# Game Theoretic Modeling of Cooperation among Service Providers in Mobile Cloud Computing Environments

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***Abstract*—Mobile cloud computing aims at improving the performance of mobile applications and to enhance the resource utilization of service providers. In this paper, we consider a mobile cloud computing environment in which the service providers can form a coalition to create a resource pool to support the mobile applications. First, an admission control mechanism is used to provide services of mobile applications to the users given the available long-term reserved resources in a pool. An optimization formulation is introduced to obtain the optimal decision of admission control. Then, for a given coalition of service providers, the revenue obtained from utilizing the resource pool has to be shared among the service providers. A coalitional game model is developed for sharing the revenue. In addition, since the service providers can decide on short-term capacity expansion of the resource pool, a game model is introduced to obtain the optimal strategies of service providers on capacity expansion such that their profits are maximized.**

***Index Terms*—Mobile cloud Computing, cooperative game, and the core.**

## I. Introduction

Mobile cloud computing combines wireless access service and cloud computing to improve the performance of mobile applications. With cloud computing, mobile applications can offload some computing modules to be executed on a powerful server in a cloud. As a result, mobile cloud computing introduces a variety of benefits over traditional mobile services [1]. First, the power consumption of the mobile device can be reduced since the complicated computations can be performed on a server. Second, computing modules can communicate with and access other entities and services on Internet easily. Third, reliability and security of mobile application are enhanced since the full protection (e.g., antivirus software) can be deployed in a cloud. Due to these benefits, many mobile applications are developed under mobile cloud computing concept including e-commerce [2], healthcare [3], and computer games [4]. For mobile cloud computing, the issue of offloading has been studied extensively in the literature [1]-[6]. In [5], an architecture to dynamically partition an application at a runtime was introduced. The code portability is used to create two versions of a mobile application, one for the local execution on mobile devices and the other for the remote execution in a cloud. In [6], an offloading method was proposed in which the online statistics of the computation time are used to compute optimal timeout. If the computation on the mobile device is not completed before the timeout, this computation will be offloaded to the server.

Apart from offloading, resource management has emerged to be an important issue. Resource management for mobile cloud computing must take into account not only the radio resource for wireless access, but also the computing resource for data processing. In [7], an architecture to provide an intelligent network access strategy for mobile users to meet the application requirements was proposed. A context management architecture (CMA) to acquire, manage, and distribute a context information was also introduced. In [8], a security service admission model was developed based on semi-Markov decision process to support critical security (CS) and normal security (NS) services for cloud users. The objective of this model is to maximize the system reward (i.e., cloud income minus cost of the resource occupation) with resource consumption of the applications given the state (i.e., ongoing users).

In this paper, we consider a scenario where multiple service providers cooperatively offer mobile services (e.g., online gaming in mobile environments) to the users. The mobile service providers can form a coalition to create a resource pool to improve the efficiency and utilization of long-term reserved wireless access bandwidth and servers in data centers (which are presumably owned by cloud service providers). Three issues are addressed in this scenario: admission control of the mobile applications to the resource pool owned by the coalition of mobile service providers, revenue sharing among the mobile service providers, and optimal short-term capacity expansion by the mobile service providers. An admission control scheme is developed based on a linear programming optimization formulation to determine the number of instances for the mobile applications (i.e., the number of supported users) such that the maximum revenue can be obtained from a resource pool. Given the admission control policy, a coalitional game model is introduced for sharing the revenue among providers. The solution in terms of dual payoff ensures that none of the providers receives a revenue that is less than that achieved without joining a coalition. Then, providers may have a choice to expand their capacity to contribute more resources to a pool. This can be modeled as a game and the Nash equilibrium solution ensures that the profit (i.e., revenue minus cost of expansion) of a provider cannot be improved if other providers do not change their strategies of capacity expansion.

The rest of this paper is organized as follows: Section II presents the system model. The admission control and revenue sharing schemes are presented in Section III. Section IV describes the game model to obtain an optimal capacity expansion strategy of the service providers. The numerical results are presented in Section V. Section VI draws the conclusions.

## II. System Model

In this section, we first introduce a mobile cloud computing environment under consideration. The definition of the resources to support mobile applications in such an environment is then given. The description of the cooperation among mobile cloud service providers to create a resource pool is presented.

### A. Mobile Cloud Computing

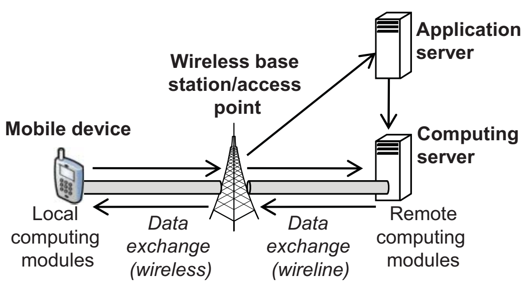


Fig. 1. Mobile cloud computing model.

We consider a mobile cloud computing environment in which a mobile application is divided into two parts, i.e., local and remote computing modules running on a mobile unit and on a server, respectively (Fig. 1). The communications between these modules are through a wireless access.[1] Therefore, both radio and computing resources are required to run mobile applications. Wireless access points provide radio resource (i.e., bandwidth), while data centers provide computing resources (e.g., CPU, memory, and storage) to support different mobile applications.

As shown in Fig. 1, a user requests to run a mobile application from an application server belonging to a mobile cloud service provider (i.e., provider in short). An application server performs an admission control by checking the availability of the radio and computing resources at the associated wireless access point and data center. If there are enough resources, the application server initializes the remote computing modules on a server in the data center. Then, a mobile application is run.

[1]Wired network is required for communications between mobile unit and server as well. However, in this paper, we assume that the bandwidth of wired network is much larger than that of wireless access.

To provide seamless mobile service, it is assumed that a mobile service provider reserves in advance the radio resources in its access network and computing resources from data center (owned by cloud service provider) in a long term basis, respectively. Note that reserving resource in a long term (e.g., 1 year) is cheaper compared with on-demand basis (e.g., 1 day). Given the reserved resources, the number of application instances (i.e., the number of users running an application) to be able to support is determined and used for admission control. Multiple mobile service providers (or network operators) can cooperate by creating a pool to share their reserved radio and computing resources, and admission control is performed accordingly. In addition, each service provider can decide to expand the capacity by reserving more resources in a short-term and on-demand basis. However, there will be a cost incurred to the provider.

### B. Wireless Network and Data Center

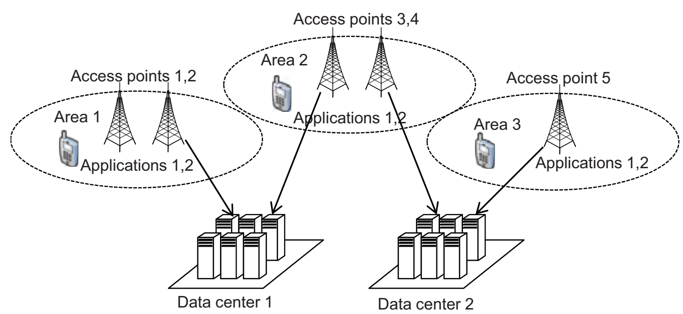


Fig. 2. System model of mobile cloud computing.

In a mobile cloud computing environment, there is a set of areas (i.e., coverage areas of wireless access points) denoted by $\mathcal{A} = \{1, \ldots, A\}$ where $A$ is the total number of areas. A set of access points is denoted by $\mathcal{B} = \{1, \ldots, B\}$ where $B$ is the total number of access points. The availability of an access point $b \in \mathcal{B}$ to the user in area $a \in \mathcal{A}$ is denoted by $\alpha_{a,b}$ where $\alpha_{a,b} = 1$ if user in area $a$ can connect and use bandwidth from access point $b$, and $\alpha_{a,b} = 0$ otherwise. There are $P$ mobile applications offered in this mobile cloud computing environment, and the set of mobile applications is denoted by $\mathcal{P} = \{1, \ldots, P\}$. A set of data centers is denoted by $\mathcal{D} = \{1, \ldots, D\}$ where $D$ is the total number of data centers. The accessibility of a data center by a user using a mobile application is denoted by $\beta_{a,d,p}$ where $\beta_{a,d,p} = 1$ if user in area $a \in \mathcal{A}$ using application $p \in \mathcal{P}$ can run remote computing module on a server in data center $d \in \mathcal{D}$, and $\beta_{a,d,p} = 0$ otherwise. An example of mobile cloud computing environment is shown in Fig. 2. There are three areas and five access points. Access points 1 and 2, 3 and 4, and 5 provide wireless access for areas 1, 2, and 3, respectively. Data center 1 provides computing resource for users in areas 1 and 2, while data center 2 provides computing resource for users in areas 2 and 3.

There are $S$ mobile cloud service providers whose set is denoted by $\mathbb{N}$. The reserved bandwidth of provider $s \in \mathbb{N}$ at access point $b$ is denoted by $K_{b,s}^{\text{bw}}$. The number of servers reserved by provider $s$ at data center $d$ is denoted by $K_{d,s}^{\text{cp}}$. The bandwidth required per instance of application $p$ is denoted by $R_p^{\text{bw}}$. For computing resource, we assume that one server can accommodate $1/R_p^{\text{cp}}$ instances of application $p$. In other words, $R_p^{\text{cp}}$ can be considered as the "server utilization" required per application instance. Supporting one instance of mobile application $p$ generates revenue of $V_p$ for the service provider.

### C. Service Provider Cooperation and Resource Pool

To increase the available resource for mobile applications, multiple providers can cooperate and create a resource pool. A resource pool is logically composed of the reserved bandwidth from access points and servers in data centers to support mobile applications. Let $\mathbb{S} \subseteq \mathbb{N}$ denote a set of providers (i.e., coalition) cooperating to create a resource pool. $K_b^{\text{bw}}(\mathbb{S})$ and $K_d^{\text{cp}}(\mathbb{S})$ are the total reserved bandwidth and the total number of reserved servers at access point $b$ and at data center $d$ given coalition $\mathbb{S}$, respectively. They can be obtained from

$$K_b^{\text{bw}}(\mathbb{S}) = \sum_{s \in \mathbb{S}} K_{b,s}^{\text{bw}}, \text{ and } \quad K_d^{\text{cp}}(\mathbb{S}) = \sum_{s \in \mathbb{S}} K_{d,s}^{\text{cp}}. \quad (1)$$

The revenue obtained from a resource pool is aggregated for all cooperative providers in a coalition.

With the cooperation among providers to create a resource pool, a couple of issues arise. First, the revenue obtained from a resource pool must be shared among cooperative providers. Second, the providers have to decide the strategy of contribution to a resource pool (i.e., to expand their capacity to gain higher profit or not). To address these issues, in the following, a coalitional game model will be developed.

## III. Admission Control of Mobile Cloud Users

In this section, an admission control mechanism to support mobile applications in mobile cloud computing environments is presented. First, an optimization problem is formulated to obtain the optimal number of instances for running mobile applications. Then, a linear programming game model is developed to obtain the revenue sharing among providers.

### A. Linear Programming Formulation

The objective of admission control is to determine the number of application instances (i.e., the number of active users) that maximizes the revenue. Let $x_{a,b,d,p}$ denote the number of instances from users in area $a$ running application $p$ using bandwidth from access point $b$ and server from data center $d$. Given the reserved bandwidth from access points and reserved servers in a resource pool for coalition $\mathbb{S}$, the optimal number of application instances can be obtained by solving the linear programming (LP) formulation defined as in (2)-(8).

The objective function defined in (2) is to maximize the revenue obtained from users in all areas with all access points and data centers. The constraints in (3) and (4) are based on the reserved bandwidth and number of reserved servers in a resource pool. The constraint in (5) defines the maximum demand of applications $D_{a,p}$. The constraints in (6) and (7) define the feasibility of supporting mobile applications from access point and data center, respectively. In this case, $M$ is the maximum number of application instances that can be supported.

$$\begin{aligned}
\max_{x_{a,b,d,p}} \quad & \sum_{a \in \mathcal{A}} \sum_{b \in \mathcal{B}} \sum_{d \in \mathcal{D}} \sum_{p \in \mathcal{P}} x_{a,b,d,p} V_p && (2)\\
\text{s.t.} \quad & \sum_{a \in \mathcal{A}} \sum_{d \in \mathcal{D}} \sum_{p \in \mathcal{P}} x_{a,b,d,p} R_p^{\text{bw}} \leq K_b^{\text{bw}}(\mathbb{S}), \quad b \in \mathcal{B} && (3)\\
& \sum_{a \in \mathcal{A}} \sum_{b \in \mathcal{B}} \sum_{p \in \mathcal{P}} x_{a,b,d,p} R_p^{\text{cp}} \leq K_d^{\text{cp}}(\mathbb{S}), \quad d \in \mathcal{D} && (4)\\
& \sum_{b \in \mathcal{B}} \sum_{d \in \mathcal{D}} x_{a,b,d,p} \leq D_{a,p}, \quad a \in \mathcal{A}, p \in \mathcal{P} && (5)\\
& \sum_{d \in \mathcal{D}} \sum_{p \in \mathcal{P}} x_{a,b,d,p} \leq M\alpha_{a,b}, \quad a \in \mathcal{A}, \quad b \in \mathcal{B} && (6)\\
& \sum_{b \in \mathcal{B}} x_{a,b,d,p} \leq M\beta_{a,d,p}, \quad a \in \mathcal{A}, d \in \mathcal{D}, p \in \mathcal{P} && (7)\\
& x_{a,b,d,p} \geq 0 \quad a \in \mathcal{A}, b \in \mathcal{B}, d \in \mathcal{D}, p \in \mathcal{P} && (8)
\end{aligned}$$

### B. Linear Programming Game of Revenue Sharing

While the LP formulation defined in (2)-(8) determines the optimal number of instances of mobile applications, revenue sharing is also an important issue. Therefore, a linear programming game which is a coalitional game with transferable utility (TU) is formulated and solved.

A general coalitional game is defined as $(\mathscr{M}, v(\cdot))$ where $\mathscr{M}$ is a set of players and $v(\cdot)$ is a value function. A value function $v(\mathbb{S})$ is a mapping from nonempty coalition $\mathbb{S}$ to a real number. A value function $v(\mathbb{S})$ is the maximum aggregated payoff available for division among players who are members of coalition $\mathbb{S}$.

A linear programming game of revenue sharing among all mobile cloud service providers is defined by $\mathscr{M} = \mathbb{N}$ (i.e., *grand coalition*). The value function is obtained as follows:

$$\begin{aligned}
v(\mathbb{S}) = \max_{\mathbf{x}} \quad & \mathbf{v}^T \mathbf{x} && (9)\\
\text{s.t.} \quad & \mathbf{A}\mathbf{x} \leq \mathbf{g}(\mathbb{S}), && (10)\\
& \mathbf{x} \geq \mathbf{0}, && (11)
\end{aligned}$$

where $\mathbf{x}$ is a vector of decision variables $x_{a,b,d,p}$ (i.e., number of application instances) and $\mathbf{v}$ is a vector of revenue per application instance $V_p$. Specifically, each element of $\mathbf{x}$ is $x_{a,b,d,p}$ and each element of $\mathbf{v}$ is $V_p$ as defined in (2). Matrix $\mathbf{A}$ is composed of coefficients $R_p^{\text{bw}}$, $R_p^{\text{cp}}$, and constant 1 defined in (3)-(8). $\mathbf{g}(\mathbb{S})$ is a vector of constants $K_b^{\text{bw}}(\mathbb{S})$, $K_d^{\text{cp}}(\mathbb{S})$, $D_{a,p}$, $M\alpha_{a,b}$, and $M\beta_{a,d,p}$ defined in (3)-(8).

$$\min_{z_b^{\rm bw}, z_d^{\rm cp}, z_{a,p}^{\rm dm}, z_{a,b}^{\alpha}, z_{a,d,p}^{\beta}} \quad \sum_{b\in\mathcal{B}} z_b^{\rm bw} K_b^{\rm bw}(\mathbb{S}) + \sum_{d\in\mathcal{D}} z_d^{\rm cp} K_d^{\rm cp}(\mathbb{S}) + \sum_{a\in\mathcal{A}}\sum_{p\in\mathcal{P}} z_{a,p}^{\rm dm} D_{a,p} + \sum_{a\in\mathcal{A}}\sum_{b\in\mathcal{B}} z_{a,b}^{\alpha} M\alpha_{a,b} + \sum_{a\in\mathcal{A}}\sum_{d\in\mathcal{D}}\sum_{p\in\mathcal{P}} z_{a,d,p}^{\beta} M\beta_{a,d,p} \quad (12)$$

$$\text{s.t.} \quad z_b^{\rm bw} R_p^{\rm bw} + z_d^{\rm cp} R_p^{\rm cp} + z_{a,p}^{\rm dm} + z_{a,b}^{\alpha} + z_{a,d,p}^{\beta} \geq V_p, \quad a\in\mathcal{A}, b\in\mathcal{B}, d\in\mathcal{D}, p\in\mathcal{P}, \quad (13)$$

$$z_b^{\rm bw}, z_d^{\rm cp}, z_{a,p}^{\rm dm}, z_{a,b}^{\alpha}, z_{a,d,p}^{\beta} \geq 0, \quad a\in\mathcal{A}, b\in\mathcal{B}, d\in\mathcal{D}, p\in\mathcal{P}. \quad (14)$$

$$\mu_s(v(\mathbb{N})) = \sum_{b\in\mathcal{B}} z_b^{\rm bw*} K_{b,s}^{\rm bw} + \sum_{d\in\mathcal{D}} z_d^{\rm cp*} K_{d,s}^{\rm cp} + \sum_{a\in\mathcal{A}}\sum_{p\in\mathcal{P}} z_{a,p}^{\rm dm*} D_{a,p} + \sum_{a\in\mathcal{A}}\sum_{b\in\mathcal{B}} z_{a,b}^{\alpha*} M\alpha_{a,b} + \sum_{a\in\mathcal{A}}\sum_{d\in\mathcal{D}}\sum_{p\in\mathcal{P}} z_{a,d,p}^{\beta*} M\beta_{a,d,p} \quad (15)$$

The dual payoff is considered to be a solution of the linear programming game defined in (9)-(11). To obtain the dual payoff, the dual problem of (2)-(8) is required, which can be expressed as in (12)-(14). $z_b^{\rm bw}$, $z_d^{\rm cp}$, $z_{a,p}^{\rm dm}$, $z_{a,b}^{\alpha}$, and $z_{a,d,p}^{\beta}$ are the dual variables corresponding to the constraints in (3)-(8). Their optimal solutions are denoted as $z_b^{\rm bw*}$, $z_d^{\rm cp*}$, $z_{a,p}^{\rm dm*}$, $z_{a,b}^{\alpha*}$, and $z_{a,d,p}^{\beta*}$. With a grand coalition, the revenue of cooperative provider $s\in\mathbb{N}$ denoted as $\mu_s(v(\mathbb{N}))$ can be obtained from (15).

## IV. Optimal Capacity Expansion Strategy of Mobile Cloud Service Providers

The providers can decide on an additional capacity to be contributed into a resource pool through the short-term capacity expansion. Given the admission control decision and dual payoff obtained from Section III, optimal capacity expansion strategies of service providers can be determined based on game model. Also, the distributed algorithm to reach the equilibrium strategy is presented.

### A. Game Formulation

Although capacity expansion can increase the revenue obtained from a resource pool, it incurs a certain cost to a provider. Therefore, the strategies of providers to expand their capacities in a resource pool have to be optimized. The capacity expansion game defined as $<\mathbb{N}, \{\mathcal{T}_s,\}, \{u_s(\cdot)\}>$ can be developed to model and obtain the equilibrium strategies. $\mathbb{N}$ is a set of players (i.e., providers). The strategy is the capacity (i.e., reserved bandwidth and servers) to be expanded. Let the strategy space of provider $s$ be a discrete set defined as $\mathcal{T}_s = \{t_s = (K_{b,s}^{\rm bw}(i), K_{d,s}^{\rm cp}(i)); i\in\{1,\ldots,I_s\}$ where $I_s$ is the total number of options for capacity expansion of provider $s$. Note that $K_{b,s}^{\rm bw}(i=1) = K_{b,s}^{\rm bw}$ and $K_{d,s}^{\rm cp}(i=1) = K_{d,s}^{\rm cp}$ are the original reserved bandwidth and servers, respectively. The payoff of provider $s$ is a profit defined as $u_s(t_s, \mathbf{t}_{-s}) = \mu_s[v(\mathbb{N}), (t_s, \mathbf{t}_{-s})] - C_s(i)$, where $t_s$ is a strategy of provider $s$ and $\mathbf{t}_{-s}$ are the strategies of all providers except provider $s$. In this case, the dual payoff $\mu_s(\cdot)$ from (15) of provider $s$ is defined as a function of capacity expansion strategies of all providers (i.e., $t_s$ and $\mathbf{t}_{-s}$). $C_s(i)$ is the fixed cost incurred to provider $s$ associated with strategy expansion index $i$. Note that the admission control and revenue sharing utilizes the results of resource capacity from the capacity expansion game as an input. Also, the capacity expansion game uses the dual payoff from the admission control and revenue sharing to determine the solution.

The Nash equilibrium is considered to be a solution of this game $<\mathbb{N}, \{\mathcal{T}_s,\}, \{u_s(\cdot)\}>$. The Nash equilibrium strategies are defined as $t_s^\star$ and $\mathbf{t}_{-s}^\star$ which satisfy the following condition:

$$u_s(t_s^\star, \mathbf{t}_{-s}^\star) \geq u_s(t_s, \mathbf{t}_{-s}^\star), \quad \forall t_s\in\mathcal{T}_s, \forall s\in\mathbb{N}. \quad (16)$$

### B. Distributed Algorithm

To reach a Nash equilibrium of the capacity expansion game of mobile cloud service providers defined in (16), the distributed algorithm can be developed (Algorithm 1). In each iteration, one player is randomly selected to evaluate its current strategy (line 3). In this case, for most of the time (i.e., with probability $1-\epsilon$ where $\epsilon$ is a small probability, e.g., $\epsilon = 10^{-4}$), the player optimally chooses the current best strategy (line 5). However, with small probability $\epsilon$, the player chooses a random strategy to explore possible choices (line 7). Note that $rand()$ is a random number generator.

## V. Performance Evaluation

### A. Parameter Setting

We consider 3 mobile cloud service providers and 15 service areas. There are 30 access points in these service areas in which access points 1 and 2 are in area 1, access points 3 and 4 in area 2, and so on. There are two data centers. Data centers 1 and 2 can support mobile applications from users in areas 1-10 and 6-15, respectively. Providers 1, 2, and 3 reserve bandwidth of 1, 2, and 1 Mbps at each access point, respectively. Providers 1, 2, and 3 reserve 20, 10, and 10 servers at each data center, respectively. Two game applications are considered, i.e., World of Warcraft game [9] and Plane-Shift game [10]. World of Warcraft game requires 500kbps of bandwidth and 40% of server utilization. The

**Algorithm 1** Distributed algorithm for capacity expansion game of mobile cloud service providers

Each player $s$ initializes strategy $t_s[n]$ at iteration $n \leftarrow 0$
**loop**
  Player $s$ is randomly selected to perform strategy switching
  **if** $rand() < 1 - \epsilon$ **then**
    Player $s$ optimally chooses the new strategy $t_s[n+1] \leftarrow \arg\max_{t_s} u_s(t_s[n], \mathbf{t}_{-s}[n])$
  **else**
    Player $s$ chooses the new strategy randomly
  **end if**
  $n \leftarrow n + 1$
**end loop**

revenue of running this game is 5 money units (MUs) per instance. Plane-Shift game requires 400kbps of bandwidth and 80% of server utilization, and generates revenue of 6 MUs.

### *B. Numerical Results*

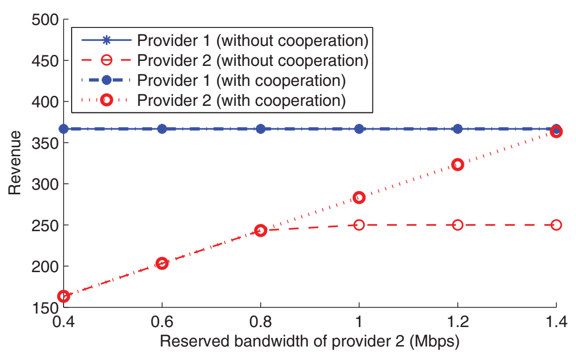


Fig. 3. Revenue of service providers 1 and 2 with and without cooperation under different amount of reserved bandwidth of provider 2.

We first consider two providers (i.e., 1 and 2) with and without cooperation. Fig. 3 shows the revenue of both providers when the reserved bandwidth of provider 2 is varied. Without cooperation, revenue of provider 1 remains constant, while that of provider 2 increases at the beginning. However, when reaching a certain point (i.e., about 0.8 Mbps) where the servers reserved by provider 2 are not enough to support mobile applications, the revenue of provider 2 remains constant since no more application instances (i.e., users) can be supported. However, with a cooperation, provider 2 can utilize the servers reserved by provider 1, and consequently, the revenue of provider 2 increases. Note that a similar result can be observed when the number of reserved servers in a data center is varied. This numerical result is omitted for brevity of the paper.

In addition to dual payoff solution, the core of a grand coalition is considered. Let $r_s$ denote a revenue of provider $s$.

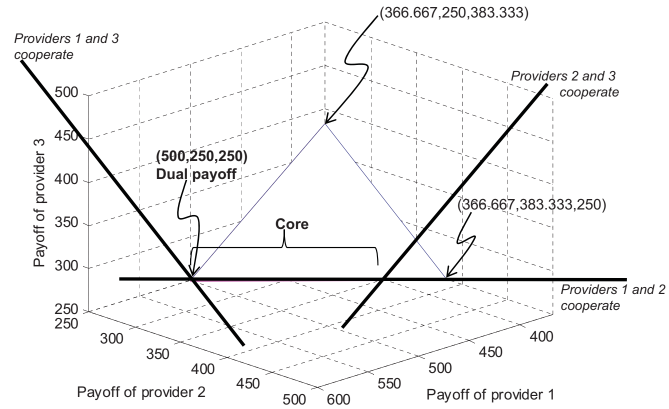


Fig. 4. Barycentric coordinates of the core and dual payoff.

The core can be defined as follows:

$$\mathcal{C} = \left\{ \mathbf{r} \left| \sum_{s \in \mathbb{N}} r_s = v(\mathbb{N}), \sum_{s \in \mathbb{S}} r_s \geq v(\mathbb{S}), \forall \mathbb{S} \subseteq \mathbb{N} \right. \right\} \quad (17)$$

where $\mathbf{r}$ is a vector of $r_s$. In short, at the core of grand coalition, the sum of payoffs of providers in any subcoalition $\mathbb{S}$ is always equal to or larger than the value of that coalition.

Fig. 4 shows the barycentric coordinates of the core and dual payoff of the coalitional game of mobile cloud service providers. Without cooperation, the payoff of providers 1, 2, and 3 are (366.667,250,250), respectively. A set of efficient payoff shares is defined as a set of payoff shares of all providers such that the sum of shares equals to the maximum payoff of all providers. This set can be shown as a plane with coordinates (366.667, 250, 383.333), (500, 250, 250), and (366.667, 383.333, 250). The coordinate indicates the payoffs of providers 1, 2, and 3, respectively. The dual payoff is located at (500, 250, 250). To determine the core, there are three cooperation structures which define the constraints of a set of efficient payoff shares. First, when providers 1 and 2 cooperate, the value of this cooperation is $v(\{1, 2\}) = 750$, and the corresponding constraint is shown to be a line at the bottom of a plane. When providers 1 and 3 cooperate, the value is $v(\{1, 3\}) = 650$, and that of providers 2 and 3 is $v(\{2, 3\}) = 500$. We observe that the core in this case is on the line along the constraint when providers 1 and 2 cooperate. Dual payoff is part of the core.

Then, we consider the case that the providers can expand their capacities by 10% (i.e., by reserving more bandwidth and servers). With the cost of 40 MUs, again a set of efficient payoff shares can be shown as a plane (Fig. 5) with coordinates (580,250,250), (366.667,463.333,250), and (366.667,250,463.333). In this case, the cost of capacity expansion is small. As a result, a plane of efficient payoff shares is above that without capacity expansion. Also, the core exists as a plane. Note however that if the cost of capacity expansion is high, a set of efficient payoff shares will decrease and the core may not exist. In this case, the strategies of capacity expansion must be optimized.

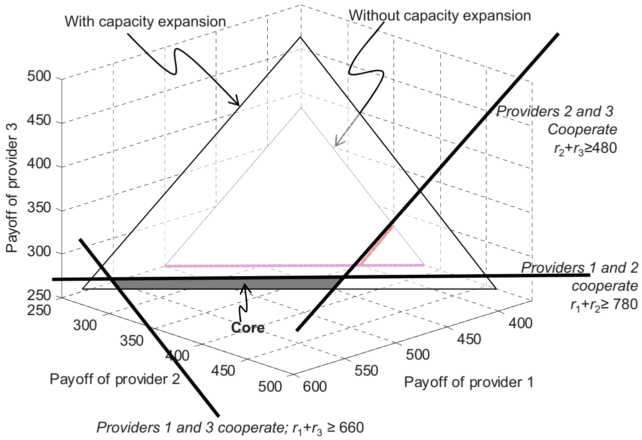


Fig. 5. Barycentric coordinates with capacity expansion.

TABLE I
GAME IN A MATRIX FORM

| | | Provider 3 | | |
|---|---|---|---|---|
| P1 | P2 | 2 | 1 | 0 |
| 2 | 2 | **(620,270,270)*** | (620,270,260) | **(620,270,270)*** |
| 2 | 1 | (620,260,270) | (620,260,260) | (620,260,250) |
| 2 | 0 | (433.333,270,316.667) | (433.333,270,300) | (420,270,270) |
| 1 | 2 | (560,270,270) | (560,270,260) | (560,270,270) |
| 1 | 1 | (560,260,270) | (560,260,260) | (560,260,270) |
| 1 | 0 | (400,270,316.667) | (400,270,300) | (460,270,270) |
| 0 | 2 | (500,270,270) | (500,270,260) | (500,190,270) |
| 0 | 1 | (500,260,270) | (500,260,260) | (500,230,270) |
| 0 | 0 | (500,270,190) | (500,270,230) | **(500,270,270)*** |

Table I shows the game in a matrix form when providers 1, 2, and 3 can choose to expand their resource capacity (i.e., reserved bandwidth at the access points and reserved servers at the data centers). In this case, strategies 0, 1, and 2 mean no expansion, 10% expansion, and 20% expansion, respectively. The costs per 10% and 20% expansion are 40 and 80 MUs, respectively. Note that "P1" and "P2" stand for providers 1 and 2, respectively. From this matrix form of a capacity expansion game, the Nash equilibria can be determined (i.e., with "*" in Table I). Given the proposed distributed algorithm, the probability of choosing strategies for capacity expansion by providers 1, 2, and 3 is shown in Fig. 6. It is clear that the strategies with non-zero probability correspond to the Nash equilibria of the game.

## VI. CONCLUSION

We have considered a mobile cloud computing environment in which some computing modules of mobile applications can be run remotely on a powerful server in a cloud. Mobile applications are supported by the mobile cloud service providers in which the radio and computing resources in terms of bandwidth and servers are reserved for the users, respectively. To improve the resource utilization and revenue, mobile service providers can cooperate to form a coalition and create a resource pool for users running mobile applications. The admission control of this cooperative environment has been developed based on optimization formulation. Also, the revenue sharing among cooperative providers has been introduced based on a coalitional game (i.e,. linear programming game). With a coalition, providers can optimize the capacity expansion, which determines the reserved bandwidth and servers to be contributed to a resource pool. The objective of provider is to maximize the profit from supporting mobile applications through a resource pool.

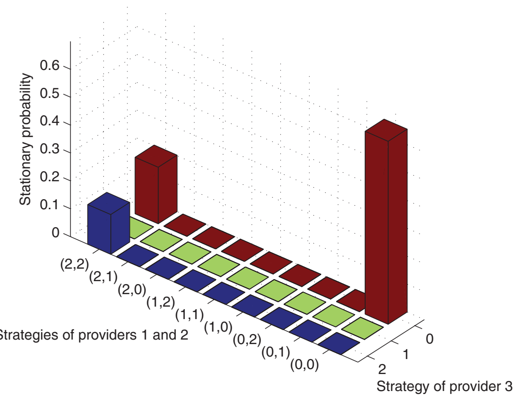


Fig. 6. Probability of using strategies by service providers 1, 2, and 3.

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