation is an ecosystem consists of different providers that are interconnected in a cooperative decentralized environment, who voluntarily collaborate with each other by sharing their resources [21], [22]. Thanks to the federation, virtual resources and services can be moved among providers, leading to handful advantages such as resource optimization, scalability, profit enhancement, and geographic distribution [7], [23], [24]. For more details about the cloud federation, its characteristics and the main projects related to interconnected clouds, please refer to [19], [21], [22].

Besides the mentioned benefits, cost efficiency and energy saving are other key advantages can be provided by this new technology [22]. Federated clouds enable the usage of more flexible energy management strategies, by using the more energy-efficient resources, or spatially migrating the workload towards clouds that pay less for the energy, which leads to lower electricity bill [8]. In order to exploit the potential of energy cost saving of cloud federations, it is necessary to investigate how federations should be formed, how the resources should be managed respect to this goal, and how the clouds should interact with the power grid within the federation ecosystem.

B. DATA CENTER DEMAND RESPONSE

Smart grid, known as the next generation of the power grid, leverages information and communications technology to deliver the electricity in a smart way from points of generation to consumers [25], [26]. One of the key features of the smart grid technology is *demand response*. Based on the US Department of Energy, demand response defines as "a tariff or program established to motivate changes in electric use by end-use customers, in response to changes in the price of electricity over time, or to give incentive payments designed to induce lower electricity use at times of high market prices or when grid reliability is jeopardized" [27].

Among the various classes of electricity customers, data centers are characterized as a good target for these schemes, as they are large and yet flexible energy load profiles-data center workload can be shifted in time, or even geographically. To exploit this potential flexibility, the smart grid operators seek to design suitable programs to improve sustainability as well as the reliability of the smart grid. These policies are not only valuable for the smart grid, but will also be beneficial for data centers operators, as can mitigate the skyrocketing energy cost of them. As a result, data center demand response can be seen as a "win-win" solution for both sides-the smart grid and the data center operators [3].

III. RELATED WORK

The existing body of related work can be classified into two categories. The first category studies the participation of geo-distributed data centers in demand response programs [9]–[13].The second category investigates how to exploit the potential of the cooperation among cloud providers for the purpose of energy cost saving and increasing the stability of the smart grid [8], [14]–[16].

Among all efforts have been made in managing the participation of data centers in demand response programs, [9]–[13] have considered the interaction of multiple geographical data centers, belongs to one provider with the smart grid. The authors in [10] proposed an auction mechanism for demand response from a geo-distributed cloud in a DR program. This work was then extended in [9] to investigate the problem of bilateral electricity trade between a cloud with geo-distributed hybrid data centers and corresponding grid utilities. Moreover, in [11] and [12], the authors formulated the demand response of geo-distributed data centers using a two-stage Stackelberg game model. The work in [13] studied the same problem using bilevel programming model.

In contrast to these work, we focus on the participation of multiple independent cloud providers, not a cloud with multiple geo-distributed data centers, in a demand response program. In the case of geo-distributed data centers belonging to a cloud provider, all data centers collaborate to maximize the profit of the cloud provider. This assumption is not true for different cloud providers, as they are often selfish entities who collaborate with each other only when cooperation is beneficial for them.

In the second category, there are a significant number of work that addressed the problem of cooperation among cloud providers for different purposes such as overcoming resource limitation or improving resource utilization [28]–[31]. However, only a handful of studies focused on federation formation among cloud providers as a solution to the problem of reducing the data centers' energy cost and improving the energy sustainability [8], [14]–[16], [32]–[37]. The authors in [8] addressed the problem of cloud federation formation with the aim of the energy cost reduction. [14] proposed a methodology for enabling sustainable cooperating clouds. The authors in [15] presented a capacity-sharing mechanism based on the cooperative game theory to maximize the social welfare of federated clouds. [16] is specified some scenarios that current energy aware cloud solutions as the isolated IaaS cannot handle, but federation provides some opportunities. In this way, the authors in [16] proposed different approaches for enabling an energy-aware cloud federation. The author in [32] presented an analytical model to investigate the cost/benefit of different energy saving strategies in IaaS federated clouds. The authors in [33] tackled the workload scheduling problem in a federation of green-powered data centers.

In comparison to the aforementioned work, we consider the cooperative workload management of cloud providers with the purpose of energy cost reduction *in the context of a demand response program*. In particular, we study the problem of the demand response-aware federation formation among cloud providers. Also, we study the impact of the cooperation on the smart grid performance.

Beyond the aforementioned prior art, two other relevant recent studies include the work in [17] and [18] that addressed the demand response problem for cooperative cloud providers. Here, the work in [17] studied the participation of cooperative cloud providers in a capacity bidding program for power reduction via aggregation. Meanwhile, authors in [18] modeled the process of cloud providers' electricity procurement through load aggregation to decrease the power demand uncertainty in the wholesale electricity market. Although the authors of [17] and [18] assumed that data centers are operated by different owners, they are all serviced by a single smart grid. In contrast to these researches, we consider the cooperative workload management of geo-distributed cloud providers that couple *multiple regional smart grids*. Because of the geographical distribution of cloud providers, they can take advantage of the variety in the electricity prices as well as demand response programs to minimize their costs.

IV. SYSTEM MODEL

We consider a system consists of multiple cloud providers which interact with their corresponding smart grids. At the start of each scheduling period, each smart grid utility submits a number of sealed power demand bids along with some monetary rebates to its corresponding data center. The power demand levels have different values for the smart grid. Consequently, various power bids include different rebates, and more desirable power level has the highest rebate. The smart grid seeks to encourage the corresponding cloud provider to adopt its load according to the more desirable power level. After receiving the bids, each cloud provider should determine its actual power demand. In the process of choosing their winning bids, cloud providers can cooperate with each other through the federation formation to cooperatively serve their workload. Therefore, each cloud provider should decide whether it will be beneficial to cooperate with other cloud providers and, if so, which cloud providers it should cooperate with. This process, is shown in Figure 1 for four cloud providers. In the following, we describe our system model with more details.

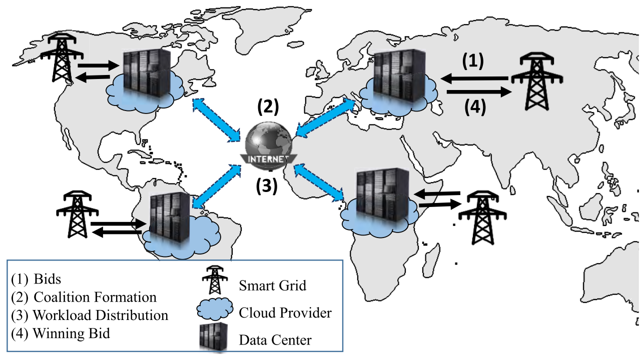


FIGURE 1. An illustration of system model and the process of cloud providers participation in the demand response program.

A. CLOUD PLATFORM MODEL

Consider a set $\mathcal{N}$ of N cloud providers that operate a number of data centers.[1] We assume that data centers are geo-distributed and located in the regions with different smart grids. Each data center $i \in \mathcal{N}$ consists of M_i homogeneous processing servers. In our model, the servers belonging to the various data centers may be different depending on their processing capacity and on the provided amount of memory. Cloud providers provide their resources in the form of virtual machines (VMs). Each cloud provider can offer several VM classes to its clients. Each class of VMs consists of a particular number of CPU cores and specific amount of memory. All the VMs in the same class are homogeneous in terms of processor and memory size. Without loss of generality, we focus on one VM class, i.e., all cloud providers provide the same VM class. Nonetheless, our model can be extended to the case in which each cloud provider provides several VM classes.

When a VM is allocated to a server, it uses a certain fraction of CPU capacity and a certain share of memory. In general, each server has adequate resources for running multiple VMs at a specific time. Thus, we define a_i as the total number of VMs that can be served simultaneously by a single server of data center i. Hence, $Q_i = M_i a_i$ is the processing capacity of cloud provider i.

In a specific scheduling period, the incoming workload to cloud provider i is W_i, which represents the set of VMs that compose this workload. $W_N = \cup_{i=1}^{N} W_i$ denotes the set of all cloud providers workloads. In our model, the workload of a cloud provider can be served either by its local data center or possibly by the servers of the others.

B. DATA CENTER POWER CONSUMPTION

In our model, we focus on the server power consumption while ignoring the energy used by the other facilities such as cooling devices and unit power supplies as these are roughly proportional [38]. We define $P_k^{\text{idle}} + U(P_k^{\text{peak}} - P_k^{\text{idle}})$ as the server power consumption model for any server k. Here, P^{peak} represents the server power when it is fully utilized, P^{idle} denotes the amount of server power consumption in idle state, and U is the fraction of CPU capacity being used. This model, albeit simple, provides an accurate estimate of the power consumption for different server types [39]. Therefore, the total power demand at any data center j, $j \in \mathcal{N}$, can be calculated as follows:

$$e_j = \left[M_j P_j^{\text{idle}} + \left(P_j^{\text{peak}} - P_j^{\text{idle}}\right) m_j\right] \gamma_j, \tag{1}$$

where m_j is the number of active servers of data center j, and calculated as Y_j/a_j, where Y_j is the number of VMs will be processed by this data center, and a_j is the total number of VMs can be served simultaneously by a single server. γ is the power usage efficiency (PUE), which is defined as a ratio between the total power amount used by the entire data center facility (consisting of servers, cooling devices, etc.) and the power consumption of the IT equipment. This parameter usually has a value in the range of [1.1, 3]. A larger value indicates an inefficient data center in terms of power consumption [10].

C. DEMAND RESPONSE PROGRAM

In our model, we consider that each cloud provider has a single data center located within a geographical span of a regional smart grid. We assume that data centers are the only flexible demand in the system. All other loads are inflexible and can be predicted by the smart grid utility. At the beginning of each scheduling period, each smart grid utility j predicts the values of inelastic power demands and renewable generation. Based on these values, the smart grid utility computes the desired power consumption E_j' by data center j. In addition, the smart grid utility computes lower bound (E_j^-) and upper bound (E_j^+) of the actual power consumption of the corresponding data center, in a way that minimize the voltage violation. Let e_j be the actual valid power consumption of data center. This value should lie within the interval of feasible power consumption of data center j, which is represented by $[E_j^{\min}, E_j^{\max}]$. Hence, $E_j^- \geq E_j^{\min}$, and $E_j^+ \leq E_j^{\max}$. As a demand response program, each smart grid offers a number of sealed power demand bids along with some rebate (a similar demand response program has been applied in [10]). The smart grid computes the rebate for every offered power level using a function of the values of E_j', E_j^-, and E_j^+. When $e_j \in [E_j^-, E_j']$, this function is increasing and strictly concave; and when $e_j \in [E_j', E_j^+]$, it is decreasing and strictly concave. Furthermore, when e_j is out of the interval $[E_j^-, E_j^+]$, the value of the rebate is equal to zero. This function format encourages a data center to request a power demand that is as close as possible to E_j'.

Each smart grid j submits l_j number of valid power demand bids $(e_j^1, b_j^1), \ldots, (e_j^{l_j}, b_j^{l_j})$.

Each bid (e_j^k, b_j^k) captures the willingness of the smart grid j to pay b_j^k amount of rebate for the data center's power

[1]The words cloud provider and data center are used interchangeably hereinafter as we assume that each cloud provider has only one data center.

consumption e_j^k. Among the bids submitted by each local smart grid, only one should be selected by the corresponding data center. As each data center would always cause a non-zero energy consumption, then it should only select one bid. If $(e_j^{m_j}, b_j^{m_j})$ denotes the winning bid of the smart grid corresponding to data center j, we have $(e_j^{m_j}, b_j^{m_j}) \in \{(e_j^1, b_j^1), \ldots, (e_j^{l_j}, b_j^{l_j})\}$.

D. UTILITY OF NONCOOPERATIVE CLOUD PROVIDERS

The utility of a cloud provider consists of the revenues gained from the users for processing their workload minus the incurred cost. Each cloud provider j has a revenue policy for charging their customers. In other words, depending on the capacity of each VM type, providers define a per unit price to charge users for VM usage. We denote by r_j the cloud provider's charge for a VM j. In the noncooperative case, a cloud provider should process all of its workload. Thus, the total received gain from users will be $W_j r_j$.

In addition to the received benefit from users, a cloud provider incurs some costs for providing services. Here, we focus on the energy cost, as this cost is a substantial portion of the cloud providers' costs. Other related costs can be easily accommodated into our formulation. Given (e_j, b_j) as the selected bid by data center j, where e_j and b_j represent, respectively, the corresponding power consumption and the corresponding rebate with p_j being the power price, the total payment to the smart grid is: $C_i^{\text{elec}} = e_j p_j - b_j$, where e_j is calculated by (1). Therefore, we can compute the utility/net profit of cloud provider j as follows:

$$U_j^{\text{CP}}(p_j) = W_j r_j + b_j - e_j p_j. \tag{2}$$

In general, cloud providers support two types of workloads: interactive and batch. While the interactive workload is delay-sensitive, batch jobs do not have a strict delay constraint. Hence, they are flexible to be shifted in time. Therefore, cloud providers can schedule batch workload across a time interval to take advantage of time-varying demand response programs. But, this is not applicable to the interactive jobs. Generally, smart grid's demand response programs are not only time-dependent, but also location-dependent. In this regard, cloud providers can improve their benefits (i.e., reduce their costs) by spatially migrating interactive loads from one data center to others located in the regions with cheaper electricity prices. In the noncooperative case, spatially migrating is restricted to a few large cloud providers (such as Google) with several geographically data centers. To overcome this limitation, small to medium cloud providers can cooperate and collaboratively manage their workloads. In this regard, in the following section, we analyze how cloud providers can cooperatively manage their workloads in the proposed demand response program.

V. CLOUD PROVIDERS COALITIONAL GAME

In this section, we study how cloud providers can form coalitions, divide the coalition profit and optimally allocate the coalition workload so as to maximize their net profits. This process is represented in Figure 2. We use the coalitional game theory to study the cooperative behavior of the cloud providers. Coalitional game theory is an analytical tool to study the behavior of the rational entities when they cooperate [40]. In particular, coalition formation games [41] are a special class of cooperative games that can be used for analyzing the coalition formation process among rational players. In our model, we investigate the dynamic formation of cloud providers federations and analyze their characteristics. Therefore, it is appropriate to use this type of games.

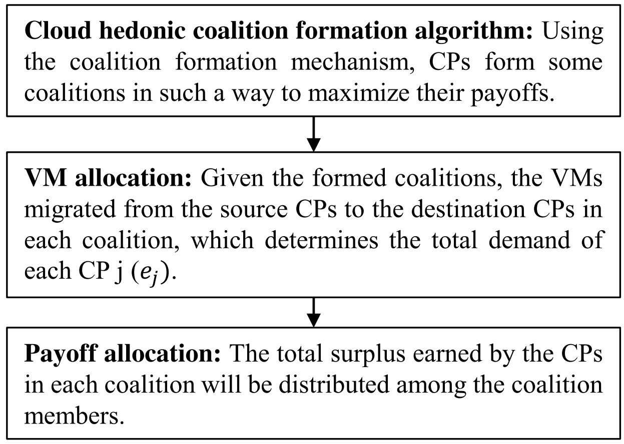


FIGURE 2. CPs coalition formation process.

Given the set of cloud providers, there are many coalitions with different properties that can be formed and they can lead to different benefits for their participants. Particularly, stability is one of the main properties that must be considered. Stability property guarantees that none of the cloud providers can earn more benefits by breaking the coalition and joining other coalitions. In addition to creating stable coalitions, the coalition utility should divide in a fair manner among the partner. Here, fairness indicates that a cloud provider's profit should be proportional to its economic contribution in the utility of the federation. Additionally, as cloud providers are rational entities, they seek to maximize their net profits in the formed coalitions. Hence, they should distribute the coalition's workload optimally.

A. COALITIONAL GAME CHARACTERISTICS

Given the set $\mathcal{N}$ of cloud providers (as players), a coalition (federation) $\mathcal{S} \subseteq \mathcal{N}$ is defined as a subset of players who agree to form a cloud federation and act as a single entity. We assume that the formed cloud provider coalitions are disjoint. We denote the set of all coalitions at any given time by $\prod = \{\mathcal{S}_1, \mathcal{S}_2, \ldots, \mathcal{S}_l\}$. When a cloud coalition is formed, the users' workload of coalition members can be migrated from one cloud provider to another within the associated coalition for processing. In addition to the players, the second essential concept of a coalitional game is the *coalition value*. It defines the worth of a coalition in a cooperative game [42].

We associate a value $v(\mathcal{S})$ to each coalition $\mathcal{S}$, to quantify the net profit of that coalition. To determine the coalition value, we should define the revenue and cost rate of a coalition $\mathcal{S}$. These are the summation of revenues and costs for individual VMs which are served by the coalition members.

The revenue and cost of a coalition can be seen as an extended form of the cloud providers' utilities in the noncooperative case, i.e., (2). In addition to the energy cost consumed for serving the users' requests, we also consider workload migration cost among coalition partners (e.g., due to network bandwidth used for migration) [43]. Hence, we define $v(\mathcal{S})$ as follows:

$$v(\mathcal{S}) = \sum_{j\in\mathcal{S}}\sum_{k\in W_j} r_{k,j} + \sum_{j\in\mathcal{S}} b_j^{m_j} - \sum_{j\in\mathcal{S}} p_j e_j^{m_j} - \sum_{i\in\mathcal{S}}\sum_{j\in\mathcal{S}} \omega_{ij} C_{i,j}^{M}, \tag{3}$$

where $C_{i,j}^{M}$ is the hourly migration cost of a VM from cloud provider i to cloud provider j, and ω_{ij} represents the number of the migrated VMs. Other parameters are defined in (2).

First, we note that the coalition value $v(\mathcal{S})$ depends entirely on the members of that coalition, with no dependence on how the players are partitioned in the other coalitions. So, our cooperative game is a characteristic form [42]. Moreover, the proposed game has transferable utility (TU) because the coalition value of the cloud providers coalition game in (3) is the amount of money gained by this coalition, and can be divided among the coalition members in an arbitrary manner.

B. OPTIMAL WORKLOAD ALLOCATION

When a cloud's coalition $\mathcal{S}$ is formed, its members should decide how to distribute the coalition workload across their data centers' servers. As cloud providers are rational entities, they seek to maximize their profits. Consequently, they should allocate the VMs in a way that maximize the overall coalition value. Hence, we model the workload allocation problem for a coalition $\mathcal{S}$ as an optimization problem as follows:

$$\max_{\omega_{ij}, e_j^{m_j}, b_j^{m_j}} \; v(\mathcal{S}), \tag{4}$$

$$s.t. \; \sum_j \omega_{ij} = W_i, \quad \forall i \in \mathcal{S}, \tag{5}$$

$$\sum_i \omega_{ij} \le Q_j, \quad \forall j \in \mathcal{S}, \tag{6}$$

$$e_j^{m_j-1} \le \left[M_j P_j^{\text{idle}} + \left(P_j^{\text{peak}} - P_j^{\text{idle}}\right)\left(\frac{\sum_i \omega_{ij}}{a_j}\right)\right]\gamma_j \le e_j^{m_j}, \quad \forall j \in \mathcal{S}, \tag{7}$$

$$\left(e_j^{m_j}, b_j^{m_j}\right) \in \left\{ \left(e_j^1, b_j^1\right), \ldots, \left(e_j^{l_j}, b_j^{l_j}\right) \right\}, \quad \forall j \in \mathcal{S}, \tag{8}$$

$$\omega_{ij} \in \mathbb{Z}^+, \quad \forall i, j \in \mathcal{S}. \tag{9}$$

In (4), $e_j^{m_j}$, $b_j^{m_j}$ and ω_{ij} are decision variables, with $(e_j^{m_j}, b_j^{m_j})$ being the selected bid by cloud provider j. (5) ensures that all workloads are served. (6) guarantees that the total workload assigned to a cloud provider will not exceed its capacity. (7) captures the power demand of any cloud provider j, which is a function of the ω_{ij}. The final selected bid will be determined according to the amount of the power demand. Constraint (8) states that the winning bid should be selected from the offered bids by the smart grid, and constraint (9) defines the domain of the decision variables ω_{ij}.

C. PAYOFF ALLOCATION

After forming coalitions, the coalition revenue must divide among the cooperative parties. Each cloud provider i receives a fraction of the coalition value $v(\mathcal{S})$, as its payoff, denoted by ϕ_i. Hence, we need a payoff allocation rule to determine how to distribute the total surplus generated by the coalition partners among them. It should assign as high as possible payoff to each cloud provider without violating the fairness property, that is introduced in Section V. We use Shapley value [44] as the allocation rule. The Shapley value is a well-developed allocation rule which is based on the marginal contribution of players, associates with every coalitional game a unique payoff vector. This value for $i \in \mathcal{S}$ in a coalition formation game with transferable utility can be calculated as:

$$\phi_i(\mathcal{S}) = \sum_{\mathcal{F}\subseteq\mathcal{S}\setminus\{i\}} \frac{|\mathcal{F}|!(|\mathcal{S}| - |\mathcal{F}| - 1)!}{|S|!}[v(\mathcal{F}\cup i) - v(\mathcal{F})], \tag{10}$$

where $|\mathcal{S}|$ is size of coalition $\mathcal{S}$, and $v(\mathcal{F}\cup i) - v(\mathcal{F})$ is the marginal contribution of player i in a coalition $\mathcal{F}$.

D. CLOUD HEDONIC COALITION FORMATION ALGORITHM

Having defined the characteristics of our coalition game as well as a payoff allocation rule, we need to design a coalition formation algorithm to model cloud providers federation formation process. Our coalition formation algorithm is a dynamic, distributed algorithm, based on a class of the coalitional games named hedonic games.

Dynamic coalition formation can be done in a centralized or distributed manner. Although centralized approaches can find an optimal coalition partition, they are generally NP-complete. Additionally, they require finding a trusted third party to compute the coalition sets. In contrast, distributed methods avoid the complexity of centralized approaches and enable each player to autonomously decide to whether or not to join a coalition [42].

A well-known class of distributed coalition formation games is hedonic games [45] which have received significant attention in recent years and applied in many applications including cloud federation formation [8], [46], [47]. Players in a hedonic game take their decisions about joining or leaving the coalitions based on a preference relation. In particular, a coalitional game classifies as a hedonic game if satisfied the following key properties:

1) Each player should have a preference over all its possible coalitions.
2) The payoff of any player only depends on the composition of its coalition with no dependency on the other coalition's members.

As we can see from (3) and (10), the payoff of any cloud provider in its federation solely depends on the members of that coalition. Furthermore, we can define a proper preference relation for cloud providers in order to compare different coalitions. Therefore, we believe that hedonic games are a suitable choice for modeling the federation formation process among the cloud providers in the proposed demand response program.

Having defined the hedonic games, we designate a preference relation by $\succeq_i$ for any cloud provider i over the coalitions $\{\mathcal{S}_k \subset \mathcal{N},\ i \in \mathcal{S}_k\}$. This is a reflexive, complete, and transitive binary relation. Having the preference relation, player i can compare any two coalitions $\mathcal{S}_1, \mathcal{S}_2 \in \mathcal{N}$ where $i \in \mathcal{S}_1$ and $i \in \mathcal{S}_2$. The strict asymmetric relation of $\succeq_i$ denoted by $\succ_i$ means that cloud provider i strictly preferred a coalition over the other one. We define the preference relation in cloud providers hedonic coalition game as follows:

$$\mathcal{S}_1 \succ_i \mathcal{S}_2 \iff u_i(\mathcal{S}_1) > u_i(\mathcal{S}_2), \tag{11}$$

where:

$$u_i(\mathcal{S}_k) = \begin{cases} \phi_i(\mathcal{S}_k) & \text{if } \mathcal{S}_k \notin h(i), \\ -\infty & \text{otherwise,} \end{cases} \tag{12}$$

where $\phi_i(\mathcal{S}_k)$ is the payoff received by cloud provider i when joins to coalition $\mathcal{S}_k$ and computes by (10), and $h(i)$ represents the history set of cloud provider i. The history set $h(i)$ keeps the coalitions that cloud provider i was a member of them at any time in the past, before the formation of the current partition $\prod_c$. It means that cloud provider i already joined and left that coalition, because it has found another coalition with a higher individual payoff. The use of a history set prevents a cloud provider from visiting a coalition twice. Having defined the required concepts, the next step is to propose a distributed algorithm for forming the coalitions. The algorithm is shown in Table 1 and proceeds as follows. It starts by initializing the current partition (e.g., with single member coalitions of $i \in N$) and the history sets, which are initially empty sets. After initialization, the algorithm takes three phases as the coalition formation game to reach the final coalition. In the first phase, cloud providers receive some information about the bids and electricity prices from their local smart grids. After that, they communicate with each other to exchange this information as well as the characteristics of their workloads. Suitable techniques for neighbor discovering and communication must be used in this phase. Different algorithms that have been proposed in literatures for distributed systems can be used for this purpose. This phase is shown as Step (1) in Figure 1.

As it is shown in Figure 1, in Phase II the algorithm is invoked by the cloud providers in a random order. It consists of three steps and repeats until all cloud providers converge to a final partition which is a stable partition. In a stable situation, no cloud provider has an incentive to unilaterally leave its current coalition and join other coalitions. Given the current partition, each cloud provider i compares its payoff with the current coalition $\mathcal{S}_{\prod_c}$ and with the other possible coalitions in set $\mathcal{P}_i = \{\{\prod_c \backslash \mathcal{S}_{\prod_c}(i)\} \cup \emptyset\}$ by (12). Particularly, it seeks to find a coalition set $\mathcal{Q}_i \subseteq \mathcal{P}_i$ such that $\mathcal{S}_k \cup \{i\} \succ_i \mathcal{S}_{\prod_c}(i),\ \forall \mathcal{S}_k \in \mathcal{Q}_i$. If $\mathcal{Q}_i \neq \emptyset$, it computes the top preferred coalition $\mathcal{S}_l$, where $argmax_{\mathcal{S}_l \in \mathcal{Q}_i} \phi_i(\mathcal{S}_l \cup \{i\})$. Next, it leaves the current coalition, joins the new coalition $\mathcal{S}_l$, and updates its history as well as the current partition. Otherwise, the current partition remains unchanged. As mentioned, this

TABLE 1. Distributed coalition formation algorithm based on the hedonic game for the clouds federation formation in the smart grid demand response program in a period.

Initial state: Initialize the history set and initial coalition partition:

$$\prod_0 = \{\{1\}, \{2\}, ..., \{N\}\},$$
$$h(i) = \emptyset, \forall i \in N$$

Hedonic coalition formation game: Three phase algorithm

Phase 1: Information exchange:

a) cloud providers receive some information about offered bids and electricity prices from their local grids.
b) cloud providers exchange this information as well as information about their workloads.

Phase 2: Coalition formation:

The following steps are performed by cloud providers in a random order in a scheduling period.

Step 1: Given the current partition, each cloud provider i

investigate the preference relation for coalitions in

$$\mathcal{P}_i = \{\{\prod_c \backslash \mathcal{S}_{\prod_c}(i)\} \cup \emptyset\}$$

to find coalition set $\mathcal{Q}_i \subseteq \mathcal{P}_i$ such that:

$$\mathcal{S}_k \cup \{i\} \succ_i \mathcal{S}_{\prod_c}(i),\ \forall \mathcal{S}_k \in \mathcal{Q}_i$$

Step 2:

If $\mathcal{Q}_i \neq \emptyset$, clouds i performs the following actions:

a) Finds the top preferred coalition $\mathcal{S}_l$, where:

$$\arg\max_{\mathcal{S}_l \in \mathcal{Q}_i} \phi_i(\mathcal{S}_l \cup \{i\})$$

b) Leaves its current coalition $\mathcal{S}_{\prod_c}(i)$.
c) Joins to the new coalition $\mathcal{S}_l$.
d) Updates its history by adding coalition $\mathcal{S}_{\prod_c}(i)$.
e) Updates the current partition as:

$$\prod_{c+1} = \{\prod_c \backslash \{\mathcal{S}_{\prod_c}(i), \mathcal{S}_l\}\} \cup \{\mathcal{S}_l \cup \{i\}, \mathcal{S}_{\prod_c}(i) \setminus \{i\}\}$$

Else, cloud provider i does not change its current coalition.

Step 3: Repeat Step 1 and 2 until all providers converge to a final partition $\prod_f$.

Phase 3: Workload distribution:

a) The cloud providers are partitioned using $\prod_f$.
b) The coalition workload of each coalition $\mathcal{S}_k \in \prod_f$ distributes among the coalition members.
c) Each cloud provider informs its power demand e_i to the local smart grid.

process repeats until converges to a final partition. Although this phase of the algorithm does not search the space consists of the all coalition partitions, but enables cloud providers to examine all possible coalitions in the current partition in their turn to find the most preferred one. Hence, it is more likely to find a coalition with higher payoff compared to hedonic-based algorithms presented in the other work (such as [8]) which are opportunistic and select the first preferred coalition.

Following Phase II and after converging to a stable partition, in the last phase, the workload of each coalition should be distributed among the coalition partners. Hence, the coalition workload migrates from the source cloud providers to the destinations to processed by them. Subsequently, the required power demand of all cloud providers (the winning bids) will be determined, and informed to the local smart grids. This phase is consistent with Steps (3) and (4) in Figure 1.

Note that the algorithm should repeat whenever a change occurs in the partition. For example, it may run when a new cloud provider adds or a cloud provider leaves the federation, e.g., because it does not comply any more with the federation level agreements. Additionally, once the workload of cloud providers changes or when smart grids change their offers.

E. CONVERGENCE AND STABILITY OF CLOUDS HEDONIC COALITION FORMATION GAME

In this section, we investigate the convergence of the coalition formation phase in the proposed algorithm, as well as the stability of the final partition.

Authors in [48] showed that the hedonic coalition formation phase of this algorithm, starting from any initial coalition partition $\prod_0$, always converges to a final partition $\prod_f$, which is a Nash-stable partition. They have proved the convergence by using of history sets and the fact that the number of coalition partitions is finite (given by the Bell number [49]) as follows. Given any initial partition $\prod_0$, coalition formation algorithm switches from the current partition $\prod_c$ to another partition $\prod_{c+1}$ and so on until reaches to the final partition. According to the preference relation in (11) and the definition of history sets, cloud providers will not revisit any coalition that has been visited before and left. Therefore, any switch from $\prod_c$ to $\prod_{c+1}$ leads a new partition that is not visited in the past. From this and as the number of coalition partitions is finite, it follows that the number of switches is finite and the sequence of switch operations always leads to a final partition.

Before discussing about the stability of the coalition formation phase, let's review some stability concept of the hedonic games [45].

Definition 1: Nash-stability. A partition Π is Nash-stable if $\forall i \in \mathcal{N}$, $\mathcal{S}_{\Pi}(i) \succeq_i \mathcal{S}_k \cup \{i\}$ for all $\mathcal{S}_k \in \Pi \cup \emptyset$.
Once the players reach a Nash-stable partition, they have no incentive to leave their current coalitions and join another one or act alone. In other words, all players prefer being in the current coalitions rather than joining to the other ones or form single-member coalitions.

Definition 2: Individual stability. A partition Π is individually stable if there does not exist a player $i \in \mathcal{N}$, and a coalition $\mathcal{S}_k \in \Pi \cup \emptyset$ so that $\mathcal{S}_k \cup \{i\} \succ_i \mathcal{S}_{\Pi}(i)$ and $\mathcal{S}_k \cup \{i\} \succeq_j \mathcal{S}_k$ for all $j \in \mathcal{S}_k$.
In other words, a coalitional partition Π is individually stable if there exists no coalition $\mathcal{S}_k$ that a cloud provider i prefers over its current coalition $\mathcal{S}_{\Pi}(i)$, without hurting other members of $\mathcal{S}_k$. Given the definitions of Nash and individual stability, it can be easily verified that any Nash-stable partition is also individually stable.

In [48], authors prove that any final partition $\prod_f$ resulting from the hedonic coalition phase is Nash-stable, and, consequently, individually stable.

VI. SIMULATION RESULTS AND ANALYSIS

A. SIMULATION SETUP

We set the number of data centers to six, except when explicitly indicated, which are operated by six independent cloud providers. We assume that all clouds use the same charging policy, that is they receive $0.3\$/h$ for processing each VM. The PUE (γ_i) of all data centers is set to 1.1 [3]. The idle and peak power of clouds servers and electricity price ranges for different regions are reported in Table 2. The cost of a VM migration from cloud provider i to j is calculated as the product of the cost rate of transferring data, data rate, and the time of migration. Data cost rate is set to 0.001 \$/GB according to the Amazon EC2 data transfer pricing [51], and we assume that data would be sent in a fixed rate of 100 Mbit/s. Migration time is a random number from the Normal distribution with mean 554 sec and standard deviation of 364 sec [8].

TABLE 2. Same simulation parameters for all scenarios [8].

$DC\#$	P^{idle} (KW)	P^{peak} (KW)	p_i $(\$/KWh)$
1	0.086	0.274	$[0.665, 0.742]$
2	0.143	0.518	$[0.626, 1.035]$
3	0.490	1.117	$[0.67, 0.88]$
4	0.086	0.274	$[0.75, 1]$
5	0.143	0.518	$[0.35, 0.45]$
6	0.490	1.117	$[1.038, 1.09]$

We performed the experiments with three workloads: First, a set of synthetic workload simulates a two day load randomly generated in $[Q_i/2, Q_i]$ for each cloud, second, a real-world trace based on data retrieved from the Microsoft Azure [52], [53], and third, one-day HP request trace reported in [10], [50], which has a great variability. For the second scenario, we extract the workload arrival rate as well as the VM lifetime for six days, and assign the pattern of each day to one cloud. Also, without loss of generality and for ease of simulation, we scale down the requested VMs to maximum 5000. The trace in scenario 3 is also scaled proportionally to the total capacity of data centers (Figure 3). Then, the workload of each hour randomly is distributed among data centers based on their capacity.

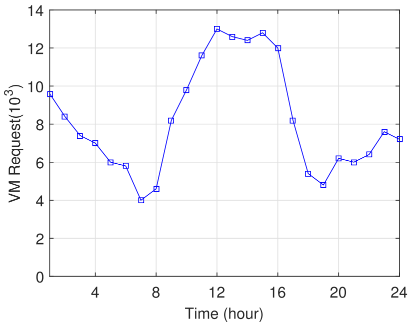


FIGURE 3. Total VM request for HP trace [10], [50].

TABLE 3. Simulation parameters -number of servers and the VM capacity of each server -for different scenarios.

$DC\#$	Scenario 1 M_i	a_i	Scenario 2 M_i	a_i	Scenario 3 M_i	a_i
$1, 4$	1000	2	6000	1	1000	1
$2, 5$	1000	4	3000	2	1000	2
$3, 6$	1000	6	2500	4	1000	4

In addition to the number of hourly VM requests, lifetime of VMs and the variability of workload patterns, the scenarios are different in terms of the number of servers and capacity of data centers, which are represented in Table 3. Moreover, in each scenario, the electricity prices, and the values of desirable power consumption (E') are different from one hour to the other. For each scenario, we conduct the coalition formation algorithm to converge to the final federation set.

In the smart grid side, we assume that each smart grid j submits 50 bids in the first scenario and 100 bids in two other scenarios, which are normally distributed in the interval $[E_j^{\max}, E_j^{\min}]$. As the bidding function, we consider $b_j(e_j) = \max[B_{\max} - \beta(E_j' - e_j)^2, 0]$ (a similar function is applied in [10]), where B_{max} is the maximum rebate price. This parameter for cloud provider i is set to $2 \times E_i^{\min} \times p_i$.

We implement our algorithm in MATLAB and use the YALMIP toolbox [54], [55] and CPLEX [56] to solve the MILP optimization problem described in Section V-B.

B. SIMULATION RESULTS

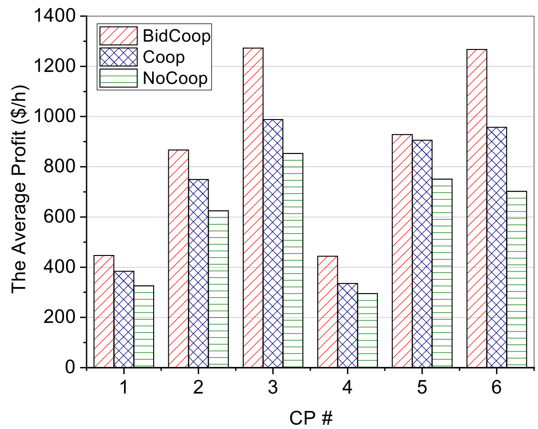
In addition to our algorithm (BidCoop), we also simulate two other approaches: a noncooperative algorithm (NoCoop), and a cooperative approach aimed at minimizing energy cost (Coop).

In the NoCoop, there is no cooperation among cloud providers and they are individually participate in the demand response program. This comparison demonstrates the benefits brought by the cooperative participation of cloud providers in demand response programs. Coop scheme is a coalition formation algorithm in which the goal of cloud federation formation is minimizing the energy cost, whereas ignoring the demand response program (such as the algorithm presented in [8]). We simulate this case and then, adopt it with the demand response program to be comparable with our algorithm. This will show that energy-aware federation formation, without considering the smart grid's demand response programs necessarily does not lead us to the best results, compared to a DR-aware federation formation approach.

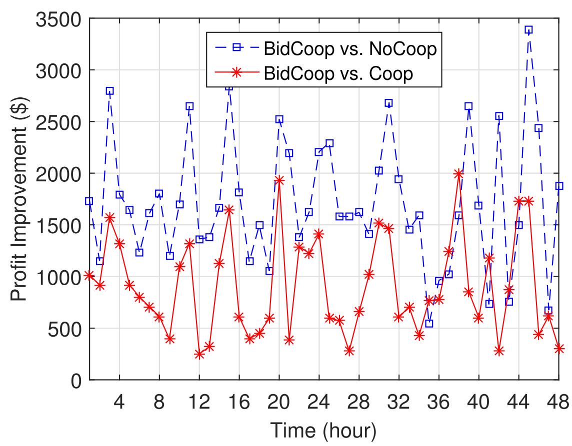
In the following subsections, we first present the effectiveness of our proposed algorithm in term of clouds' profit for all scenarios. Then, we assess the influence of the clouds' cooperation on the smart grid performance and report the results for one scenario. Finally, we investigate the effect of different parameters, such as the maximum bidding price on the performance of the proposed algorithm for one scenario. However, we report some results just for one scenario, the other scenarios shows the same trend in the results.

1) CLOUDS' PROFIT IMPROVEMENT

Figures 4-6 show the results for cloud providers' profit for different scenarios. In these figures, the average profit earned by different clouds, and the aggregated profit improvement of BidCoop compared to the other two approaches are depicted.



(a)



(b)

FIGURE 4. Simulation results for clouds' profits under different approaches for scenario 1 (a) The average profits, (b) Aggregated profit improvement.

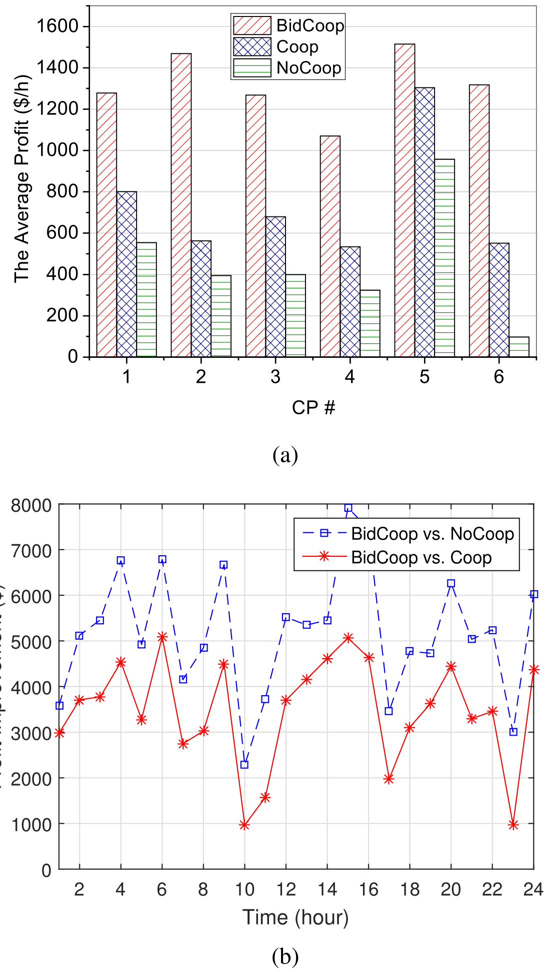


FIGURE 5. **Simulation results for clouds' profits under different approaches for scenario 2 (a) The average profits, (b) Aggregated profit improvement.**

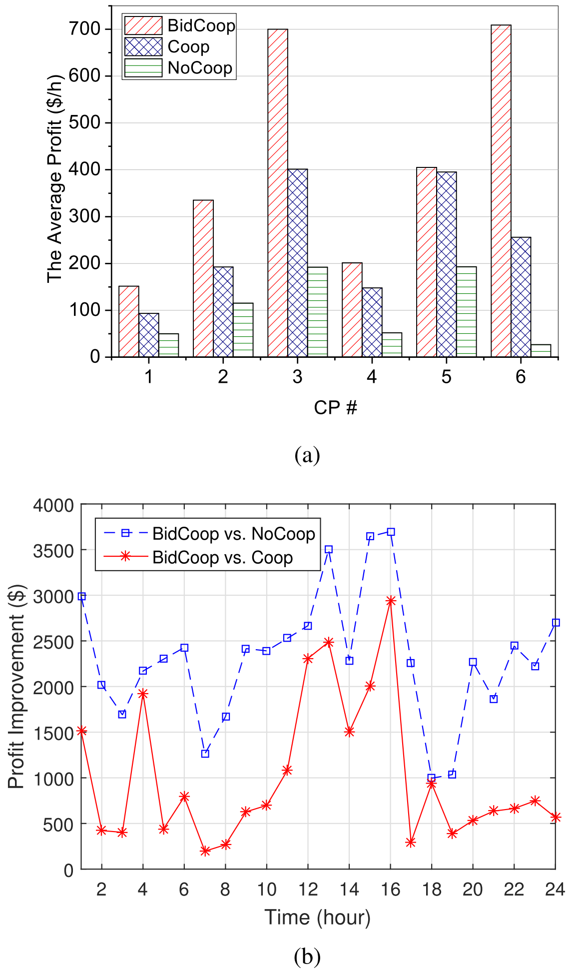


FIGURE 6. **Simulation results for cloud providers profits under different approaches for scenario 3 (a) The average profits, (b) Aggregated profit improvement.**

Considering the above figures, we can make the following observations: 1) BidCoop improves the total cloud providers' profits compared to both other approaches (NoCoop and Coop), which is demonstrating the economic efficiency of our mechanism. 2) Our algorithm compared to NoCoop approach leads to more improvement in term of clouds profit. Moreover, as can be seen from Figure 4, the amount of profit improvement of BidCoop compared to Coop approach is not the same for all clouds (For example, CP 5 experienced small improvement). This is intuitive since cooperation among cloud providers, even in Coop scheme, provides some level of flexibility, leads to more benefits compared to the non-cooperative case.

Intuitively, we expect whatever the amount of a cloud provider participation is greater than the others, it earns more benefit in the cooperation. In this regard, we investigate the average of the cloud providers contribution percentage in scenario 1 (Table 4). The contribution percentage of a cloud provider is defined as the percentage of the federation workload which is served by it. Values in this table confirm our claim. In the simulations, cloud providers 3 and 6 have the most contributions, which are 23% and 22%, in average. As a result, these cloud providers earned the highest profits (Figure 4(a)). The contribution percentage of a cloud provider is directly related to its capacity. As the capacity of these two cloud providers is more than the others (values of $M_i a_i$ in Table 2), they have the highest contribution percentage.

We run additional simulations in which we increased the number of cloud providers to $N = 7$ and $N = 8$. The number of servers for cloud providers 7 and 8 is set to 1500, and the other server configuration of these two cloud providers, respectively are similar to cloud providers 1 and 2. The power price of cloud provider 7 is set to a random number in $[0.5, 0.8]$, and for cloud provider 8 takes a random number from $[0.8, 0.95]$. Figure 7 (a) presents the average cloud providers profit in BidCoop, and Figure 7 (b) shows the average percentage of the profit improvement of BidCoop compared to NoCoop for different cloud providers. The average profits of cloud providers have been slightly affected by the increasing the number of the cloud providers (Figure 7 (a)). Clouds 3, 6 and 8, obtain the highest average profits. Again, cloud provider 6 earns the most average percentage of the

TABLE 4. Average contribution percentage of cloud providers in scenario 1.

DC#	Contribution (%)
1	7 %
2	20 %
3	23 %
4	10 %
5	18 %
6	22 %

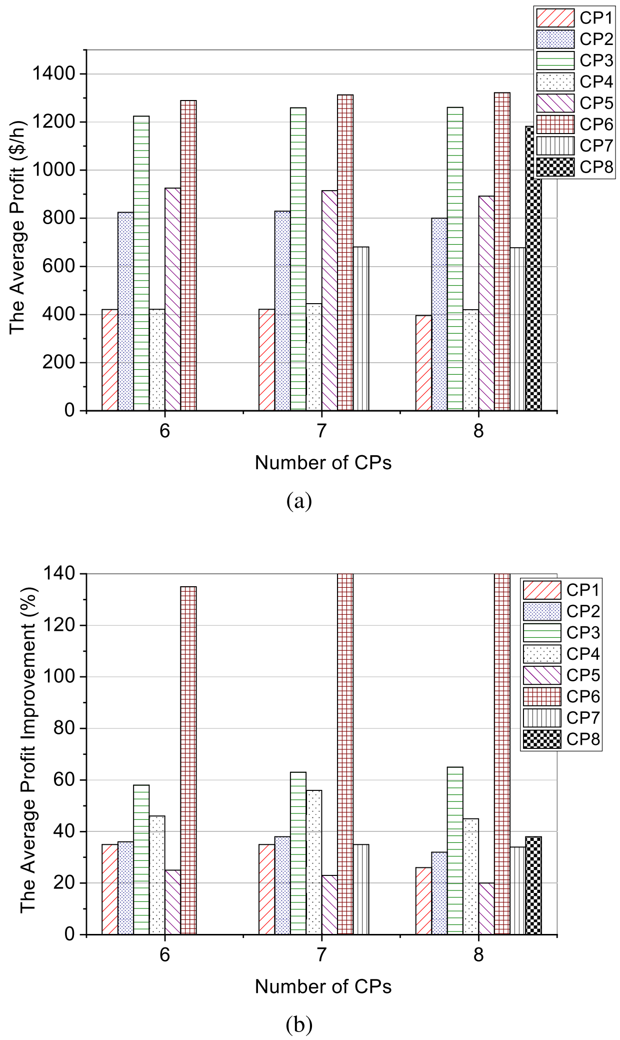


FIGURE 7. Simulation results for clouds' profits in the environment with 6, 7 and 8 clouds for scenario 1 (a) The average profits of cloud providers in BidCoop approach (b) The average percentage of profit improvement for BidCoop approach compared to NoCoop.

profit improvement in all cases (Figure 7 (b)), because of its features such as server configuration as well as the power price range.

2) CONVERGENCE SPEED

We designate the convergence speed as the number of iterations required by the coalition formation algorithm to reach to the final partition. Figure 8 shows that the minimum and

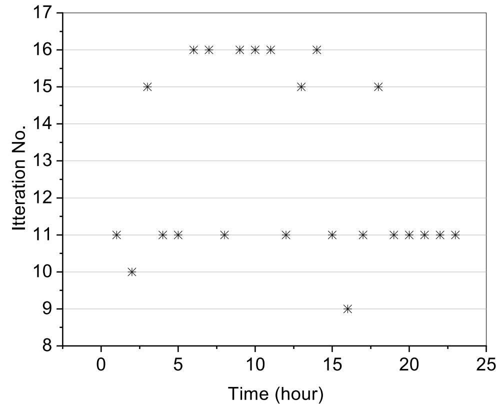


FIGURE 8. Algorithm speed: The number of iterations needed to algorithm reaches the final partition in scenario 2.

the maximum number of iterations are 9 and 16, respectively, for scenario 2. Furthermore, the system converges in 13 iterations, on average (For two other scenarios, the average speed is equal to 13 and 14). This is a reasonable number with respect to the number of the coalition partitions which is equal to Bell number (Bell number for six cloud providers is equal to 203).

3) IMPACT OF THE CLOUDS COOPERATION ON THE SMART GRID PERFORMANCE

Next, we focus on the effect of the cloud providers' cooperation on the smart grids' performance. We define the power demand deficit (PDD) for smart grid j as the gap between the data center j actual power consumption (i.e., e_j) and desirable power consumption level of the smart grid (i.e., E_j'), similar to [10]. Figure 9 shows the results for scenario 2. Note that in this simulation, all smart grids use the same bidding function. As can be seen in this figure, the cloud cooperation in the proposed approach has the positive impact on the smart grid performance, leads to less PDD compared to the noncooperation case.

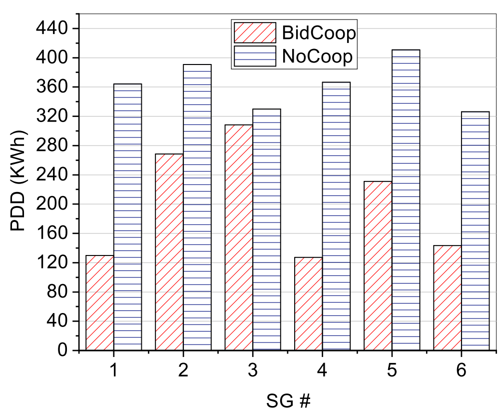
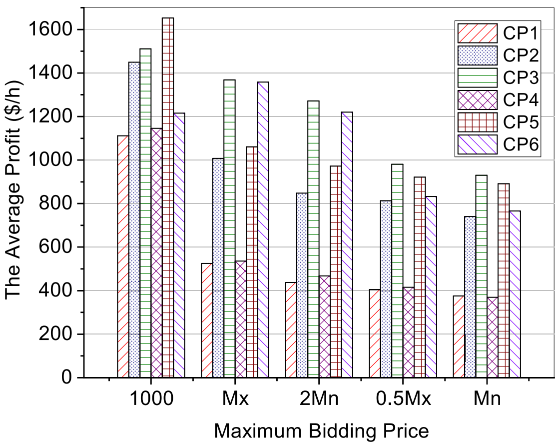


FIGURE 9. The average PDD of smart grids in scenario 2.

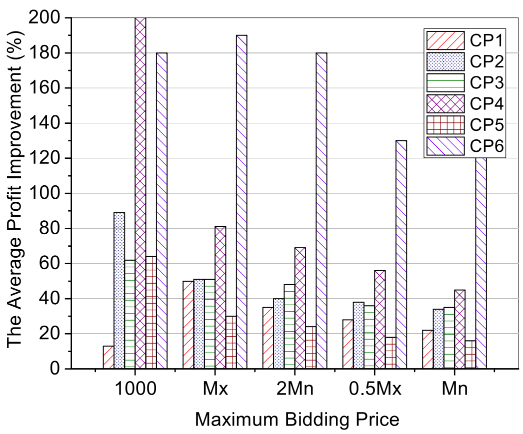
4) INFLUENCE OF MAXIMUM BIDDING PRICE

We also investigate the impact of the maximum bidding price, i.e., $B_{\max}$, which was set to $2E_i^{\min}p_i$. We assign different values such as 1000, $C_{\mathrm{Max}} = E_i^{\max} p_i$, $0.5C_{\mathrm{Max}} = 0.5E_i^{\max} p_i$, and $C_{\mathrm{Min}} = E_i^{\min} p_i$ to this parameter. Even though the value of the energy cost is not fixed and depends on the cloud provider configuration, and the electricity tariff, we have the following relationship between these values: $C_{\mathrm{Min}} < 0.5C_{\mathrm{Max}} < 2C_{\mathrm{Min}} < C_{\mathrm{Max}} < 1000$.

We plot the average cloud providers profit, and the average of clouds profit improvements for scenario 1 in Figure 10. Intuitively, by increasing the maximum bidding price, whenever the unit electricity price remains fix, the total payment of cloud providers to the smart grids decreases. Therefore, the CPs profit increases with the higher value of $B_{\max}$. The results in Figure 10 (a) confirms it.



(a)



(b)

FIGURE 10. Simulation results for clouds' profits under different $B_{\max}$ values for scenario 1 (a) The average profits of cloud providers in BidCoop approach (b) The average profit improvement of clouds in BidCoop compared to NoCoop.

Additionally, when the value of $B_{\max}$ depends on the cloud providers' energy cost, we have a trend in the profit improvement by growing the value of $B_{\max}$ (Figure 10 (b)). But, this trend has not been followed in the case of a fixed value of 1000. Particularly, assigning this value to $B_{\max}$ causes the federation formation as well as the workload distribution changes in such a way that the cloud provider 4 obtains the maximum profit improvement.

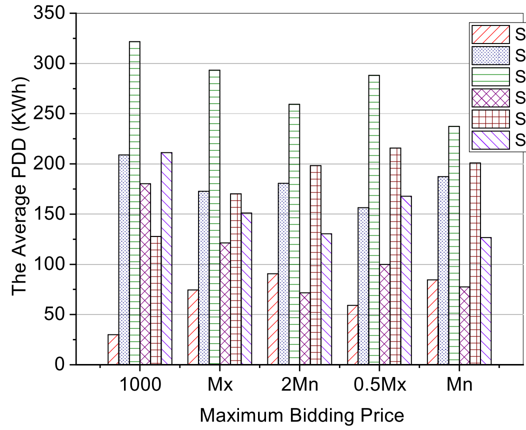


FIGURE 11. The average power demand deficit for various smart grids under different $B_{\max}$ values for scenario 1.

Figure 11 presents how changes in the value of $B_{\max}$ affects the power demand deficit. Different values for $B_{\max}$ leads to different behavior for smart grids. Although, for smart grid 1, the minimum PDD is associated with 1000, this value for smart grid 3 causes the most PDD. This observation indicates that increasing the value of $B_{\max}$ does not always reduce the PDD for all smart grids. Meanwhile, various smart grids achieve the minimum PDD under different settings for $B_{\max}$.

In all previous simulation scenarios, we assume that all smart grids set the same values for $B_{\max}$. However, smart grids can dynamically change the value of $B_{\max}$. To investigate the effect of the different values of $B_{\max}$, we consider a setting with the following values for $B_{\max}$ of different smart grids: $[1000, 0.5C_{\mathrm{Max}}, C_{\mathrm{Min}}, 2C_{\mathrm{Min}}, 500, C_{\mathrm{Max}}]$. We present the results in Figure 12 (a)-(c).

Figures 12 (a) and (b) show the average profit of BidCoop and the average profit improvement of BidCoop compared to NoCoop approach, respectively. Assigning different values to $B_{\max}$ leads to higher profits as well as profit improvement for cloud providers 1, 4, 5 and 6. The profit of cloud provider 2 has not much affected and cloud provider 3 has experienced a profit reduction. The average percentage of profit improvement of all cloud providers improved from 54% for same $B_{\max}$ values to 70% for different $B_{\max}$. Moreover, we plot the average PDD values in Figure 12 (c). The PDD of smart grids 1, 4, 5 and 6 have been reduced. But, smart grids 2 and 3 experienced the higher PDD under this setting. Although, the value of the PDD has been increased under $B_{\max}$ values for some grids, but, they have experienced 27% reduction on the PDD values, on average. In summary, the presented results show that smart grids can improve the clouds profits and their performance, by choosing suitable $B_{\max}$ values.

However, in addition to dynamic changing $B_{\max}$ values, smart grids can change the form of the bidding function. Meanwhile, each smart grid can better achieve its goals by considering the competition among smart grids that serve

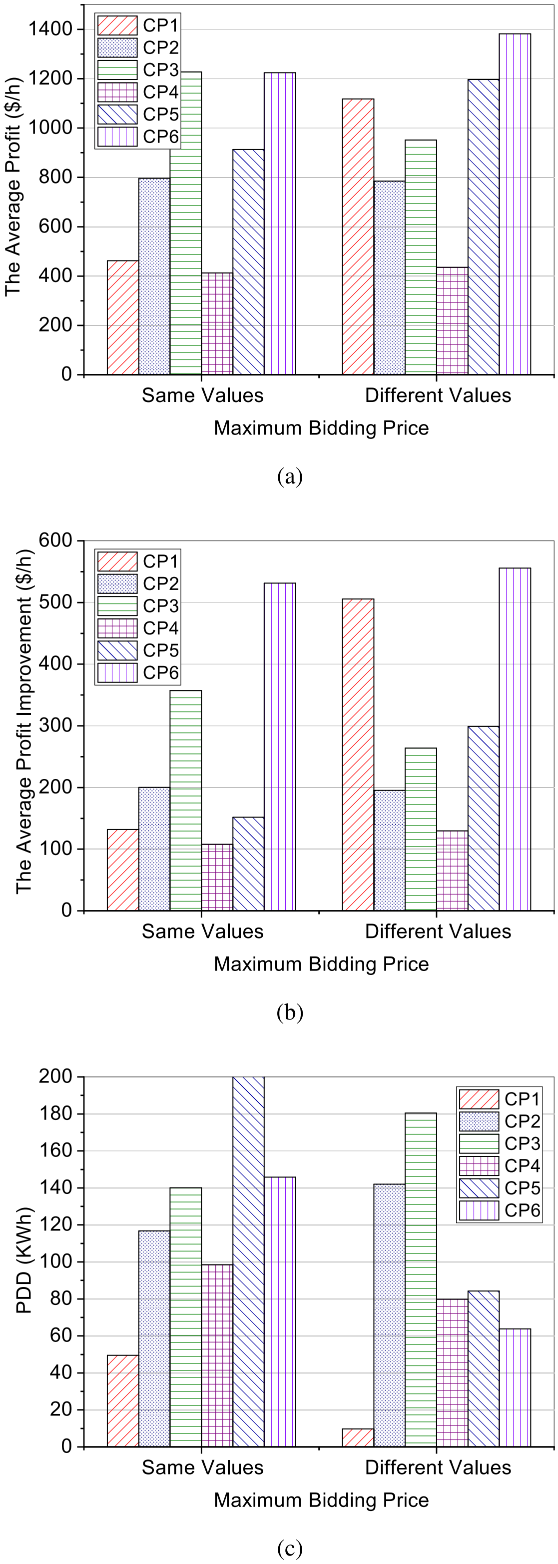


FIGURE 12. Simulation results for clouds' profit and smart grids' PDD under two cases, same and different $B_{\max}$ values for scenario 1 (a) The average profits of clouds in BidCoop (b) The average profit improvement of cloud providers for BidCoop compared to NoCoop (c) The average PDD.

different data centers. In particular, when geo-distributed data centers cooperate with each others and form federations, they couple multiple smart grids. Hence, a smart grid utility needs not only to anticipate the corresponding cloud's response to its demand response programs, but also to consider the impact of other smart grids' decisions on the corresponding cloud providers' response. These variations can be considered in the future work.

VII. CONCLUSION AND FUTURE WORK

In this paper, we have investigated the participation of the cooperative cloud providers in the smart grid demand response. To this end, we have considered a scenario in which each smart grid utility submits a number of sealed power demand bids along with some rebates to the corresponding data center. After receiving the bids, each cloud provider must decide about the winning bid, which is its actual power demand. In this stage, cloud providers can cooperate with each other and migrating their workloads to the other partners. We have modeled this scenario as a hedonic coalition formation cooperative game. Numerical results have shown that cooperation improves the cloud providers' profits in respect to the noncooperative case. Furthermore, our simulation results have indicated that cloud cooperation has a positive impact on the performance of the involved smart grids.

For future work, we plan to study the effect of the renewable-powered data centers. Additionally, we would like to extend our work to the overlapping coalition formation, rather than disjoint ones.

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