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Joint Cloud and Wireless Networks Operations in Mobile Cloud Computing Environments with Telecom Operator Cloud

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***Abstract*—In mobile cloud computing systems, cloud computing has a significant impact on wireless networks. Cloud computing and wireless networks have traditionally been addressed separately in the literature. In this paper, we jointly study the operations of cloud computing and wireless networks in mobile computing environments, where the objective is to improve the end-to-end performances of cloud mobile media delivered through mobile cloud computing systems. Unlike most existing studies on wireless networks, where only the spectrum efficiency is considered, we consider not only the spectrum efficiency in wireless networks but also the pricing information in the cloud, based on which power allocation and interference management in the wireless networks are performed. We formulate the problems encountered in the operations of mobile cloud computing environments, including determining the price to charge for media services, resource allocation, and interference management, as a Stackelberg game model. Moreover, we extend this game model with multiple players through network virtualization technology, and adopt the replicator dynamics method to solve the evolutionary game between the different groups of small cells. Furthermore, a backward induction method is used to analyze the proposed Stackelberg game. Simulation results are presented to show the effectiveness of the proposed techniques.**

***Index Terms*—Mobile cloud computing, telecom operator cloud, small cells**

I. Introduction

Recently, cloud computing has drawn a lot of attentions from both academia and industry [1]. It has advantages over traditional computing paradigms, such as avoiding capital investments and operational expenses for end-users. The essential characteristics of cloud computing include on-demand self-service, broadband network access, resource pooling, rapid elasticity, and measured service [2], [3]. Furthermore, with recent advances in mobile communication technologies, mobile devices, and mobile applications, more and more end-users access cloud computing systems via mobile devices, such as smart phones. As much, mobile cloud computing is widely considered as a promising computing paradigm with huge markets [4]–[6]. It can bridge the gap between multimedia demands of end-users and the capacity of mobile networks. In traditional mobile computing systems, mobile devices usually have limited computing and storage capabilities. In contrast, utilizing the powerful computing and storage resources available in cloud environments, mobile cloud computing can enable the use of cutting-edge multimedia services. In the cloud, the resources have much higher processing and storage capacities compared to what traditional mobile devices can provide. And thus, the cloud can offer a much richer media experience than current mobile applications [7].

There are many promising *cloud mobile media* (CMM) services based on mobile cloud computing, including media storage and downloading services, audio services, and interactive services (e.g., multi-way video conferencing, advertisements, and mobile multiplayer gaming) [8]. CMM services will not only make the end-users enjoy a richer media experience from a mobile device, but a more important aspect is that CMM services will also offer new opportunities for CMM *service providers* (SPs) and telecom operators to offer end-users rich media services that can be delivered efficiently such that end-users are satisfied and have a good quality of experience [4], [9]. For telecom operators, CMM services will narrow the increasing gap between the growth in data usage by end-users and revenue earned by SPs.

Despite the potential of CMM services, several research challenges still need to be addressed. These include the following: the availability and accessibility of media services, mobile data integrity, user privacy, energy efficiency, response time, and the *quality of service* (QoS) over wireless networks [10]. Among these challenges in deploying CMM services, an important one is the response time experienced by end-users, which is highly dependent on the quality and speed of the network [11], [12]. Indeed, networking has become a bottleneck, and thus, it has a significant impact on the quality of cloud services. This problem becomes more severe in CMM services due to the scarce network capacity, higher bit error rate, and user mobility in wireless networks [13]. One reason caused the above

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problem is that cloud computing and communication networks are not jointly designed and optimized [3], [14]. Therefore, when the end-users use CMM services they may suffer long response times and a degraded QoS. In this paper, we propose an approach based on game theory to consider the joint design of cloud computing and wireless networks. In addition, we introduce the deployment of the *telecom operator cloud* (TOC) as a promising approach for "interchanging and mixing" the CMM services from different third party CMM SPs.

Most current CMM services are offered by *over-the-top* (OTT) players, which provide easy-to-adopt, on-demand services by exploiting ubiquitous connectivity [15]. OTT SPs can offer tons of CMM services, which contain media storage services, downloading services, and interactive services (e.g., multi-way video conferencing, and cloud gaming) [16]. However, these OTT players do not provide communication or connectivity services, which are offered by traditional telecom operators. Thus, it is necessary to provide a quantitative approach to jointly consider the following problems in a mobile cloud computing environment: the price to charge end-users for CMM services, resource allocation, and the interference management of wireless networks.

Although some recent works have been done to study cloud computing and wireless networks, these two important areas have traditionally been addressed separately in the literature. However, from the end-to-end applications' perspective, both the cloud and wireless networks are parts of the entire system. The experience in end-to-end applications (e.g., video and TCP-based applications) indicates that the optimized performance in one segment of the whole system does not guarantee the end-to-end performance [17]. To ensure the optimal usage of the resources of both clouds and wireless networks and enable the scalability of the CMM service users, joint cloud and wireless networks operations should be used for each CMM service client [18].

In addition, we introduce the deployment of the *telecom operator cloud* (TOC) as a promising approach for "interchanging and mixing" the CMM services from different third party CMM SPs [3].

In this paper, we jointly study the operations of cloud computing and wireless networks in a mobile computing environment with a TOC. The objective is to improve CMM service. To the best of our knowledge, the design of joint cloud and wireless networks has not been addressed in previous literature. The distinct features of this work are outlined below.

- We consider a mobile cloud computing system with TOC, in which CMM SPs and the size of the CMM service can be dynamically selected. In this way, a telecom operator can strengthen its relationships with end-users and third party CMM service providers by acting as a service and billing aggregator. This can be accomplished using network virtualization technology [3], [19].
- The operations of wireless networks (e.g., resource allocation and interference management) are optimized according to the following: the CMM traffic, the real-time price provided by the CMM SPs, and the cost associated with the CMM services.

TABLE I
ACRONYMS

Acronyms	Description
AWGN	Additive White Gaussian Noise
CMM	Cloud Mobile Media
HWNs	Heterogeneous Wireless Networks
MBS	Macro Base Station
MUs	Macrocell Users
MaaS	Mobile Network-as-a-Service
OTT	Over-the-Top
OFDMA	Orthogonal Frequency-Division Multiple Access
QoS	Quality of Service
SBSs	Small Base Stations
SP	Service Provider
SSU	Small Cell Secondary User
TCP	Transmission Control Protocol
TOC	Telecom Operator Cloud

- We formulate the problem of determining the CMM service price decision, resource allocation of wireless network resources, and interference management as a multi-level Stackelberg game. The Stackelberg game has been successfully used in cooperative communication networks, and other areas [20]. To analyze the proposed game, we use the backward induction method [21] that can capture the sequential dependencies of the decisions in the stages of the game model. In addition, we propose an iteration algorithm to obtain the Stackelberg equilibrium solution.
- Extensive simulations are performed to investigate the performance of the proposed techniques. Based on the simulation results, we verify the convergence of the Stackelberg equilibrium iteration algorithms. Then, we show the performance gain of the proposed resource allocation method comparing to an existing scheme.

New challenges arise, which have not been addressed by existing research, when jointly considering the dynamics of cloud, CMM services, and wireless networks. We believe that the research and results that are presented will open a new avenue and motive additional research for considering the operations of cloud and wireless networks in mobile cloud computing environments.

The rest of paper is organized as follows. We describe the system and game formulation in Section II. The proposed game is analyzed in Section III. Simulation results are presented and discussed in Section IV. Finally, we conclude this study in Section V with future work.

II. System Description and Formulation

In this section, we consider a mobile cloud computing system with several third party CMM SPs. The system has a telecom operator cloud that can "mix and interchange" resources offered by different third party CMM SPs, and HWNs contains both macro and small cell base stations. In addition, the problem of joint cloud and wireless networks operations in this system is formulated as a three-stage Stackelberg game.

The acronyms used in this paper are listed in Table I.

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A. Telecom Operator Cloud and Third Party CMM SPs

Future media service will definitely be provided by clouds. The multimedia service may come from different cloud service providers, different network types, different technologies, etc. In this paper, we mainly consider the CMM service model provided by different third party CMM SPs. Different CMM SPs offer rich multi-media services to the end-users, including the streaming media, interactive service, and mobile gaming, etc. In the previous paper, we have discussed that most of the CMM SPs will choose to partner with the telecom operators rather than to pay. In this scenario, telecom operators will pool variety of third party CMM SPs and offer a virtually unlimited selection of customized and diverse services for end-users.

Telecom operators are making a stronger push to monetize data traffic through OTT-style services and applications. They also attempt to restrict these traffic-heavy, low-revenue OTT services such as streaming media, but this may have negative impacts on user experiences, even violates the regulations sometimes.

Operators can play a natural role in the cloud computing, providing the reliable and low-cost connectivity service for any other third party clouds, but this is just an initial step. Some of the pioneers in this area have already explored a new TOC model [3]. On one hand, telecom operators can use the powerful storage and computing capabilities offered by the cloud for network management, such as billing. In this case, telecom operators are cloud users. On the other hand, telecom operators can also be cloud providers as well. For example, the telecom operators can leverage the network assets to aggregate and resell the services of third party clouds.

Similar to the cloud computing model, for achieving low-cost media services by using the “pay-per-use” approach, mobile cloud computing can also adopt the utility billing model to require resources and provide *Mobile Network as a Service* (MNaaS). As shown in Fig. 1, TOC is in an unique position of being as a cloud “broker” between the wireless networks and the third party SPs, and can manage connectivity and offer flexibility in acquiring network resources on-demand and in real-time.

There are three major roles, namely, cloud connectivity, delivery of cloud-based capabilities, and leveraging network assets to enhance cloud offerings. This TOC model can align itself in the cloud value chain [3].

Furthermore, MNaaS can use network virtualization technique to make the connectivity much easier, since it allows the operator to set up multiple channels over the same infrastructure and use whichever network layer is the most appropriate to deliver the required QoS to suit a particular CMM service with the need of end-users. Most scenarios using MNaaS as a delivery model are that virtual networks are on the top of the existing infrastructure to enable the telecom operator integrate its new services without affecting the existing business. Therefore, telecom operators can provide all their network resources, and the other third-party players can focus on the operation of virtual networks leased from the telecom operator cloud to set up their own dynamic pricing schemes.

Pricing is an important issue in cloud computing. There are several studies about pricing schemes and algorithms for cloud services [22]. We can group them mainly into two categories, namely static pricing and dynamic pricing. In static pricing schemes, prices cannot be changed in a relatively short period, and the telecom operator cloud does not adapt to real-time congestion conditions, and there is no usage incentives. By contrast, dynamic pricing can adjust the prices in nearly real-time via MNaaS technique in response to the observed network conditions [22]. In mobile cloud environments considered in this research, end-users have the abilities to communicate with TOC in real-time. In addition, end-users can easily control their own usage on the individual devices and applications. Therefore, in this paper, we adopt a dynamic pricing scheme.

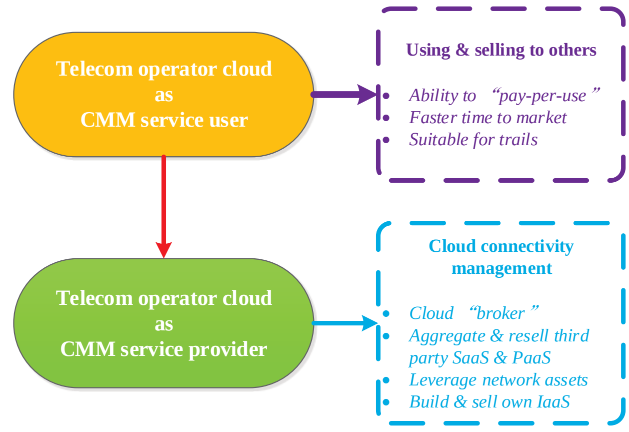

Fig. 1. Telecom operator cloud.

B. Heterogeneous Wireless Networks with Small Cells

A promising approach to improve the network performance in terms of capacity and energy efficiency is to use a multi-tier or hierarchical structure with small cells [23]. This architecture represents a novel wireless networking paradigm based on the idea of deploying short-range, low-power, and low-cost base stations, which operate in conjunction with macrocells [24].

Telecom operators have to deploy multiple wireless access networks with different technologies nowadays to meet the growing demands of users in regards to bandwidth and mobility. HWNs is one of the solutions to make the handover between these technologies more transparent for the end-users, and to facilitate a more seamless experience for roaming. One of the key features in HWNs is to always provide the best data service and network connectivity to the end-users via different available wireless access networks when subjected to different interworking scenarios appearing throughout the time of handover and roaming procedures.

Fig. 2 shows HWNs model, in which there is one *macrocell base station* (MBS) and multiple *small cell base stations* (SBSs). Each SBS is connected to the MBS via a broadband connection such as a cable modem or *digital subscriber line* (DSL). The MBS and the small cells have a cognitive capability

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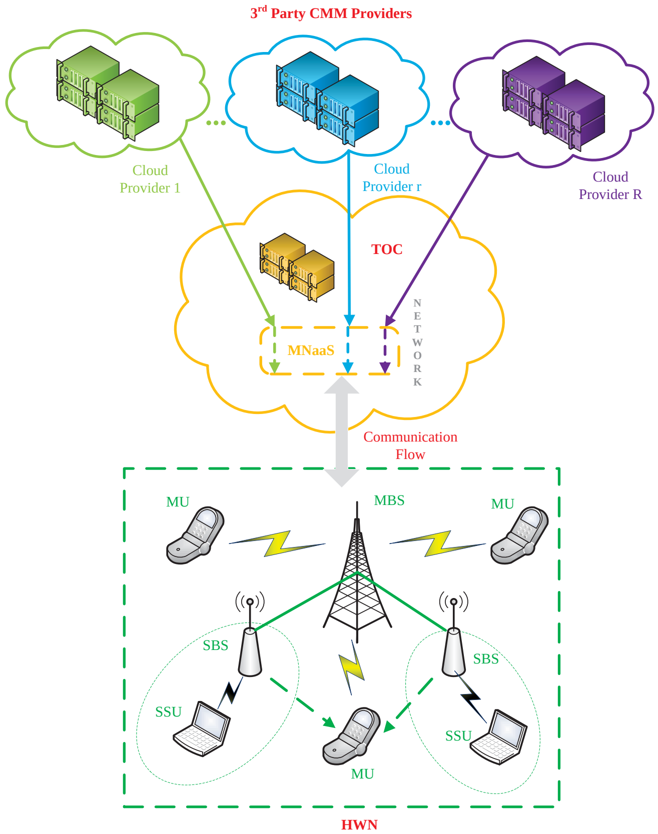

Fig. 2. A mobile cloud computing system with telecom operator cloud.

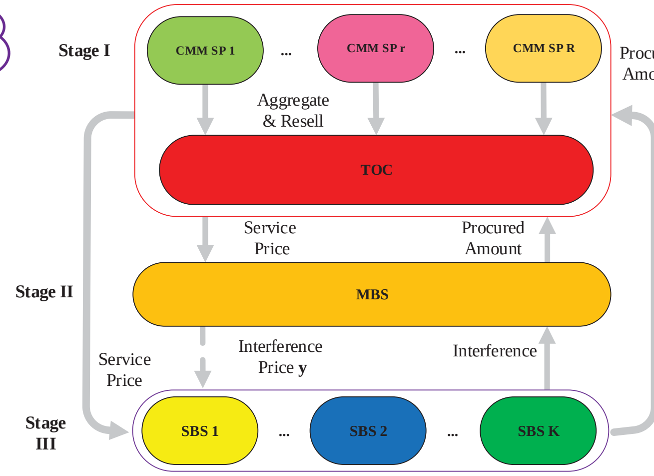

Fig. 3. Three-stage Stackelberg game model.

TABLE II
NOTATIONS

Notation	Description
x_r	Cloud media service price
c_r	Cost of CMM SP r
y	Interference price
s_m	Amount of service (MBS purchased from CMM SP r)
s_k	Amount of service (SBS purchased from CMM SP r)
B_{rm}	Whether MBS m purchases service from provider r
B_{rk}	Whether SBS k purchases service from provider r
W	Transmission bandwidth of each channel
h_m	Channel gain between MBS and MU m
h_k	Channel gain between SBS k and SSU k
p_m	Transmit power of MBS to MU m
p_k	Transmit power of SBS k
σ_m	AWGN with zero mean and unit variation
σ_k	AWGN with zero mean and unit variation
g_{km}	Channel gain between the small cell k and the MU m
α and β	Tradeoff among the transmission rate, service cost and interference cost
μ_k and λ_k	Tradeoff among the transmission rate, service cost and interference cost

and can sense the channel state information. There are multiple *macrocell users* (MUs) and *Orthogonal frequency-division multiple access* (OFDMA) technology is used. We assume that each small cell serves only one *small cell secondary user* (SSU) [1]. All the small cells are deploy sparsely to avoid mutual interference. The macrocell and the small cells are considered to be perfectly synchronized and the whole system is operated in a time-slotted manner.

As we consider that the macrocell and the small cell share the spectrum in the mobile network, there will be cross-tier interference between them, which will significantly affect the performance. To guarantee the QoS of end-users and reduce this effect, we introduce an interference price charged by MBS to protect itself from the SSU. According to this price and the channel condition, the small cell will change the sub-bands they access and their transmission power.

C. A Game-Theoretic Approach

In this paper, the problem of joint operations of telecom operator cloud and heterogeneous wireless network is formulated as a three-stage Stackelberg game, which is shown in Fig. 3. The main notations used in this paper are listed in Table II. Each third party CMM SP is a leader that provides a cloud media service price x_r to the macrocell and small cells. All the MUs and the SSUs, which are playing the part of followers, decide the amount of media service from the CMM SPs to purchase according to the service price x_r in Stage I of the game. We measure the media service in *bits per second* (bps) to meet the end-user's media demand by guaranteeing performance. In Stage II, firstly, the MBS decides as a follower from which CMM SP to buy the media service, then it acts as a leader to offer an interference price y to the small cells to reduce the interference effect. In Stage III, each SBS decides which CMM SP to buy the service from, based upon the service price x_r and the interference price y charged by MBS.

a) Cloud Level Game: For the CMM SPs, we assume that each of them is selfish and independent of gaining the revenue as much as possible. Each CMM SP's profit depends on its own

[1]In practical networks, there are up to 4 users per small cell. However, they use different channels. So the proposed scheme can be easily extended to the practical case.

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resource cost and the service price, as well as the price offered by the other SPs. For an arbitrary provider, we can formulate the utility function $U_r(x)$ below,

$$U_r(x) = (x_r - c_r)\left(s_m B_{rm} + \sum_{k=1}^{K} s_k B_{rk}\right). \quad (1)$$

The price vector **x** ($\mathbf{x} = \{x_1, \ldots, x_r, \ldots, x_R\}$) denotes the prices offered by the SPs, and c_r denotes the cost of the CMM SP (e.g., the server cost, infrastructure cost, power usage, and the networking cost) [25]. The set $\boldsymbol{R}$ ($\boldsymbol{R} = \{1, \ldots, r, \ldots, R\}$) denotes the number of the game players - CMM SPs. K is the number of SBSs. We assume that the cost of each CMM SP is different from the others. s_m and s_k denote MBS m and SBS k purchase the amount of CMM service from CMM SP r. $B_{rm} \in \{0,1\}$ and $B_{rk} \in \{0,1\}$ denote whether MBS m and SBS k purchase the service from the SP r or not, where 1 means yes and 0 means no. The SP needs to find an optimal price to the MBS and SBSs in order to maximize its own revenue, which can be solved by the following problem:

$$\max_{x_r \geq c_r} U_r(x). \quad (2)$$

b) MBS Level Game and SBS Level Game: We need to consider both transmission data rate and computing resource consumption. To these ends, the MBS needs to limit the interference from small cells by offering the interference price y. We have the MBS's net utility function defined below,

$$\begin{aligned} &U_m(s_m, p_m, y) \\ &= \min\left(W \log_2\left(1 + \frac{p_m h_m^2}{\sigma_m^2 + \sum_{k=1}^{K} g_{km}^2 p_k}\right), s_m\right) \\ &\quad - \alpha x_r s_m B_{rm} + \beta y \sum_{k=1}^{K} g_{km}^2 p_k. \end{aligned} \quad (3)$$

W denotes the transmission bandwidth of each channel, h_m denotes the channel gain from MBS m to its scheduled macrocell user including the path-loss and the small-scale fading process, p_m denotes the transmit power of MBS m to its scheduled MU, here we assume this power is fixed. σ_m is AWGN with zero mean and unit variation, and g_{km} denotes the channel gain between the small cell k and the scheduled MU served by MBS m including the path-loss and the small-scale fading process, and y denotes the interference price.

The $\min$ operator means that we should consider the smaller value of either demand or supply. We assume that we do not know the size of the capacity of MBS m and the amount of CMM service requested from the end-user scheduled by MBS m. If the size of the requirements is greater than the capacity of MBS m, we have to choose the capacity to adapt the real environment, and vice versa.

α and β denote weights, which represent the tradeoff among the transmission rate, service cost and interference revenue. Moreover, to make all the sub-formulas keep the operator symbols unchanged, we assume that α and β are greater than 0. The optimization problem for the MBS can be formulated as,

$$\max_{s_m > 0, y \geq 0} U_m(s_m, y). \quad (4)$$

The net utility function for an arbitrary SBS k ($k \in \{1 \ldots K\}$) can be defined below,

$$\begin{aligned} U_k(s_k, p_k) = &\min\left(W \log_2\left(1 + \frac{p_k h_k^2}{\sigma_k^2}\right), s_k\right) \\ &- \mu_k(x_r s_k B_{rk}) - \lambda_k y g_{km}^2 p_k. \end{aligned} \quad (5)$$

The symbol h_k denotes the channel gain between SBS k and SSU k, including the path-loss and the small-scale fading process, p_k denotes the transmit power of SBS k, and σ_k is AWGN. μ_k and λ_k denote weights, which represent the tradeoff among the transmission rate, service cost and interference cost. Moreover, μ_k and λ_k are greater than 0.

The $\min$ operator means that we should consider the smaller value of either demand or supply. We assume that we do not know the size of the capacity of SBS k and the amount of CMM service requested from the end-user scheduled by SBS k. If the size of the requirements is greater than the capacity of the SBS k, we have to choose the capacity to adapt the real environment, and vice versa.

The optimization problem for an arbitrary small cell k can be formulated as,

$$\max_{s_k > 0, p_k \geq 0} U_k(s_k, p_k). \quad (6)$$

III. Three-Stage Game Analysis

In this section, we analyze the proposed three-stage Stackelberg game. Then we obtain the equilibrium to this game. Based on the description of the system, we know that each strategy will affect the others. Hence, we will use a backward induction method to solve this game.

A. SBS level Game Analysis

For maximizing the utility function of SBSs, each SBS will choose a proper CMM SP to purchase the CMM service according to the service price x_r, and the interference price y charged by MBS. For an arbitrary SBS k, its utility function will be defined in two cases: (1) $W \log_2\left(1 + \frac{p_k h_k^2}{\sigma_k^2}\right) \leq s_k$; (2) $W \log_2\left(1 + \frac{p_k h_k^2}{\sigma_k^2}\right) > s_k$. The first case is the most common condition in real mobile cloud computing environments. In the most cases, the transmission rate of the CMM SP is larger than the transmission rate in the sub-band.

For the first case, we can obtain the utility function as:

$$\begin{aligned} U_k(s_k, p_k) = &W \log_2\left(1 + \frac{p_k h_k^2}{\sigma_k^2}\right) \\ &- \mu_k x_r s_k B_{rk} - \lambda_k y g_{km}^2 p_k. \end{aligned} \quad (7)$$

When $1 - \mu_k x_r B_{rk} > 0$, in order to maximize U_k, we can use the decomposition theory. We decompose the optimization problem into two sub optimization problems, fix s_k then make p_k^* to be optimum to obtain the optimal s_k^*. So, its utility

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function is a concave function of p_k based on the definition (7), since

$$\frac{\partial^2 U_k}{\partial {p_k}^2} = -\frac{W {h_k}^4 (1-\mu_k x_r B_{rk})}{\ln 2 (p_k {h_k}^2 + {\sigma_k}^2)} < 0. \tag{8}$$

Therefore, we can obtain the optimal power allocation strategy p_k^* below:

$$p_k^* = \left[\frac{W(1-\mu_k x_r B_{rk})}{\ln 2 \lambda_k y g_{km}^2} - \frac{\sigma_k^2}{h_k^2} \right]^+ . \tag{9}$$

Because the function of s_k is monotonic decreasing, then we know that it will achieve the maximum when s_k takes the minimum, that is,

$$\begin{aligned} s_k^* =& W \log_2 (1 + \frac{p_k^* h_k^2}{\sigma_k^2}) \\ =& \left[W \log_2 \left(\frac{h_k^2 W (1-\mu_k x_r B_{rk})}{\ln 2 \lambda_k y g_{km}^2 \sigma_k^2} \right) \right]^+ . \end{aligned} \tag{10}$$

When $1-\mu_k x_r B_{rk} < 0$, the utility function of p_k is a convex function, then we can obtain the minimum of the function as below,

$$p_k = \left[\frac{W(1-\mu_k x_r B_{rk})}{\ln 2 \lambda_k y g_{km}^2} - \frac{\sigma_k^2}{h_k^2} \right]^+ , \tag{11}$$

Hence, s_k can achieve optimal when $p_k = 0$. The utility function can be a monotonic decreasing function with s_k: $U_k(s_k, p_k) = -\mu_k x_r s_k B_{rk}$. So when $s_k^* = 0$, the function will get the maximum value, but this situation makes no sense in the real environment. Since an SSU applies for service from a mobile provider, its transmission rate should retain above zero.

For the second case, we can obtain the utility function of s_k as,

$$\begin{aligned} U_k(s_k) =& s_k - \mu_k (x_r s_k B_{rk}) - \lambda_k y g_{km}^2 p_k \\ =& (1-\mu_k x_r B_{rk}) s_k - \lambda_k y g_{km}^2 p_k . \end{aligned} \tag{12}$$

When $1-\mu_k x_r B_{rk} > 0$, $U_k(s_k)$ is a monotonic increasing function. To obtain the maximum value from this function, we know that $s_k^* = [W \log_2 (1 + \frac{p_k^* h_k^2}{\sigma_k^2})]^+$. Here, we will keep the transmission power p_k unchanged to make s_k achieve the optimal value.

When $1-\mu_k x_r B_{rk} < 0$, $U_k(s_k)$ is a monotonic decreasing function. So when $s_k^* = 0$, the function will get the maximum value, but this situation makes no sense in the real environment as well due to the reasons described above.

B. MBS Level Game Analysis

The MBS, in order to maximize its utility function, will firstly as a follower choose a proper CMM SP to purchase the CMM service based on the CMM service price. Then it acts as a leader to offer an interference price to the SBSs. We will obtain U_m, a function of transmission rate s_m and interference price y. Here, we consider the most common situation and also use the decomposition method to solve this problem. Firstly we keep the interference price y unchanged to get the optimal s_m^* to maximize U_m, and then we obtain the desirable value of y. We assume that,

$$\begin{aligned} I_m =& \sigma_m^2 + \sum_{k=1}^{K} g_{km}^2 p_k^* \\ =& \sigma_m^2 + \sum_{k=1}^{K} g_{km}^2 \left[\frac{W(1-\mu_k x_r B_{rk})}{\ln 2 \lambda_k y g_{km}^2} - \frac{\sigma_k^2}{h_k^2} \right]^+ . \end{aligned} \tag{13}$$

In the MBS level, it will choose the CMM SP with the lowest service price x_r^*. For MBS m, its utility function will be defined in two cases: (1) $W \log_2 \left(1 + \frac{p_m h_m^2}{\sigma_m^2 + \sum_{k=1}^{K} g_{km}^2 p_k} \right) \leq s_m$; (2) $W \log_2 \left(1 + \frac{p_m h_m^2}{\sigma_m^2 + \sum_{k=1}^{K} g_{km}^2 p_k} \right) > s_m$.

For the first case, this situation is the most common condition in real mobile cloud computing environments. In most scenarios, the transmission rate of the CMM SP is larger than the sub-band transmission rate.

For the second case, it is a rare scene, but we cannot neglect it.

We obtain the utility function in the first case,

$$\begin{aligned} U_m(s_m, y) =& W \log_2 \left(1 + \frac{p_m h_m^2}{I_m} \right) \\ & - \alpha x_r^* s_m + \beta y \sum_{k=1}^{K} g_{km}^2 p_k^* . \end{aligned} \tag{14}$$

Because $\alpha, x_r \geqslant 0$, the utility function is monotonic decreasing of s_m, when s_m chooses the minimum value, the function will achieve the maximum value. Then we can obtain the optimum of

$$s_m^* = \left[W \log_2 \left(1 + \frac{p_m h_m^2}{\sigma_m^2 + \sum\limits_{k=1}^{K} g_{km}^2 \left(\frac{W(1-\mu_k x_r B_{rk})}{\ln 2 \lambda_k y g_{km}^2} - \frac{\sigma_k^2}{h_k^2} \right)} \right) \right]^+ . \tag{15}$$

And the utility function in the second condition is shown below,

$$U_m(s_m, y) = s_m (1 - \alpha {x_r}^*) + \beta y \sum_{k=1}^{K} g_{km}^2 p_k . \tag{16}$$

When $1 - \alpha {x_r}^* > 0$, to maximize the function, the value of s_m will be

$$s_m^* = \left[W \log_2 \left(1 + \frac{p_m h_m^2}{\sigma_m^2 + \sum\limits_{k=1}^{K} g_{km}^2 p_k *} \right) \right]^+ . \tag{17}$$

When $1 - \alpha {x_r}^* \leqslant 0$, it is a monotonic decreasing function. To obtain the maximum of the function, $s_m = 0$, but this situation makes no sense in the real environment. Since an MU applies for service from a mobile provider, its transmission rate should retain above zero. And we have discussed that only in the condition of $1 - \mu_k x_r B_{rk} > 0$, parameter p_k^* can get the optimal value. Hence, we will continue the steps in the above default condition.

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Due to the piece nature of interference price y, we present an indicator function,

$$D_k = \begin{cases} 1, & y < \frac{h_k^2 W(1-\mu_k x_r B_{rk})}{\ln 2\lambda_k \sigma_k^2 g_{km}^2}, \forall k, \\ 0, & \text{otherwise}. \end{cases} \tag{18}$$

We can rewrite U_m which is shown as (19).

Because U_m is a piecewise function of y, we cannot solve it by derivation directly. When the value of D_k is given, we can obtain the function U_m as a continuous differentiable function. We let N_k be,

$$N_k = \frac{h_k^2 W(1-\mu_k x_r B_{rk})}{\ln 2\lambda_k \sigma_k^2 g_{km}^2}, \forall k. \tag{20}$$

After having sorted all N_k in ascending order, like $N_1 \leqslant N_2 \leqslant \ldots \leqslant N_k$, and hence, we get K intervals $[0, N_1), (N_2, N_3), \ldots, (N_{k-1}, N_k)$. Then, by piecewise differentiating of function U_m in each interval, we can easily obtain it is concave except most N non-differentiable points by analogizing as below,

$$\begin{aligned}\frac{\partial U_m(y)}{\partial y} =& (1-\alpha x_r^*)\sum_{k=1}^{K}\frac{W^2 p_m h_m^2 (1-\mu_k x_r B_{rk})}{(\ln 2)^2 y^2 I_m(y)(p_m h_m^2 + I_m(y))\lambda_k} \\ & -\beta\sum_{k=1}^{K} g_{km}^2 \frac{\sigma_k^2}{h_k^2}.\end{aligned} \tag{21}$$

Based on (21), we know $\frac{\partial^2 U_m(y)}{\partial y^2}$ is shown as (22).

$$\begin{aligned}\frac{\partial^2 U_m(y)}{\partial y^2} =& -(1-\alpha x_r^*)\sum_{k=1}^{K}\frac{W^2 p_m h_m^2 (1-\mu_k x_r B_{rk})}{(\ln 2)^2 \lambda_k y^3 (p_m h_m^2 I_m + I_m^2)^2} \\ & \left(p_m h_m^2 I_m + (p_m h_m^2 + 2I_m)\left(\sigma_m^2 - \sum_{k=1}^{K} g_{km}^2 \frac{\sigma_k^2}{h_k^2}\right)\right) < 0.\end{aligned} \tag{22}$$

Therefore, $U_m(y)$ is a concave function, and then this noncooperative interference price game is a concave game. According to the formulation (19), this game exists at least one Nash equilibrium, which can be obtained as follows.

Then, from (22), we can know that $\frac{\partial U_m(y)}{\partial y}$ is a strictly monotonic decreasing function of y.

Obviously, we find that,

$$\lim_{y\to\infty} I_m = \sigma_m^2 - \sum_{k=1}^{K} g_{km}^2 \frac{\sigma_k^2}{h_k^2} > 0, \tag{23}$$

then,

$$\lim_{y\to\infty} \frac{\partial U_m(y)}{\partial y} = -\beta\sum_{k=1}^{K} g_{km}^2 \frac{\sigma_k^2}{h_k^2} < 0. \tag{24}$$

For the case of $y \to 0$ we can obtain that,

$$\lim_{y\to 0} \frac{\partial U_m(y)}{\partial y} = \infty > 0. \tag{25}$$

Therefore, the utility function U_m is firstly increasing with the interference price y, then at the certain point begins to decrease with y. So this utility function is a concave function without some non-differentiable points N_k, $k \in (1, \ldots, K)$. That is, this non-cooperative competitive game exists at least one Nash equilibrium. We can find this optimal value of y in each interval by multiple methods (e.g., a binary search algorithm and a gradient based algorithm).

C. CMM SP Level Game Analysis

The Bertrand game is a popular tool to model competition among firms (sellers) that set prices and their customers (buyers) that choose quantities at the price set. The Bertrand game has been successfully applied in cognitive radio networks, and other areas [26]. In our scheme, we use the Bertrand game to model the competition among CMM SPs. We assume that each CMM SP is independent, acts selfishly, and the target is to gain as much revenue as possible. If the CMM SPs act noncooperatively, it will lead a monopoly situation. All the CMM SPs are eager to set their service prices as the same, and try to maximize their own profits. The profit of an arbitrary CMM SP r depends not only on the service price x_r and the cost c_r, but also on the service prices x_{-r} offered by the other cloud SPs.

Each CMM SP decides its action independently and simultaneously. And the CMM SP with the lowest price will occupy the entire service market. Hence, every CMM SP tries to reduce its service price until hitting the bottom with zero profit. As discussed in Section II, the set of the game players is $\mathbf{R} = \{1, \ldots, r, \ldots, \mathcal{R}\}$, the strategy set is x_r, and the payoff function of the CMM SP is U_r. The NE of this problem gives the set of prices such that neither CMM SP can increase its net profit U_r by unilaterally changing the price. Without loss of generality, let the cost set in an ascending order $c_1 < c_2 < \ldots < c_{\mathcal{R}}$.

Proposition 1. *The NE of the proposed homogeneous Bertrand game with multiple CMM SPs is shown as below,*

$$x^* = \{x_1^*, c_2, c_3, \ldots, c_{\mathcal{R}}\}, \tag{26}$$

where x_1^* denotes the price strategy of the first CMM SP at the Nash-equilibrium, which can be formulated as,

$$x_1^* = \arg\max_{c_1 \le x_1 < c_2} U_1^M(x_1), \tag{27}$$

where U_1^M is the utility function of provider 1 when it supplies the whole market, shown as (28).

Proof: By observing the (19), we know that U_1^M is the utility function of x_1. Assume in a Bertrand condition, there are only two CMM SPs, provider 1 and provider 2 in the competition. The costs are defined as c_1 and c_2, and we let $c_1 < c_2$. According to the assumption about the Bertrand competition model, both providers have the incentives to reduce their service prices down to their own margin cost to undercut the other and capture the whole market to almost double its profit. That is to say, if one provider sets its price equals to the marginal cost, and the other provider tries to raise its service price over the cost, then it will earn nothing. Since all the end-users would purchase the service from the provider that is still setting the competitive price. If one provider has a minor

$$U_m(y) = (1-\alpha x_r^*) W \log_2 \left(1 + \frac{p_m h_m^2}{\sigma_m^2 + \sum_{k=1}^{K} g_{km}^2 D_k \left(\frac{W(1-\mu_k x_r B_{rk})}{\ln 2 \lambda_k y g_{km}^2} - \frac{\sigma_k^2}{h_k^2} \right)} \right) + \beta y \sum_{k=1}^{K} g_{km}^2 D_k \left(\frac{W(1-\mu_k x_r B_{rk})}{\ln 2 \lambda_k y g_{km}^2} - \frac{\sigma_k^2}{h_k^2} \right). \tag{19}$$

$$U_1^M = (x_1 - c_1) \left(B_{rm} \left[W \log_2 \left(1 + \frac{p_m h_m^2}{I_m} \right) \right]^+ + \sum_{k=1}^{K} B_{rk} \left[W \log_2 \left(\frac{h_k^2 W (1-\mu_k x_1 B_{rk})}{\ln 2 \lambda_k y g_{km}^2 \sigma_k^2} \right) \right]^+ \right). \tag{28}$$

average cost, it will charge the highest price that is lower than the average cost of the other one and takes all the business. So provider 1 has the incentive to make its price between the set of $[c_1, c_2)$ to maximize its own profit. ■

Though it is irrational to set the price below the marginal cost, the two CMM SPs would make the prices lower than their own monopoly price. If provider 2 presents a high enough price, provider 1 can definitely ignore the affection of provider 2 and set its price by the optimal monopoly price.

Due to the piecewise property about x_1, to maximize the utility function U_1^M, for all $k \in \{1, 2, \ldots, K\}$, we introduce the indicator function as below,

$$V_m = \begin{cases} 1, & x_1 < \frac{W - \ln 2\lambda_k y \left[\frac{1}{K}(p_m h_m^2 - \sigma_m^2) + g_{km}^2 \frac{\sigma_k^2}{h_k^2} \right]}{W \mu_k B_{rk}}, \forall k, \\ 0, & \text{otherwise}, \end{cases} \tag{29}$$

$$V_k = \begin{cases} 1, & x_1 < \frac{W h_k^2 - \ln 2 \lambda_k y g_{km}^2 \sigma_k^2}{W h_k^2 \mu_k B_{rk}}, \forall k, \\ 0, & \text{otherwise}. \end{cases} \tag{30}$$

Thus by substituting (29) and (30) into (28), we can know that the utility function is a piecewise function about x_1 due to those indicator functions V_m and V_k, which cannot obtain the derivative directly to solve x_1. However, if determined V_m and V_k, we still can get a continue differentiable function.

Therefore, we let,

$$F_m = \frac{W - \ln 2\lambda_k y \left[\frac{1}{K}(p_m h_m^2 - \sigma_m^2) + g_{km}^2 \frac{\sigma_k^2}{h_k^2} \right]}{W \mu_k B_{rk}}, \tag{31}$$

$$F_k = \frac{W h_k^2 - \ln 2 \lambda_k y g_{km}^2 \sigma_k^2}{W h_k^2 \mu_k B_{rk}}. \tag{32}$$

Then sort all $F_1, F_2, \ldots, F_m$, and F_k in an ascending order $F_1 \leq F_2 \leq \ldots F_m \leq F_k$, without loss of generality. Hence we can get K intervals, $[0, F_1), (F_2, F_3), \ldots, (F_m, F_k)$. By piecewise differentiating of the utility function in the first interval, we assume that $0 < x_1 < F_1$, the second derivative of $U_1^M(x_1)$ is shown as (33).

We have known the definition of I_m from (13), for substituting it into (33), we can obtain that the second derivative $\frac{\partial^2 U_1^M(x_1)}{\partial {x_1}^2}$ is less than 0, which means that $\frac{\partial U_1^M(x_1)}{\partial x_1}$ is a monotonic decreasing function of x_1. Obviously, we obtain function (34). From (34), we have,

$$\lim_{x_1 \to 0} \frac{\partial U_1^M(x_1)}{\partial x_1} > 0. \tag{35}$$

When $x \to F_1$, we can get two cases as follows:

$$\begin{aligned} &(1) \lim_{x \to F_1} \frac{\partial U_1^M(x_1)}{\partial x_1} \geq 0; \\ &(2) \lim_{x \to F_1} \frac{\partial U_1^M(x_1)}{\partial x_1} < 0. \end{aligned} \tag{36}$$

For the first case, the utility U_1^M is strictly monotonic increasing about x_1 at the initial interval $[0, F_1)$. Therefore, for the second case, we know that the utility function U_1^M firstly climbs up with x_1. After reaching the optimal point, it drops down with x_1. Hence, the utility function U_1^M is a concave function at the first interval, and it is easily to prove the utility function U_1^M is the concave function at the other intervals. That is to say, for $x_1 < F_k$, the utility function is a concave function without the most K non-differentiable points at $F_1, F_2, \ldots, F_m$, and F_k. We can solve x_1 at each interval by many methods (e.g., a binary search algorithm and a gradient based algorithm).

D. Service Allocation Iteration Algorithm

It is important to investigate the uniqueness and the existence of the Stackelberg equilibrium. In the duopoly case, the convexity of the follower's reaction function is essential for uniqueness of the Stackelberg equilibrium [27]. Hence, we will prove that for our model of Stackelberg game exists an unique equilibrium.

Theorem 1. *The unique Nash equilibrium exists in the proposed Stackelberg game.*

Proof: In our Stackelberg game model, each stage has its flawless equilibrium in a Nash equilibrium respectively: the service price strategies x^* in (26) offered by the CMM SPs, the service allocation strategy s_m^*, the interference price, and the service allocation strategy s_k^* in (10). Because we have proven that each stage exists a perfect equilibrium in a Nash equilibrium, the Nash equilibrium of the proposed Stackelberg game model exists. We also know that the subgame perfect equilibrium in each stage is unique. Therefore, the total Stackelberg Nash equilibrium is unique. ■

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$$\begin{aligned}\frac{\partial^2 U_1^M(x_1)}{\partial {x_1}^2} =& 2\left\{\sum_{k=1}^{K}\frac{W^2\mu_k B_{rk}B_{rm}p_m h_m^2}{(\ln 2)^2\lambda_k y I_m(p_m h_m^2+I_m)}-\sum_{k=1}^{K}\frac{B_{rk}^2 W\mu_k}{\ln 2(1-\mu_k x_1 B_{rk})}\right\}\\ &+(x_1-c_1)\left\{\sum_{k=1}^{K}\frac{W^3\mu_k^2 B_{rk}^2 B_{rm}p_m h_m^2(p_m h_m^2+2I_m)}{(\ln 2)^3\lambda_k y I_m^2(p_m h_m^2+I_m)^2}-\sum_{k=1}^{K}\frac{W B_{rk}^3\mu_k^2}{\ln 2(1-\mu_k x_1 B_{rk})^2}\right\}.\end{aligned} \tag{33}$$

$$\begin{aligned}\frac{\partial U_1^M(x_1)}{\partial x_1} =& B_{rm}W\log_2\left(1+\frac{p_m h_m^2}{I_m}\right)+\sum_{k=1}^{K}B_{rk}W\log_2\frac{W h_k^2(1-\mu_k x_1 B_{rk})}{\ln 2\lambda_k y g_{km}^2\sigma_k^2}\\ &+(x_1-c_1)\left\{\sum_{k=1}^{K}\frac{W^2\mu_k B_{rk}B_{rm}p_m h_m^2}{(\ln 2)^2\lambda_k y I_m(p_m h_m^2+I_m)}-\sum_{k=1}^{K}\frac{B_{rk}^2 W\mu_k}{\ln 2(1-\mu_k x_1 B_{rk})}\right\}.\end{aligned} \tag{34}$$

Algorithm 1 Service Allocation Iteration Algorithm

Initialization:

Initialize the cloud computing service prices, i.e., for each CMM SP r, randomly offers the service price x_r, where $x_r \geq 0$.

Repeat Iterations:

a) The MBS offers the interference price y to the SBSs and decides which CMM SP to purchase the service from based upon x_r and the amount of computing service.

b) Each SBS performs its service allocation.

c) CMM SPs update their prices:

$x_r[t] = \mathcal{B}_r(x_{-r}[t-1])$

d) *Until:* $\|x[t]-x[t-1]\|/\|x[t-1]\| \leq \varepsilon$ or reach the preset maximum number of iterations.

End Iteration

To get the Nash equilibrium of the three-stage Stackelberg game, we use a backward induction to solve the problem and present the service iteration algorithm.

In the above method, we defined the other CMM SPs' strategies as $x_{-r} = (x_1, x_2, \dots, x_{r-1}, x_{r+1}, \dots, x_R)$. When x_{-r} is given at iteration $t-1$, we present the best response function $\mathcal{B}_r(x_{-r}[t-1])$ of CMM SP x_r at the iteration t to maximize its total revenue. The condition $\|x[t]-x[t-1]\|/\|x[t-1]\| \leq \varepsilon$ is the stop criteria. In the proposed algorithm, the MBS decides the interference price y offering to SBSs and the amount of service purchased from the CMM SPs based on the service price x_r. The SBS then allocates the power. The algorithm will stop until the service price x_r converges.

In practice, the proposed iterative algorithm to obatin the threee-stage Stackelberg game equilibrium can be implemented as follows,

1) The CMM SPs randomly offer the CMM service price to the MBS and SBSs.
2) The MBS receives the channel state information from the SBSs and the MUs.
3) The MBS decides which provider to purchase the service from and the interference price offering to the SBSs.
4) The SBSs perform their power allocation.
5) The CMM SPs update their prices and repeat steps 2, 3 and 4 until the prices converge.

To ensure the convergence to the NE for the Algorithm 1, some sufficient conditions have been proposed in the existing literature. The convergence condition was first provided by [28] for the two-user case and extended for the N-users in [29]. Moreover, the conditions of the convergence were further proved in [30], [31]. However, as the pricing factor x_r is recalculated in every iteration, the algorithm is actually a time-varying over iterations. Thus the fixed-point theorem proposed in [30], [31] may not be applied here. The convergence proof under a time-varying mapping function is a challenging problem and will be left for the future work. Nevertheless, convergence has always been observed in our simulations.

IV. Simulation Results and Discussions

In this section, we use computer simulations to evaluate the performance of the proposed scheme. The main system parameters in HWNs are adopted from 3GPP [32], as listed in Table III. In the simulations, we assume that there are 2 CMM SPs. The MUs and small cells are located in the macrocell randomly, and small cells deploy sparsely with each other at $50m$ to $150m$ far from the MBS. Following [32], we set the path loss between SSU and MBS as $15.3 + 37.6\log_{10}(D_{ms} + L_{ow})$, and the path loss between SSU and SBS as $46.86 + 20\log_{10}(D_{ss} + L_{iw})$. D_{ms} is the distance between the MBS and the SSU. D_{ss} is the distance between the SBS and the SSU. L_{ow} means the penetration loss of exterior wall, and L_{iw} means the penetration loss of the interior wall. They are set as $20dB$ and $10dB$, respectively. We can also find the parameters of the small scale and shadow fading in [32]. The others are shown as below. The transmission bandwidth W is $5MHz$ in the MBS and the transmission power is fixed as $46dBm$ from [32]. The general parameters are set as, $\mu_k = 0.05$, $\lambda_k = 1$, $\alpha = 0.03$, $\beta = 10$, B_{rk} and $B_{rm} = 1$.

Firstly, we evaluate the performance of the CMM service purchased by BSs with the various lowest prices. Fig. 4 shows that, with the increase of the lowest service price x_r, SBS_1 and SBS_2 have to decrease their transmission rate by performing

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TABLE III
SIMULATION PARAMETERS AND ASSUMPTIONS FOR PERFORMANCE EVALUATIONS

Parameters	Values/Assumptions
Deployment of stand-alone small cells	Randomly deployed at 50m to 150m far from the MBS
Path loss: MBS ↔ SSU	$15.3 + 37.6 \log_{10} D_{ms} + L_{ow}$ [1]
Path loss: SSU ↔ SBS	$46.86 + 20 \log_{10} D_{ss} + L_{iw}$ [2]
Penetration loss of exterior wall L_{ow}	$20dB$
Penetration loss of interior wall L_{iw}	$10dB$
The MBS transmission bandwidth	$5MHz$
MBS TX power	$46dBm$
Number of sub-channel in each BS	50
Diameter of Macro-cell coverage	$1000m$
Diameter of Small cell coverage	$20m$
Minimum distances among stand-alone small cells	$> 5m$

[1] D_{ms} is the distance between the MBS and the SSU
[2] D_{ss} is the distance between the SBS and the SSU

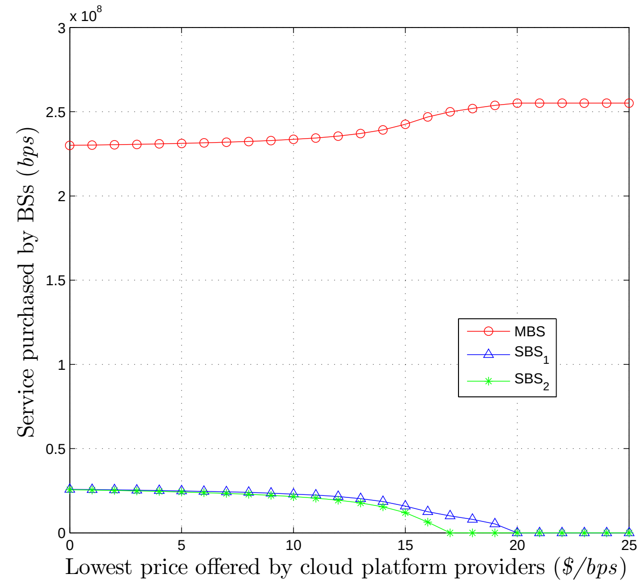

Fig. 4. Service allocation with various lowest prices offered by the CMM service providers.

the energy-efficiency power allocation. Due to the fixed transmission power of the MBS, it performs an increasing trend with x_r^*. The reason is that, by increasing x_r^*, the transmission power of SBS decreases as well, which in turn leads to the decrease of interference between the MBS and the SBS. Hence, the transmission rate of the MBS has the same variation trend with the service price x_r^*. When the service price is too high to afford for the SSUs, the SBSs will lower their transmission rate step by step until stop transmitting anything. Because the SBSs stop their transmission, the SSUs choose another method to receive the CMM service due to the high service prices. The MBS will reach its highest level of the transmission rate shown in Fig. 4. The shape of the curve can change with the parameters. However, the insight remains the same in the figure.

Then we compare the CMM service purchased by one SBS with three different values of x_r^*. Fig. 5 shows that the SBS tries to reduce its interference cost y by decreasing its transmission rate s_k when given the value of service price offered by the CMM SP. Fig. 5 also shows that, in the condition of the same interference price, the lower service price offered by the CMM SPs, the higher transmission rate we can obtain.

We also study the service allocation in the MBS with various service prices offered by the CMM SPs in Fig. 6. The interference between the MBS and SBSs will be reduced by the increasing trend of the service price x_r. That is because the transmission power p_m is fixed in the MBS, the transmission rate of MBS will increase with the service price until it reaches the highest level, then the interference turns to zero. We can find how the value of α effects the shape of the transmission rate s_k in MBS, the smaller the value of α, the higher level of transmission rate we can obtain. As α increases, there is tradeoff among the transmission rate, service cost and interference revenue in the MBS.

Fig. 7 shows that the utility function of SBS is a concave function, which is proven in Subsection III-A. In this figure,

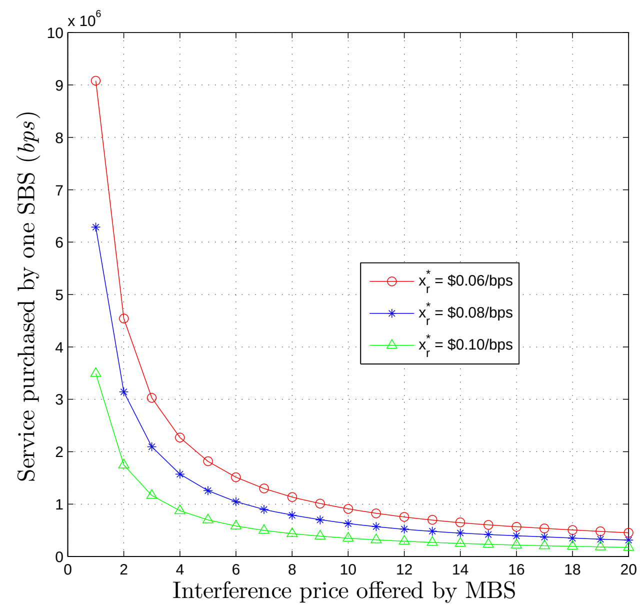

Fig. 5. Service allocation in one SBS with various lowest service prices offered by the MBS.

we know that the utility of SBS, firstly, increases as the power. After it reaches the optimal level, the utility of SBS begins decreasing, because the gain of the transmission rate cannot offset the increase trend of the service cost and interference price. This figure also tells us that the higher the interference price is, the lower utility of SBS will be.

In addition, we find that the transmission rate of the MBS correspondingly increases with the interference price in Fig. 8. That is because the higher interference price forces the SBSs to reduce their transmission power. We also observe that the higher the service price x_r^* is, the lower the interference from the SBSs

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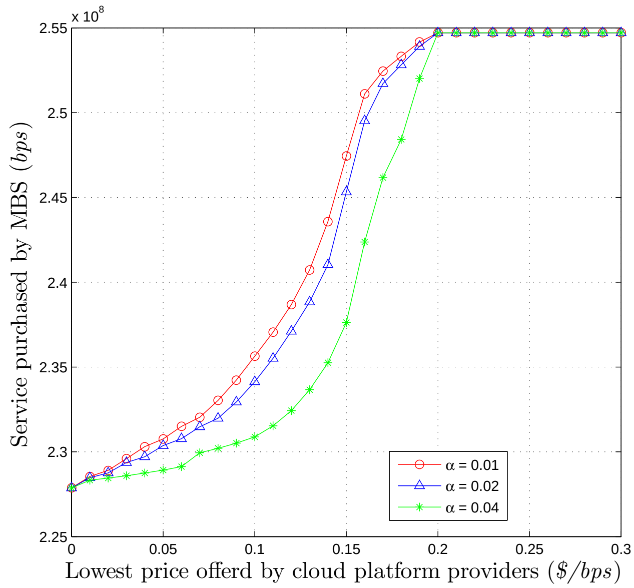

Fig. 6. Service allocation in the MBS with various values of α parameter.

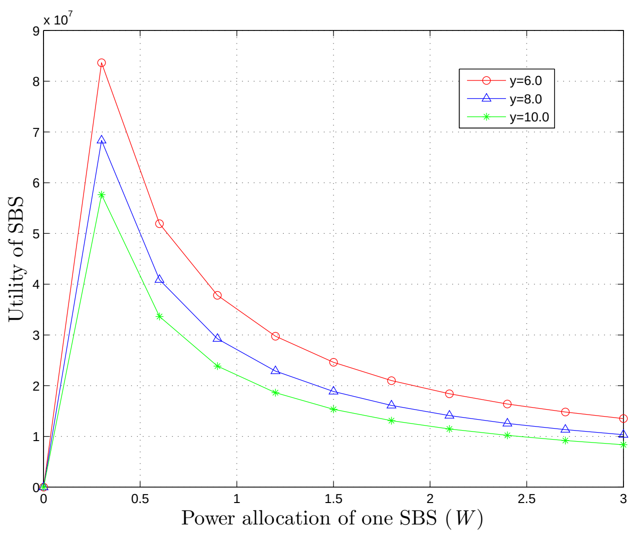

Fig. 7. Utility function of one SBS.

will be. Hence, the transmission rate will reach a higher level in the MBS with a more expensive service price offered by the CMM SPs.

Fig. 9 shows the convergence of the proposed Stackelberg equilibrium iteration algorithm. We evaluate the performance of the CMM service over the iteration steps. From the figure, we can observe the service of the MBS and SBSs can converge after a few iteration steps because of the convergence of the service price x_r^*. Hence, we will obtain the NE by the algorithm.

Then, we study the frame rate (frames per second) and latency of the CMM service in mobile cloud computing environments under two different configurations: the local servers and the remote cloud computing servers over a $100Mb/s$ network with the output viewed through the *virtual network computing* (VNC) protocol, which have the different latency due to the different

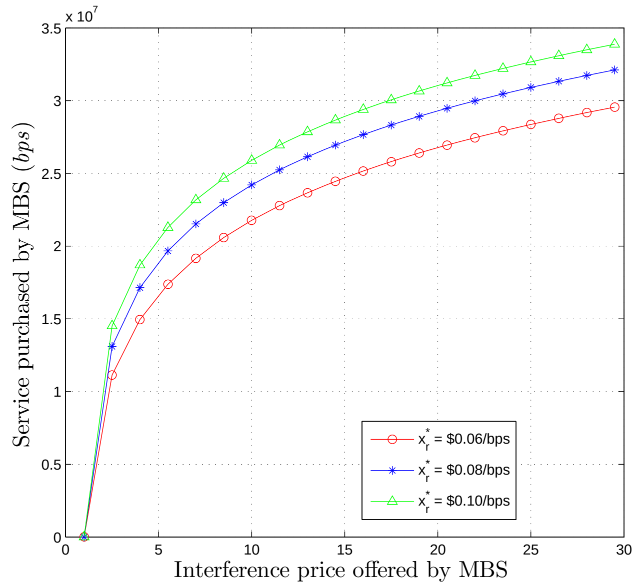

Fig. 8. The performance of CMM service in the MBS.

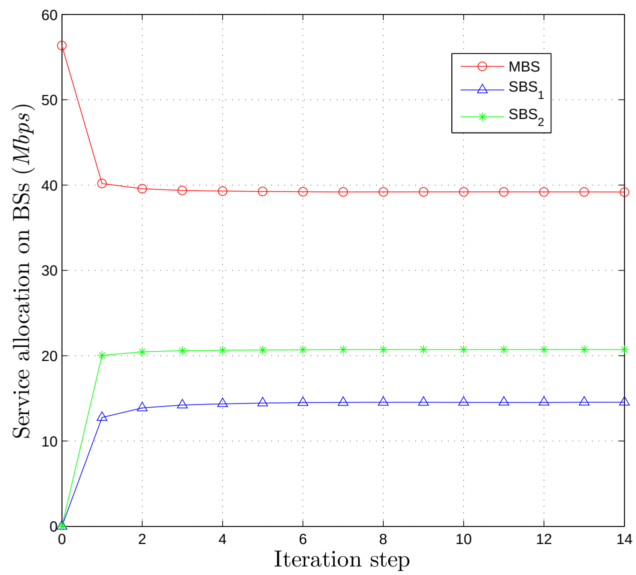

Fig. 9. CMM service iteration step.

distances among the remote servers. Fig. 10 demonstrates that a high frame rate provides the illusion of smoothness to an end-user. Even a modest latency of $33ms$ can cause the frame rate to drop dramatically from that experienced with a local server. Although the VNC protocol strives to keep the frame rate at an acceptable level, it offers sluggish interaction. Hence, the user experience is considerably poorer than that for the local media service interaction.

Finally, the average profit for our proposed scheme compared with an existing scheme [33] is evaluated in Fig. 11. In the existing scheme, multiple services prices are offered to the SUs. This service pricing scheme adopts the non-incentive compatible differentiated type, which can show the theoretical upper bound of the overall profit of this method. The transmission

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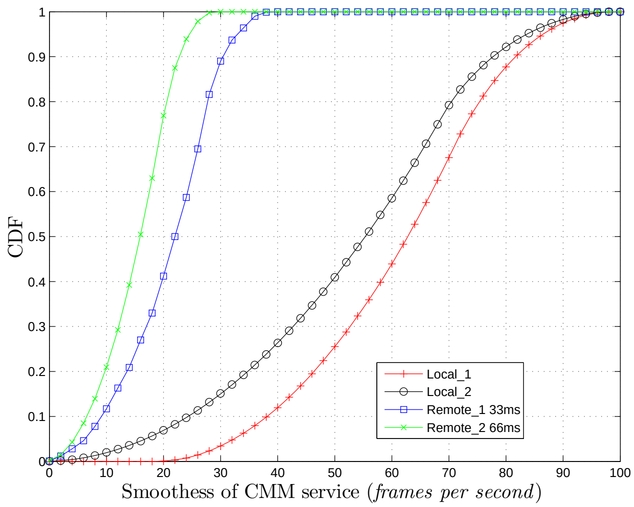

Fig. 10. Network latency hurts interactive performance even with good bandwidth.

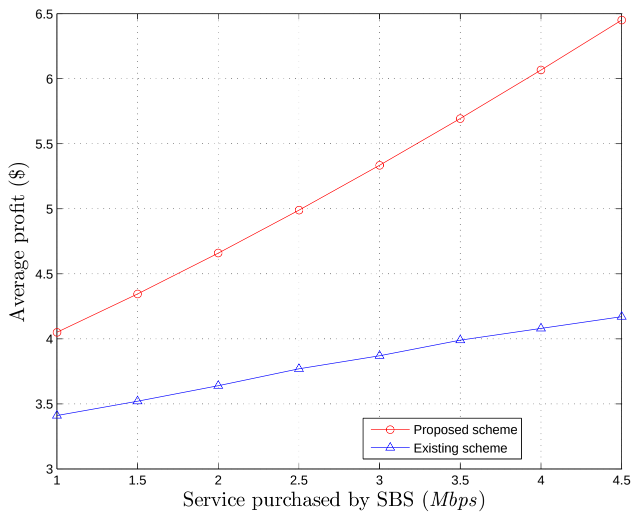

Fig. 11. The average profit versus service allocation on one SBS.

rate is controlled between 1 and $4.5\ Mbps$. We recalculate the profits of the CMM SPs 1000 times at each $0.5\ Mbps$ interval, then obtain the average profits. In the figure, we compare the average profit in our scheme and the existing scheme based on the CMM service purchased by the SBSs. We can find that the profits in the two schemes both have the growing trends with the increasing CMM service purchased by the SBS. Simulation results show that the proposed scheme can gain more profit than the existing one in the same service allocation condition. That is because the existing scheme does not consider the dynamic resource allocation method.

V. Conclusions and Future Work

In this paper, we have studied the issues that arise when jointly considering the operations of cloud and wireless networks in mobile cloud computing environments with the telecom operator cloud. We introduced a system model, which jointly considers the CMM SPs and HWNs with small cells. Multiple CMM SPs offer CMM service prices to the heterogeneous networks. Then the MBS and SBSs adjust the amount of service they procured by performing resource allocation. We formulated the problems of determining a CMM service price, wireless power allocation, and interference management as a three-level Stackelberg game. We also presented an interference price to measure and mitigate the cross-tier interference between the macrocell and small cells. The MBS is allowed to protect its own users by charging the SBSs. At the CMM SP's level, we proposed a homogeneous Bertrand game with asymmetric costs to model the CMM service decisions and used a backward induction method to solve the whole model. Finally, we presented an iteration algorithm to obtain the equilibrium of the Stackelberg Game. Simulation results have been presented to show that the dynamics of cloud operations have a significant impact on the heterogeneous wireless network, and joint optimization is necessary for the operations of cloud and wireless networks. This is due to unique dynamics tied with cloud, CMM services and wireless networks. By jointly optimizing the operations of clouds and wireless networks, the proposed scheme can significantly improve the performance of the mobile cloud computing systems.

Future work is in progress to consider wireless network virtualization, which enables abstraction and sharing of infrastructure and radio spectrum resources, and the overall expenses of deployment and operation can be reduced significantly. It is interesting to integrate wireless network virtualization with our proposed mobile cloud computing framework.

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