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Adaptive Data Center Management Algorithm Based on the Cooperative Game Approach

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ABSTRACT Recently, data centers (DCs) have become an indispensable part of modern computing infrastructures. However, DCs often consume a significant amount of energy and lead to the workload unbalance with increasing service requests. Keeping focus on this point, in this paper, we propose a novel energy-aware DC management scheme. To design an efficient DC control algorithm, the main challenge is uncertainties such as uncertain energy price and unpredictable users' demands. In response to these uncertainties, we adopt the idea of cooperative game theory, and introduce a new two-phase bargaining model to get the mutual advantage. To decide the energy price, we formulate the Stackelberg bargaining game while adapting the current system situation. To balance the workloads among DCs, the migration bargaining game is developed. These two game models are tightly coupled to achieve greater and reciprocal advantages during dynamic DC operations. The main novelty of our proposed two-phase bargaining approach is to handle comprehensively contradictory requirements for the DC management. Finally, extensive experiment results validate the efficiency of our proposed algorithm by comparing with the existing state-of-the-art DC management protocols in terms of average payoff of all DCs, system throughput and fairness among DCs.

INDEX TERMS Data centers, smart grid, Stackelberg bargaining game, migration bargaining game, cooperative game theory.

I. INTRODUCTION

Data center (DC) has emerged as one of the leading ICT-based infrastructures for providing on-demand services to the end users. As a cost-effective platform for hosting large-scale Internet applications, the DC may enjoy economies of scale by amortizing long-term capital investments over a considerable number of computing machines. It creates multiple copies of virtual resources deployed over a physical server to provide services such as network, storage, and computational power to end users. However, multiple DCs incur enormous energy costs. In 2013, the energy consumption of DCs was almost 91 billion KWh, and it is expected to grow to 8 percent of the global electricity supply at each year. Currently, data centers use about 200 TWh per year, or 1% of global electricity demand, but it is projected as up to 13% of global power demand by 2030. Therefore, energy efficiency in DCs has an attractive and primary concern from both the research community and the industry [1], [2].

The electronic power transmission grid has been progressively developed for over a century. Traditionally, the power grid is typically seen as a transmission system that transfers electricity from bulk generation systems to power distribution substations, and each substation finally delivers electricity at a low voltage to their end users. Recently, the development of human society and economic needs drive the revolution of transmission grids stage-by-stage with the aid of innovative technologies. As a new backbone used to deliver electricity from points of generation to the consumers, smart grid (SG) refers not only to the physical power grid, but also to the controls and devices supporting the function of the intelligent power grid. As an exponential increase in energy demands,

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the SG has become one of the most powerful technologies of the modern era. Especially, it forms an intelligent web of distributed generation, transmission, delivery, and storage of energy with an inclusion of information and communication technologies [2], [3].

To make the SG more reliable and robust, tremendous research efforts have focused on running DCs in SG system; it is a good choice to enhance the energy efficiency, sustainability and reliability of electrical services. Moreover, the SG system can facilitate the integration of distributed renewable power generations such as wind energy, solar energy, and other renewable energy sources. To be specific, some geo-distributed DCs are deployed in the self-owned SG and the energy demand of DCs could be satisfied by multiple energy resources. Usually, the energy cost is dominating all other types of costs in the DC system. Therefore, the major objective of DC management is to minimize the expected energy cost by considering the time-coupling uncertainties in electric price, renewable energy and arrival workloads [4], [5].

The current SG technology is undergoing a transformation from a centralized, producer-controlled platform to a distributed and consumer-interactive network. Therefore, power generation companies can employ a location-dependent dynamic pricing strategy while incentivizing the workload shifting mechanism from one physical DC location to another DC location. In addition, the dynamic pricing policy is extremely useful to effectively integrate renewable power generation facilities into the SG system despite their intermittent nature. Therefore, DCs in different locations can take advantage of dynamic pricing policy to develop an efficient DC management algorithm that adaptively re-distributes the workload among DCs in multiple locations. In this way, the key idea is to constantly monitor the energy prices of different region DCs and may shift the workloads toward DCs to minimize the total electric cost. With the appropriately designed dynamic pricing policy, it is possible to formulate the interactions between SG system and DCs based on the active control decisions on both sides [5].

In this study, we design a new DC management algorithm with the goal of improving the overall system performance. By taking into account the strategic properties of SG and DCs' behaviors, we adopt the basic idea of game theory. Especially, we transform the functional space of DC management algorithm into a mathematical space of a formulated two-stage cooperative game, and implement two different bargaining solutions for each stage game. For the first-stage game procedure, the energy price is dynamically decided for each geo-distributed SG by adopting the Stackelberg bargaining approach. For the second-stage game procedure, the migration bargaining approach is implemented to balance the workload among DCs by dispatching computation tasks to neighboring DCs. Based on the dynamic online process, two game steps work together in a coordinated manner toward an appropriate system performance.

As an intelligent control paradigm, cooperative game theory is a cross-discipline subject to study the interactions and competitions among rational game players. In 1950, the earliest major contribution for cooperative games was made by J. Nash. It is a bargaining solution, which became associated with his name as well. Classical Nash bargaining solution (*NBS*) is the unique solution to a two-person bargaining problem based only on information about each player's preferences. The *NBS* is formulated by expected utility functions over the set of feasible agreements and the outcome which would result in case of disagreement. However, one of the criticisms of *NBS* is precisely that it is not fair, in the sense that it ignores the players' ideal payoffs [6], [7].

The *Raiffa-Kalai-Smorodinsky* bargaining solution (*RKSBS*) was designed to argue that one player's gain should be proportional to his maximum gain but the *NBS* fails to satisfy this requirement. The *RKSBS* places the same weight on individual player's gain and other players' losses. The *modified Thomson* bargaining solution (*MTBS*) maximizes the sum of all game players' normalized payoffs. The *RKSBS* and *MTBS* are very helpful for reaching a fairer and more efficient solutions to solve the DC management problem [6], [7]. With the *RKSBS* and *MTBS*, we develop a two-stage cooperative game model to implement our proposed scheme. In a cooperative and coordinated manner, each individual agent in the SG-DC combined platform makes decisions to reach a mutually acceptable agreement.

Based on the current system workload situation, SG and DCs have different viewpoints for the energy price and workload balancing issues. With the combination of *RKSBS* and *MTBS*, control decisions are made sequentially to leverage the full synergy of different bargaining solutions. Our two-step bargaining process, SG and DCs cause cascade interactions to find the most profitable solution. Therefore, the main novelty of our proposed scheme is its adaptability, flexibility and responsiveness to current SG and DC system conditions.

The rest of this paper is organized as follows. Related work is reviewed in Section II. Section III describes the SG-DC system platform and basic assumptions. And then, we introduce the basic ideas of *RKSBS* and *MTBS* to design our DC management scheme. In a sequential cooperative fashion, the energy price decision and DCs' workload migration problems are formulated as a novel two-phase bargaining game model. To increase readability, the main steps of our proposed algorithm are given. Section IV presents the performance evaluation results to validate the performance and effectiveness of the proposed algorithm. Finally, the study is summarized and some concluding remarks are provided in Section V.

II. RELATED WORK

In this section, we present a brief review of some related work. The papers [16]–[21] adopt the idea of game theory for the SG-based energy management problem. In [16], the pricing strategy in the SG is analyzed by modelling the economic dispatch problem as a bi-level game in the electricity market. To guarantee the profit of the energy generation company and the social welfare of the utility companies simultaneously, the Nash bargaining solution is adopted to find an optimal wholesale price. In the retail market, the Shapley value is utilized to achieve profit distribution among the utility companies, and then a distributed gradient algorithm is proposed to search for the optimal retail price. The paper [17] proposes a novel two-stage game-theoretic residential photovoltaic (PV) panels planning scheme for distribution grids with potential PV prosumers. In the first stage, a Stackelberg game based stochastic bi-level energy sharing model is proposed to determine the optimal sizing of PV panels with uncertain PV energy output, load demand, and electricity price. In the second stage, a stochastic programming based residential PV panels deployment model is proposed for all PV prosumers.

The authors in [18] introduce a hierarchical system model where multiple providers and prosumers interact to define the best price and demands. They highlight the capacity of a prosumer to produce energy and minimize the dependency on the providers in the overall proposed energy management. The paper [19] has demonstrated a viable method to discriminate price per unit of energy between different energy users in a smart grid system when the energy users sell their surplus energy to a shared facility controller. Based on the cake cutting game model, this approach can leverage the generation of discriminate pricing within a constrained budget of the shared facility controller.

Recently, Kai Ma *et al.* propose new SG management protocols [20], [21]. In [20], they propose an economic dispatch strategy for the electricity system, and formulate a wholesale price negotiation problem between the generation company and multiple utility companies. Then, they prove that the negotiation problem between the generation company and multiple utility companies is a bargaining problem. In [21], they employ the base stations as relays and formulate the electricity costs-based upon the regulation errors and the packets loss model. Specifically, they formulate the interactions between the utility company and the relay as a bargaining problem. Second, we utilize the Nash bargaining solution and *Raiffa–Kalai–Smorodinsky* bargaining solution to achieve the Pareto-optimal outcome.

Earlier our study [22] explores the triple-bargaining game model to balance electric power production and consumption within the hierarchical smart grid infrastructure. With the Nash, extended-egalitarian and proportional bargaining solutions in three control levels, the total energy of smart-grid system is hierarchically controlled, and the smart-grid utility is maximized adaptively to increase the system reliability. Even though research literatures in [16]–[22] introduce some interesting methods for the energy management and price decision problems, they mainly focus on the SG control issues without considering the SG-DC combined platform.

To address various DC control problems, multiple literature papers have been published. This section presents prior efforts related to the DC management issue. The paper [8] propose the *QoS-Efficient DC Management* (*QEDCM*) scheme to operate the virtual machine (VM) placement. This scheme adopts the idea of a non-cooperative game to simultaneously improve energy efficiency and guarantee quality of service (QoS). This game formulates a strategic relationship between the volume of the resources requested by VMs and the supply volume of physical resources. It models the essence of the limited virtual resource scheduling and re-allocation during the VM placement process. And then, the *QEDCM* scheme searches the corresponding VM placement method for each item of game strategies. Finally, the Nash equilibrium solution for the game matrix is obtained via payment function values of different VM placement methods. Simulation results and their analytical comparison demonstrate that the *QEDCM* scheme can achieve an optimum balance between improving energy efficiency and guaranteeing QoS [8].

The Fair Cost DC Control (*FCDCC*) scheme is developed based on the cooperative game, which is adopted to determine the price that end-users would pay for their requested VMs [9]. To achieve an optimal fair solution for the VM pricing problem, a coalition structure has been adopted under a cooperative environment, and queuing techniques are implemented to handle large sets of incoming VM requests onto DCs. And then, *Shapley value* is used to estimate the fraction of capital expenditure that would be included in the VM price. During the VM placement process, *Shapley value* is computed to estimate the placement cost of each VM in a cooperative game situation. Finally, an integer linear programming is proposed to reduce the energy consumption, which contributes toward reduction in operational cost and VM price. Simulation results show that the cooperative game based VM placement approach can achieve a low price for different VM configurations [9].

R. Kaewpuang et al propose the *Cooperative Virtual Machine Control and Management* (*CVMCM*) scheme to reduce the total system cost [10]. To achieve an optimal and fair solution, they develop a new framework composed of virtual machine allocation, cost management, and cooperation formation model. Due to the SG's uncertainties, the stochastic programming method is designed to obtain the optimal decisions to allocate VMs to the available resources while managing the DC's power consumption under various conditions. To reduce the execution time of obtaining the VM allocation solution, the *Benders* decomposition algorithm has been applied. The cost management among cooperative end-users is formulated as the coalitional game, and the fair share of the total cost is obtained according to the *Shapley value*. In addition, the *Markov* chain model has been implemented to obtain the stable cooperation formation of end-users. The major contributions of the *CVMCM* scheme are at the mathematical modeling and analysis which provide tools for designing the optimal DC resource management [10].

Although a lot of researches have exploited extensively the DC management techniques to improve the system performance, fair-efficient control solutions for the

SG-DC combined platform have not been fully utilized. In addition, none of the researches in the literature consider the two-phase bargaining approach to handle the DC management problem from an interactive perspective. As an extended version of our earlier work published in [22], we integrate the SG and DCs by considering the active decisions on both sides, and formulate the interactions between SG and DCs as a two-phase cooperative game model. Different from existing *QEDCM*, *FCDCC* and *CVMCM* protocols, our proposed scheme can reach an agreement that gives mutual advantage, and has more potential benefits in terms of average payoff, system throughput and fairness.

III. THE BASIC IDEAS AND PROPOSED SCHEME FOR THE SG-DC MANAGEMENT

In this section, we first present the basic ideas of *RKSBS* and *MTBS* to design our two-phase bargaining game model. And then, we introduce the SG-DC combined system infrastructure, and explain in detail the proposed DC management algorithm.

A. THE BASIC CONCEPTS OF RKSBS AND MTBS

In a bargaining problem, a group of two or more game players is faced with a set of feasible outcomes, any one of which will be the result if it is specified by the unanimous agreement of all players. Let $\boldsymbol{N} = \{1, \ldots, n\}$ be a finite set of game players, and $\mathbb{R}^{\boldsymbol{N}}$ is the n -fold Cartesian product of real number set $\mathbb{R}$. A feasible set $\boldsymbol{S}$ is a subset of the payoff space, and points in $\mathbf{S} \subseteq \mathbb{R}^{\boldsymbol{N}}$ represent the feasible utility levels that the individual players can get. If agreement is not reached, they will use a given disagreement outcome (d) as the result. Any point $\mathfrak{U} \leq \boldsymbol{S}$ represents an outcome of the bargaining problem. The i^{th} coordinate of $\mathfrak{U}$, i.e., $\mathfrak{U}_i$, is the i^{th} player's payoff. Given τ, τ' in $\mathbb{R}^{\boldsymbol{N}}$, $\tau \succcurlyeq \tau'$ means $\tau_i \succcurlyeq \tau_i'$ and $\tau \neq \tau'$ for all $i \in \boldsymbol{N}$; $\tau \succcurlyeq \tau'$ means $\tau_i \succcurlyeq \tau_i'$ and for all i. A bargaining problem can be described as a pair $(\boldsymbol{S}, d)$, and denote the family of all bargaining problems by $\sum$. $\prod$ denotes the class of permutations of order $\boldsymbol{N}$. Given $\boldsymbol{S}$ in $\sum$ and π in Π, $\pi(\boldsymbol{S}) = \left\{y \in \mathbb{R}^{\boldsymbol{N}} \mid y = \pi(x), x \in \boldsymbol{S}\right\}$. Note that for π in $\prod$, if $\boldsymbol{S}$ is in $\sum$, so is $\pi(\boldsymbol{S})$, and if $(\boldsymbol{S}, d)$ is in $\sum'$, so is $(\pi(\boldsymbol{S}), \pi(d))$. A bargaining solution defined on $\sum$ is a rule which associates to every bargaining probiem $(\boldsymbol{S}, d)$ in $\sum$ a unique point $\mathfrak{P}$. Usually, $\mathfrak{P}$ is called as a bargaining solution for $(\boldsymbol{S}, d)$ [14], [15].

Usually, bargaining solutions can be analyzed using a weighting factor, players' preference and utility functions. Let ψ, v_i and $\mathfrak{U}_i^{max}$ be the weighting factor, player i' preference function, and maximum utility payoff, respectively. The ψ measures the trade-off between player's gain and another's loss. The ψ - dependent bargaining outcome, i.e., $\mathfrak{U}^*(\psi)$, is the solution to [7];

$$\begin{aligned}\mathfrak{U}^*(\psi) = \mathbf{max} \prod\nolimits_{i \in \boldsymbol{N}} \boldsymbol{v}_i(\psi) \\ \text{s.t., } v_i(\psi) = (\mathfrak{U}_i - d_i) \\ + \left(\left(\frac{\psi}{|\boldsymbol{N}| - 1} \times \left(\sum_{j \in \boldsymbol{N}, j \neq i} \left(\mathfrak{U}_j^{max} - \mathfrak{U}_j\right)\right)\right)\right)\end{aligned} \quad (1)$$

where $\psi = 0, 1\ (|\boldsymbol{N}|\text{-}1)$ corresponds to the *NBS*, *RKSBS* and *MTBS*, respectively. Approaches to bargaining problems fall into strategic or axiomatic categories. In the strategic bargaining, solution emerges as the equilibrium of a sequential game in the bargaining process. Without the bargaining process, axiomatic bargaining assumes some desirable properties about the outcome, and identifies axioms that guarantee this outcome. Generally, much of the literature dealing with bargaining problems may use axiomatic approach; the *NBS*, *RKSBS* and *MTBS* are also axiomatic bargaining solutions. That is, axioms are specified that serve to characterize the solutions uniquely. Since each solution satisfies different axioms, they must have different properties. Based on preferences towards these properties, we may choose a specific bargaining solution. Usually, axiomatic bargaining solutions are characterized by a collection of desirable axioms like as, *Pareto Optimality* (***PO***), *Symmetry* (***S***), *Invariance with Respect to Affine Transformation* (***IRAT***), *Independence of Irrelevant Alternatives* (***IIA***), *Monotonicity* (***M***), and *Weak Inverse Monotonicity* (***WIM***). The axioms involved in the characterization of *NBS* are ***PO***, ***S***, ***IRAT***, and ***IIA***. The *RKSBS* satisfy the axioms of ***PO***, ***S***, ***IRAT***, and ***M***. The *MTBS* may satisfy the ***PO***, ***S***, ***IRAT*** and ***WIM*** axioms [7], [14], [15].

- ***PO:*** $\sum' \equiv \{(\boldsymbol{S}, d) \exists \sum \times \mathbb{R}^{\boldsymbol{N}} | d \in \boldsymbol{S}; \exists \tau \in \boldsymbol{S}, \tau > d\}$. $\forall \boldsymbol{S}' = (\boldsymbol{S}, d) \in \sum', \forall y \in \boldsymbol{S}, y \not\geq f\left(\boldsymbol{S}'\right)$.
- ***IIA:*** $\forall \boldsymbol{S}' = (\boldsymbol{S}, d), \boldsymbol{T}' = (\boldsymbol{T}, d_0) \in \sum', [d = d_0, \boldsymbol{T} \subset \boldsymbol{S}, f(\boldsymbol{S}') \in \boldsymbol{T}] \Rightarrow f(\mathbf{T}') = f(\boldsymbol{S}')$.
- ***IRAT:*** Given $e = (a, b)$ in $\mathbb{R}_{++}^{\boldsymbol{N}} \times \mathbb{R}^{\boldsymbol{N}}$, and x in $\mathbb{R}^{\boldsymbol{N}}$, $\boldsymbol{V}_e(x)$ is the vector of $\mathbb{R}^{\boldsymbol{N}}$ whose i^{th} coordinate is $(a_i \cdot x_i) + b_i$. Given $\boldsymbol{S}$ in $\sum$, $\boldsymbol{V}_e(\boldsymbol{S}) \equiv \left\{y \in \mathbb{R}^{\boldsymbol{N}} \mid y = \boldsymbol{V}_e(x), x \in \boldsymbol{S}\right\}$ and if $(\boldsymbol{S}, d)$ is in $\sum'$ so is $(\boldsymbol{V}_e(\boldsymbol{S}), \boldsymbol{V}_e(d))$. $\forall \boldsymbol{S}' = (\boldsymbol{S}, d) \in \sum', \forall e = (a, b) \in \mathbb{R}_{++}^{\boldsymbol{N}} \times \mathbb{R}^{\boldsymbol{N}}, f(V_e(\boldsymbol{S}), V_e(\text{d})) = V_e\left(f\left(\boldsymbol{S}'\right)\right)$.
- ***M:*** If $\boldsymbol{S}_j \subseteq \boldsymbol{S}_i$, $\mathbf{max}\{\mathfrak{U}_i \mid \mathfrak{U} < \boldsymbol{S}_i\} = \mathbf{max}\{\mathfrak{U}_i | \mathfrak{U} < \boldsymbol{S}_j\}$ and $\mathbf{max}\left\{\mathfrak{U}_j \mid \mathfrak{U} < \boldsymbol{S}_j\right\} \leq \mathbf{max}\{\mathfrak{U}_j | \mathfrak{U} < \boldsymbol{S}_i\}$, then $\mathfrak{U}_j\left(\mathfrak{P}_j\right) \leq \mathfrak{U}_i(\mathfrak{P}_i)$, where $\mathfrak{P}_i$ is the solution for $(\boldsymbol{S}_i, d)$.
- ***WIM:*** If $\boldsymbol{S}_j \subseteq \boldsymbol{S}_i$, $\mathfrak{P}(\boldsymbol{S}_i) < \boldsymbol{S}_j$, $\mathbf{max}\{\mathfrak{U}_i \mid \mathfrak{U} < \boldsymbol{S}_i\} = \mathbf{max}\{\mathfrak{U}_i | \mathfrak{U} < \boldsymbol{S}_j\}$ and $\mathbf{max}\left\{\mathfrak{U}_j \mid \mathfrak{U} < \boldsymbol{S}_j\right\} \leq \mathbf{max}\{\mathfrak{U}_j | \mathfrak{U} < \boldsymbol{S}_i\}$, then $\mathfrak{U}_j\left(\mathfrak{P}\left(\boldsymbol{S}_j\right)\right) \geq \mathfrak{U}_j(\mathfrak{P}(\boldsymbol{S}_i))$.
- ***S:*** $\forall \boldsymbol{S} \in \sum, \left[\forall \pi \in \prod, \pi(\boldsymbol{S}) = \boldsymbol{S}\right] \Longrightarrow f_i(\boldsymbol{S}) = f_j(\boldsymbol{S})$, for $\forall i, j \in \mathbb{R}^{\boldsymbol{N}}$.

B. SG-DC COMBINED SYSTEM INFRASTRUCTURE

Each individual DC consumes a large amount of energy power and incurs a significant cost. In addition, due to the increased flexible energy demands in the DC, we may face more and more uncertainties from the overall workload. Therefore, efficient energy policy becomes a major concern for the multiple DC management. To improve the efficiency of an electricity power system, the SG technology has been introduced. Facilitated by advanced communication and computation, the SG system provides opportunities to satisfy the needs of DC electricity while minimizing their energy cost. Also, the SG system includes renewable power sources to improve the energy availability while promoting sustainable green energy. So, the SG system can offer significant opportunities for the DC management problem to intelligently control their energy needs with the aid of advanced metering technique and two-way real time communication [10], [11].

With the growing demand of various application services, more and more DCs were deployed globally. However, their resource utilization has found to be low. Virtualization is one of the critical technologies to transform DCs. The main goal of virtualization is to tackle the low-utilization problem for DC resources. Specifically, a virtualized server, referred to as a VM, can be dedicated to a particular application. If all the VMs are packed into a few physical machines, the energy consumption in the data center will be significantly reduced. In recent years, researchers have focused on the VM migration problem in order to reduce the energy cost of DCs. Usually, VM migration can provide various benefits, such as load balancing and performance optimization. However, the VM migration imposes new challenges on DC operations. For example, placing an excessive number of VMs on one physical DC will result in substantial poor system performance. Therefore, we should pay more attention to build a reasonable trading between multiple VMs and physical DCs [12], [13].

In this paper, we study the DC management problem based on the independencies between DCs and the SG system. It is worth noting that our work can accommodate a variety of flexible workloads among DCs with the dynamic energy price policy. To provide opportunities to wisely operate the SG-DC combined system, we incorporate the role of two-phase bargaining game model into the DC management scheme. First, we regulate the energy price at each local SG site while integrating renewable energy sources energy; the dynamically decided energy price can reflect the current demand-supply power grid condition at that local area. Second, workload balancing through the VM migration method enables DC operators to better manage their energy consumptions. Based on our two-step approach, we implement our advanced interactive mechanism while facilitating the information exchange between SG and DC at each local site via smart meters.

We consider a discrete time model $T \in \{t_1, \ldots, t_c, t_{c+1}, \ldots\}$, where the length of a time slot matches the time-scale at which the dynamic energy price decisions and workload migrations are updated. Let $\mathbb{D} = \{\mathcal{D}_1, \ldots, \mathcal{D}_n\}$ denote the set of geographically dispersed DCs where each $\mathcal{D}_{1\le i\le n}$ supports various kinds of task applications, and $\boldsymbol{\mathcal{L}} = \{\mathcal{L}_1, \ldots, \mathcal{L}_n\}$ is the set of SG local operators where $\mathcal{L}_{1\le i\le n}$ is assigned to control the local area electricity including the $\mathcal{D}_i$. Usually, the software stack required by end-users can be packed into VMs and then physical machines in each $\mathcal{D}$ are used to host VMs; VMs will be hosted in the computing resources. There is a set $\boldsymbol{V} = \{\mathcal{V}_1^{\mathcal{D}}, \ldots, \mathcal{V}_m^{\mathcal{D}}\}$ of VMs, and the pool of computing resources and services can be consolidated by multiple VMs to save the total cost. The computation demand to accommodate $\mathcal{V}_{1\le j\le m}$ is denoted by $\mathcal{Q}^{\mathcal{V}_j}$, and $\mathbb{V}_{\mathcal{D}} = \{\ldots V_k \ldots\}$ is the set of VMs, which are generated in the $\mathcal{D}_i$. In the multiple DC environments, the computing resources of DCs can be shared by VMs so that the total cost is reduced due to the increasing resource and service utilization [10].

In this study, a modeling situation for the $\mathbb{D}$, $\boldsymbol{\mathcal{L}}$ and $\boldsymbol{V}$'s interaction process is formulated as a two-phase bargaining game ($\mathbb{G}$) in a coordination manner; $\mathbb{G}$ is subdivided into $\mathbb{G}^F_{\mathcal{D},\mathcal{L}}$ and $\mathbb{G}^S_{\mathcal{L},\boldsymbol{V}}$ to develop the two-phase bargaining algorithms. Based on the interactive feedback manner, the $\mathbb{G}^F_{\mathcal{D},\mathcal{L}}$ and $\mathbb{G}^S_{\mathcal{L},\boldsymbol{V}}$ games are repeated sequentially in a slotted time structure. Therefore, our DC management scheme is operated each time period during the step-by-step iteration. Formally, we define game entities for the SG-DC combined system, i.e., $\mathbb{G} = \{\mathbb{G}^F_{\mathbb{D},\mathcal{L}}, \mathbb{G}^S_{\mathcal{L},\boldsymbol{V}}\} = \{\{\mathbb{D}, \boldsymbol{\mathcal{L}}, \boldsymbol{V}\}, \{\mathbb{I}_{BCU}, \mathbb{R}_{BCU}\}, \mathcal{F}_{1\le i\le n}, \{\mathcal{D}_{1\le i\le n} \in \mathbb{D} | \mathfrak{T}_{\mathcal{D}_i}, U_{\mathcal{D}_i}\}, \{\mathcal{L}_{1\le i\le n} \in \boldsymbol{\mathcal{L}} | \mathfrak{N}^R_{\mathcal{L}_i}, U_{\mathcal{L}_i}, \mathcal{C}_{\mathcal{L}_i}\}, \mathbb{P}^{\mathcal{L}}, \{\mathcal{V}_{1\le j\le m} \in \boldsymbol{V} | \mathcal{Q}^{\mathcal{V}_j}, \vartheta^{\mathcal{V}_j}\}, T\}$ of gameplay, and Table 1 lists the notations used in this paper.

- $\mathbb{G}$ is a two-phase bargaining game consisting of $\mathbb{G}^F_{\mathbb{D},\mathcal{L}}$ and $\mathbb{G}^S_{\mathcal{L},\boldsymbol{V}}$ games; they are related in a manner of mutual and reciprocal interdependency.
- $\mathbb{G}^F_{\mathbb{D},\mathcal{L}}$ is a first-phase bargaining game to decide the energy price. The interaction of each individual pair $(\mathcal{L}_i, \mathcal{D}_i)$ is formulated as a Stackelberg bargaining model.
- $\mathbb{G}^S_{\mathcal{L},\boldsymbol{V}}$ is a second-phase bargaining game to migrate VMs. The interaction of DCs with VMs is designed as a migration bargaining model.
- $\mathbb{I}_{BCU}$ is a basic computation unit for VM, and $\mathbb{R}_{BCU}$ is a basic energy unit to process one $\mathbb{I}_{BCU}$.
- $\mathcal{F}_{1\le i\le n}$ represents all customers of $\mathcal{L}_i$; they are assumed as a single follower in the $\mathbb{G}^F_{\mathbb{D},\mathcal{L}}$.
- $\mathfrak{T}_{\mathcal{D}_i}$ and $U_{\mathcal{D}_i}$ are the total computation request and utility function of $\mathcal{D}_i$, respectively.
- $\mathfrak{N}^R_{\mathcal{L}_i}$ is the $\mathcal{L}_i$'s renewable power amount, and $U_{\mathcal{L}_i}$ is the $\mathcal{L}_i$'s utility function. $\mathcal{C}_{\mathcal{L}_i}$ is the computation request without $\mathcal{D}_i$ in the $\mathcal{L}_i$'s covering local area.
- $\mathbb{P}^{\mathcal{L}} = \left\{\Theta^{\mathcal{L}}_{min} \ldots \Theta^{\mathcal{L}}_{h} \ldots \Theta^{\mathcal{L}}_{max}\right\}$ is the set of $\mathcal{L}$'s price strategies where $\Theta^{\mathcal{L}}_h$ means the h^{th} price level to compute one $\mathbb{I}_{BCU}$.
- $\mathcal{Q}^{\mathcal{V}_j}$ is the computation demand, and $\vartheta^{\mathcal{V}_j}$ is the operation time requirement of the $\mathcal{V}_j$, respectively. $\mathfrak{T}_{\mathcal{D}_i}$ is total sum of $\mathcal{Q}^{\mathcal{V}_j}$ where $\mathcal{V}_j \in \mathbb{V}_{\mathcal{D}_i}$.
- $T = \{t_1, \ldots, t_c, t_{c+1}, \ldots\}$ denotes time, which is represented by a sequence of time steps.

As a kind of game theory, the Stackelberg game is a non-cooperative game model based on two kinds of different game players; a leader and followers. They are forced to act according to their positions while attempting to maximize their satisfaction. Usually, the Stackelberg game model is widely used to decide the price for the system resource [6]. In this paper, each individual $\mathcal{L}_i$ adopt the Stackelberg game to decide its local energy price. Simply, we assume that the $\mathcal{L}_i$ is a leader, and all customers of $\mathcal{L}_i$ are assumed as a single follower, who is represented as $\mathcal{F}_i$. Based on the feedback mechanism, the price decision of $\mathcal{L}_i$ might affect the behavior of $\mathcal{F}_i$. Therefore, the energy price is dynamically

TABLE 1. The notations for abbreviations, symbols and parameters.

Acronyms	Explanations
DC	data center
SG	smart grid
NBS	Nash bargaining solution
RKSBS	the Raiffa-Kalai-Smorodinsky bargaining solution
MTBS	the modified Thomson bargaining solution
QEDCM	the QoS-efficient DC management
VM	virtual machine
QoS	quality of service
FCDCC	the fair most DC montrol
CVMCM	the cooperative VM Control Management
PO	Pareto Optimality
S	Symmetry
IRAT	Invariance with Respect to Affine Transformation
IIA	Independence of Irrelevant Alternatives
M	Monotonicity
WIM	Weak Inverse Monotonicity
Notations	**Explanations**
$\mathbb{D}$	the set of geographically dispersed DCs
$\mathcal{D}_{1\le i\le n}$	DCs
$\boldsymbol{\mathcal{L}}$	the set of SG local operators
$\mathcal{L}_{1\le i\le n}$	SG local operators
$\boldsymbol{V}$	the set of virtual machines
$\mathcal{V}_{1\le j\le m}$	virtual machines
$Q^{\mathcal{V}_j}$	The computation demand for $\mathcal{V}_j$
$\mathbb{G}^F_{\mathbb{D},\mathcal{L}}$, $\mathbb{G}^S_{\mathcal{L},V}$	The first and second phase bargaining games
$\mathbb{I}_{BCU}$	a basic computation unit for VM
$\mathbb{R}_{BCU}$	a basic energy unit to process one $\mathbb{I}_{BCU}$
$\mathfrak{T}_{\mathcal{D}_i}$	the total computation request of $\mathcal{D}_i$
$U_{\mathcal{D}_i}$	the utility function of $\mathcal{D}_i$
$\mathfrak{N}^R_{\mathcal{L}_i}$	the $\mathcal{L}_i$'s renewable power amount
$U_{\mathcal{L}_i}$	the $\mathcal{L}_i$'s utility function
$\mathfrak{C}_{\mathcal{L}_i}$	the computation request without $\mathcal{D}_i$ in the $\mathcal{L}_i$'s covering local area
$\mathbb{P}^{\mathcal{L}}$	the set of $\mathcal{L}$'s price strategies
$\Theta^{\mathcal{L}}_h$	the h^{th} price level to compute one $\mathbb{I}_{BCU}$
$\vartheta^{\mathcal{V}_j}$	the operation time requirement of the $\mathcal{V}_j$
$\boldsymbol{N}$	a finite set of game players
$\mathbb{R}^{\boldsymbol{N}}$	the n-fold Cartesian product of real numbers
$\boldsymbol{S}$	a subset of the payoff space
d	disagreement outcome
$\sum$	the family of all bargaining problems
ψ	the weighting factor
v_i	The player i' preference function
$U_{\mathcal{L}_i}(\Theta^{\mathcal{L}}_h)$	the $\mathcal{L}_i$'s utility function with $\Theta^{\mathcal{L}}_h$
δ, β, γ	adjustment parameters for the $\mathcal{F}_s(\Theta^{\mathcal{L}}_h)$
ϱ, α, θ	adjustment parameters for the $\mathcal{F}_a(\Theta^{\mathcal{L}}_h)$
$U^{\mathcal{L}_i}_{\mathcal{F}_i}(\Theta^{\mathcal{L}}_h)$	the $\mathcal{F}_i$'s utility function with $\Theta^{\mathcal{L}}_h$
ξ, φ, μ	control parameters for the $U^{\mathcal{L}}_{\mathcal{F}}(\Theta^{\mathcal{L}}_h)$
$U^{max}_{\mathcal{L}}$	maximum payoffs of $\mathcal{L}$
$U^{max}_{\mathcal{F}}$	maximum payoffs of $\mathcal{F}$
$d_{\mathcal{L}}$, $d_{\mathcal{F}}$	disagree points of $\mathcal{L}$ and $\mathcal{F}$
ζ	a control factor for $v(\cdot)$
η , κ	control factors for the $U_{\mathcal{D}}(\cdot)$
$U^{max}_{\mathcal{D}}$	he $\mathcal{D}$'s maximum payoff
$d_{\mathcal{D}}$	the disagree point of $\mathcal{D}$

decided by considering the interactions of $\mathcal{L}_i$ and F_i. Unlike traditional Stackelberg game model, we formulate the complicated interactive situation in the local SG-DC system as a new cooperative Stackelberg game $\left(\mathbb{G}^F_{\mathcal{D},\mathcal{L}}\right)$ with bargaining idea. To provide the fairness for asymmetric game players, the ***M*** axiom is necessary. Therefore, we adopt the idea of *RKSBS* for our Stackelberg bargaining approach. As a leader, the $\mathcal{L}_i$'s utility function with price strategy $\Theta^{\mathcal{L}}_h$, i.e., $U_{\mathcal{L}_i}\left(\Theta^{\mathcal{L}}_h\right)$, is defined with purely selfish and altruistic subjects. Formally, $U_{\mathcal{L}_i}\left(\Theta^{\mathcal{L}}_h\right)$ is given by;

$$U_{\mathcal{L}_i}\left(\Theta^{\mathcal{L}}_h\right) = \mathbf{max}\left(\left(\left\lfloor\frac{\mathfrak{T}_{\mathcal{D}_i}+\mathfrak{C}_{\mathcal{L}_i}}{\mathbb{I}_{BCU}}\right\rfloor - \left\lceil\frac{\mathfrak{N}^R_{\mathcal{L}_i}}{\mathbb{R}_{BCU}}\right\rceil\right), \varepsilon\right) \times \left(\mathcal{F}_s\left(\Theta^{\mathcal{L}}_h\right) - \mathcal{F}_a\left(\Theta^{\mathcal{L}}_h\right)\right)$$

$$\text{s.t.,}\begin{cases}\mathcal{F}_s\left(\Theta^{\mathcal{L}}_h\right) = \left(\left(\dfrac{\delta}{exp\left(-\beta\times\Theta^{\mathcal{L}}_h\right)}\right)+\gamma\right)\\ \mathcal{F}_a\left(\Theta^{\mathcal{L}}_h\right) = \left(\left(\varrho\times exp\left(-\alpha\times\Theta^{\mathcal{L}}_h\right)\right)+\theta\right) \text{ and}\\ \mathfrak{T}_{D_i} = \sum_{V_k\in\mathbb{V}_{D_i}} Q^{V_k}\end{cases} \tag{2}$$

where ε is a control factor for the $U_{\mathcal{L}_i}\left(\Theta^{\mathcal{L}}_h\right)$. δ, β, γ are adjustment parameters for the $\mathcal{F}_s\left(\Theta^{\mathcal{L}}_h\right)$ and ϱ, α, θ are adjustment parameters for the $\mathcal{F}_a\left(\Theta^{\mathcal{L}}_h\right)$. $\left(\mathfrak{T}_{\mathcal{D}_i}+\mathfrak{C}_{\mathcal{L}_i}\right)$ is the total computation amount in the $\mathcal{L}_i$. As a follower, the $\mathcal{F}_i$'s utility function with price strategy $\Theta^{\mathcal{L}}_h$, i.e., $U^{\mathcal{L}_i}_{\mathcal{F}_i}\left(\Theta^{\mathcal{L}}_h\right)$, is formally derived as follows.

$$U^{\mathcal{L}_i}_{\mathcal{F}_i}\left(\Theta^{\mathcal{L}}_h\right) = \mathbf{max}\left(\left(\left\lfloor\frac{\mathfrak{T}_{\mathcal{D}_i}+\mathfrak{C}_{\mathcal{L}_i}}{\mathbb{I}_{BCU}}\right\rfloor - \left\lceil\frac{\mathfrak{N}^R_{\mathcal{L}_i}}{\mathbb{R}_{BCU}}\right\rceil\right), \varepsilon\right) \times \left(\xi - \log\left(\left(\xi+\Theta^{\mathcal{L}}_h\right)^{\varphi}+\mu\right)\right) \tag{3}$$

where ξ, φ and μ are control parameters for the $U^{\mathcal{L}_i}_{\mathcal{F}_i}\left(\Theta^{\mathcal{L}}_h\right)$. By using the solution concept of *RKSBS*, the $\mathcal{L}_i$'s price strategy at time t_c, i.e., $\Theta^{\mathcal{L}}_k(t_c)\in\mathbb{P}^{\mathcal{L}}$, is decided as follows;

$$RKSBS = \mathbf{max}_{\Theta^{\mathcal{L}}_{min\le k\le max}(t_c)} \prod_{c\in\{\mathcal{L},\mathcal{F}\},} v_c\left(\Theta^{\mathcal{L}}_k(t_c)\right)$$

$$\text{s.t.,}\begin{cases} v_{\mathcal{L}}\left(\Theta^{\mathcal{L}}_k(t_c)\right) = \left(U_{\mathcal{L}_i}\left(\Theta^{\mathcal{L}}_k(t_c)\right) - d_{\mathcal{L}_i}\right)\\ \quad + \left(\zeta\times\left(U^{max}_{\mathcal{F}_i} - U^{\mathcal{L}_i}_{\mathcal{F}_i}\left(\Theta^{\mathcal{L}}_k(t_c)\right)\right)\right)\\ v_{\mathcal{F}}\left(\Theta^{\mathcal{L}}_k(t_c)\right) = \left(U^{\mathcal{L}_i}_{\mathcal{F}_i}\left(\Theta^{\mathcal{L}}_k(t_c)\right) - d_{\mathcal{F}_i}\right)\\ \quad + \left(\zeta\times\left(U^{max}_{\mathcal{L}_i} - \mathcal{U}_{\mathcal{L}_i}\left(\Theta^{\mathcal{L}}_k(t_c)\right)\right)\right)\end{cases} \tag{4}$$

where $U^{max}_{\mathcal{L}_i}$ and $d_{\mathcal{L}_i}$ (*or* $U^{max}_{\mathcal{F}_i}$ and $d_{\mathcal{F}_i}$) are the $\mathcal{L}_i$'s maximum payoff and disagree point (*or* the $\mathcal{F}_i$'s maximum payoff and disagree point). ζ is a control factor for $(\cdot)$. According to (4), the energy price for each individual $\mathcal{L}$ is decided, and this information is announced to its corresponding DC.

In the second-stage game $\left(\mathbb{G}^S_{\mathcal{L},V}\right)$, individual DCs are symmetric game players, and dynamically adjust their workloads toward an appropriate system performance. In this study, DCs are assumed to work together in a cooperative manner, and they negotiate with each other to migrate their VMs to maximize the efficiency of SG-DC system. As a game player, the $\mathcal{D}_i$'s utility function is defined with the set of its VMs $\left(\mathbb{V}_{\mathcal{D}_i}\right)$ and the $\mathcal{L}_i$'s price strategy $\left(\Theta_h^{\mathcal{L}_i}\right)$. Formally, $U_{\mathcal{D}_i}\left(\mathbb{V}_{\mathcal{D}_i}, \Theta_h^{\mathcal{L}_i}\right)$ is defined as follows;

$$U_{\mathcal{D}_i}\left(\mathbb{V}_{\mathcal{D}_i}, \Theta_h^{\mathcal{L}_i}\right) = X_{\mathcal{D}_i}\left(\mathbb{V}_{\mathcal{D}_i}, \Theta_h^{\mathcal{L}_i}\right) - Y_{\mathcal{D}_i}\left(\mathbb{V}_{\mathcal{D}_i}, \Theta_h^{\mathcal{L}_i}\right)$$

$$\text{s.t.,} \begin{cases} X_{\mathcal{D}_i}\left(\mathbb{V}_{\mathcal{D}_i}, \Theta_h^{\mathcal{L}_i}\right) \\ = \exp\left(\left(\sum_{\mathcal{V}_k \in \mathbb{V}_{\mathcal{D}_i}} \mathcal{Q}^{\mathcal{V}_k} / \mathcal{A}_{\mathcal{V}}\right) \times \Theta_h^{\mathcal{L}_i}\right)^{-1} + \eta \\ Y_{\mathcal{D}_i}\left(V_{\mathcal{D}_i}, \Theta_h^{\mathcal{L}_i}\right) \\ = \log\left(\left(\left(\sum_{\mathcal{V}_k \in \mathbb{V}_{\mathcal{D}_i}} \mathcal{Q}^{\mathcal{V}_k} / \mathcal{A}_{\mathcal{V}}\right) \times \Theta_h^{\mathcal{L}_i}\right) + \kappa\right) \\ \mathcal{A}_{\mathcal{V}} = \left(\sum_{\mathcal{D}_e \in \mathbb{D}} \sum_{\mathcal{V}_j \in V_{\mathcal{D}_e}} \mathcal{Q}^{\mathcal{V}_j}\right) / |\mathbb{D}| \end{cases} \quad (5)$$

where η and κ are control factors for the $U_{\mathcal{D}}(\cdot)$. To provide the fairness for symmetric game players, the ***WIM*** axiom is more suitable. Therefore, we choose the concept of *MTBS* for our migration bargaining approach. By using the solution concept of *MTBS*, the VM migration strategy among DCs at time t_c with $\mathbb{V}_{\mathcal{D}_i}$ and $\Theta_k^{\mathcal{L}}(t_c)$ is decided as follows;

$$MTBS = \mathbf{max} \prod_{\mathcal{D}_i \in \mathbb{D}} \mathcal{V}_{\mathcal{D}_i}\left(\mathbb{V}_{\mathcal{D}_i}, \Theta_k^{\mathcal{L}_i}(t_c)\right)$$
$$\text{s.t., } \mathcal{V}_{\mathcal{D}_i}\left(\mathbb{V}_{\mathcal{D}_i}, \Theta_k^{\mathcal{L}_i}(t_c)\right) = \left(U_{\mathcal{D}_i}\left(\mathbb{V}_{\mathcal{D}_i}, \Theta_h^{\mathcal{L}_i}\right) - d_{\mathcal{D}_i}\right)$$
$$+ \left(\sum_{\mathcal{D}_j \in \mathbb{D}, \mathcal{D}_j \neq \mathcal{D}_i} \left(U_{\mathcal{D}_j}^{max} - U_{\mathcal{D}_j}\left(\mathbb{V}_{\mathcal{D}_j}, \Theta_h^{\mathcal{L}_j}\right)\right)\right) \quad (6)$$

where $U_{\mathcal{D}_j}^{max}$ is the $\mathcal{D}_j$'s maximum payoff, and $d_{\mathcal{D}_i}$ is the disagree point of $\mathcal{D}_i$. According to (6), the VMs in each DC are migrated to get a fair-efficient system solution.

C. MAIN STEPS OF PROPOSED TWO-PHASE BARGAINING SCHEME

The emergence of future networks has established a trend toward building massive, energy-hungry, and geographically distributed DCs. In recent years, the workloads of DCs are large and are still increasing dramatically. Therefore, the total energy consumed by DCs has been also risen. Due to their enormous energy consumption, DCs are expected to have a major impact on the SG technology. In this paper, we study the DC management issue by using the bargaining game theory. Based on the SG-DC combined platform, we adaptively explore the interaction of SG and DCs, and design our two-phase DC management scheme to solve the price decision and workload balancing problems. Under widely different and diversified energy and workload situations, our two-phase bargaining game model can offer many advantages to find an adaptable solution to effectively operate the SG-DC combined system. The main steps of the proposed scheme can be described, and they are described by the following flowchart as follows:

Step 1: For our simulation model, the values of system parameters and control factors can be discovered in Table 2, and the simulation scenario is given in Section IV.

Step 2: In each system operation period, individual DCs $\left(\mathcal{D}_{1\le i\le n}\right)$ generate their VMs, and contact their corresponding local SG operator $\left(\mathcal{L}_{1\le i\le n}\right)$. Each individual $\mathcal{L}_i$ also gets its current $\mathfrak{R}_{\mathcal{L}_i}^R$ and $\mathcal{C}_{\mathcal{L}_i}$ to handle adaptively the energy control problem.

Step 3: At the first phase, the Stackelberg bargaining model is formulated. As a leader, the $\mathcal{L}_i$'s utility function $\left(U_{\mathcal{L}_i}(\cdot)\right)$ is defined by using (2). As a follower, the $\mathcal{F}_i$'s utility function $\left(U_F^{\mathcal{L}_i}(\cdot)\right)$ is formally derived from (3).

Step 4: By using the solution concept of *RKSBS*, the $\mathcal{L}_i$'s price strategy at time t_c $\left(\Theta_k^{\mathcal{L}}(t_c)\right)$ is decided according to (4).

Step 5: At the second-phase, individual DCs trade their VMs by interacting with other DCs to dynamically adjust their workloads. The $\mathcal{D}_i$'s utility function $\left(U_{\mathcal{D}_i}(\cdot)\right)$ is formally defined by using (5).

Step 6: By using the solution concept of *MTBS*, the VM migration strategy among DCs is decided according to (6).

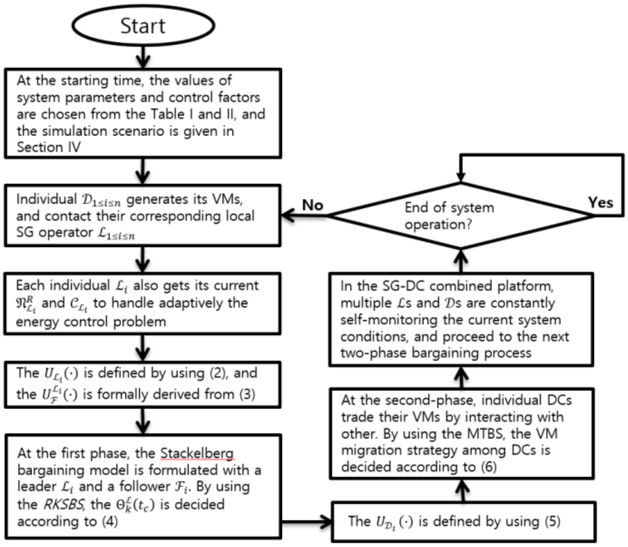
Step 7: In the SG-DC combined platform, multiple $\mathcal{L}_{1\le i\le n}$ and $\mathcal{D}_{1\le i\le n}$ collaborate with another in a

TABLE 2. System parameters used in the simulation experiments.

Parameter	Value	Description
n	10	the number of DCs and local SG operators in the SG-DC system
$\Theta_{min}^{\mathcal{L}}$, $\Theta_{max}^{\mathcal{L}}$	0.2 , 1	the pre-defined minimum and maximum energy prices
ε	1	control factor for the $U_{\mathcal{L}}(\cdot)$
δ , β , γ	1, 0.2, 1	adjustment parameters for the $\mathcal{F}_s(\Theta_h^{\mathcal{L}})$
ϱ, α, θ	0.5, 1.5, 0.5	adjustment parameters for the $\mathcal{F}_a(\Theta_h^{\mathcal{L}})$
ξ, φ, μ	0.5, 0.3, 1	control parameters for the $U_{\mathcal{F}}^{\mathcal{L}}(\cdot)$
ζ	1	a control factor for $v(\cdot)$
$d_{\mathcal{L}}$, $d_{\mathcal{F}}$	0, 0	disagree points of leader and follower, respectively
η , κ	2, 1	control factors for the $U_{\mathcal{D}_i}(\cdot)$
VM Types	Computation Requirement ($\mathcal{Q}^{\mathcal{V}}$)	Operation Time Requirement ($\vartheta^{\mathcal{V}}$)
VM_I	10 GHz	120 ts
VM_{II}	15 GHz	150 ts
VM_{III}	50 GHz	90 ts
VM_{IV}	25 GHz	180 ts
VM_V	30 GHz	60 ts
VM_{VI}	40 GHz	120 ts

coordinated manner to strike the appropriate performance balance while adaptively manipulating the current energy and DC's workload situations.

Step 8: Constantly, multiple $\mathcal{L}$ s and $\mathfrak{D}$s are self-monitoring the current SG-DC combined system conditions, and proceed to Step 2 for the next two-phase bargaining process.



FLOWCHART 1. Flowchart of the proposed algorithm.

IV. PERFORMANCE EVALUATION

In this section, we evaluate our proposed scheme by conducting extensive simulations. To validate our approach, we compare the system performance with other existing protocols; the *QEDCM*, *FCDCC* and *CVMCM* schemes [8]–[10]. To develop our simulation model, we have used the simulation language 'MATLAB' to evaluate the proposed scheme and compare it to other schemes. MATLAB is widely used in academic and research institutions as well as industrial enterprises. First, we describe the experiment settings and simulation scenario, and then, present the numerical analysis. The assumptions of our simulation environments are as follows:

- The simulated SG-DC combined platform consists of 10 DCs ($\mathfrak{D}$s) and 10 local SG operators ($\mathcal{L}$s) where $|\mathbb{D}| = 10$ and $|\mathcal{L}| = 10$.
- DCs are geographically dispersed over the global SG area, and each DC is connected to its corresponding $\mathcal{L}$.
- The process for VM generations is Poisson with rate Λ (services/ t), and the range of offered VM was varied from 0 to 3.0.
- Six different kinds of VM tasks are assumed based on operation duration and computation requirement. In each DC, VMs are generated randomly, and they are assumed the DC's workload
- The $\mathcal{L}$'s price strategy set $\mathbb{P}^{\mathcal{L}} = \{\Theta^{\mathcal{L}}_{min=1} \ldots \Theta^{\mathcal{L}}_{max=5}\}$ is defined as $\Theta^{\mathcal{L}}_1 = 0.2$, $\Theta^{\mathcal{L}}_2 = 0.4$, $\Theta^{\mathcal{L}}_3 = 0.6$, $\Theta^{\mathcal{L}}_4 = 0.8$, and $\Theta^{\mathcal{L}}_5 = 1$.
- To reduce computation complexity, the amount of VM's computation workload is specified in terms of basic computation unit ($\mathbb{I}_{BCU}$), where one $\mathbb{I}_{BCU}$ is the minimum amount (e.g., 10 GHz in our system) of computation process.
- To process one $\mathbb{I}_{BCU}$, one basic energy unit ($\mathbb{R}_{BCU}$) is needed, where one $\mathbb{R}_{BCU}$ the minimum amount (e.g., 10 kW in our system) of computation process.
- $\mathfrak{N}^R_{\mathcal{L}}$ is generated randomly within a range [100MW, 1GW], and $\mathcal{C}_{\mathcal{L}}$ is generated randomly within a range [80GHz, 12THz].
- We restrict *RKSBS* and *MTBS* models to the case of $d_{\mathcal{L}} = 0$ and $d_{\mathcal{F}} = 0$. Therefore, the utilities of disagreement points are zeros in our system.
- System performance measures obtained on the basis of 100 simulation runs are plotted as a function of the offered VM request load.
- Performance measures obtained are average payoff of all DCs, system throughput and fairness among DCs in the SG-DC combined platform.

Fig.1 compares all DC management schemes in terms of normalized average payoff of all DCs. In the viewpoint of system operators, this performance criterion is a main concern. When the VM generation ratio is low, i.e., $\Lambda \le 0.25$, the performance of the all schemes is almost the same. This is because all schemes can handle the enough system resource to accept the requested workloads. As the DC workload rate increases, the available system resource decreases. Thus, the normalized average payoff is likely to be decreased. However, our proposed scheme performs better than the other compared protocols. The above analysis shows that our two-phase game model proposed in this paper effectively facilitates the system resource while ensuring DC task services. It can increase the average payoff by an average of 10% than the *QEDCM*,

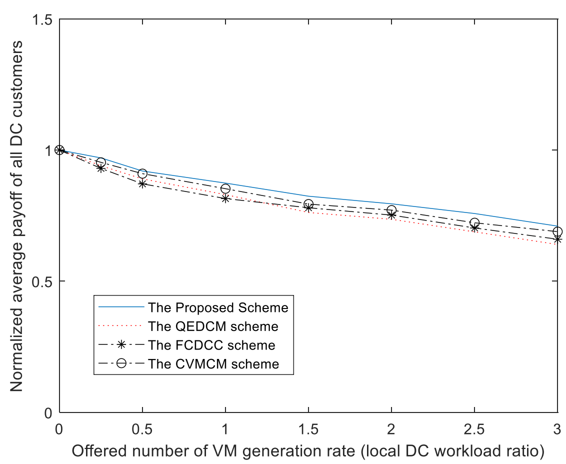


FIGURE 1. Normalized average payoff of all DCs.

FCDCC and *CVMCM* schemes, and confirms that the advantage of our proposed approach.

Fig.2 provides the comparison of system throughput for different DC management schemes. Traditionally, the system throughput is estimated as the successfully completed DC task services. Therefore, as the DC workload rate increases, the throughput of the SG-DC combined system is also risen. As expected, we observe that our proposed scheme has a comparatively better system throughput under light to heavy workload distributions. In our approach, the limited system resource is fair-efficiently shared while effectively migrating VMs to balance the system workload. Due to this reason, our proposed method is significantly superior to the *QEDCM*, *FCDCC* and *CVMCM* schemes; specifically, we can achieve an average of 10% higher system throughput than other existing methods.

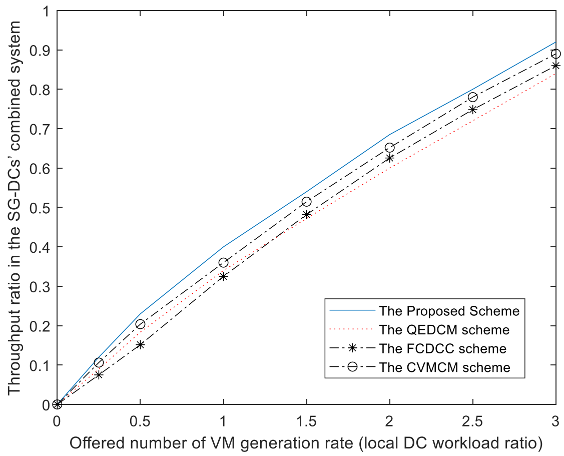


FIGURE 2. Throughput ratio in the SG-DC combined system.

In order to effectively operate the SG-DC combined infrastructure, the fairness issue for each individual DC is very important. Usually, the major challenge to develop novel bargaining solutions is to provide the most proper combination of the efficiency and fairness. Based on the ideas of *RKSBS* and *MTBS*, our two-phase bargaining approach can effectively provide the most proper fairness among DCs. As a consequence of iterative two-phase bargaining process, our proposed scheme can improve the fairness index by an average of 15% than the existing *QEDCM*, *FCDCC* and *CVMCM* schemes. From the simulation results in Fig.1-Fig.3, it is evident that, in general, our two-phase bargaining game model is a promising approach to meet the demands of SG-DC combined system under diversified workload condition changes.

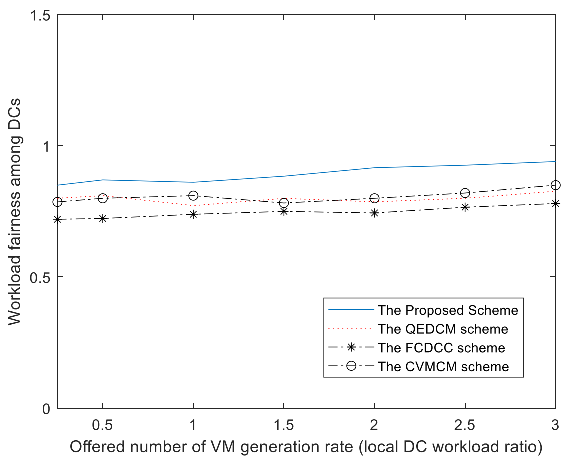


FIGURE 3. Workload fairness among data centers.

V. SUMMARY AND CONCLUSION

Recently, the DC management in SG system has been an active research area. In this paper, we consider an interactive SG-DC system to take into account the price control and workload balancing problems. By analyzing the strategic relationship between SG and DC, we adopt the concept of cooperative game, and formulate a novel two-phase bargaining model based on the idea of *RKSBS* and *MTBS*. At the first-phase, we use the Stackelberg bargaining approach to decide the dynamic energy price according to the *RKSBS*. At the second-phase, multiple DCs fair-efficiently share their workloads by adopting the *MTBS*. Our major challenge is to leverage the synergistic features of two different bargaining solutions; they are sophisticatedly combined and act cooperatively to strike the appropriate performance balance. Finally, we conduct a simulation analysis, and verify the superiority of our two-phase bargaining approach as compared with the existing *QEDCM*, *FCDCC* and *CVMCM* protocols. Major lesson that we have learnt from this study is the feasibility and effectiveness of our proposed two-phase bargaining approach while ensuring different viewpoints of SG and DC.

Research on DC management is still in its infancy. For the future work, our current study can be extended in a number of ways. One future direction is to minimize the control time with the consideration of backup generators and the charging-discharging battery policy. Another potential direction for the future research is to investigate equilibrium pricing strategies using standard convex optimization techniques. In addition, we will develop a new backward induction method by using heuristic search techniques to derive the near-optimal or suboptimal strategies of DC management issues.

COMPETING OF INTERESTS

The author declares that there are no competing interests regarding the publication of this article.

AUTHOR' CONTRIBUTION

The author is a sole author of this work and ES (i.e., participated in the design of the study and performed the statistical analysis).

AVAILABILITY OF DATA AND MATERIAL

Please contact the corresponding author at *swkim01@sogang.ac.kr*.

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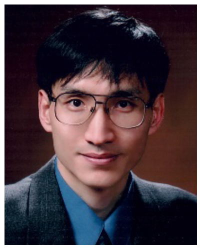

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