Game-Theoretic Resource Allocation for Fog-Based Industrial Internet of Things Environment

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***Abstract*—The significant volume, variety, and velocity of data received from the many Industrial Internet of Things (IIoT) devices and other systems in a cloud-based or fog-based environment can complicate an organization's effort in ensuring high quality of experience for data users (DUs). For example, how do we efficiently and fairly allocate resources among cloud centers (CCs), fog service providers (FSPs), and DUs? This is particularly crucial for the IIoT environment, such as those in critical infrastructure sectors, such as energy and dams. Therefore, in this article, we propose an optimal resource allocation scheme for a fog-based IIoT environment. Specifically, we introduce fog nodes (or FSPs) that compete with each other to provide services for the DUs using resources from the CC. To maximize resource utilization, we model the resource allocation problem as a double-stage Stackelberg game and propose three algorithms to achieve Nash equilibrium and Stackelberg equilibrium. Then, we evaluate the performance of our proposed scheme with and without having FSPs, as well as with another competing scheme. The findings demonstrate the importance of fog computing in resource allocation, and the performance of our scheme outperforms that of the other scheme.**

***Index Terms*—Fog computing, industrial wireless sensors, resource allocation, Stackelberg game.**

I. Introduction

INTERNET of Things (IoT) [1] can be found in both commercial and industrial settings [and the latter is also referred to Industrial IoT (IIoT)]. A typical IIoT setting, such as in energy and dams sectors, comprises a (large) number of wireless sensors and computing devices (will be collectively referred to as IIoT devices) tasked with sensing of environmental and/or other relevant data [2]. Such data are then uploaded to the cloud center (CC) for processing. However, such a process can be inefficient due to bandwidth limitations (e.g., due to competing demand for bandwidth [3], [4]) and consequently, results in latency. The latter can be a limiting factor in critical infrastructure or time-sensitive applications.

Hence, there has been a shift toward fog computing [5], [6] by processing the data closer to its source. Such a move allows one to achieve faster service delivery and consequently better quality-of-experience (QoE) and improved user service. In addition to achieving reduced latency and higher energy efficiency [7], [8], we can also achieve better user privacy [9]–[11]. However, to deploy fog computing in an IIoT environment is not without challenges. For example, the significant volume, variety, velocity of data, and heterogeneity of processing resources complicate the task of efficient resource utilization [12]–[14]. Hence, there has been significant interest from the research community to design approaches for resource allocation in a fog-cloud architecture [14]–[22]. In other words, fog computing complements existing cloud computing infrastructure by addressing limitations, such as latency and bandwidth.

In addition to the existing approaches, we posit the potential of using game theory to optimize the resource allocation in a fog-cloud architecture, for example, by jointly considering both QoE and the costs of data users (DUs), the utilization of resources associated with the CC, and the diversity of resource. This is the approach we take in this article. Specifically, we use the Stackelberg game [23] to propose an optimal resource allocation scheme between the CC and DUs by introducing fog service providers (FSPs). This allows DUs to minimize their costs but achieving higher QoE, and the CC to maximize their resource utilization.

We will now briefly introduce the Stackelberg game [23]. This is the study of conflict and cooperation between intelligent rational decision makers (players), and the players are the leader and the follower. Particularly, the follower chooses the best response based on the strategy executed by the leader. The combination of the optimal strategy for the leader and the follower's best response forms a Stackelberg equilibrium. Here, a double-stage Stackelberg game is used to model the interactions among CC, FSPs, and DUs. For the FSPs, we model their competition as a noncooperative game. Each

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player has an objective to participate in the scheme, such as minimizing costs and satisfying DUs' QoE, maximizing the profits for FSPs, and improving the utilization of resources while guaranteeing profit maximization for the CC. We also propose three algorithms to find the Nash equilibrium among all FSPs and the Stackelberg equilibrium among all players. The main contributions of this article can be summarized as follows.

1) The design of a novel resource allocation scheme among the CC, FSPs, and DUs. A double-stage Stackelberg game is then applied to model the interactions among these three parties.
2) A Stackelberg equilibrium of these three parties and the Nash equilibrium among all FSPs can be obtained using our three proposed algorithms.

The remainder of this article is organized as follows. In the next two sections, we introduce some related work and the architecture of our scheme, respectively. Then, we present our proposed approach in Section IV, and the optimal strategy by calculating the Stackelberg equilibrium and Nash equilibrium in Section V. Section VI presents our evaluation findings. Finally, we conclude this article in Section VII.

II. Related Work

Chiang and Zhang [14] summarized the opportunities and challenges of fog computing and the networking context of IoT. One of these challenges is resource allocation [14], [15], as decisions on how to efficiently allocate computing resources rely on many factors.

Agarwal *et al.* [16] presented an efficient architecture and algorithm for resource provisioning in the fog environment by using virtualization. Gupta *et al.* [17] proposed iFogSim to simulate the IoT and fog environment, which can then be used to quantify the impact on latency, network congestion, energy consumption, and costs associated with resource management. Modeling fog-cloud architecture as an integer optimization problem, Souza *et al.* [18] presented a quality-of-service (QoS)-aware service allocation problem. Offloading a mobile device's tasks to nearby cloudlets, which consist of clusters of computers, is another approach that has been used to reduce the completion time of an application [19]. Liu *et al.* [20] studied the energy consumption, execution delay, and costs incurred by the offloading processes in a fog computing system and applied queuing theory to resolve a multiobjective optimization problem. This includes minimizing the energy consumption, execution delay, and payment cost by finding the optimal offloading probability and transmitting power for each mobile device.

As an effective mathematical tool to study the conflict and cooperation between intelligent rational decision makers (players), game theory obtains increasingly widely research [28]. We observe that a number of approaches use game theory to build a resource allocation scheme in cloud computing and to optimize the results by calculating the game equilibrium. However, surprisingly the use of game theory in a fog environment is less explored. Jie *et al.* [21] investigated the interactions between a fog agent and users to enhance real-time resource utilization and service quality. Specifically, the interactions are modeled as a repeated Stackelberg game. Zhang *et al.* [22] proposed a joint optimization framework to achieve optimal resource allocation in fog computing based on the Stackelberg game. Although game theory has been applied to research resource allocation for fog computing, satisfying the QoE, minimizing the cost requested by DUs, meeting other potential demands for resources with respect to the CC, and competitions among FSPs are usually neglected. This is the gap we seek to address in this article.

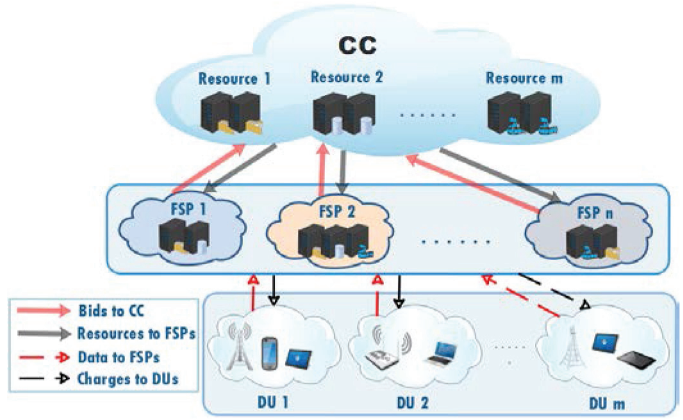

Fig. 1. System architecture among CC, FSPs, and DUs scenarios.

There have been other fog-related research efforts. In [24], for example, BodyEdge was proposed to reduce transmitted data and processing time. The key components of BodyEdge include a mobile client module and an edge gateway. Duan *et al.* [25] proposed using hybrid industrial wireless networks to address task scheduling by designing a task assignment method and a collaborative routing algorithm. Luo *et al*. [26], [27] focused on a smart factory environment and integrated wired/wireless fieldbus networks and wireless sensor networks to increase data delivery efficiency and reduce energy usage.

III. Proposed Architecture

In this section, we introduce the proposed resource allocation scheme architecture, as shown in Fig. 1. The architecture consists of three parties, namely, CC, FSPs, and DUs. The CC possesses m types of resources that are used to meet a variety of demands. It determines the number of resources allocated to the FSPs, depending on the bids, to request resources from them. FSPs comprise n individuals, and each individual utilizes resources purchased from the CC to provide paid services for other relevant DUs. Considering that the estimation of QoE [29] among similar data is approximated, we assume that any type of DU is a group of users whose data are similar. Each DU type will select one or more FSPs to process the data. To guarantee both efficiency and speed in the scheme, we assume that the relationship of resources and DUs is a one-to-one match. Hence, both the numbers of DU types and resources are equal.

Generally, we can gauge the demand for various resources based on historical/archival data (e.g., sales data). There are also instances where current demand for a service may deviate from past demands, and this is also considered in the design of our scheme. Also, in our scheme, we consider the scenario where noncooperating FSPs compete for resources from a given CC, and we assume that the CC is a rational player seeking to improve the utilization of its resources.

A. Cloud Center

Given a finite amount for each resource type, the CC needs to consider factors, such as the cost to maintain resources and the amount of reserved resources required to handle data for its potential users. Here, we assume that the set of resource types is denoted as $M_r = \{1, 2, \ldots, m\}$, i.e., the number of resource types is m, and the total amount of resource i is B_i, where $i \in M_r$. Thus, the CC's strategy is the amount of all types of resources provided to FSPs $\mathbf{b} = \{b_1, b_2, \ldots, b_m\}$, where $b_i = \sum_{j=1}^{n} b_{ij} \in [0, B_i]$, and b_{ij} denotes the amount of resources i allocated to FSP j from the CC. Meanwhile, to mitigate the potential conspiracy of FSPs, for example, in forcing prices down, the CC can also provide services (resources) for some potential users. Specifically, the revenue for one unit of resource from potential users will influence the CC's strategy, and the amount of resources i allocated to potential users from the CC is $B_i - b_i$. Since the CC provides a range of resources, scalability is crucial to its operation. In this scheme, $\mathbf{B} = \{B_1, B_2, \ldots, B_m\}$ denotes the total amount of various resources, and the individual resource does not have any influence and restriction over other resources. Here, we can unilaterally decide the amount of any resource type $B_i, i \in M_r$ based on the actual demand. This is to avoid resource wastage or having insufficient resources (i.e., ensure the scheme's scalability).

B. Fog Service Providers

We model the role of FSP as an individual who has a set of fog nodes that are placed close to the IIoT devices. We assume the existence of noncooperating FSPs, competing to buy resources from the CC in order to provide paid services to DUs. Here, we denote $N = \{1, 2, \ldots, n\}$ as the set of FSPs, i.e., there exist n different FSPs in our scheme. The strategy is two-tuple, which can be formulated as $(\mathbf{f}_j, \mathbf{p}_j)$, where for any FSP $j \in N$, $\mathbf{f}_j = \{f_{j1}, f_{j2}, \ldots, f_{jm}\}$ denotes the bid for one unit to request resources from the CC, and $\mathbf{p}_j = \{p_{j1}, p_{j2}, \ldots, p_{jm}\}$ denotes the prices for one unit to charge DUs.

C. Data Users

The DUs rely on remote computing resources to process data, and these DUs want to minimize the cost of data processing without having unacceptance delay in getting access to the processed data. Thus, the objective of DUs is to minimize the cost and obtain an acceptable QoE. Here, $M_u = \{1, 2, \ldots, m\}$ denotes the set of DUs types. T_i is the total data belonging to DU i that should be delivered to one or more FSPs and is formulated as $t_i = \{t_{i1}, t_{i2}, \ldots, t_{in}\}$, where $T_i = \sum_{j=1}^{n} t_{ij}, i \in M_u$ and t_{ij} indicates the amount of data delivered to FSP j from DU i.

D. Quality-of-Experience

QoE is used to quantify the user's experience, which takes into account that the delay at the FSPs should not exceed the DUs' acceptable threshold, mathematically expressed as follows:

$$g(p_{ji}) = 1 - e^{\omega_{ij}\left(\frac{p_{ji}}{p_i\text{th}} - 1\right)}. \tag{1}$$

In (1), $g(p_{ji})$ denotes the tolerance function of DU i with FSP j. ω_{ij} can be defined as the trust preference of DU i for FSP j based on past ratings of FSP j's services. Such ratings are from DUs who had prior interactions with FSP j [30], [31]. p_ith represents the threshold value for one unit of DU i and follows a linear function of distance l_i from DU i to the service providers and the amount of DU i's data T_i that should be processed, i.e., $p_i\text{th} = \theta \cdot l_i T_i$, where θ is scalar.

In comparison to the distance from DU i to the CC, the distances between DU i and all FSPs are relatively small, which can be considered to be equal. Furthermore, the threshold value with respect to fog nodes is relatively smaller (in comparison to the cloud), and the threshold value with respect to less data is also smaller than that with respect to more data. Here, higher trust preference and larger threshold value will result in larger tolerance. Inversely, the tolerance $g(p_{ji})$ will reduce the growth of price p_{ji} charged by FSP j. To guarantee better service delay limited by lower tolerance and minimize the total cost of DU i, less data will be delivered to FSP j (see also Section IV). On the other hand, (1) also can be used to measure the service delay directly provided by the CC in the nonfog environment. As discussed above, the threshold p_ith is quantified by distance l_i from DU i to the service providers. Then, we can adjust the value of l_i to study the service delay in a nonfog environment.

To further explain (1), the findings using p^{th}s and ωs are shown in Fig. 2. The value of the function decreases quickly as the price to DU increases. Clearly, a DU with a larger p^{th} and higher ω indicates that the DU has a higher acceptable threshold. Also, given p_ith and the price charged, if $\omega_{ij} > \omega_{ij'}$, i.e., the preference of DU i to FSP j is higher than j', then $g(p_{ji}) > g(p_{j'i})$, i.e., the acceptable threshold of DU i with FSP j is higher than j'. On the other hand, for any FSP j, given $\omega_{ij} > \omega_{i'j}$ and price charged, if $p_i\text{th} > p_{i'}\text{th}$, i.e., the acceptable threshold of DU i is larger than that of DU i', then $g(p_{ji}) > g(p_{ji'})$, i.e., DU i is more tolerant of FSP j compared with DU i'.

IV. Proposed Scheme

In this section, we describe our proposed resource allocation scheme based on the Stackelberg game.

A. Scheme

As previously discussed, we introduce FSPs to the setup; hence, resulting in three parties in our resource allocation scheme. Clearly, the parties' selections can be affected by each other. For example, a lower bid from the FSPs may lead to fewer resources offered by the CC. Similarly, a higher price charged by the FSPs may result in less data from DUs. A summary of notation used is presented in Table I.

The scheme uses a double-stage Stackelberg game to derive the optimal result by calculating the equilibrium. For simplicity, we select one FSP, one resource type, and the

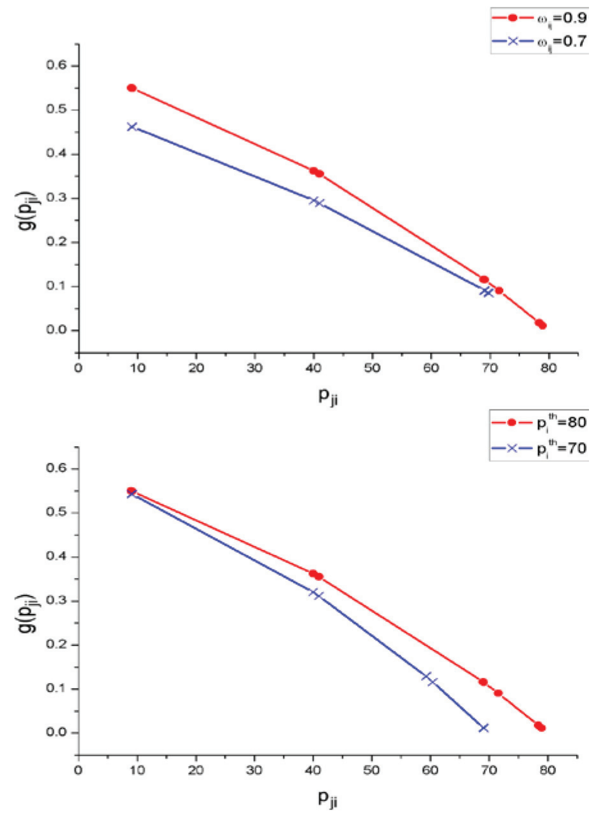

Fig. 2. Tolerance with different threshold values.

TABLE I
SUMMARY OF NOTATIONS

Notation	Definition
$M_r(M_u)$	Set of resource (DU) types, $\lvert M_r\rvert=\lvert M_u\rvert=m$
N	Set of FSPs, $\lvert N\rvert=n$
B_i	Total amount of resource i
r_i	Revenue for one unit of resource i from potential users
$c_{i1}(c_{i2})$	Cost for one unit of resource i with potential users (FSPs)
d_i	Demand for one unit of resource i from potential users
ρ_i	Priority for CC on resource i
$\mathbf{b}$	Strategy of CC, $\mathbf{b}=\{b_i\}, b_i\in[0,B_i]$
b_i	Amount of resource i allocated to all FSPs
b_{ij}	Amount of resource i allocated to FSP j from CC
F_i	Total bids for resource i from all FSPs
L_j	Budget for one unit of FSP j
$(\mathbf{f}_j,\mathbf{p}_j)$	Strategy of FSP j, $\mathbf{f}_j=\{f_{ji}\},\mathbf{p}_j=\{p_{ji}\}$
f_{ji}	Bid for one unit of FSP j to request resource i from CC
p_{ji}	Price for one unit of FSP j to charge DU i
g	Tolerance function of DUs about services
ω_{ij}	Preference of DU i to FSP j
p_i^{th}	Threshold value for one unit of DU i
T_i	Total data owned by DU i
$\mathbf{t}_i$	Strategy of DU i, $\mathbf{t}_i=\{t_{ij}\}$
t_{ij}	Amount of data delivered to FSP j from DU i
C,θ	Scalars
l_i	Distance from DU i to service providers
U	Expected utility

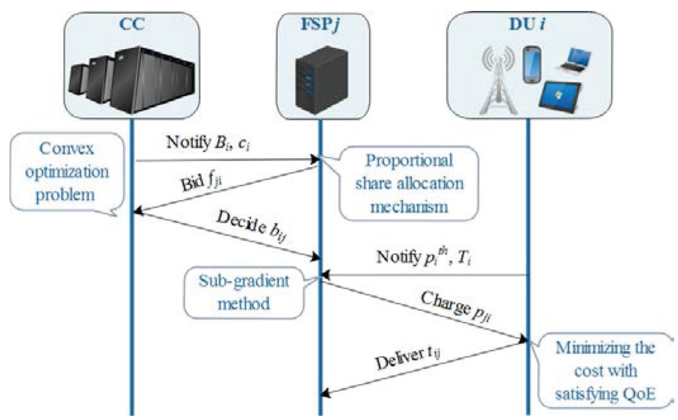

Fig. 3. Double-stage Stackelberg game for CC, FSP j, and DU i.

corresponding DU type to explain the flow of our scheme in Fig. 3. We assume that all players in this game are rational and their objective is to maximize their utility. In the framework used, with trading between the CC and FSPs and between FSPS and DUs, it is challenging to achieve maximum utility for all of them simultaneously. We need to consider a sequential decision-making process.

In the first stage, the CC will determine the amount of available resource i and the cost for one unit to maintain resource i, denoted as B_i and c_i, including c_{i1} used for potential users and c_{i2} used for FSPs, respectively, to FSP j. Based on the situation of DU i, as the leader in the Stackelberg game, FSP j decides upon the bid for one unit to request resource i from the CC, denoted as f_{ji}. Note that competition exists among all FSPs. Hence, we propose Algorithm 4 based on the proportional share allocation mechanism [32] to calculate the optimal bid strategy. Then, given the bids of all FSPs, including FSP j, the demand d_i, and the revenue r_i from potential users, as the follower in the Stackelberg game, the CC determines the amount of resource i allocated to FSP j, denoted as b_{ij}. This is calculated with a convex optimization problem.

In the second stage, DU i will determine the threshold value for one unit and the total amount of data to be processed, denoted as p_ith and T_i, respectively, to FSP j. As the leader in the Stackelberg game, FSP j gives the price for one unit to charge DU i for providing services. To resolve the competition among all FSPs, we propose Algorithm 3 based on the subgradient method [33], [34] to obtain the Nash equilibrium. Then, given the price for one unit of FSP j and that of the other FSPs, as the follower in the Stackelberg game, DU i determines the optimal data allocation, which is computed using Algorithm 1.

B. Models

We will now present the models of the CC, FSPs, and DUs, respectively.

1) CC: As the owner of resources, the CC wants to maximize the utility, which includes gaining revenue from selling of resources to FSPs and providing services to users. We can formulate the utility as follows:

$$U(\mathbf{b}) = u_{ou}(\mathbf{b}) + u_{cu}(\mathbf{b}) \tag{2}$$

where

$$u_{ou}(\mathbf{b}) = \sum_{i=1}^{m}(r_i - c_{i1})\left(B_i - b_i + \rho_i \ln \frac{B_i - b_i}{d_i}\right) \tag{3}$$

$$u_{cu}(\mathbf{b}) = \sum_{i=1}^{m}\sum_{j=1}^{n} b_{ij}(f_{ji} - c_{i2}). \tag{4}$$

Here, $u_{ou}(\mathbf{b})$ denotes the revenue of providing services to its users, and $u_{cu}(\mathbf{b})$ is the revenue from FSPs. For $u_{ou}(\mathbf{b})$, we need to consider the satisfaction of the remaining resources that are providing services, denoted as $\rho_i \ln (B_i - b_i)/d_i$, where d_i represents the ideal demand for resource i from its potential users, and $B_i - b_i$ is the actual remaining resource i. The satisfaction function is defined to characterize the quantitative difference between the ideal demand and actual provision. ρ_i is the importance of the services' satisfaction on resource i. r_i is the revenue for one unit of resource i from users. c_i is the cost for one unit of resource i. As users directly communicate with the CC without involving the FSPs, the corresponding cost c_{i1} is larger than the cost c_{i2} used for FSPs. $u_{cu}(\mathbf{b})$ is equal to the sum of revenue associated with all resources from all FSPs, where the revenue of resource i from FSP j is the product of the amount of resource b_{ij} and the net profit for one unit $f_{ji} - c_{i2}$. Thus, the optimization problem for the CC can be formulated as

$$\max_{\mathbf{b}} \ U(\mathbf{b}) \tag{5}$$

$$\text{s.t. } b_i \in [0, B_i], \quad i = 1, 2, \ldots, m. \tag{6}$$

2) FSPs: By purchasing resources from the CC, each FSP provides paid services for one or more DUs. Thus, the objective is to maximize the utility that equates the total revenue obtained from DUs, excluding the cost of buying the resources. The utility of FSP j can be formulated as

$$U_j(\mathbf{f}_j, \mathbf{p}_j) = R_j(\mathbf{p}_j) - C_j(\mathbf{f}_j) \tag{7}$$

where

$$R_j(\mathbf{p}_j) = \sum_{i=1}^{m} t_{ij}p_{ji} \tag{8}$$

$$C_j(\mathbf{f}_j) = \sum_{i=1}^{m} b_{ij}f_{ji} = \sum_{i=1}^{m} b_i \frac{f_{ji}}{F_{i-j} + f_{ji}} f_{ji}. \tag{9}$$

Here, $R_j(\mathbf{p}_j)$ denotes the total revenue from DUs and equals the sum of revenue from all DUs, where the revenue of each DU is the product of the amount of data delivered to FSP j and the price for one unit paid by the DU. $C_j(\mathbf{f}_j)$ is the cost paid to the CC. We apply the proportional share allocation mechanism, in which each FSP submits bids for the various resources and gets a fraction that is proportional to the FSP bid and inversely proportional to the sum of all other FSP bids for the same resource. Stated more formally, the total bids of resource i equals $F_i = \sum_{j=1}^{n} f_{ji}$, and FSP j receives a fraction $q_{ji} = f_{ji}/F_i$ of resource i. F_{i-j} denotes the total bids provided by all FSPs except for FSP j for resource i. $b_i f_{ji}/(F_{i-j} + f_{ji})$ is the amount of resource i allocated to FSP j denoted as b_{ij}. Therefore, the optimization problem for FSP j can be formulated as

$$\max_{\mathbf{f}_j, \mathbf{p}_j} \ U_j(\mathbf{f}_j, \mathbf{p}_j) \tag{10}$$

$$\text{s.t. } f_{ji} < p_{ji}, \quad i = 1, 2, \ldots, m \tag{11}$$

$$t_{ij} < b_{ij} = b_i \frac{f_{ji}}{F_{i-j} + f_{ji}}, \quad i = 1, 2, \ldots, m \tag{12}$$

$$\sum_{i=1}^{m} f_{ji} \le L_j. \tag{13}$$

These constraints are practical considerations. The price must be higher than the bid restricted by (11). The constraint in (12) guarantees that FSPs have sufficient resources to provide services for DUs, and the constraint in (13) indicates that the total bids for buying resources cannot be more than the budget L_j.

3) DUs: As the owner of data, each DU needs one or more FSPs to process the relevant data on a paid basis. Thus, the objective of each DU is to minimize the cost paid to FSPs, which can be defined as

$$U_i(\mathbf{t}_i) = \sum_{j=1}^{n} t_{ij}p_{ji}. \tag{14}$$

Although minimizing cost is our objective, QoE should not be ignored. Hence, the optimization problem for DU i can be formulated as

$$\max_{\mathbf{t}_i} \ -U_i(\mathbf{t}_i) \tag{15}$$

$$\text{s.t. } 0 < \frac{C}{b_{ij} - t_{ij}} \le g(p_{ji}), \quad j = 1, 2, \ldots, n \tag{16}$$

$$\sum_{j=1}^{n} t_{ij} = T_i \tag{17}$$

$$t_{ij} \ge 0, \quad j = 1, 2, \ldots, n \tag{18}$$

$$t_{ij}\big(p_{ji} - p_i\text{th}\big) \le 0, \quad j = 1, 2, \ldots, n. \tag{19}$$

Note that $g(p_{ji})$ is formulated by (1). The constraint in (16) is the tradeoff between cost and service delay. Particularly, based on the price charged by FSP j, the value of tolerance function $g(p_{ji})$ can be obtained, which can be regarded as the constraint of service delay provided by FSP j, i.e., the service delay $C/(b_{ij} - t_{ij})$ cannot surpass the tolerance $g(p_{ji})$. The function of such constraint is to avoid unilateral minimizing cost at expense of service delay. Then, DU i will decide the amount of data t_{ij} based on the constraint in (16) and the values of b_{ij} and $g(p_{ji})$. Here, the service delay is reflected by the inverse of difference between b_{ij} and t_{ij}, i.e., $C/(b_{ij} - t_{ij})$, where parameter C is scalar. A larger difference between the amount of service b_{ij} and that of arrival t_{ij} will result in reduced delay. The principle of the constraint in (16) is that higher quality services will be constrained by lower tolerance $g(p_{ji})$ generated by higher price p_{ji}. Then, DU i will deliver less data to FSP j to decrease cost as well as guarantee the service delay. The constraints in (17) and (18) imply that the data of DU i can be delivered to one or more FSPs until all data are complete. The constraint in (19) guarantees that DU i may deliver

Algorithm 1 DU i's Best Response Algorithm

Input: Threshold value of price p_ith; Total data T_i;
Step value Δp_ith
Output: Best data distribution $\mathbf{t}_i^* = (t_{i1}^*, t_{i2}^*, \ldots, t_{in}^*)$
1 $t_i \leftarrow$**DATA DISTRIBUTION**
2 **while** $\sum_{j=1}^{n} t_{ij} < T_i$ **do**
3 $p_i\text{th} \leftarrow p_i\text{th} + \Delta p_i\text{th}$ and repeat step 1 **until** $\sum_{j=1}^{n} t_{ij} = T_i$
4 return $\mathbf{t}_i^* = (t_{i1}^*, t_{i2}^*, \ldots, t_{in}^*)$
5 **end while**

Algorithm 2 Data Distribution

Input: Amount of resources $b_{i1}, b_{i2}, \ldots, b_{in}$;
Prices to charge $p_{1i}, p_{2i}, \ldots, p_{ni}$;
Threshold value of price p_ith; Total data T_i;
Preference $\omega_{i1}, \omega_{i2}, \ldots, \omega_{in}$
Output: Data allocation $\mathbf{t}_i$
1 Initialization $T_i^{'} = 0$;
2 **for** $j = 1, 2, \ldots, n$ **do**
3 **if** $p_{ji} \geq p_i$th **then** $t_{ij} = 0$
4 **else**
5 Arrangement p_{ji} in increasing order, where $p_{1i} \leq p_{2i} \leq \ldots \leq p_{ki}$, and $k \leq n$
6 **end if**
7 **end for**
8 **for** $j = 1, 2, \ldots, k$ **do**
9 **if** $b_{ij} \leq C \Big/ [1 - e^{\omega_{ij}(\frac{p_{ji}}{p_i\text{th}} - 1)}]$ **then** $t_{ij} = 0$
10 **else**
11 **if** $T_i^{'} + b_{ij} - C \Big/ [1 - e^{\omega_{ij}(\frac{p_{ji}}{p_i\text{th}} - 1)}] \leq T_i$ **then**
$t_{ij} = b_{ij} - C \Big/ [1 - e^{\omega_{ij}(\frac{p_{ji}}{p_i\text{th}} - 1)}], T_i^{'} \leftarrow T_i^{'} + t_{ij}$
12 **else**
13 $t_{ij} = T_i - T_i^{'}$
14 **end if**
15 **end if**
16 **end for**

data to the FSPs, whose charged prices are lower than the threshold value of DU i. Otherwise, no data will be delivered.

V. Equilibrium Analysis for Resource Allocation

In this section, we compute the Stackelberg equilibrium of the three parties (i.e., CC, FSP, and DU) and the Nash equilibrium among all FSPs. Particularly, for the double-stage Stackelberg game, we use the backward induction method to analyze this game, as it can reflect the sequential dependence of decisions decided by all parties and is an effective approach to calculate the Stackelberg equilibrium. Note that the proofs for the lemmas in this section can be found in the Appendices.

A. Data Delivered by DUs in Stage II

Different types of data can be processed by different resources; hence, there is no competition among these DUs. Based on (15)–(19), Algorithm 1 is used to calculate the best strategy $\mathbf{t}_i^* = (t_{i1}^*, t_{i2}^*, \ldots, t_{in}^*)$ of DU i, for any $i \in M_u$.

To minimize the cost, DU i first applies (16)–(19) as the criteria to deliver data $\mathbf{t}_i$, which can be generated by the function named Data Distribution (line 1). Then, DU i begins to adjust the price until all the data have been submitted (lines 2–5). In Algorithm 2, to satisfy the objective function, DU i first selects the lower prices as the candidates to deliver data (lines 1–7). Then, setting (16) as the baseline, the data begin to be distributed to different FSPs (lines 8–16).

Lemma 1: Given $\mathbf{p}_i$, DU i's optimal strategy $\mathbf{t}_i^*$ satisfies

$$t_{ij}^* = \begin{cases} b_{ij} - C \Big/ \Big[1 - e^{\omega_{ij}(p_{ji}/p_i\text{th} - 1)}\Big], & j \in P_1 \backslash k \\ T_i - \sum_{j \in P_1 \backslash k} b_{ij} - C \Big/ \Big[1 - e^{\omega_{ij}(p_{ji}/p_i\text{th} - 1)}\Big], & j = k \\ 0, & j = P_2 \bigcup Q \end{cases}$$

where P is the sequential set with respect to the value of $\mathbf{p}_i$, and $|P| = z$. Note that the elements in P should satisfy the conditions $p_{ji} < p_i$th and $b_{ij} > C/[1 - e^{\omega_{ij}([(p_{ji})/(p_i\text{th})] - 1)}]$. Inversely, the remaining $n - z$ inadequate elements are contained in the set Q. Here, as the amount of data T_i is limited, no data may be delivered to some of FSPs whose charges belong to P. Hence, P is divided into P_1 including the first k and P_2 including the remaining $z - k$. The FSPs whose charges belong to P_1 can obtain the data delivered by DU i, while the ones whose charges belong to P_2 failed.

Lemma 2: Given the strategies of all FSPs, each DU has a unique optimal strategy.

B. Resources Allocation by CC in Stage I

Given the bids to request various resources provided by all FSPs $(\mathbf{f}_1, \mathbf{f}_2, \ldots, \mathbf{f}_n)$ and the rewards from potential users $(r_1, r_2, \ldots, r_m)$, we give the optimal CC strategy, denoted as $\mathbf{b}^* = (b_1^*, b_2^*, \ldots, b_m^*)$ by calculating a convex optimization problem based on (2)–(6).

Lemma 3: The strategy set of CC is nonempty, convex, and noncompact.

Lemma 4: Given $\mathbf{f}_i = (f_{1i}, f_{2i}, \ldots, f_{ni})$, the optimal CC allocation strategy on resource i satisfies

$$b_i^*(\mathbf{f}_i) = \begin{cases} 0, & F_i \leq \underline{F_i} \\ B_i - \frac{\rho_i(r_i - c_{i1})}{\sum_{j=1}^{n} \frac{f_{ji}(f_{ji} - c_{i2})}{F_{i-j} + f_{ji}} - (r_i - c_{i1})}, & \underline{F_i} < F_i < \overline{F_i} \\ B_i - \varepsilon, & F_i = \overline{F_i} \end{cases}$$

where $\varepsilon \to 0$, F_i denotes the total bids offered by FSPs, $\overline{F_i}$ is under threshold of total bids when b_i is equal to 0, and $\underline{F_i}$ is over threshold of total bids when b_i is equal to B_i. The values of $\overline{F_i}$ and $\underline{F_i}$ can be calculated by the proof of Lemma 3 in Appendix C.

Lemma 5: Given the strategies of all FSPs, the optimal CC strategy is unique.

C. Noncooperation Among FSPs in Stages I and II

In stage II, based on the prediction of DUs' optimal response, all FSPs compete with each other to derive the maximum utility by deciding the best strategy $\mathbf{p}_j^*$. Here, Algorithm 3 is used to compute the Nash equilibrium of all FSPs. As there is no relationship among these different types of resources when charging different types of DUs, we can maximize the utility obtained from each DU separately. Hence, for any $i \in M_u$, our goal is

$$\max_{p_{ji}} u_j\Big(p_{ji}, \mathbf{p}_{-ji}^*\Big) = t_{ij}^* p_{ji} - b_i^* \frac{f_{ji}}{F_{i-j} + f_{ji}} f_{ji} \tag{20}$$

where $\mathbf{p}_{-ji}^*$ denotes the best prices to charge DU i, except that FSP j. $u_j(p_{ji}, \mathbf{p}_{-ji}^*)$ represents the utility of FSP j about

Algorithm 3 Optimal Price Strategy of All FSPs

Input: Step value Δ; Threshold value $p_1\text{th}, p_2\text{th}, \ldots, p_m\text{th}$
Output: Best price strategy $\mathbf{p}_1^*, \mathbf{p}_2^*, \ldots, \mathbf{p}_n^*$
1 Initially, each FSP sets an initial price $p_{ji} = p_i\text{th}$. Then no data has been submitted by any DU as the prices exceed the thresholds
2 While At least one FSP adjusts its price **do**
3 **for** DU i **do**
4 Applying Algorithm 1 to calculate the optimal data distribution based on the price sets $(p_{1i}, p_{2i}, \ldots, p_{ni})$ by all FSPs
5 **end for**
6 **for** FSP j **do**
7 Each FSP stores the current value of the service prices $\mathbf{p}_j^{old} = (p_{j1}^{old}, p_{j2}^{old}, \ldots, p_{jm}^{old})$
8 Each FSP tries to increase or decrease its price with a small step Δ, and calculates his\her own utility based on the prediction of the DUs' optimal data distributions
9 **if** $u_j(p_{ji}^{old}, \mathbf{p}_{-ji}^{old*}) \le u_j(p_{ji}^{old} + \Delta, \mathbf{p}_{-ji}^{old*})$ and $u_j(p_{ji}^{old} - \Delta, \mathbf{p}_{-ji}^{old*}) \le u_j(p_{ji}^{old} + \Delta, \mathbf{p}_{-ji}^{old*})$ **then**
$p_{ji} = \min\{p_{ji}^{old} + \Delta, p_i\text{th}\}$
10 **if** $u_j(p_{ji}^{old}, \mathbf{p}_{-ji}^{old*}) \le u_j(p_{ji}^{old} - \Delta, \mathbf{p}_{-ji}^{old*})$ and $u_j(p_{ji}^{old} + \Delta, \mathbf{p}_{-ji}^{old*}) \le u_j(p_{ji}^{old} - \Delta, \mathbf{p}_{-ji}^{old*})$ **then**
$p_{ji} = \max\{p_{ji}^{old} - \Delta, 0\}$
11 **else**
12 $p_{ji} = p_{ji}^{old}$
13 **end if**
14 **end if**
15 **end for**
16 end while

resource i given the prices of others. As the value of the second derivative of $u_j(p_{ji}, \mathbf{p}_{-ji}^*)$ for p_{ji} is negative, $u_j(p_{ji}, \mathbf{p}_{-ji}^*)$ is a concave function.

In Algorithm 3, given the prices of all FSPs, each type of DU begins to deliver their data depending on Algorithm 1. Then, the FSPs begin to change their prices to obtain maximum utility (lines 3–5). In each round of the circulation, for each type of resource, each FSP changes the price with the fixed value Δ. If the utility of the price increasing with Δ is higher than the prices decreasing with Δ and remains unchanged, then in the next round, the price changes to $p_{ji}+\Delta$. If the utility of the price decreasing with Δ is higher than the prices increasing with Δ and remains unchanged, then in the next round, the price changes to $p_{ji} - \Delta$. Otherwise, the price remains unchanged. When all FSPs cannot deviate from their current price unilaterally for higher utility, the circulation ends (lines 6–16).

Lemma 6: The Nash equilibrium in Algorithm 3 is unique.

Lemma 7: The unique optimal bid strategy of FSP j calculated by Algorithm 4 satisfies

$$f_{ji}^* = \begin{cases} \sqrt{b_i F_{i-j}^2 \Big/ (b_i - \beta)} - F_{i-j}, & i \in \Omega' \\ 0, & i \in \Omega''. \end{cases} \tag{21}$$

In stage I, given the forecast of the CC's best response, we propose Algorithm 4 as the best strategy $\mathbf{f}_j^*$ based on the Lagrange multiplier [35].

Algorithm 4 is allocated in the sense that each FSP searches the set of prices that maximize the utility, when the prices as provisioned by the other FSPs have been determined. Following an iterative process of updating the vector of the price, the preceding algorithm will converge to an efficient equilibrium, and then the optimal price set for each FSP can be

Algorithm 4 Optimal Bid Strategy of FSP j

Input: Total bids except j $(F_{1-j}, F_{2-j}, \ldots, F_{m-j})$; Budget L_j
Output: Best bid strategy $\mathbf{f}_j^* = (f_{j1}^*, f_{j2}^*, \ldots, f_{jm}^*)$
1 Initially, FSP j give the bid strategy **0**, i.e., $f_{ji} = 0$. Then no resource has been allocated to it. $\Omega' = \Omega'' = \emptyset$
2 **for** resource i **do**
3 Applying (5), (6) to calculate the resource allocation b_i based on the total bids F_i. Then arrangement $b_i \big/ F_{i-j}$ in decreasing order
4 **end for**
5 **While** $\left|\Omega'\right| < \lambda$ **do**
6 **for** $i = 1, 2, \ldots, m$ **do**
7 **if** $\frac{t_{ij} F_{i-j}}{b_i - t_{ij}} < f_{ji} \le p_{ji}$ and
$\beta = \arg \sum_{i=1}^m \sqrt{b_i F_{i-j}^2 \Big/ (b_i - \beta)} - L_j - \sum_{i=1}^m F_{i-j} = 0$ **then**
$\Omega' \leftarrow i$ and $f_{ji}^* = \sqrt{b_i F_{i-j}^2 \Big/ (b_i - \beta)} - F_{i-j}$
8 **else**
9 $\Omega'' \leftarrow i$ and $f_{ji}^* = 0$
10 **end if**
11 **end for**
12 **end while**

TABLE II
SYSTEM PARAMETERS

Parameters	Value range	Parameters	Value range
B	[60,100]	t	[10,25]
T	[40,80]	ρ	(0,1)
d	[40,80]	ω	[0.5,0.9]
b	[15,30]	c_2	[10,15]
r	[20,40]	c_1	[15,20]
p	[30,60]	L	[100,200]
p^{th}	[50,80]	f	[20,40]

obtained. Here, we apply dichotomy to calculate the approximate value of β. We can get the following theorem based on the above-mentioned lemmas.

Theorem 1: A unique Stackelberg equilibrium exists among the CC, all FSPs, and all DUs in our proposed double-stage Stackelberg game.

VI. Performance Evaluation

A. Setting of Simulation Parameters

In this section, we considered different parameters to quantify the performance of our scheme. We used C++ to code the Stackelberg equilibrium under different optimization strategies and performed the evaluations on a personal computer (PC) with Intel Core 3.40-GHz CPU and 8-GB memory.

The physical machine topology of the data center is generated randomly in order to be as realistic as possible. Meanwhile, to ensure the heterogeneity of resource (DU) types, CC provides physical machines with different specifications, such as CPU, memory, hard disk storage, and so on. Naturally, the number of resource (DU) types is 3. Here, we also set the number of FSPs as 3. The values of resource parameters and correlation coefficients with respect to the simulated physical machine are shown in Table II.

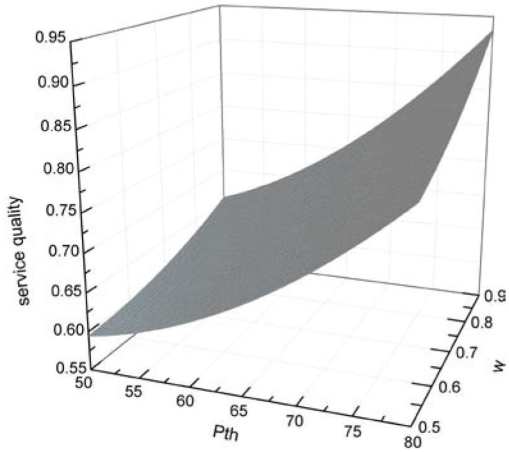

Fig. 4. Influence of p^{th} and ω on service quality.

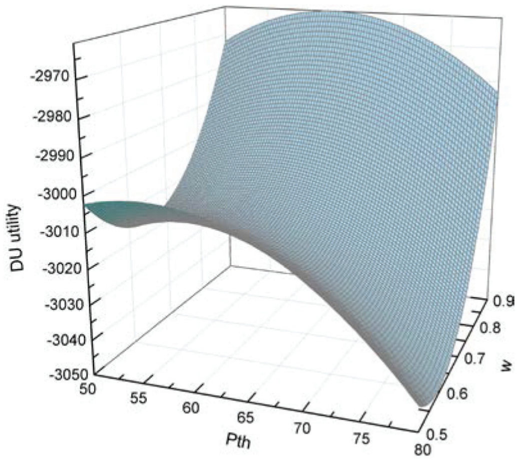

Fig. 5. Influence of p^{th} and ω on DU utility.

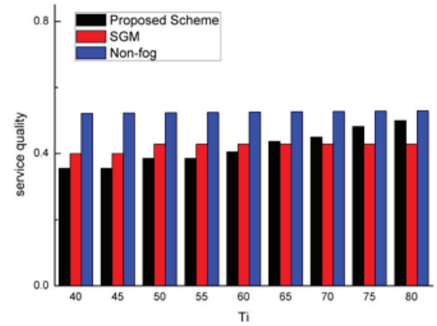

Fig. 6. Influence of T on service quality.

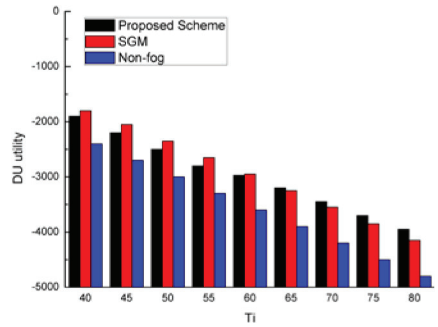

Fig. 7. Influence of T on DU utility.

B. Simulation Results

Fig. 4 illustrates the service quality with varying values of ω and p^{th}. As ω increases, the service quality decreases. The main reason is that higher trust preference ω will result in larger tolerance. Akin to ω, such results may also be obtained with respect to p^{th}. However, the growth rate of p^{th} increases with T, due to the relationship between p^{th} and total data T. In other words, the service quality deteriorates when more data are processed. Fig. 5 shows the utility of DU with varying values of ω and p^{th}. As ω increases, so does DU's utility (an opposite trend from service quality). This is because given the total data T, the DU first selects lower prices as the candidates to deliver data. A larger threshold value p^{th} will result in more requests for service quality but less cost for delivering the data. However, compared with the significant volume of data reflected by larger p^{th}, the cost used to deliver data has to increase regardless of the request for service quality.

Figs. 6 and 7 show the utility of DU and service quality received for different total data Ts. Here, we compare our scheme with both SGM presented in [22] and our scheme without FSPs (i.e., nonfog). Specifically, Zhang *et al.* [22] proposed a joint optimization framework to achieve optimal resource allocation in fog-cloud computing and used the Stackelberg game to analyze pricing problem for data service operators, as well as the resource allocation problem for data service subscribers and the matching game to investigate pairing problem between data service operators and fog nodes. Here, the roles of data service operators, fog nodes, and data service subscribers respectively, correspond to CC, FSPs, and DUs discussed in our scheme. First, as the remote distance between the CC and DUs increases, both utility and service quality of nonfog worsen. Note that as the change of the amount of data is relatively small compared to the remote distance, the effect of the amount of data on the service quality is weak. Also, the utility of our scheme is better than that of SGM when T is large, while the service quality of our scheme is better than that of SGM when T is small. Intuitively, SGM only considers the influence of price on the service quality, i.e., they are inversely proportional to each other. Hence, the request for service quality of SGM is quite loose than that of ours when the prices of candidates are lower as T is smaller; thus, resulting in reduced cost but also less desirable service quality. However, with the growth of T, the prices of candidates also increase. A more rigorous request for service quality will incur a higher cost for the SGM, in comparison to our proposed scheme.

Fig. 8 illustrates the convergence of FSP's utility in Algorithm 3. Here, the utility of FSP will gradually increase with the growth of iterations and finally converge to be optimal with several iterations. Hence, in terms of simulation, a unique Nash equilibrium among all FSPs can be obtained by Algorithm 2.

Fig. 9 shows the utility of FSP for varying received data. As the amount of received data increases, so does the profit of FSP. The performance of our proposed scheme outperforms

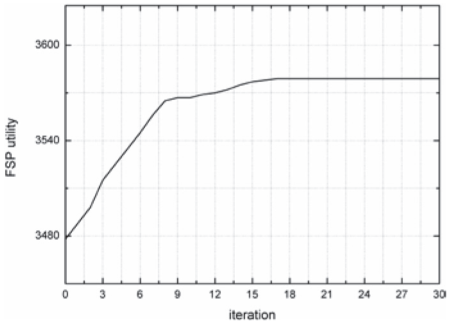

Fig. 8. Convergence of FSP utility.

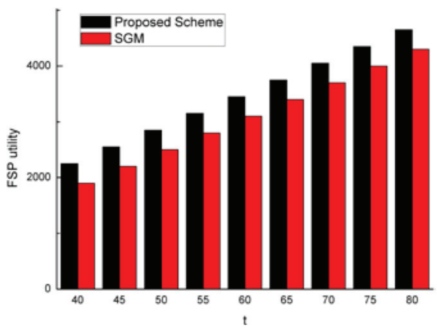

Fig. 9. Influence of received data on FSP utility.

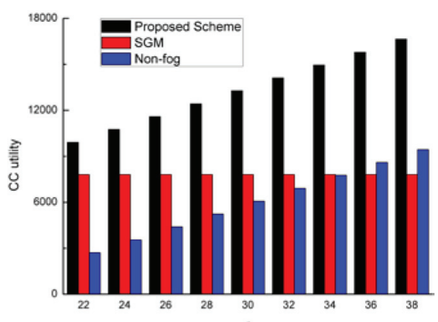

Fig. 10. Influence of r on CC utility.

that of SGM, as FSPs in our scheme provide services to DUs based on the amount of resources obtained from the CC. On the contrary, the FSPs in SGM first receive the data from DUs and then try to obtain resources used to provide services. Additional cost associated with the purchase of resources occurs when the resources from the CC are not sufficient to provide services for DUs.

Figs. 10 and 11 show the utility of the CC for both non-fog and SGM with varying r and d, respectively. As SGM does not consider providing services for users and only allocates resources to the given FSPs according to the preference, its utility will be worse and does not change with r and d. The utility of the proposed scheme and nonfog decreases as d increases, but as r increases, the proposed scheme outperforms nonfog. This is because without FSPs, the CC has to increase the cost to cope with additional logistics due to remote distances between the CC and DUs. Hence, this reinforces the importance of fog computing in resource allocation and the superiority of our scheme.

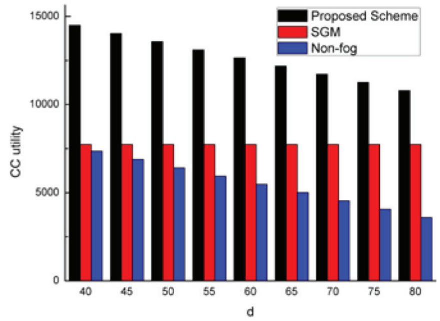

Fig. 11. Influence of d on CC utility.

VII. Conclusion

Given the increasing popularity of fog computing in an industrial setting, resource distribution optimization techniques were explored in this article. Specifically, we proposed a novel scheme to optimize resource allocation, formulated as a double-stage Stackelberg game. We demonstrated how we can achieve Stackelberg equilibrium among DUs, FSPs, and the CC, and Nash equilibrium among noncooperative FSPs, using our proposed algorithms.

Future research will include implementing a prototype of the proposed approach in a real-world fog-based IIoT environment and extending the exploration of relationships among DUs. These will allow us to fine-tune the modeling and achieve better performance.

Appendix A
Proof of Lemma 1

Proof: To maximize the utility and guarantee the service quality, DU i will deliver the data strictly according to (16) when the equality holds. Hence, the candidates must satisfy conditions $p_{ji} < p_i\text{th}$ and $b_{ij} > C \Big/ [1 - e^{\omega_{ij}(p_{ji}/p_i\text{th}-1)}]$, which can be obtained by (16). Given the sequential set P, the deliver process will stop until the limited data T_i have been submitted successfully to the sequential set P_1. Note that the FSP whose price is the last one in P_1 may receive the actual left data. Finally, no data will be delivered to the FSPs whose prices belonging to P_2 and Q. ∎

Appendix B
Proof of Lemma 2

Proof: According to Lemma 1, DU i does not deliver data to FSP j when the price p_{ji} is larger than the threshold value of DU i. Additionally, when $p_{ji} < p_i\text{th}$, we get

$$\frac{\partial t_{ij}^*}{\partial p_{ji}} = \frac{-C \cdot \omega_{ij} \big/ p_i\text{th} \cdot e^{\omega_{ij}(p_{ji}/p_i\text{th}-1)}}{\left[1 - e^{\omega_{ij}(p_{ji}/p_i\text{th}-1)}\right]^2} < 0. \quad (22)$$

Then, we can guarantee that the larger price the FSP charges, the less data the DU delivers to. Meanwhile, in this scheme, each DU's utility cannot be influenced by other DUs' strategies. Hence, given the strategies of all FSPs, each DU has a unique optimal strategy. ∎

Appendix C
Proof of Lemma 3

Proof: According to (2) and (3), the first- and second-order derivatives of $U(b)$ for b_i are as follows:

$$\frac{\partial U(\mathbf{b})}{\partial b_i} = (r_i - c_{i1})\left(-1 - \frac{\rho_i}{B_i - b_i}\right) + \sum_{j=1}^{n} \frac{f_{ji}\left(f_{ji} - c_{i2}\right)}{F_{i-j} + f_{ji}} \tag{23}$$

$$\frac{\partial^2 U(\mathbf{b})}{\partial b_i^2} = -\frac{\rho_i(r_i - c_{i1})}{(B_i - b_i)^2}. \tag{24}$$

As $\partial^2 U(\mathbf{b}) \big/ \partial b_i^2 < 0$, thus $U(\mathbf{b})$ is a concave function with respect to b_i. Given $\mathbf{f}_i = (f_{1i}, f_{2i}, \ldots, f_{ni})$ and $r_i > c_{i1}$, let $\partial U(\mathbf{b}) \big/ \partial b_i$ be equal to 0, then we can derive the best CC response about resource i as follows:

$$b_i^*(\mathbf{f}_i) = B_i - \rho_i(r_i - c_{i1}) \Bigg/ \left[\sum_{j=1}^{n} \frac{f_{ji}(f_{ji} - c_{i2})}{F_{i-j} + f_{ji}} - (r_i - c_{i1})\right]. \tag{25}$$

At the same time, we consider the threshold values of bids about resource i by setting $b_i = 0$ and $b_i = B_i$, denoted as

$$\underline{F_i} = \underline{\sum_{j=1}^{n} f_{ji}} = \arg b_i^*(\mathbf{f}_i) = 0 \tag{26}$$

$$\overline{F_i} = \overline{\sum_{j=1}^{n} f_{ji}} = +\infty. \tag{27}$$

Hence, the allocated resources and the bids are searched in unlimited regions, this lemma holds. ■

Appendix D
Proof of Lemma 4

Proof: First, if $F_i \le \underline{F_i}$, then no resource will be offered by CC, i.e., the optimal CC strategy for resource i is 0. Second, given r_i, if $F_i = \overline{F_i}$, which means that the bid for one unit of resource i provided by the FSPs is far greater than the payment for one unit of resource i from potential users, thus the vast majority of resource i should be offered to the FSPs. Finally, if $\underline{F_i} < F_i < \overline{F_i}$, then the optimal CC strategy is decided by (25). ■

Appendix E
Proof of Lemma 5

Proof: According to Lemma 4, for any resource i, if the total bid F_i is less than the threshold value $\underline{F_i}$, then the CC does not provide resource i to all FSPs. If all FSPs give a quite huge bid for resource i, then almost resource i can be sold to them. For $\underline{F_i} < F_i < \overline{F_i}$, we have

$$\frac{\partial b_i^*}{\partial f_{ji}} = \rho_i(r_i - c_{i1}) \cdot \left[\frac{f_{ji}}{F_{i-j} + f_{ji}} + \frac{F_{i-j}(f_{ji} - c_{i2})}{(F_{i-j} + f_{ji})^2}\right] \times \Bigg/ \left[\sum_{j=1}^{n} \frac{f_{ji}(f_{ji} - c_{i2})}{F_{i-j} + f_{ji}} - (r_i - c_{i1})\right]^2 \tag{28}$$

$$\frac{\partial^2 b_i^*}{\partial f_{ji}^2} = \frac{2\rho_i(r_i - c_{i1})}{\left[\sum_{j=1}^{n} \frac{f_{ji}(f_{ji}-c_{i2})}{F_{i-j}+f_{ji}} - (r_i - c_{i1})\right]^2} \times \left\{ \frac{F_{i-j}(f_{ji} - c_{i2})}{(F_{i-j} + f_{ji})^3} - \frac{\left[\frac{f_{ji}}{F_{i-j}+f_{ji}} + \frac{F_{i-j}(f_{ji}-c_{i2})}{(F_{i-j}+f_{ji})^2}\right]^2}{\sum_{j=1}^{n} \frac{f_{ji}(f_{ji}-c_{i2})}{F_{i-j}+f_{ji}} - (r_i - c_{i1})} \right\}. \tag{29}$$

Here, $\partial b_i^* \big/ \partial f_{ji} \ge 0$ implies that the larger bid the FSPs provide, the more resources the CC allocates. Additionally, the value of (29) is negative. Then, by (28) and (29), we know that b_i^* is an increasing concave function of f_{ji}. To sum up, the optimal CC strategy is unique. ■

Appendix F
Proof of Lemma 6

Proof: According to [33] and [34], the subgradient algorithm can solve the convex optimization to obtain an optimal solution with small ranges. Hence, each FSP cannot unilaterally adjust the price to derive higher utility when the subgradient algorithm obtains an optimal solution. Furthermore, giving the fixed starting price and the original Δ, we can use the inductive assumption method to show that the prices in each iteration are fixed. Hence, Algorithm 3 can obtain the unique Nash equilibrium. ■

Appendix G
Proof of Lemma 7

Proof: Let β be the Lagrange multiplier, and the FSP j's model shown as (7)–(9) be relaxed as follows:

$$L(f_{ji}, \beta) = \sum_{i=1}^{m}\left(t_{ij}p_{ji} - b_i \frac{f_{ji}}{F_{i-j} + f_{ji}} f_{ji}\right) - \beta\left(\sum_{i=1}^{m} f_{ji} - L_j\right). \tag{30}$$

Then, the conditions and constraints of the Kuhn–Tucker first-order derivatives are as follows:

$$\frac{\partial L}{\partial f_{ji}} = b_i \frac{2f_{ji}F_{i-j} + f_{ji}^2}{\left(F_{i-j} + f_{ji}\right)^2} - \beta = 0 \tag{31}$$

$$\frac{\partial L}{\partial \beta} = \sum_{i=1}^{m} f_{ji} - L_j = 0. \tag{32}$$

Based on (31) and (32), we have

$$f_{ji} = \sqrt{b_i F_{i-j}^2 \Big/ (b_i - \beta)} - F_{i-j} \tag{33}$$

$$\sum_{i=1}^{m} f_{ji} = \sum_{i=1}^{m} \sqrt{b_i F_{i-j}^2 \Big/ (b_i - \beta)} - F_{i-j} = L_j \tag{34}$$

where $\beta = \arg \sum_{i=1}^{m} \sqrt{b_i F_{i-j}^2 \big/ (b_i - \beta)} - L_j - \sum_{i=1}^{m} F_{i-j} = 0$. According to (11) and (12), we arrange $b_i \big/ F_{i-j}$ in decreasing order and divide the first λ satisfying $t_{ij}F_{i-j} \big/ (b_i - t_{ij}) < f_{ji} \le p_{ji}$ into set Ω', while the left ones are divided into set Ω''. ■

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