Game Theoretic Resource Allocation in Media Cloud With Mobile Social Users

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***Abstract*—Due to the rapid increases in both the population of mobile social users and the demand for quality of experience (QoE), providing mobile social users with satisfied multimedia services has become an important issue. Media cloud has been shown to be an efficient solution to resolve the above issue, by allowing mobile social users connecting it through a group of distributed brokers. However, as the resource in media cloud is limited, how to allocate resource among media cloud, brokers and mobile social users becomes a new challenge. Therefore, in this paper, we propose a game theoretic resource allocation scheme for media cloud to allocate resource to mobile social users though brokers. Firstly, a framework of resource allocation among media cloud, brokers and mobile social users is presented. Media cloud can dynamically determine the price of resource and allocate its resource to brokers. Mobile social user can select his broker to connect media cloud by adjusting the strategy to achieve the maximum revenue, based on the social features in the community. Next, we formulate the interactions among media cloud, brokers and mobile social users by a four-stage Stackelberg game. In addition, through the backward induction method, we propose an iterative algorithm to implement the proposed scheme and obtain the Stackelberg equilibrium. Finally, simulation results show that each player in the game can obtain the optimal strategy where Stackelberg equilibrium exists stably.**

***Index Terms*—Mobile social networks (MSNs), Media cloud, Resource allocation, Stackelberg game.**

I. Introduction

RECENTLY with the rapid advance of mobile social networks (MSNs), more and more mobile social users can obtain various multimedia content by having interaction with each other [1]-[3]. Related studies [4] show that the number of mobile social users keeps increasing and the traffic of mobile data will be nearly tenfold in 2019, compared with that in 2014. Especially, with the popularity of shared data plan in the near future, mobile social users may not only obtain and but also share more multimedia contents with others who have social relations with them. Therefore, providing mobile social users with efficient multimedia services becomes more important than before.

However, to provide mobile social users with satisfied multimedia services, there exist some new problems to be resolved. On one hand, due to the explosive growth of volume of multimedia and the high demand of quality of experience (QoE), providing mobile social users with multimedia services needs a large amount of resource. But, the local mobile devices in mobile social users always have a limited resource such as, capacity, bandwidth, buffer etc. New consideration needs to be give to reduce the consumed resource. On the other hand, multimedia content servers are remotely placed from mobile social users. It takes time for mobile social users to obtain the requested multimedia content, resulting in a further QoE degradation. For example, if a mobile social user wants to watch a movie with his mobile device, the content of movie has to be retrieved from a remote multimedia content server to him through a large number of routing nodes.

To resolve the above issues, media cloud has been advocated with the following reasons [5]. Firstly, media cloud can deploy cloud resource to process multimedia tasks. Some complicated computations or large-sized multimedia content storage which need extra resource can be performed at the side of media cloud, where the required resource can be reduced for mobile social users. Therefore, the media cloud can help mobile social users to save their resource. Secondly, a broker [6] can be placed between media cloud and mobile social users. As the broker can act as a proxy which is close to mobile social users, mobile social users can connect media cloud through the broker for obtaining multimedia services. With the high-speed communication links between media cloud and the broker, mobile social users can obtain multimedia services faster than contacting the remote multimedia content servers.

As the resource to be allocated among media cloud, brokers and mobile social users is limited, resource allocation becomes a very important challenge to apply media cloud to provide mobile social users with multimedia services. However, the conventional resource allocation schemes can not be directly used to allocate resource among these three parties. There are some reasons as follows. First, there exist some significant social features in media cloud with mobile social users. For example. mobile social users within the same community may have the same interest and social activities [7]-[9], resulting in the similar demand of QoE for multimedia services. Therefore, social features should be considered to determine the resource allocation. Besides, mobile social users in the same community can know the information of each other. Thus, the decision of a mobile social user on the selection of broker may be influenced by others. As a result, the affection and competition among different parties should also be taken into consideration for resource allocation.

Although some related studies have been carried out to study resource allocation about cloud computing and mobile networks [10] [11], few of works have studied the resource allocation problem based on the social features in media cloud. In addition, most of them mainly focus on behaviors of servers, instead of three parties including media cloud, brokers and mobile social users. Therefore, it is still a new and open problem to design resource allocation scheme of media cloud with mobile social users.

In this paper, based on the competitions among media cloud, brokers, and mobile social users on cloud resource, we propose a novel resource allocation scheme in media cloud with mobile social users for maximizing the utilities of the above three parties. Specifically, media cloud sells the cloud resource to brokers to obtain revenue. The brokers employ the cloud resource to process media tasks for mobile social users. Mobile social users determine their own brokers to connect to obtain cloud service according to the competition with each other. Besides, to model the interactions among media cloud, brokers, and mobile social users on cloud resource, the resource allocation problem is formulated by a four-stage Stackelberg game. In addition, an iteration algorithm is proposed to obtain the Stackelberg equilibrium. The main contributions of this paper can be summarized as follows.

1)A framework of resource allocation among media cloud, brokers, and mobile social users is presented. Media cloud can dynamically allocate its resource to mobile social users through brokers. And mobile social user can select his broker by adjusting his strategy to achieve the maximum revenue, based on the social features in the community.

2)The interactions among media cloud, brokers, and mobile social users are modeled by a four-stage Stackelberg game. For mobile social users, an evolution game is applied to study their behaviors. Mobile social users in the same community can observe and affect each other's strategy. For brokers, a non-cooperative game model is employed to study their interactions. Their strategies are comprised of the size of resource to lease and the price to charge mobile social users.

3)An iteration algorithm is proposed to obtain the Stackelberg equilibrium of the proposed scheme. Simulation results show that each player can obtain the optimal strategy and the Stackelberg equilibrium exists stably.

The rest of this paper is organized as follows. The related work is reviewed in section II. In section III, the detailed system model is described. In section IV, we present the problem formulation and define utility functions. In section V, the analysis of the formulated Stackelberg game is proposed. In section VI, we show the performance evaluation of the proposal. Finally, in section VII, we give the conclusion.

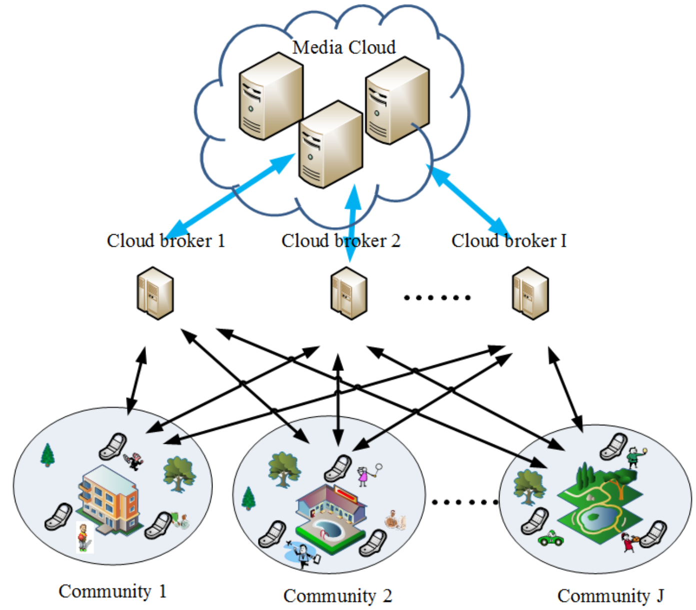

Fig. 1. System model.

II. Related Work

A. Multimedia Social Networks with Mobile Users

Recently, there has been an increasing interest in studying models and schemes for multimedia social network with mobile users. Chang *et al*. [12] presented a general architecture of MSNs where the major components are client devices, wireless access network, and server, to increase the social connection and improve the quality of social service. Wu *et al*. [13] designed a novel routing scheme by considering the internal social features of nodes, including both social feature extraction and multi-path routing. Wang *et al*. [14] presented a cloud-based multicast scheme in MSNs, where the message forwarding strategy is based on a metric iteratively refined from the feedback control mechanism. Lu *et al*. [15] designed a community based distributed set-cover algorithm to identify the users who have the maximum influence on information diffusion in MSNs. Li *et al*. [16] proposed a novel data forwarding approach with a space-crossing community detection method to improve the data forwarding efficiency in MSNs. Yin *et al*. [29] proposed a photography model to assist mobile users for capturing high quality photos with mobile devices and crowd sourced social media. Wang *et al*. [30] proposed a novel mobile streaming framework with two main parts: adaptive mobile video streaming and efficient social video sharing. We have developed an analytical model [35] to mimic information dissemination among mobile social users. By introducing pre-immunity and immunity elements, the proposed model can show the change of mobile nodes' interests during information dissemination efficiently. Although these works have studied several aspects of multimedia social networks with mobile users, the details on resource allocation problem with media cloud have not been given.

B. Resource Allocation with Media Cloud

The resource allocation in media cloud have been studied extensively. Alasaad *et al*. [17] proposed an algorithm for resource reservation in media cloud based on the prediction of demand for streaming capacity. It can maximally exploit the discounted rates offered in the tariffs, while ensuring the sufficient resource to be reserved. Hong *et al*. [18] presented a media task QoS based resource allocation algorithm in media cloud, by considering the service satisfaction of multitask. Magedanz *et al*. [19] evaluated the effects of multiple factors in a large-scale cloud environment, by defining the metric for assessing the performance of cloud brokering systems. Yin *et al*. [20] studied the operations of cloud computing and wireless networks in mobile computing environments by considering not only the spectrum efficiency but also the pricing information in the cloud. Sardis *et al*. [21] introduced a novel concept of cloud-based mobile media service delivery in which services run on the localized public clouds. Ren *et al*. [26] developed an online algorithm that cloud operator can dynamically adjust the resource provisioning according to the time-varying wireless channel conditions. Aggarwal *et al*. [27] introduced a generalized framework to compute the amount of resource to support media services with a generic cost function. Lu *et al*. [28] proposed a service provisioning model to manage the resources in the hybrid cloud where the profit can be maximized. We have presented an incentive scheme [36] for the relay selection to encourage selfish mobile nodes to participate in bundle delivery, where the relay resource can be allocated based on a game theoretical model. Although the above works have made a lot of efforts for the resource allocation, the characteristics of mobile users have not been considered enough. In addition, how to efficiently use cloud brokers to allocate cloud resource has not been mentioned either.

III. System Model

A. System Model

As it is shown in Fig.1, there are three parts which are media cloud, brokers, and mobile social users within the communities, respectively. The media cloud is composed of a large number of servers which can be used to compute, store, and provide media contents and media application. The brokers can be seen as proxies to process the media tasks of mobile social users, where the brokers receive the media tasks from mobile social users and then buy the corresponding resources to process the tasks. Mobile social users with the similar interest can form a community. In the community, mobile social user can select a broker to obtain the resource and observe others' strategies on the selections of brokers. The system model consists of the following components:

- ***Mobile social users***: With mobile devices, mobile social users can have the demands for media applications and send tasks to media cloud for processing [32][33]. A social community is formed by a group of mobile social users, who have the similar interests, goals or locations. Usually, the users in the same community have social relations with each other, where a user can know the information of others. Let $\mathbb{J} = \{1, 2, \cdots, J\}$ denote the set of communities in the network, where the number of communities is *J*. The set of mobile social users in community j is denoted as $\mathbb{U}_j = \{u_{j,1}, u_{j,2}, \cdots, u_{j,k}, \cdots, u_{j,N_j}\}$ and there are N_j mobile social users in this community.
- ***Cloud brokers:*** The set of cloud brokers is denoted as $\mathbb{I} = \{1, 2, \cdots, I\}$, where there are I cloud brokers in total. The cloud brokers are placed closely to mobile social users. Besides, the media cloud and cloud brokers are connected with high speed communication links. In practice, the cloud brokers [6] can be seen as the proxy between media cloud and mobile social users, where the cloud brokers receive the media tasks from mobile social users and then buy the corresponding resources to process the tasks. The advantages of introducing cloud brokers are as follows. Firstly, due to the high speed communications between media cloud and cloud brokers, the service response time can be significantly reduced so that mobile social users can obtain the media services quickly. Secondly, for media cloud, as it directly connects cloud brokers and the number of brokers is less than mobile social users, media cloud can decrease the cost of access control and transmission.
- ***Media cloud:*** Media cloud can provide virtual resources (computing, storage, and cloud service etc) to mobile social users via cloud brokers. Based on [34], in this paper the resource of media cloud can be described as the processing rate which media cloud can provide to deal with the multimedia tasks. Media cloud is responsible to process mobile social users' media tasks sent from cloud brokers, and then return the corresponding results to mobile social users via broker with an allocated processing rate. We assume that the media cloud can totally provide *B* resource to mobile social users via brokers.

Based on [38], the broker in our system can have five modules, which are high speed communication module, wireless communication module, price decision-making module, task receiving module and task delivering module. The high speed communication module is used to communicate with media cloud through the wired connection with high speed. The wireless communication module is used to communicate with model devices with wireless connection. The price decision-making module is to decide the price of resource to sell to mobile social users. In addition, the task receiving module is to sell resource to mobile social users and receive tasks from mobile devices. The task delivering module is to buy resource from cloud and deliver tasks to media cloud for processing.

Mobile devices can connect with brokers through wireless connection, where there is a wireless communication module in each broker. Firstly, the brokers buy the resource from the media cloud after determining the price of resource. Then, mobile social users determine the optimal strategy on the resource demand. Next, mobile social users send the corresponding tasks to brokers with wireless communication. In addition, the brokers deliver the tasks to media cloud by wired module. At last, the results of tasks are delivered back to mobile social users.

Mobile social user can adjust and change his section of broker based on the strategies of others in the community. Specifically, if a mobile user observes another's utility is larger than his utility, this user can change his selection. The selection of mobile social users can be modeled as the evolution game, where the result of game is that all mobile users in the community have the identical utility. Besides, mobile social users can check the brokers which are in the communication coverage and then determine one broker of them to connect. Therefore, mobile social user can determine a suitable broker to obtain its maximum utility based on the geolocation and communication range.

B. QoE Model

QoE is to measure mobile social users' satisfactory when multimedia services are provided. In this paper, due to the feature of media cloud, we present a QoE model by defining the obtained cloud processing rate of r, where *Q(r)=h(r)*. Moreover, based on [31], we assume that the QoE function has the following properties:

- $h(r)$ is positive;
- $h(r)$ is concave with respect to r;
- $h(r)$ is continuous and twice differentiable for r.

Note that mobile social users QoE follows the logarithmic law and QoE function can be modeled in the logarithmic form for applications of multimedia task [22]. Therefore, we adopt the QoE model as the logarithmic function, which is defined as

$$Q(r) = h(r) = \begin{cases} q_{\max}, & r > r_{\max} \\ \alpha \log_2(\beta r), & r_{min} \le r \le r_{\max} \\ q_{\min}, & r < r_{\min} \end{cases} \tag{1}$$

where α and β are two constant parameters. Both of them are positive and can be different for various types of applications. The $q_{\max}$is the maximum of QoE when mobile social user obtains the highest processing rate $r_{\max}$, and the $q_{\min}$ is the minimum of QoE when mobile social user obtains the lowest process rate $r_{\min}$.

As QoE function is continuous, $r_{\min}$ can be obtained by

$$r_{\min} = \frac{2^{\frac{q_{\min}}{\alpha}}}{\beta} \tag{2}$$

Similarly, $r_{\max}$ can be obtained by

$$r_{\max} = \frac{2^{\frac{q_{\max}}{\alpha}}}{\beta} \tag{3}$$

C. Design Goals

Our design goals have two desirable objectives as follows: on one hand, mobile social user can obtain sufficient cloud resource from media cloud to achieve a satisfied QoE. On the other hand, media cloud can achieve the maximum profit with an optimal price of cloud price.

IV. Problem Formulation

In this section, we propose a resource allocation among mobile social users, brokers, and media cloud. Firstly, the resource allocation framework is introduced. Then the utility function of each player is defined. Next, the structure of game is elaborated in detail.

A. Resource Allocation Framework

There are three parties in the resource allocation framework, which are media cloud, brokers, and mobile social users. Media cloud determines the price of cloud resource p, which denotes the unit of resource to be paid by brokers. Each broker i decides the amount of cloud resource E_i to buy, and then announces the price of the bought resource p_i to mobile social users. Each mobile social user decides a broker to connect for acquiring media service and obtaining the satisfied QoE. Due to the social features of MSNs, mobile social users in the same community are friends who can communicate with each other. Thus, in the same community, each user can know the information of others' connections and then compare the utility of his connection with others. If someone's utility is better than his, he can change his connection.

The choices of three parties can mutually affect the decision of each other. The higher price of resource is determined by a media cloud, the less cloud resource that the brokers may decide to purchase, even this broker having heavy tasks. At the same time, if one broker announces a higher price to mobile social users, the mobile social user will connect other broker who announces lower price.

To allow the coordination among three parties to choose the proper parameter for enhancing performances, we propose a resource allocation framework with four steps. Firstly, the media cloud determines the price of its cloud resource and broadcasts it to brokers, aiming to acquire the revenue. There is a tradeoff between the revenue and the price for media cloud, e.g., if the price is too high, the demand of cloud resource will be reduced, which will affect the overall revenue. Secondly, after receiving the price of resource, each broker can buy a certain size of cloud resource from the media cloud to satisfy the demand of mobile social users who connect to this broker. Thirdly, each broker decides the price of resource to achieve revenue from mobile social users. At last, each mobile social user will select a broker for connection and send his task to the broker.

B. Utility Functions

The utility functions of mobile social users: To quantify the utility obtained from the resource, mobile social user utility considers the price of resource and the processing rate according to acquired resource. According to the logarithmic function of allocated resource [23], the payoff of a mobile social user can be formulated as

$$s(r) = \varepsilon \log((1 + f(r)) \tag{4}$$

where ε is a payoff parameter and $f(r)$ is the function of the acquired cloud resource from the connected broker.

Here, mobile social user in community *j* will select a proper broker to buy cloud resource, aiming to maximize his payoff with the least cost. Therefore, the utility function of a mobile social user in community *j* is defined as the difference between the payoff and cost on resource by

$$U_{i,j}(r_i) = s_{i,j}(r_i) - C_{i,j}(r_i) \tag{5}$$

where $s_{i,j}(r_i)$ denotes the payoff of a mobile social user in community *j* who connects broker *i*, and $C_{i,j}(r_i)$ is defined as the cost for buying the cloud resource from broker *i*. According to (4), the payoff can be obtained by

$$s_{i,j}(r_i) = \varepsilon_{i,j} \log\left(1 + Q_{i,j}(\frac{r_i}{n_i})\right) \tag{6}$$

Here, $Q_{i,j}(\frac{r_i}{n_i})$ denotes the QoE of a mobile social user in community *j* who connects broker *i*. And broker *i* has bought r_i resource from media cloud. n_i is the number of mobile social users who connect broker *i*. As users in the same community may share the resource of broker *i*, mobile social users have the identical amount of resource when connecting broker *i*. Thus, the QoE of mobile social users *j* connecting broker *i* can be defined as

$$Q_{i,j} = \alpha_{i,j} \log_2\left(\beta_{i,j}\frac{r_i}{n_i}\right) \tag{7}$$

Here $\alpha_{i,j}$ and $\beta_{i,j}$ are two constants of a mobile social user in community *j* who connects broker *i*, and they are related to media applications, which imply the sensitivity of a mobile social user on satisfaction of the obtained resource. For example, the sensitivity of watching video is higher than listening to the music with media cloud.

The cost for buying the cloud resource from broker *i* can be obtained by

$$C_{i,j}(r_i) = p_i \tag{8}$$

where p_i is the price of resource. Therefore, the utility function of a mobile social user in community *j* who has the connection with broker *i* can be defined as

$$U_{i,j}(r_i) = \varepsilon_{i,j} \log\left(1 + \alpha_{i,j}\log_2(\beta_{i,j}\frac{r_i}{n_i})\right) - p_i \tag{9}$$

The objective of mobile social user is to achieve a large QoE with a cost as low as possible, in order to maximize its utility. Thus, the optimization problem for a mobile social user in community *j* connecting broker *i* can be formulated by

$$\max_{r_i} U_{i,j}(r_i) \tag{10}$$

$$s.t. \begin{cases} r_i & \geq 0 \\ \log_2\left(\beta_{i,j}\frac{r_i}{n_i}\right) & > 0 \end{cases} \tag{11}$$

The utility functions of brokers: For each broker, it provides the cloud resource for processing mobile social users' media tasks. The utility of broker is the revenue obtained from mobile social users minus the cost to buy cloud resource from media cloud. Thus, the utility of broker *i* can be defined as

$$U_i(p_i, E_i) = R_i(p_i) - C_i(E_i) \tag{12}$$

where $R_i(p_i)$ is the revenue through selling cloud resource from broker *i* to mobile social users, and $C_i(E_i)$ denotes the cost to obtain cloud resource from the media cloud.

We can obtain the revenue from selling the cloud resource by

$$R_i(p_i) = n_i p_i \tag{13}$$

According to the pricing strategy of media cloud, the cost function can be denoted by

$$C_i(E_i) = p(D_i + E_i) \tag{14}$$

where p is the real-time price of cloud resource. D_i denotes the cloud resource to support the basic operation of broker *i*, It can be seen as the reserved resource which is provided to brokers by media cloud. E_i denotes the additional cloud resource to conduct the media task when broker *i* is busy. Therefore, the utility function of broker *i* is

$$U_i(p_i, E_i) = n_i p_i - p(D_i + E_i) \tag{15}$$

We assume that there is a discount when brokers obtain cloud resource from media cloud due to the transmission loss between media cloud and brokers. Thus,

$$r_i = \varsigma E_i \tag{16}$$

where ς is the discount parameter.

The objective of broker is to achieve the revenue and reduce the cost as much as possible, for maximizing its utility. Thus, the optimization problem for broker *i* can be formulated as

$$\max_{p_i, E_i} U_i(p_i, E_i) \tag{17}$$

$$s.t. \begin{cases} r_i & = \varsigma E_i \\ p_i & \geq 0 \\ E_i & \geq 0 \end{cases} \tag{18}$$

The utility function of media cloud: By selling the cloud resource with a certain price to brokers, media cloud can obtain the corresponding revenue. In addition, the cost for processing media task should be also considered. Thus, the utility function of media cloud is defined as the difference between the revenue and the cost by

$$U_r(p) = R_r(p) - C_r \tag{19}$$

where $R_r(p)$ denotes the revenue that cloud resource can obtain and C_r is the cost of media cloud for operation.

The revenue of media cloud by selling of cloud resource can be obtained by

$$R_r(p) = \sum_{i=1}^{I} p(D_i + E_i) \tag{20}$$

The cost for processing tasks is defined as

$$C_r = \sum_{i=1}^{I} c_r(D_i + E_i) \tag{21}$$

where c_r denotes the unite cost. Therefore, the utility function of cloud becomes

$$U_r(p_r) = \sum_{i=1}^{I} p(D_i + E_i) - \sum_{i=1}^{I} c_r(D_i + E_i) \tag{22}$$

The objective of media cloud is to achieve a large revenue for maximizing its utility. Thus, the optimization problem for media cloud can be formulated as

$$\max_{p} U_r(p) \tag{23}$$

$$s.t. p \geq 0 \tag{24}$$

C. Four Stage Stackelberg Game

We formulate the above problem as a four stage Stackelberg game, by considering the utility maximization of media cloud, brokers and mobile social users. In stage I, as a leader in the Stackberg game, media cloud offers a real-time cloud resource price p to brokers. In stage II, as a follower in Stage I, the broker decides the amount of cloud resource E_i based on the price offered by media cloud. Next, the broker acts as the leader in stage III, and offers the resource price to mobile social users. In stage IV, each mobile social user selects a proper broker to connect to acquire media service, based on the resource price and availability of cloud resource offered by the broker.

V. Analysis of the Proposed Four Stage Game

In this section, we analyze the proposed four-stage Stackelberg game, and obtain its Stackelberg equilibrium. Based on the above analysis, it is known that each stage's strategy may affect other stages' strategies. Therefore, we use a backward induction method to analyze the proposed game, as it can capture the sequential dependence of the decision in each stage of the game.

A. Evolution Game among Mobile Social Users in Stage IV

Communities are formed by groups of mobile social users with media service demands. Especially, mobile social users in the same community are friends of each other. They can communicate with each other, where the information can be exchanged among them. Therefore, mobile social users in the same community can observe others' decisions on the selection of brokers, and then adjust his strategy to be optimal. We propose an evolutionary game model to solve the broker selection problem. In the evolutionary game, mobile social users are the players of the game. The community can be seen as a population in the game.

Replicator dynamic is crucial to analyze the evolution game to obtain the game equilibrium, where the utility of all users in a community are identical. And no player will change his current strategy because the rate of strategy change is zero. For community j, the proportion of mobile social users who select broker i to acquire media service becomes

$$x_{i,j} = \frac{n_{i,j}}{N_j} \tag{25}$$

where $n_{i,j}$ is the number of mobile social users in community j to connect broker i, and N_j is the number of mobile social users in community j. We denote the state of community as the proportions of mobile social users to connect brokers. Thus, the state of community j can be obtained by

$$\mathbf{x}_j = [x_{1,j}, x_{2,j}, \cdots, x_{i,j}, \cdots, x_{I,j}] \tag{26}$$

In the replicator dynamic, the share of a strategy in community grows at a rate which is directly proportional to the difference between the users utility and the average utility. It can be denoted as

$$\dot{x}_{i,j}(t) = \lambda x_{i,j}(t)(U_{i,j}(t) - \tilde{U}_j(t)) \tag{27}$$

where λ is the multiplier of the difference between the user's utility and the average utility. $\tilde{U}_j(t)$ is the average utility of the entire community j. It can be calculated by

$$\tilde{U}_j(t) = \sum_{i=1}^{I} x_{i,j} U_{i,j}(t) \tag{28}$$

From (8), it can be obtained $\sum_{i=1}^{I} \dot{x}_{i,j}(t) = 0$, therefore $\sum_{i=1}^{I} \dot{x}_{i,j} = 1$ is satisfied during the broker selection process. Substituting (9) into (27) , we have

$$\begin{aligned} \dot{x}_{i,j}(t) = \lambda x_{i,j}(t) \Bigg(& \varepsilon_{i,j} \log(1 + \alpha_{i,j} \log_2(\beta_{i,j} \frac{r_i}{N_i})) \\ -p_i - \sum_{i=1}^{I} & x_{i,j}(\varepsilon_{i,j} \log(1 + \alpha_{i,j} \log_2(\beta_{i,j} \frac{r_i}{N_i})) - p_i) \Bigg) \end{aligned} \tag{29}$$

We consider the evolutionary equilibrium as the solution to the broker selection game among mobile social users. An evolutionary equilibrium is a fixed point of the replicator dynamic. At the fixed point, which can be obtained numerically, the payoff of all users in community j are identical. In other words, since the rate of strategy adaptation is zero, the equilibrium can be obtained by solving

$$\dot{x}_{i,j}(t) = 0, \ 1 \leq i \leq I, \ 1 \leq j \leq J \tag{30}$$

To evaluate the stability at the fixed point $x^*_{i,j}$, which is obtained by solving (30), the eigenvalues of the Jacobian matrix which is corresponding to the replicator dynamic needs to be evaluated. The fixed point is stable if each eigenvalue has a negative real part [24]. Here we have the evolutionary equilibrium for any community j as follows.

$$\mathbf{x}^*_j = \left(x^*_{1,j}, x^*_{2,j}, \cdots, x^*_{i,j}, \cdots, x^*_{I,j}\right) \tag{31}$$

B. Non-cooperative Game among Brokers in Stage II and Stage III

Based on the result of the evolutionary game for mobile social users, the brokers compete with each other and choose the proper strategies on the price to obtain the maximum utilities. Thus, the non-cooperative game is introduced to model the competition among brokers, and the Nash equilibrium is considered as the solution to the game.

According to the price of the cloud resource determined by media cloud, each broker decides the amount of cloud resource to purchase and then determines the price of cloud resource to charge. Considering the competition, the utility of broker i can be defined as

$$U_i(E_i, p_i, \mathbf{E}_{-i}, \mathbf{p}_{-i}) = p_i \sum_{j=1}^{J} x_{i,j}^* N_j - p(D_i + E_i) \tag{32}$$

Here $\mathbf{E}_{-i}$ denotes the vectors of the resource size that brokers have, except broker i. $\mathbf{p}_{-i}$ means the price of cloud resource offered by brokers, except broker i.

The Nash equilibrium is considered as the solution of the game, where each broker has an optimal strategy to maximize the utility. In this case, we use the best response function of each broker to find Nash equilibrium, which is the best strategy of a broker based on others' best strategies. Therefore, when others' strategies are determined, the best response function of broker i can be defined by

$$\mathbb{B}(\mathbf{E}_{-i}, \mathbf{p}_{-i}) = \arg\max_{E_i, p_i} U_i(E_i, p_i, \mathbf{E}_{-i}, \mathbf{p}_{-i}) \tag{33}$$

Let $\mathbf{p}^* = (p_1^*, p_2^*, \cdots, p_I^*)$ and $\mathbf{E}^* = (E_1^*, E_2^*, \cdots, E_I^*)$ denote Nash equilibrium of the cloud resource price and the cloud resource size obtained from media cloud, respectively. The Nash equilibrium of the game can be obtained by solving

$$p_i^* = \mathbb{B}(\mathbf{E}_{-i}, \mathbf{p}_{-i}^*) \tag{34}$$

$$E_i^* = \mathbb{B}(\mathbf{E}_{-i}^*, \mathbf{p}_{-i}) \tag{35}$$

where $\mathbf{p}_{-i}^*$ and $\mathbf{E}_{-i}^*$ is the set of Nash equilibrium of brokers except broker i.

From the above analysis, for a broker to obtain the Nash equilibrium, the strategy of other brokers and the evolutionary equilibrium of evolutionary game among mobile social users are needed. However, this information may not be available in a practical broker system. Therefore, each broker can only employ the local information and mobile social users demands to adapt the offered prices and the obtained cloud resource. Then, each broker should adjust its strategy in the direction of utility maximization. Therefore, broker i updates the price of cloud resource and the cloud resource size by

$$p_i(\tau+1) = p_i(\tau) + \omega_{i,p} \frac{\partial U_i(\mathbf{E}(\tau), \mathbf{p}(\tau))}{\partial p_i(\tau)} \tag{36}$$

$$E_i(\tau+1) = E_i(\tau) + \omega_{i,E} \frac{\partial U_i(\mathbf{E}(\tau), \mathbf{p}(\tau))}{\partial E_i(\tau)} \tag{37}$$

Here $p_i(\tau)$ and $E_i(\tau)$ are the price of cloud resource to sell and the size of cloud resource purchased from the media cloud. Both of them are determined by broker i at iteration τ. $\omega_{i,E}$ and $\omega_{i,p}$ are used to control the speed of adjustment on the cloud resource size and cloud resource price. The marginal payoff can be used to update the strategy for each broker [25]. It can be calculated by the variation in payoffs with a small variation φ(e.g., $\varphi = 10^{-4}$) as follows.

$$\begin{aligned} &\frac{\partial U_i(\mathbf{E}(\tau), \mathbf{p}(\tau))}{\partial p_i(\tau)} \\ \approx &\frac{U_i(\cdots, p_i(\tau)+\varphi, \cdots) - U_i(\cdots, p_i(\tau)-\varphi, \cdots)}{2\varphi} \end{aligned} \tag{38}$$

$$\begin{aligned} &\frac{\partial U_i(\mathbf{E}(\tau), \mathbf{p}(\tau))}{\partial E_i(\tau)} \\ \approx &\frac{U_i(\cdots, E_i(\tau)+\varphi, \cdots) - U_i(\cdots, E_i(\tau)-\varphi, \cdots)}{2\varphi} \end{aligned} \tag{39}$$

C. Strategy of Media Cloud in Stage I

The cloud resource can be sold to the broker to obtain revenue by media cloud. Thus, the media cloud hopes to choose a proper price of cloud resource to obtain the maximum utility. For media cloud, the optimization problem can be formulated as

$$p^* = \arg\max_{p} U_r(\mathbf{E}, p) \tag{40}$$

where p^* is the optimal strategy of media cloud on the price per cloud resource unit, $\mathbf{E}$ is the vector of cloud resource purchased by each broker, which is $\mathbf{E} = [\mathbf{E}_1, \mathbf{E}_2, \cdots, \mathbf{E}_I]^T$.

Similar to the broker iteration, we also present a media cloud iteration to adjust the cloud resource price to obtain the maximum utility. The media cloud updates its price by

$$p(t+1) = p(t) + \omega_r \frac{\partial U_r(\mathbf{E}(t), p(t))}{\partial p(t)} \tag{41}$$

where ω_r is used to control the speed of adjustment on the price of cloud resource price.

The marginal payoff can be calculated by

$$\begin{aligned} &\frac{\partial U_r(\mathbf{E}(t), p_r(t))}{\partial p(t)} \\ \approx &\frac{U_r(E(t), p(t)+\varphi) - U_r(\mathbf{E}(t), p(t)-\varphi)}{2\varphi} \end{aligned} \tag{42}$$

Here, when all mobile social users obtain the maximum utilities with the optimal strategies, the evolution game reaches the equilibrium. If someone tries to adjust his selection to connect the broker, the number of connection of this broker will become larger and the utilities of mobile social users in the same community to connect with this broker will decrease. If we assume that the equilibrium state is not Pareto efficiency, the utility of a mobile social user can be larger by adjusting strategy, where other mobile social users in the same community may imitate this selection to obtain higher utilities with the result that all mobile social users in the same community have the identical utility. In the above assumed situation, the state in evolution game is not stable, which is not the equilibrium. Therefore, as the equilibrium can be obtained which is opposite to the above assumption, the equilibrium of evolution game in our work is Pareto efficiency. In addition, when the Stackberg game reaches to the equilibrium, each broker or media cloud only has one optimal strategy. Therefore, each party can not adjust strategy to obtain higher utility when other two parties choose the optimal strategy. It also proves the Pareto efficiency of the proposal.

D. Algorithm Design for Scheme Implementation

Based on the above analysis of four-stage Stackberg game, we present an iteration algorithm to implement our scheme. For the cloud resource, it can update its cloud resource price to obtain a maximum utility and then announce this price to all brokers. Since the media cloud is not aware of the duration of each adjustment, the media cloud sets a waiting time $T_{w,mc}$ for the next strategy update. Similarly, as each broker is not aware of the duration of each evolution, it sets a waiting $T_{w,b}$ for the next strategy to update the size of the purchased cloud resource and the price to charge mobile social users. In the evolutionary game, each mobile social user randomly selects a broker to connect initially, and then changes his strategy to maximize his own utility. If a mobile social users utility is lower than the average utility of his community, this mobile social user may change his connection with a probability, denoted by

$$\theta = \frac{\tilde{U}_j - U_{i,j}}{\tilde{U}_j} \tag{43}$$

where $\tilde{U}_j$ is the average utility of community j . When all users in the same community obtain an equal utility, the evolution will be completed. We present the algorithm by Algorithm 1.

Algorithm 1 Resource allocation iteration algorithm

```
Initially, the media cloud announces the price p(0) to all brokers.
Repeat
while t ≤ T_{w,mc} do
    Each broker randomly determines the size of leased resource E_i and the price p_i.
    Repeat.
    while t ≤ T_{w,b} do
        Each mobile social user randomly makes connection.
        Repeat.
        Compute each mobile social user's utility by (22).
        Exchange connection information with each other in the community.
        Calculate the average utility \overline{U}_j by (28).
        if \overline{U}_j > U_{i,j} then
            Change the connection with probability θ.
        else
            Maintain the connection.
        end if
        Until all mobile social users in the same community have the equal utility.
    end while
    Update cloud resource size E_i(τ) and the cloud resource price p_i(τ) by equation (36)-(39).
    τ = τ + 1
    Until E_i and p_i are both unchanged.
end while
Update the price p(t) by equal (41), (42).
t = t + 1
Until p is unchanged.
```

TABLE I
SIMULATION PARAMETERS

Parameter	Value
J: the number of communities	2
N_1, N_2:the number of mobile social users in community 1 and community 2	$20, 20$
I:the number of cloud brokers in the network	2
B:the maximum of resource can be allocated by media cloud	100k(tasks/s)
$\{\alpha_{1,j}, \beta_{1,j}\}, j \in \{1, 2\}$:the parameters on QoE of mobile social users in community 1	$\{2, 10\}$
$\{\alpha_{2,j}, \beta_{2,j}\}, j \in \{1, 2\}$:the parameters on QoE of mobile social users in community 2	$\{1.5, 10\}$
$\{\varepsilon_{1,j}, \varepsilon_{2,j}\}$:the payoff parameters of mobile users in community 1 and community 2 in (16)	$\{2, 2\}$
D_i:the reserved resource provided to brokers	0
ς:the discount parameter in (16)	1
$T_{w,mc}$:the waiting time for strategy adjustment of media cloud	500
$T_{w,b}$:the waiting time for strategy adjustment of a broker	100

VI. Performance Evaluation

In this section, we evaluate the performance of the proposed game-based cloud resource allocation.

A. Simulation Setup

In the simulation, there is a media cloud to lease cloud resource to brokers. The total size of cloud resource is $B = 100k$ which denotes that the cloud can process 100x10^3 tasks per unit time. In addition, the MSN has two brokers and two communities. In each community, there are 20 mobile social users. The media cloud waits $T_{w,mc} = 500$ for the next strategy update and each broker waits $T_{w,b} = 100$ for the next generation strategy update. The speed of adjustment for each broker on the bought resource size and price are $w_{i,p} = 0.1$ and $w_{i,E} = 1$, respectively. The speed of adjustment for media cloud on price of resource is $w_r = 0.01$. The detailed values of parameters in this simulation are listed in Table I.

B. Numerical Results

Firstly, we study the evolutionary behavior of mobile social users. We set the cloud resource size and the price of two brokers as $E_1 = E_2 = 20$ and $p_1 = 0.1, p_2 = 0.5$, respectively. Fig. 2 shows the convergence of the evolutionary behavior of mobile social users when the initial state of community is $(x_{1,1}, x_{1,2}) = (0.4, 0.4)$. From Fig.2, we can observe that both of utilities of mobile social users in community 1 and community 2 are converged to be optimal with several iteration steps. In addition, it can be known that the utilities of all mobile social users in both community 1 and community 2 are nearly identical.

Fig. 3 shows the best response of each broker on the size of cloud resource purchased from media cloud. We set $p_0 = 0.1$ and choose two types of cloud service price for comparison, which are $p_1 = p_2 = 0.3$ and $p_1 = p_2 = 0.5$, respectively.

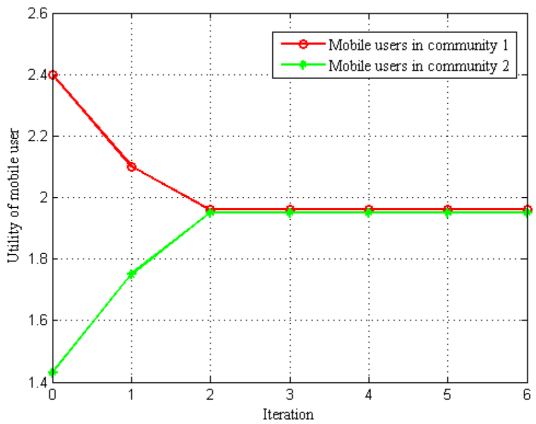

Fig. 2. Convergence of the evolution among mobile social users to the equilibrium.

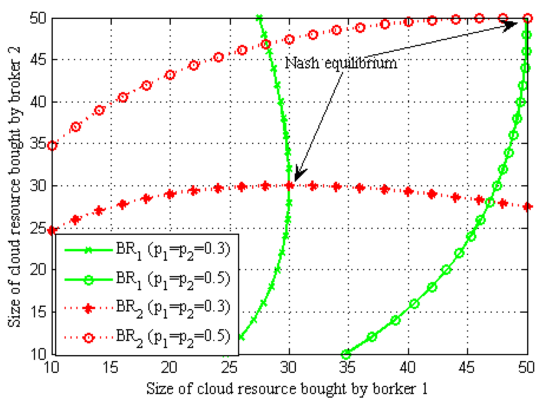

Fig. 3. Best response of each broker on the size of cloud resource purchased from the media cloud. BR_1 and BR_2 represent the best response functions of broker 1 and broker 2.

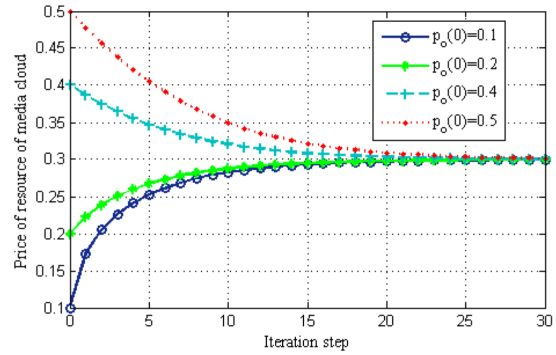

Fig. 4. Price of cloud resource determined by the media cloud versus iteration step. The initial prices $p_o(0)$ are 0.1,0.2,0.4,0.5, respectively.

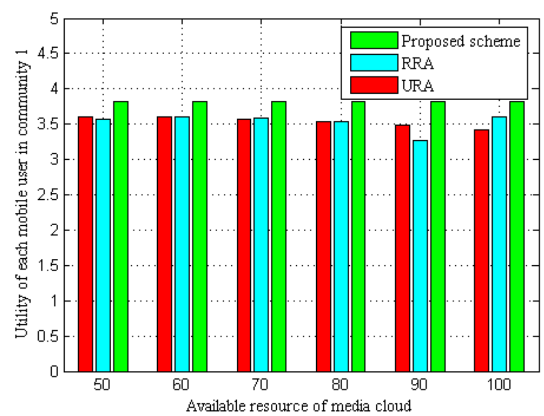

Fig. 5. Utility of each mobile social user in community 1, where the initial price of the resource determined by the media cloud is $p(0) = 0.5$.

From Fig.3, when $p_1 = p_2 = 0.5$, if broker 2 has more cloud resource, broker 1 also has a larger size of cloud resource to be the best response. When $p_1 = p_2 = 0.3$, the best response of each broker firstly increases and then decreases. In addition, with each price, there is only one intersection point in Fig. 3. It demonstrates the existence and uniqueness of the Nash equilibrium when the cloud service price is fixed.

Fig. 4 shows the convergence of the price determined by media cloud. We set four different initial prices of the cloud resource determined by the media cloud for comparison. And we set $E_2 = 10$ to study the influence between the price of cloud resource and the cloud resource demand of broker 2. From Fig. 4, we can observe that the price of cloud resource is converged to an optimal price with several steps.

In Fig. 5, we compare the proposed scheme with the existing approaches, which are Uniform Resource Allocation (URA) and Random Resource Allocation (RRA), respectively. In the URA, the total resource of media cloud is uniformly allocated to all users in the network. In the RRA, each user can obtain cloud resource from the media cloud randomly. From Fig. 5, it can be known that the proposed scheme outperforms the other two existing approaches, where mobile social user can obtain the best utility. In the URA, as the cloud resource is uniformly allocated to mobile social users, too much resource may be allocated to someone whose demand is low, while mobile social users who need more resource can not obtain enough resource. In RRA, as the resource is allocated to mobile social users randomly, mobile social users cannot obtain the resource according to their needs. In the proposed scheme, mobile social users can obtain their wanted resource according to their demands. Furthermore, with the theoretical game model, the price gradually tends to be reasonable. It makes possible that all parties can obtain the maximum utilities.

To test the performance with dynamical demands, Fig.6 shows the utility of a mobile social user in community 1 when the value of in community 1 is changed from 2 to 3.5, which shows the variation of a user's resource demand [37]. From Fig.6, it can be observed that all utilities with dynamic demands decrease and reach to the stable finally. The mobile social user with higher demand has the higher utility. The reason is that the mobile social user with higher demand can be more sensitive to the resource than the one with lower demand.

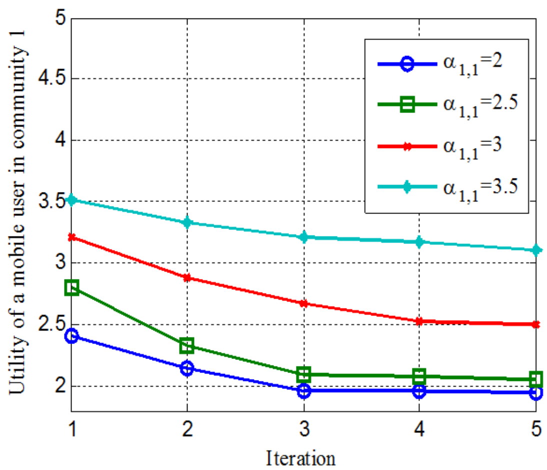

Fig. 6. The utility of mobile user in community when the demand is changed.

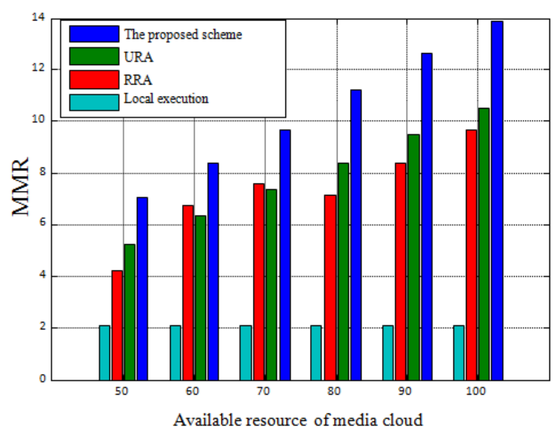

Fig. 7. Comparison of the media response ratio.

We carry out the next experiment to evaluate the media quality of the proposal. Based on [39], we define the metric to show the media quality as Media Response Ratio (MRR) = Media Runtime / Task Processing Time. The above metric can measure the quality of the media when delivering content to mobile social users through media cloud. With a given media runtime, if the task processing time is long, MRR becomes low where the playback speed of media content is slow and the media may be stunk. In opposite, if the task processing time is short, MRR becomes large where mobile social users can enjoy a high quality of media and content can be played fluently.

We compare the MRR of the proposal with RRA, URA, and the local execution scheme. Here, the local execution scheme means that the mobile device does not connect to media cloud and processes the media data on local device. According to [39], in the experiment the file size of media is determined as 307MB and the runtime is 1291 seconds. Without the cloud, the task process rate of local device is 500 tasks/s. For the task process rate of the proposal, it is decided by the proposed algorithm shown in Sect.V.D. The task process rate of RRA and URA are determined at random and uniformly, respectively. From Fig.7, we can see that the proposal can achieve the highest MRR compared to other schemes. The reason is that mobile social users can adjust the strategy to achieve the maximum revenue based on the social features in the community.

In the above experiments, it can be known that all mobile social users can choose the best strategies to obtain the optimal utility. Each broker can determine its optimal strategy on cloud service price and size to obtain the maximum utility. The price of cloud resource determined by media cloud is converged to the optimal. Therefore, the proposed resource allocation scheme is converged and the Stackelberg equilibrium exists.

VII. Conclusion

In this paper, based on the competition among media cloud, brokers and mobile social users, we have presented a resource allocation scheme for mobile social users to achieve satisfied QoE with media cloud. In the proposal, the media cloud can determine a certain price to lease cloud resource to brokers. Each broker can determine the size of cloud resource to buy and then provide the cloud resource for mobile social users with a certain price. The mobile social user can adjust his strategy to decide his connecting broker. The resource allocation problem has been formulated as a four stage Stackelberg game. Through the backward induction method, we have proposed an iterative algorithm to obtain the Stackelberg equilibrium to implement the proposed scheme. Simulation results have been presented to demonstrate the performance of the proposal.

As for the future work, we will investigate the model of information spreading during the cloud resource allocation in mobile cloud.

Acknowledgements

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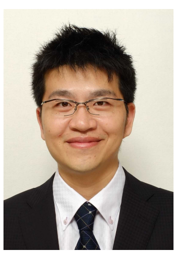

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