A Game Based Power Allocation in Cloud Computing Data Centers

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***Abstract*—The emergence of smart systems based on Internet of Things (IoT) and new technologies has led to use more cloud computing services. This incentivizes to build more geographically distributed data centers. However, the data centers consume a tremendous amount of electricity which significantly increases load on power grid. There are broad concerns about the impact that this huge consumption may cause to the power grid. Moreover, the data centers are competing to get the maximum of power from the smart grid in a selfish way, which also has a negative impact on both the smart grid and the other data centers. In this paper, we model the power allocation problem between the smart grid and cloud data centers as a non-cooperative game. The basic idea of our approach is to determine the optimal quantity of power that will be assigned to each data center, in order to have a fair power allocation. To do so, we consider the data center priority in terms of number of active servers, state of energy charge and number of running critical applications. Moreover, we prove the existence and uniqueness of Nash equilibrium, and compute the optimal quantity of power using Lagrange multipliers and KarushKuhnTucker (KKT) conditions. Simulation results confirm the effectiveness of the proposed approach, and show that our scheme can reduce the load on the power grid up to 80%.**

***Index Terms*—Cloud data centers, Smart Grid, power allocation, game theory.**

I. Introduction

Both consumer and business applications are contributing to the growing dominance of cloud services over the Internet. Also, with the emerging of Internet of Things that generally use the cloud services, Juniper Research expects total number of connected IoT sensors and devices to reach 50 billion by 2022, up from an estimated 21 billion in 2018 [1]. Furthermore, Cloud data centers traffic is expected to represent 95% of total data center traffic by 2021 [2].

The smart grid is an intelligent power infrastructure that aims to overcome the problems of the legacy grid and to make the power grid more stable, reliable and efficient. The smart grid incorporates an Advanced Metering Infrastructure (AMI), which is a set of IT infrastructure and communication networks. AMI integrates advanced communication technologies like: sensing devices and smart meters, in order to collect information from the customers. This creates a bidirectional communication, where energy and information can be exchanged between the utility company and its customers [3]. Thus, the smart grid allows integrating energy suppliers and users more effectively and having a visibility of the consumer energy behavior.

Being the source of energy of multiple systems such as Electric Vehicles, Smart cities, Smart homes, etc, the smart grid also handles the huge power demand of cloud data centers. Given the set of thousands of servers, storage equipments, cooling facilities and power transformers, that a data center owns, the data center sector is estimated to account 1.4% of the global electricity consumption [4]. Also, the data centers purchase power from the smart grid in a selfish way without considering the limited amount of energy that was assigned to serve the data centers. This may, on one hand, deprive a data center that needs more power than other data centers of having the sufficient amount of energy to perform its functions. On the other hand, it can overload the power stations and cause a serious damage to the power grid.

To overcome this problem, we model the selfish behavior of data centers as a non-cooperative game in which each data center is represented by a player of the game. The basic idea of our scheme is to assign the optimal quantity of power to each data center according to three metrics: the data centers charge priority, the critical running applications priority and the other data centers priorities, in order to have a fair power allocation. Our main contributions in this paper are as follows.

- We studied the interaction between the smart grid and cloud data centers and formulate the power allocation to the data centers as a non-cooperative game.
- We proved the existence and uniqueness of Nash Equilibrium in our game.
- We formulated the data centers payoff function as a non-linear optimization problem. We solve it then using Lagrange multipliers and KarushKuhn-Tucker (KKT) conditions so that each data center determines its optimal solution.
- We compared our game scheme with the traditional selfish scheme. Simulation results showed that our scheme is 81% more effective in terms of power assignment than the traditional one.

The rest of this paper is organized as follows. We review the related work in Section II. In Section III, we present our system model and game formulation. Section IV gives the simulation results and the evaluation of our scheme. This paper is concluded in Section V.

II. RELATED WORK

In order to reduce power load and maintain smart grid reliability, there were many research efforts toward improving energy efficiency of data centers. These works can be organized into two main categories. Assuming the availability of several data centers, the first one improves the energy consumption of each data center individually, for example, by minimizing their IT equipment use, such as CPU, while the second one considers all available data centers in the network and tries to improve their energy consumption at a whole.

In the first category, Gandhi et al [5] try to find the optimal power allocation to servers of a data center, in order to minimize their mean response time. To do so, they exploit two CPU voltage and frequency scaling mechanisms: Dynamic Frequency Scaling (DFS), and Dynamic Voltage and Frequency Scaling (DVFS) which are among the most exploited techniques used in reducing the servers' energy consumption. Di wang et al [6] present a software system to virtualize power distribution in data centers that allows applications to define their power needs and hence allocates the power in a fair way.

The second category tries to reduce both energy consumption and cost by managing data centers workload allocation, for example: adjusting the power consumption of the data centers using pricing strategies, such as Time of Use (ToU), Critical Peak Pricing (CPP), and Real-Time Pricing (RTP) that can match the supply with demand [7] [8]. In addition, works that fall into this category introduce renewable energy supplies jointly with Distributed Battery Storage Units; Gu et al [9] and [10] try to minimize both the total energy cost and the total carbon emission of the data centers through scheduling requests, and selling back the stored energy to the power grid to make profits.

The above works, especially those belonging to the second category, do not present a detailed analysis of the impact on the power grid. Wang et al [11] take the first step toward studying the impact of load distribution on power grids. They model the interaction between the data centers and power grid as a two-stage problem. They propose in the first stage, to perform power load balancing by altering the energy consumption of data centers through dynamic pricing. In the second stage, the data centers react to the energy prices and manage the computing workload assignments to minimize their total energy cost. An extension of this paper has been devoted in [12] by analyzing the worst-case performance considering the prediction error in background power load.
Mohsenian et al formulated in [13] the service request routing problem in cloud computing jointly with the power flow analysis in smart grid. As a result, a grid which takes into account the service request routing design in cloud computing may significantly help for better load balancing and more robustness in the electric grid. Yanzhi Wang et al [14] propose a nested two stage Stackelberg game based formulation between the smart grid controller and a cloud computing controller. The smart grid controller performs load balancing among buses according to its location-dependent pricing policy. While, the objective of the cloud controller is to maximize the total price obtained from serving the requests with respect to the location-dependent pricing functions. The optimal strategies were extracted based on backward induction using convex optimization. The work has been extended in [15] by considering a realistic power grid structure (the IEEE 24-bus structure) and incorporating renewable power generations into the system. Therefore, the power-dependent pricing signal at each power bus depends on both load power consumption and renewable power generation.

Most of the existing researches are relying on power energy supplies and we can note that price-awareness and utilization of renewable energy remain two main factors of energy efficiency in data centers, but they are not often mitigated with a grid-awareness. In this work, we focus on the second category trying to manage efficiently the power allocation from the smart grid system to all available data centers at a whole in a fair way.

III. SYSTEM MODEL AND GAME FORMULATION

This section gives the system model and describes our non-cooperative game scheme. Section III-A describes the system architecture and our problem formulation. Section III-B presents the game description. Section III-C detailes Nash equilibrium proof. Optimal solutions are presented in Section III-D.

A. System architecture and probleme formulation

In our system, the smart grid controller (utility company) is responsible for supplying power, responding to the power demands of the consumers. The power is delivered from several power stations that communicate with the cloud data centers (bidirectional communication). Therefore, the smart grid controller has a visibility on the power behavior of each data center. The system architecture of smart grid and cloud data centers is illustrated in Fig.1.

We consider a set of geographically distributed data centers operated by a single cloud provider. We denote by d_i data center i; $\forall i \in I$ with $I = \{1, 2, \ldots, i, \ldots, n\}$. Each data center d_i is powered by a dedicated power station and all the power stations are operated by the same smart grid controller and we assume that:

1) x_i^{Max} is the maximum quantity of power that a data center d_i can purchase.
2) Each data center has a stored energy; we denote the state of energy charge of a data center d_i as SoC_i.
3) Each data center d_i has three priorities $Cp_i, Ap_i, Tp_i \in [0, 1]\, \forall i \in I$, defined as follow:

- Cp_i: the data centers charge priority: reflects the priority of a data center in terms of the number of active servers and the state of energy charge value.
- Ap_i: the critical applications priority: denotes the priority of the data center in terms of its number of critical running applications, compared to its total running applications
- Tp_i: the total critical applications priority: reflects the priority of a data center in terms of its number of critical running applications, compared to the total critical applications running in all the data centers.

In our system, the data centers aim at purchasing the maximum of power in order to charge their energy storage and handle the maximum of applications. This will improve the cloud provider profits. Furthermore, each data center tries to increase its state of charge and demands power in a selfish way without considering the limited energy planned to serve the data centers. This may overload the power stations and cause a serious damage to the power grid.

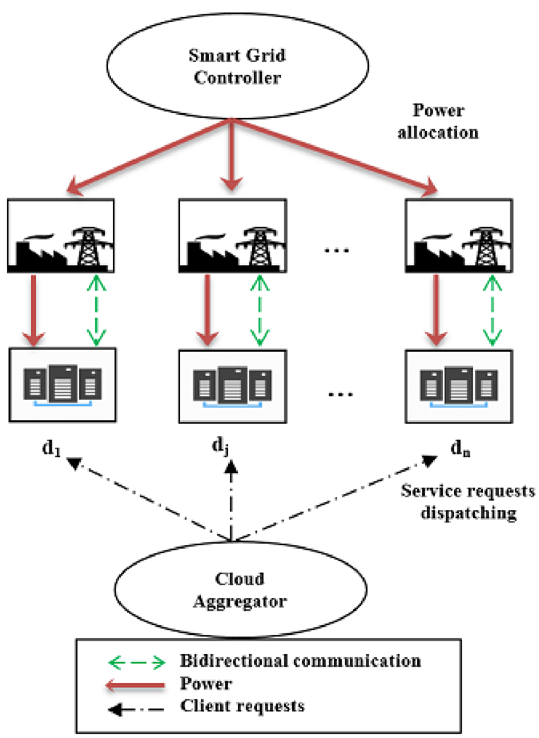


Fig. 1: the system architecture of cloud data centers and smart grid

B. Game discription

We used non-cooperative game theory to model the power allocation to data centers. Thus, we consider the game: $G = (I, S_i, gain_i)_{i \in I}$ where:

1) I: represents a set of players (data centers), $d_1, \ldots, d_j, \ldots, d_n$ where n is the number of data centers that participate in the game.
2) S_i; $\forall i \in I$: Strategies: reflects the actions the player d_i may take at any stage of the game. A player can demand a quantity of power between a minimum of zero and a maximum of x^{Max}. Therefore, $S_i = \left[0, x_i^{Max}\right]$ and the strategy profile of all players is $S = \prod_{i=1}^{n} S_i = \left[0, x_1^{Max}\right] \times \cdots \times \left[0, x_i^{Max}\right] \times \cdots \times \left[0, x_n^{Max}\right]$.
3) $gain_i : S_i \rightarrow \mathbb{R}$ represents the payoff function of player d_i $\forall i \in I$. Each player aims at maximizing its payoff function $gain$, in order to increase its profit; $0 \leq gain_i \leq x_i^{Max}, \forall i \in I$.

In our scheme, we design the payoff function to reflect four principal functions: (i) The first function calculates the data center demand for having a high quantity of power (utility function). The remaining three functions are priority cost functions that calculate respectively (ii) the cost of the data center charge priority (iii) the cost of the critical applications priority, and (iiii) the cost of the total critical applications priority.
Hence, the payoff function involves the following four functions:

1) Utility function: in our approach, the utility function was modeled such that each player gets more profit when it increases its power demand value. Among the utility functions commonly used in network research studies [16], we chose to design our utility function using the logarithmic function. Therefore, we select the utility function of a player d_i as follows:
$$\gamma_i(x_i) = log(x_i + 1), \forall i \in I \tag{1}$$
Where x_i is the quantity of power that a player d_i demands.

2) The cost function of the data centers charge priority: this function defines the penalty that the player has to pay according to its power quantity demand x_i and its charge priority Dp_i. In our approach, the priority Dp_i is calculated based on the active servers As_i and the state of charge SoC_i of player d_i as follows:
$$Dp_i = 1 - \frac{1}{As_i + SoC_i} \tag{2}$$
Hence, we have the following cost function:
$$\rho_i(x_i, Dp_i) = x_i \times Dp_i \tag{3}$$

3) The cost function of the critical applications priority: in this priority cost function, we take into consideration the critical running applications of a player d_i. In our scheme, we consider a real time application as a critical application. The function is based on the player's

power quantity demand x_i and its critical applications priority Ap_i. We calculate the priority Ap_i as the ratio of critical application noted $Critical\_apps_i$ to the total applications noted $Total\_apps_i$. Thus, we define the function as follows:

$$\sigma_i(x_i, Ap_i) = x_i \times Ap_i \tag{4}$$

Where :

$$Ap_i = 1 - \frac{Critical\_apps_i}{Total\_apps_i} \tag{5}$$

4) The cost function of the total critical applications priority: this priority cost function is based on the player power quantity demand x_i and its total critical applications priority Tp_i. The priority Tp_i is the ratio of the players critical applications to the sum of all the players' critical applications. Therefore, we have the following cost function:

$$\tau_i(x_i, Tp_i) = x_i \times Tp_i \tag{6}$$

Where:

$$Tp_i = 1 - \frac{Critical\_apps_i}{\sum_{i=0}^{n} Critical\_apps_i} \tag{7}$$

After defining the four functions of a player d_i, we give the payoff function hereafter:

$$gain_i(x_i, x_{-i}) = \alpha_i\gamma_i(x_i) + \beta_i\rho_i(x_i, Dp_i) + \omega_i\sigma_i(x_i, Ap_i) + \psi_i\tau_i(x_i, Tp_i) \tag{8}$$

Where:

- $x_{-i} = \{x_k\}_(k \in I)$ and $i \neq k$ is the vector of the demanded quantity of power (strategies) of all players except player d_i.
- $s = (x_i, x_{-i}) \in S$ is the strategy profile.
- $\alpha_i, \beta_i, \omega_i$ and ψ_i are players preference coefficients of functions $\gamma_i, \rho_i, \sigma_i$ and τ_i, respectively. These parameters are set to satisfy the system objective and requirements, for example, as ω_i value is greater the difference between the power that get players having a high critical applications ratio and those having a low critical applications ratio is higher and vice versa.

C. Nash equilibrum

In game theory, Nash Equilibrium (NE) is a fundamental concept, commonly used to predict the future behavior of all players and determine the permanent state. This means that each player in the game has no interest in changing its strategy and performs the same action. Therefore, if a NE exists, a non-cooperative game has a solution. In our game $G = (I, S_i, gain_i)_{i\in I}$ a set of strategies represents a NE if no player can increase its payoff by changing its strategy. Formally, NE is an N-tuple $s^* = [x_1^*, \ldots, x_i^*, \ldots, x_n^*]\,, s^* \in S$ represents a NE if no player can increase its payoff by changing its strategy. Formally, NE is an N-tuple $\{x_i^*\}$ satisfying:

$$gain_i(x_i^*, x_{-i}^*) \geq gain_i(x_i, x_{-i}^*), \forall x_i^*, x_i \in S_i, x_i \neq x_i^* \forall i \in I \tag{9}$$

In summary; we prove in this subsection the existence and the uniqueness of NE before computing game solution of G.

1) Existence of a Nash Equilibrium: In order to prove the existence of at least one NE we used Nikaido-Isodra theorem [17]:

theorem 1 (Nikaido-Isoda)**.** The game $G = (I, S_i, gain_i)_{i\in I}$ has at least one NE if and only if, $\forall i \in I$, a strategy set S_i is compact and convex, $gain_i(x_i, x_{-i})$ is continuous function in the profile strategies $s \in S$, and concave in S_i.

Proof.

- The strategy set for all players is $S = \prod_{i=1}^{n} S_i$, where $S = 0 \leq S_i \leq x_i^{max}$, $\forall i \in I$. As $S_i = [0, x_i^{max}]$, the strategy set of each player is closed and bounded. Then, the set S_i is compact, $\forall i \in I$.
  Consider two points $y_1, y_2 \in S_i$ and $\epsilon = [0, 1]$. Thus, we have $0 \leq \epsilon y_1 + (1-\epsilon)\, y_2 \leq x_i^{max}$, which signify that the point $\epsilon y_1 + (1-\epsilon)\, y_2 \in S_i$. Therefore, we can say that S_i is convex; $\forall i \in I$.
- The concavity of our payoff function can be proved by computing the Hessian matrix of $gain(s)$, with $s = \{x_i\} \forall i \in I$, as follows:

$$H\,(s) = \begin{bmatrix} D_{11} & D_{12} & \cdots & D_{1n} \\ D_{21} & D_{22} & \cdots & D_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ D_{n1} & D_{n2} & \cdots & D_{nn} \end{bmatrix} \tag{10}$$

Where $D_{ij} = \left(\frac{\partial^2 gain_i}{\partial x_i \partial x_j}\right), \forall i, j \in I$. Therefore, we obtain:

$$D_{ij} = \begin{cases} -\frac{\alpha_i}{(x_i+1)^2} < 0 & \text{if } \; i = j; \;\; \forall i, j \in I \\ 0 & \text{if } \; i \neq j; \;\; \forall i, j \in I \end{cases} \tag{11}$$

Giving the leading principal minor of (s) , we can see that $H(s)$ is negative definite for all strategies $s \in S$, therefore, $gain_i(x_i, x_{-i})$ is strictly concave in $S_i\ \forall i \in I$. Given these satisfying conditions and according to the Nikaido-Isodra theorem [17], our game G has at least one NE.

□

2) Uniqueness of Nash Equilibrum: Let $u = (u_1, u_2, \ldots, u_n)$ be a random vector of positive parameters We use Rosens theorem [18] to have the weighted positive sum of the payoff function $gain_i(x_i, x_{-i})$, $\forall i \in I$, which is defined as follows :

$$\delta\,(x_i, x_{-i}; u) = \sum_{i=1}^{n} u_i gain_i(x_i, x_{-i}), u_i \geq 0. \tag{12}$$

Where the pseudo-gradient of $\delta(x_i, x_{-i}; u)$ is given by:

$$g(x_i, x_{-i}; u) = \begin{bmatrix} u_1 \nabla gain_1(x_1, x_{-1}) \\ u_2 \nabla gain_2(x_2, x_{-2}) \\ \vdots \\ u_n \nabla gain_n(x_n, x_{-n}) \end{bmatrix} \quad (13)$$

With :

$\nabla gain_i(x_i, x_{-i}) = \frac{\alpha_i}{(x_i+1)^2} - \beta_i \rho_i(x_i, Dp_i) - \omega_i \sigma_i(x_i, Ap_i) - \psi_i \tau_i(x_i, Tp_i)$

In addition, the Jacobian matrix $(J(x_i, x_{-i}, u))$ of g can be defined as follows:

$$J(x_i, x_i, v) = \begin{bmatrix} B_{11} & B_{12} & \cdots & B_{1n} \\ B_{21} & B_{22} & \cdots & B_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ B_{n1} & B_{n2} & \cdots & B_{nn} \end{bmatrix} \quad (14)$$

Where $B_{ij} = u_i D_{ij}$; $\forall i, j \in I$.

Hence, we can clearly see that the symmetric matrix $\left[J + J^T\right]$ is negative definite for all $x_i, x_{-i} \in S$. Consequently, the function $\delta(x_i, x_{-i}; u)$ is diagonally strictly concave according to Rosens theorem [18]. Therefore, the game G has unique NE in its pure strategy space, according also to Rosens theorem.

3) Game solution: We compute in this subsection the optimal game solution x_i^* maximizing its profit (payoff function). To do so, we model a constrained non linear optimization problem (F) as follows:

$$\begin{aligned} \underset{i}{\text{Maximize}} \quad & gain_i(x_i, x_{-i}) \\ \text{subject to} \quad & x_i \geq 0, \\ & x_i - x_i^{max} \leq 0, \ \forall i \in I. \end{aligned}$$

To solve the problem (**F**), we used Lagrange multipliers method to maximize our function which is subject to two inequality constraints. We introduce two Lagrange multipliers, λ_i and ℓ_i, and study the Lagrange function defined by

$$L_i(x_i, \lambda_i, l_i) = gain_i(x_i, x_{-i}) + \lambda_i x_i + \ell_i (x_i^{max} - x_i) \quad (15)$$

Hence, our Lagrange function satisfies the following KKT conditions for each player d_i :

$$\begin{aligned} \lambda_i, \ell_i \geq 0 \\ x_i \geq 0 \\ x_i^{max} - x_i \geq 0 \\ \nabla_{x_i} gain_i(x_i, x_{-i}) + \lambda_i \nabla_{x_i} x_i + \ell_i \nabla_{x_j} (x_i^{max} - x_i) = 0 \\ \lambda_i x_i + \ell_i (x_i^{max} - x_i) = 0 \end{aligned}$$

After solving the problem (**F**), we determine the optimal sending data rate (x_i^*) for player d_i, $\forall i \in I$, as follows:

$$x_i^* = \begin{cases} 0 & \text{if condition 1} \\ x_i^{max} & \text{if condition 2} \\ \frac{\alpha_i}{\beta_i \rho_i(x_i, Dp_i) + \omega_i \sigma_i(x_i, Ap_i) + \psi_i \tau_i(x_i, Tp_i)} - 1 & \text{otherwise} \end{cases} \quad (16)$$

Where condition 1 and 2, respectively, are:

$$\beta_i \rho_i(x_i, Dp_i) + \omega_i \sigma_i(x_i, Ap_i) + \psi_i \tau_i(x_i, Tp_i) \geq \alpha_i \quad (17)$$

$$\beta_i \rho_i(x_i, Dp_i) + \omega_i \sigma_i(x_i, Ap_i) + \psi_i \tau_i(x_i, Tp_i) \leq \frac{\alpha_i}{x_i^{Max} + 1} \quad (18)$$

IV. Our Scheme Evaluation

In this section, we present our simulation results and demonstrate the effectiveness of our proposed game-based power allocation scheme.

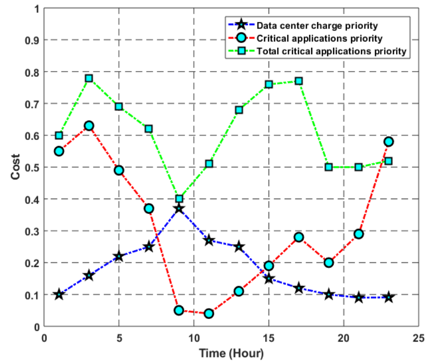
A. Simulation Setup and Parameters

To validate our scheme, we compare it with the selfish scheme in which data centers periodically request power from the smart grid controller without considering the limited amount of smart grids energy intended to serve the data centers. We consider four geographically distributed datacenters that are connected to the same smart grid controller. We suppose that each data center has at least one active server and 5 MW as a minimum of stored energy (SoC for State of Charge). We measure each data center's power demand from the smart grid controller each 2 hours. We run our simulations in two different periods: off-peak times and on-peak times, with a time horizon span of 24 hours. In off-peak times, the power and service demands are low (from 10 pm to 7 am) while in on-peak times, we have a huge power demand and the data centers execute a high number of critical applications (from 7 am to 10 pm). In our scheme, we set the parameters $\alpha_i = 6, \beta_i = 2.7, \omega_i = 2, \psi_i = 2$ and $x_i^{max} = 5MW, i \in I$. We choose $\alpha_i, \beta_i, \omega_i \ and \ \psi_i$ values such that we satisfy the system requirement and objective.

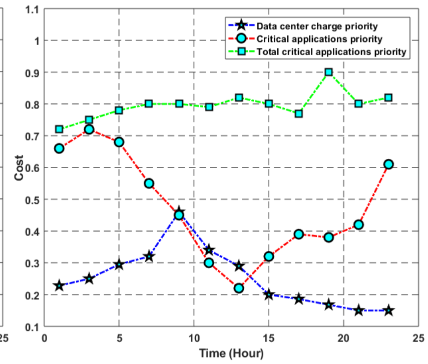
B. Simulation results

Fig.2 shows each data center varying costs across one day (the cost of data centers charge priority, critical applications priority and total critical applications priority) using equations (2), (5) and (7), respectively. We can observe that in each data center, the data center's charge priority is low at off-peak times and high at on-peak times. This can be explained by the fact that the data center has not much active servers and stored energy at off-peak times, in contrary at on-peak times when the data center has charged his energy and has a high number of active servers. On the other hand, the critical applications and the total critical applications priorities are high at off-peak times and low at on-peak times. This means that the critical applications compared to the total applications running in the data center are much more at on-peak times than the ones running at off-peak times.

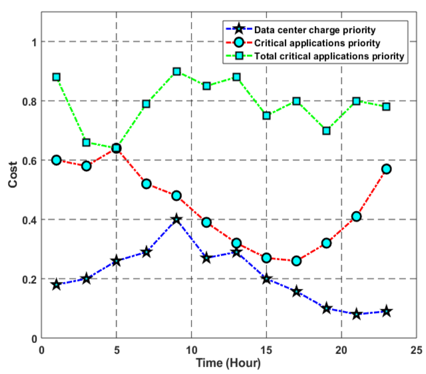
Fig.3 depicts the power assignment for the four data centers within one particular hour (hour 12pm) using our game based



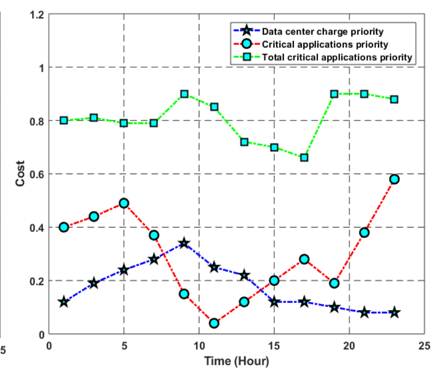
(a) Data center 1



(b) Data center 2



(c) Data center 3



(d) Data center 4

Fig. 2: Data centers varying costs

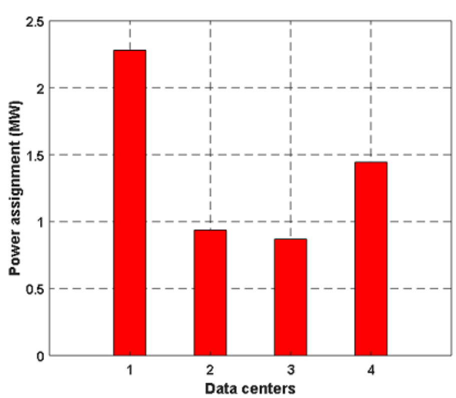


Fig. 3: Game based power assignment

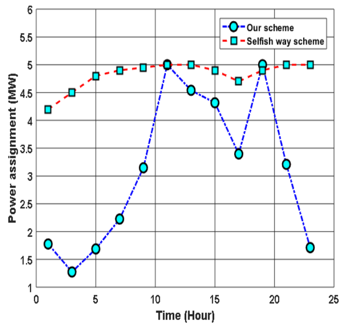
power allocation scheme. We can see that our scheme has a fair allocation according to each data center's priority costs.

Fig.4-a plots the comparison of power assignment between our scheme and the selfish way scheme, for one data center chosen randomly. We observe that the selfish way scheme is always supplied with the total requested quantity of power, whatever the critical applications or energy charge that a data center has. This may overload the power grid and surcharge the power station. On the other hand, the quantity

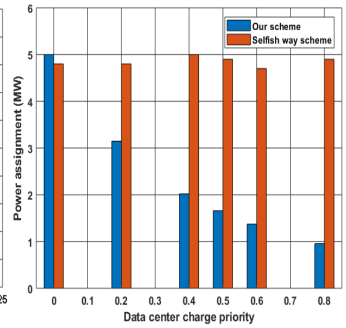
TABLE I: Game Based Power Allocation Effectiveness

Data center / Scheme	Selfish way scheme (MW)	Our scheme(MW)	Effectiveness
DC 01	5	2.28	54.39 %
DC 02	4.7	0.93	80.07 %
DC 03	4.9	0.86	62.32 %
DC 04	4.75	1.44	69.6 %

of energy assigned in our game scheme varies over time and may decrease up to 1.27 MW. This generally happens during off-peak times (for example at 3 am in Fig.4-a) when the data center is charging its energy and has not a lot of running applications. Also, it may reach the maximum value of 5 MW like at 11 am and 7 pm. The presented results are due to the game theory used in our scheme which assigns the sufficient amount of power considering (i) the active servers and state of charge of each data center, (ii) the critical applications running in the data center and (iii) the critical applications running in all data centers, as depicted in Fig.4-b, Fig.4-c and Fig.4-d, respectively. We show in Fig.4-b the power assignment values according to data centers charge priority in terms of active servers and state of charge. We can observe that the assigned power in our scheme decreases as the priority decreases. However, the selfish way scheme has always a stable power assignment without considering



(a)



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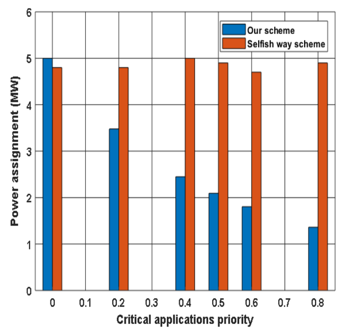

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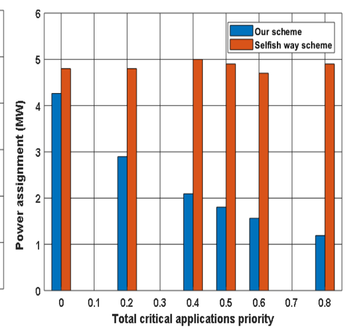

(d)

Fig. 4: Performance evaluation of our scheme comparison with the Selfish way scheme: (A) Power assignment, (B) Power assignment Vs Data centers charge priority , (C) Power assignment VS Critical Applications priority, (D) Power assignment Vs Total critical applications priority

any priority. Besides, Fig.4-c and Fig.4-d also show that the critical applications priority and the total critical applications priority, respectively have an inverse relationship with power assignment. A player has more power when its critical applications increase and vice versa.

We consider the effectiveness in our game, the percentage of power load that has been reduced on the power grid after applying our scheme. Table I shows the effectiveness of our approach, where our game scheme can reduce the stress on the power grid with a percentage of 80% and at the same time ensure the needs of data centers in energy, especially those having more priority applications.

V. CONCLUSION

In this paper, we studied the interaction between the smart grid and cloud data centers to get a fair power allocation. We modeled the power assignment to data centers as a non-cooperative game. We proved both the existence and the uniqueness of Nash equilibrium. Then we computed the optimal quantity of power assigned to each player. Simulation results showed that our approach can significantly reduce power load on power grid, compared to other schemes.
For future work, we would like to study ranking techniques, to dispatch clients workloads on cloud data centers. Also, we aim to integrate renewable energy and try to reduce both data centers energy cost and gas emission.

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