A Contract-Ruled Economic Model for QoS Guarantee in Mobile Peer-to-Peer Streaming Services

Libin Yang[1,2] and Wei Lou[1]
[1]Department of Computing, The Hong Kong Polytechnic University, Hong Kong
[2]College of Information Engineering, Northwest Agricultural and Forestry University, Shaanxi, China
Email: libiny@nwsuaf.edu.cn, csweilou@comp.polyu.edu.hk

Abstract—Current commercial mobile streaming applications call for innovative technologies for stable QoS guarantee. In this paper, we provide a comprehensive treatment of QoS guarantee through a contract-ruled approach. In particular, we envision a peer-assisted mobile peer-to-peer streaming system as a QoS trading market, where all parties involved in the system, i.e., Service Provider (SP), End User (EU) and Assisting Peers (APs), are real economic entities that are organized with contractual constraints to achieve a stable and guaranteed QoS output. The QoS trading in the market is divided into two parts. One is a basic contract that establishes the business agreement between an interested EU and a SP. We propose a QoS contingent payment to mitigate the EU's concern on the uncertainty of QoS delivery and derive an optimal contract that achieves Pareto efficiency. The other is a subcontract, in which we model transactions between the SP and contracted peers as a principal multi-agents problem, that achieves a desired joint QoS output. We further design a sharing scheme with team penalty that could overcome the free-riding problem existed in the subcontract and show that the Pareto efficiency can be achieved by setting a proper team penalty. Both numerical evaluations and prototype experiments demonstrate the effectiveness of our proposed scheme.

Index Terms—Keywords: Mobile P2P streaming; QoS guarantee; contract-ruled economic model.

1 Introduction

The increasing capability and versatility of mobile devices have fueled a growing thirst for mobile streaming services [1]. In fact, mobile multimedia services are deemed to be a new source of revenue for the wireless networks like 3G. However, current mobile streaming services are far from meeting customers' expectations, in aspects of not only the high price of transmitting data but also the lack of QoS guarantee. This is primarily due to the fact that current mobile streaming services are mostly based on a costly centralized server approach, which is characterized by poor scalability, limited access points and low user experience. The lack of QoS guarantee together with a relatively high service price significantly hinders the commercialization of mobile streaming applications and has awaken market interests in alternative solutions.

One promising solution is to introduce peer-to-peer (P2P) technology into current infrastructure to improve the service quality, namely mobile peer to peer (MP2P), where the peers close to an End User (EU) can assist a Services Provider (SP) to provide services in a fashion of P2P mode, namely *peer-assisted mode*. A typical application scenario is that, a mobile user can watch popular programs provided by the SP, which are actually hosted by some potential users roaming nearby through Wi-Fi communications. The popularity of mobile devices capable of accessing to multiple wireless networks, e.g., 3G and Wi-Fi, opens up the possibility of providing such services. In fact, MP2P has stimulated an interesting new trend that users share their content information with each other. Very recently many research projects have been reported, which implement this basic idea of mobile content sharing [2] [3] [4].

However, introducing the peer-assisted mode into mobile applications poses new challenges, among which QoS management is one of the most crucial ones. Typical mechanisms taken for the QoS performance in P2P networks, such as using optimal source scheduling [5] or incentives [6] [7], may improve the cooperation degree of the system, yet they are far from meeting the requirement of the QoS in the wireless networks. EUs in such networks tend to keep stationary temporally while nearby peers that can provide peer-assisted services are limited. Moreover, because of the limits of computation and battery power capabilities of handsets, mobile users likely decline to participate such peer-assisted services. Thus, it is important to develop a pertinent mechanism to enable an effective QoS management while allowing all participants to benefit from MP2P streaming services significantly.

Comparatively, very little attention has been focused on handling the QoS guarantee problem in mobile streaming applications in the form of contract. The contract theory, also known as principal-agent theory, investigates the dilemma between a principal (employer) and an agent (employee), where the agent has to fulfill the obligations specified in the contract, and in return it will receive some remuneration from the principal. The contract theory is appropriate for providing mobile streaming services since it can efficiently regulate the roaming peers in the context of contracts to fulfil contractual obligations, as well as motivate peers' self-interests in participating in the provision of peer-assisted services.

In this paper, we propose a comprehensive framework for QoS guarantee in mobile P2P streaming scenarios through a contract-ruled approach. We envision a mobile P2P streaming system as a QoS trading market, the parties involved in this system, including SP, EUs and Assisting Peers (APs), are all real economic entities. Specifically, we organize the involved parties with contractual constraints and divide the QoS trading in the market into two parts (as shown in Fig. 1(a)): One is a basic contract that establishes the business agreement between an interested EU and a SP, where the EU acts as a principal and the SP is an agent. The basic contract specifies the corresponding QoS requirements of the EU for a given service price. The other is a subcontract that models the transactions between the SP and APs, where the SP acts as a principal and the APs are agents, respectively.

A realization for peer-assisted mobile streaming services is exhibited in Fig. 1(b): Consider a service region where 3G and Wi-Fi are both available for EUs, e.g., in an airport lounge or at a sport arena. Generally, streaming services provided through Wi-Fi are more stable and economical than through 3G. However, by taking consideration of the fact that the commercial Wi-Fi may be difficult for EUs to connect due to various reasons, e.g., a large number of users or poor signal quality, SP may prefer to employ APs to improve its mobile streaming services through self-built Wi-Fi hotspots, for the purposes of enhancing programs' QoS and reducing their operating cost[1]. The procedure of the QoS trading is briefly described as follows:

1) An EU discovers its favorite video program via a client terminal and sends a service request to the SP. The EU could also choose a proper bandwidth according to the per-unit bandwidth price given by the SP and its price elasticity.
2) On receiving the service request, the SP indicates the EU to start a Wi-Fi hotspot.
3) The EU launches a Wi-Fi hotspot by using its client terminal. Note that the Wi-Fi hotspot built by EU should have a special SSID to distinguish itself from other Wi-Fi hotspots.
4) The EU notifies the SP after the self-built Wi-Fi hotspot is launched successfully.
5) The SP calculates the needed bandwidth resource for the EU and initiates a sealed bid auction for the prospective candidate peers $\{P_1, ..., P_n\}$ within the EU's Wi-Fi coverage. Here the prospective candidate peers refer to the peers that have reserved the caches (e.g., peers have ever watched the requested program) and are willing to get payoff by providing their resources.
6) The candidate peers submit their bids that represent their QoS information to the bidding pool.
7) The SP selects a proper number of APs $\{A_1, ..., A_m\}$ from the candidate peers according to the submitted bids.
8) The APs join the Wi-Fi hotspot and provide the agreed joint QoS to the EU after signing a subcontract with the SP. At the same time, all the APs keep 3G connections with the SP to periodically get the update information. In exchange, they get compensations to subsidize their dissipative power and bandwidth costs.

1. We deem the available bandwidth as the major metric of QoS in this paper, because for mobile streaming services, the available bandwidth determines the services' loss rate and time delay that have dominant impacts on EUs' estimation on the services.

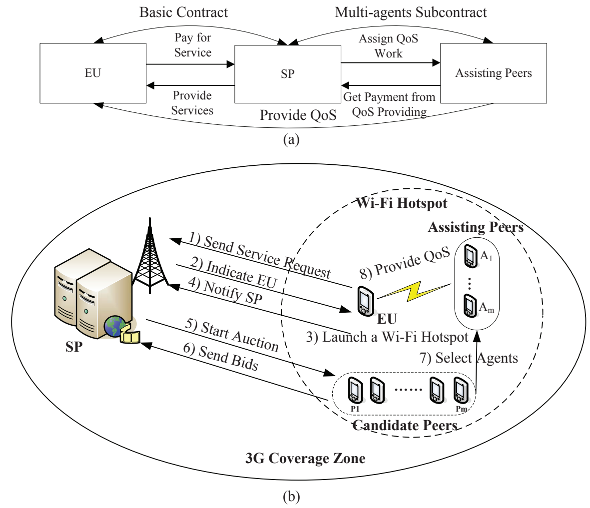


Fig. 1. The contract-ruled approach: (a) Illustration; (b) Procedure.

The proposed contract-ruled approach can be viewed as a more rigorous case of incentive mechanisms with several additional specifications. To the best of our knowledge, we are the first to tackle the QoS guarantee problem in mobile streaming applications by using a contract-ruled approach. It should be noted that the goal of this work is to design effective incentive mechanisms for MP2P streaming services. We emphasize more on the economic analysis of the approach from a macroscopic view, regardless of concentrating on the detailed technical issues of system implementation. We believe that this work can shed some light on the deployment and evolution of practical mobile streaming services.

Our major contributions in this paper are summarized as follows:

1) We present a QoS trading architecture that allows economic strategies to be employed in managing the parties involved in the QoS contracts. We concentrate on the design of both basic contract and subcontract in the context of the proposed architecture.
2) In the case of the basic contract, we propose a QoS contingent payment scheme to mitigate the uncertainty of QoS delivery for mobile streaming services. We derive the optimal price for this contingent contract and show that whether the SP possesses the private information of QoS plays a critical role in the choice of a pricing scheme. We further explore an optimal contract that achieves Pareto efficiency.
3) In the multi-agents subcontract, we find that there always exists a free-riding problem if we follow the full-sharing allocation scheme in which SP distributes the profits collected from agents' bandwidth output among the agents according to a certain specification, e.g., the contributions of the team members. To address this problem, we design a feasible allocation scheme with team penalty, in which SP sets a target of bandwidth output that the QoS work team should achieve, and a monetary profit for the joint bandwidth output will

be assigned to all of the team agents if the target is achieved; otherwise, each team agent will suffer a penalty. The proposed scheme can induce an efficient equilibrium with desired joint QoS output among the team agents.

The remainder of the paper is organized as follows. Section 2 studies the basic contract. Section 3 studies the multi-agents subcontract. Section 4 presents the numerical analysis of the proposed approach. Section 5 discusses the prototype system's implementation and performance evaluation. Related work is briefly surveyed in Section 6. Conclusions and future work are given in the last section.

2 Basic QoS Contract

In this section, we study the basic contract that deals with the economic relationship between an EU and a SP and then construct a basic contract.

2.1 Economic Model for Basic Contract

Consider a peer-assisted mobile P2P network with n mobile peers and a SP, which are all risk neutral, i.e., they make decisions merely based on the expected utility and price of the program. Each mobile peer can either be an EU or an AP. Being an EU, it entertains programs provided by the SP. As an AP, it can get payoff by contributing its idle resources in the peer-assisted mode, with the cost of sacrificing its mobility. Each peer is free to decide to be an AP or EU before it signs a contract. According to the contract, APs should provide the contracted bandwidth to the specified EU at the agreed time and place for the purpose of QoS guarantee. A peer's role is determined after signing a contract with the SP and cannot switch between AP and EU during the contract period. This arrangement is mainly due to two reasons. One is that the peer that acts as an AP should sacrifice its mobility to guarantee the QoS of EU it serves. The other one is due to the limitation of Wi-Fi channels such that a peer cannot play duel roles of AP and EU at the same time. For example, an EU, while building a Wi-Fi hotspot to allow other peers to join it, cannot associate with other Wi-Fi hotspots built by other EUs as an AP at the same time.

Normally, the SP sets a price for providing mobile streaming services with QoS guarantee to the EU, which is obligated by a contract called *basic contract*. According to the contract, the EU pays for the streaming services provided by the SP, and in return it will be served with a contractual QoS. The contract mainly consists of three components: 1) a performance component which specifies the agreed QoS metric, i.e., the bandwidth that the SP promises to provide; 2) a payment component that specifies the EU's payment; 3) a time component which defines the effective time of the contract.

In this basic contract, the SP earns revenue by providing QoS-promised MP2P streaming services. However, there may be inherent uncertainty in the MP2P streaming services due to many factors, such as unexpected disturbance in the transmission process, inefficient management of APs. Obviously, such uncertainty has negative business effects on EUs, since EUs always value a mobile streaming service in respect to its delivered quality. The service with unsatisfied quality will lead to a reduced trading probability between the SP and EUs, especially when the SP and EUs have different expectations about its service quality. To mitigate the EUs' concerns about the QoS uncertainty, a possible solution is to apply a QoS contingent price tariff with a money rebate [8], [9]. For example, when the SP promises a QoS level for the EU, the EU monitors the long-term QoS. The EU will get compensated in the form of money rebate if the actual performance is below the promised level. In other words, the SP takes the QoS uncertainty into account when setting the price for its services.

Assume the SP adopts the QoS contingent price tariff with a constant rebate, thus the basic contract can also be considered as a QoS contingent contract. We formally define a contingency price structure in the following way. The SP announces a price P associated with the promised QoS level. The final price paid by the EU is contingent, which depends on the realized QoS level. For instance, if the SP and EU have reached an agreement on a standard bandwidth $\tilde{B}$, the EU will receive a rebate $r \in [0, P]$ when the QoS performance falls below the promised bandwidth $\tilde{B}$[2]. Generally, the rebate r can be set as a fixed value or a discount, since r is used more for symbolic meaning, which is used as a tool to strengthen EUs' confidence in streaming services provided by the SP, i.e., the SP uses the rebate r as a sign to declare SP's belief on its service quality. Similar approaches can be found in some works of P2P networks [10], [11]. r is assumed the same for all EUs for ease of discussion; otherwise, it will incur more cost SP has to withstand, which will also make the discussion more complicated.

However, due to the inherent uncertainty of the mobile streaming services, in this basic contract, the committed QoS level is judged by an average QoS. This can be achieved by dividing a period of the contract time into many time slots and letting SP calculate the average QoS in this period. We consider the average QoS as the actual bandwidth received by EU. Therefore, the contingent price structure can be mathematically formulated as:

$$P_{EU} = \begin{cases} P & , \quad B \geq \tilde{B}; \\ P - r & , \quad B < \tilde{B}. \end{cases} \tag{1}$$

Here, B is the bandwidth received by the EU and $\tilde{B}$ is the promised bandwidth level. For ease of discussion, we assume the standard bandwidth $\tilde{B}$ is same for all EUs . In fact, B is the expected bandwidth of the EU. We deem it as the actual bandwidth received by the EU until the transmission uncertainty is introduced into the model in Section 3.4.

We adopt the concept of the service estimation and apply it to our model. As EUs are heterogeneous in their valuations on the services, we denote the EU's valuation on the streaming service as v to identify EU's preference on the same service and assume it is uniformly distributed in $[0, 1]$ for simplicity. v

2. SP can get the realized QoS information of EU by executing a background process in the client application. The process collects the realized QoS information and sends it to SP regularly. All transmissions of QoS information occur over an encrypted channel. This means that all the information is encrypted and cannot be read or tampered by EUs.

can also be interpreted as the "type" of the service from EU's perspective, which is different from the "quality of service".

For ease of presentation, the utility of EU, denoted as U_{EU}, will be v when the delivered service meets the promised QoS level; otherwise, if the promised QoS level is missed, the EU's utility will be negatively affected by additional utility φv, which indicates a utility loss caused by the miss of the promised QoS level. Here $\varphi \in [0, 1]$ is a coefficient that denotes the ratio of the negative utility of EU to its positive utility. We set φ in [0,1] to ensure that EU will receive a positive utility. Otherwise, if φ is greater than 1, the utility of EU will be less than 0 and EU will terminate the service. For the purpose of illustrations, we have adopted some linear functions to make the results more readable and easily understood. Note that similar treatments can be found in some works of network economics [8], [9], in which linear functions are used in their models. Of cause, more complex non-linear functions for positive or negative utilities can also be used in our model. We believe that they do not fundamentally alter the results obtained in the paper.

Thus, the expected utility of the EU is

$$U_{EU} = \begin{cases} v & , \quad B \geq \tilde{B}; \\ (1-\varphi)v & , \quad B < \tilde{B}. \end{cases} \tag{2}$$

The concept of QoS defines the parameters a service provider should guarantee. However, these parameters of QoS do not take the user experience into consideration. In our model, we assume that EU has a risk estimation about the performance of the QoS, which can be represented as a probability μ that the realized QoS is below the promised QoS level.[3] This is common for many works in IT services, e.g., voice over IP, video streaming applications [9] [12], owing to the factors such as unobservability of products, stochasticity in manufacturing or delivery processes, lack of end-to-end control. Much alike the perceived brand quality, in practice the parameter μ can be used for EU to evaluate the perceived QoS, i.e., the user's opinion about the QoS that does not meet his or her expectation, which is considered available to the SP[4]. For ease of discussion, we assume μ is the same for all EUs in this paper. Therefore, the EU with different v can estimate its expected revenue by taking account of its risk estimation μ, which is represented as follows:

$$R_{EU} = (1-\mu\varphi)v - (P - \mu r). \tag{3}$$

As for the SP, it has to undertake a constant cost C for providing the MP2P streaming services, and if the SP fails to deliver the promised bandwidth level, an additional cost c incurs due to the failure handling process, i.e., some extra efforts, such as customers' service calls or error handling, are required to manage the failure of not delivering the promised QoS level to EU. Obviously, the term c should be positive. Thus, the cost of the SP can be described as

$$C_{SP} = \begin{cases} C & , \quad B \geq \tilde{B}; \\ C + c & , \quad B < \tilde{B}. \end{cases} \tag{4}$$

The SP possesses the private information about its QoS, represented as a risk probability θ. θ is used to describe the expectation of the service fallibility from SP's perspective. Thus, SP's expected revenue function can be expressed as:

$$R_{SP} = (P - \theta r) - (C + \theta c). \tag{5}$$

Next, we investigate the benefits of applying the contingent contract. Intuitively, the contingent contract may enhance EUs' interests in the MP2P streaming services, thereby expand the trading opportunities between the SP and EUs. Especially, the SP and EUs may not agree on a single price, since they may have different estimations on the performance of the QoS. Proposition 1 formulates the intuition and shows that it is beneficial to the SP to offer a contingent contract.

***Proposition** 1: The QoS contingent contract is able to attract more EUs to subscribe MP2P streaming services comparing with the single price contract, when EUs underestimate the SP's QoS.*

Proof: In the QoS contingent contract, for an EU staying in the system, its revenue should satisfy

$$R_{EU} = (1-\mu\varphi)v - (P - \mu r) \geq 0. \tag{6}$$

For the SP, its revenue should also be positive, i.e.,

$$R_{SP} = (P - \theta r) - (C + \theta c) \geq 0. \tag{7}$$

Combining Eq. (6) with Eq. (7), we get

$$(\mu - \theta)r \geq (C + \theta c) - (1 - \mu\varphi)v.$$

In terms of the QoS contingent contract, EU's marginal value v_m, which is the minimum utility the EU achieves for staying in the system, is

$$v_m = \frac{(C + \theta c) - (\mu - \theta)r}{1 - \mu\varphi}.$$

Meanwhile, in the single price contract without a money rebate, i.e., $r = 0$, the marginal type of the EU is

$$v'_m = \frac{C + \theta c}{1 - \mu\varphi}.$$

When the SP applies the QoS contingent contract in which the SP's QoS is underestimated by the EU, i.e., $r > 0$ and $\mu > \theta$, which lead to $(\mu - \theta)r > 0$, we can get

$$1 - v_m > 1 - v'_m.$$

Hence, the QoS contingent contract can attract more EUs to subscribe the SP's services comparing with the single price contract. □

3. Generally, the probability μ will increase with the increasing of $\tilde{B}$ if the other parameters are fixed. However, with the given $\tilde{B}$, the probability μ has little relation with $\tilde{B}$.

4. As a service provider, it is reasonably assumed that SP can obtain more information than EUs by taking the consideration that the SP collaborates the whole MP2P streaming system and it could get this information through various activities, e.g., coupon or survey. While an EU just starts to use the service, it is very likely that SP's belief will be higher than EU's.

2.2 Optimal Basic Contract Payment Scheme

Given the revenue functions of EU and SP, we concentrate on investigating the strategic interaction between two parties: EUs and SP. Note that in the context of the QoS contingent contract, we consider the EUs of the entire system as a single party. In what follows, the singular term "EUS" is used to refer to all the EUs as a whole.

In the QoS contingent contract, the SP has the power to determine the service price so as to maximize its revenue. According to the given price, the EUS can decide its service demand. We define EUS' demand function as a participating probability, i.e., the probability that EUS will participate in the system, to denote EUs with different valuations to use the service. Let $D(P, r)$ denote the demand function of EUS, which characterizes the changing of the EUS' service demand in face of the SP's price changing. The bargain between the SP and EUS is naturally a two-stage Stackelberg game [13], where in the first stage, the SP acts as a leader by setting the price P and rebate r, and the EUS acts as a follower to determine the service demand. Following the market discipline, the increasing price will cause the EUS to lower its probability to participate in the system as it is less likely to get a positive revenue from the service, and thus results in the decreasing service demand, and vice versa. The SP can choose its optimal price to maximize its revenue by expecting EUS' demand function. We can derive the Sub-game Perfect Equilibrium (SPE) of the Stackelberg game by applying the concept of the backward induction. The method works as follows: Firstly, in the second stage, for the given price P and rebate r, the EUS determines its service demand. Then back to the first stage, the SP, acting as the leader of the Stackelberg game, is aware of the EUS' demand function $D(P, r)$ and seeks to choose its optimal P^* and r^* to maximize its revenue. Hence, the sub-game perfect equilibrium $\{P^*, r^*\}$ of the Stackelberg game can be found by the backward induction. The EUS' demand function is depicted in Lemma 1.

***Lemma** 1: Given EUS' valuation on the services is uniformly distributed in* $[0, 1]$*, the EUS' demand function, i.e., the probability that EUS has the willingness to subscribe the services is*

$$D(P, r) = 1 - \frac{P - \mu r}{1 - \mu\varphi}. \tag{8}$$

Proof: It can be verified that the expected revenue of EU depicted in Eq. (3) is increasing when v increases. By setting $R_{EU} = 0$, we can get the marginal type of the EU that wishes to subscribe the services:

$$v_d = \frac{P - \mu r}{1 - \mu\varphi}.$$

As the EUs with type below v_d will not subscribe the services, by further considering that EUS's type is uniformly distributed in $[0, 1]$, we can get that the service demand, i.e., the probability that the EUS has the interest to subscribe the services from the SP, is

$$D(P, r) = 1 - v_d = 1 - \frac{P - \mu r}{1 - \mu\varphi}.$$

□

Given the EUS' demand function, the SP needs to decide how to carefully set the price so as to extract maximal surplus from the EUS. The SP's expected revenue under the contingent contract is

$$R_{SP} = (P - \theta r - C - \theta c) \cdot D(P, r), \tag{9}$$

where $(P - \theta r - C - \theta c)$ is the SP's expected marginal revenue that the SP could extract from a single EU, $D(P, r)$ is the EUS' demand function indicated in Eq. (8). Thus, the optimal contingent payment provided by the SP that achieves its maximal revenue should satisfy

$$(P^*, r^*) \in \arg\max_{(P,r)} \{(P - \theta r - C - \theta c) \cdot D(P, r)\}. \tag{10}$$

By solving the above problem, we can obtain the SPE of the QoS contingent contract, which contains two possible optimal price schemes when the information about the QoS is asymmetric, i.e., $\mu \neq \theta$. The result is depicted in Lemma 2.

***Lemma** 2: The SPE of the QoS contingent contract contains two possible optimal price schemes:*
(1) contingent price with full rebate ($r = P$)

$$P^* = \frac{1}{2}\left[\frac{1 - \mu\varphi}{1 - \mu} + (C + \theta c)\frac{1 - \mu}{1 - \theta}\right], \tag{11}$$

(2) single price without rebate ($r = 0$)

$$P^* = \frac{1}{2}(1 - \mu\varphi + C + \theta c). \tag{12}$$

Proof: By applying the first order condition of Eq. (10) with respect to P and r, we get

$$\frac{\partial R_{SP}}{\partial P} = \frac{1 - \mu\varphi - P + \mu r - P + \theta r + C + \theta c}{1 - \mu\varphi};$$
$$\frac{\partial R_{SP}}{\partial r} = \frac{(P - \theta r - C - \theta c)\mu - (1 - \mu\varphi - P + \mu r)\theta}{1 - \mu\varphi}.$$

Applying the second order condition of $\frac{\partial R_{SP}}{\partial P}$ and $\frac{\partial R_{SP}}{\partial r}$ with respect to P and r, we obtain $M = \frac{\partial^2 R_{SP}}{\partial P^2} = -\frac{2}{1-\mu\varphi}$, $N = \frac{\partial^2 R_{SP}}{\partial r^2} = -\frac{2\mu\theta}{1-\mu\varphi}$, and $L = \frac{\partial^2 R_{SP}}{\partial P \partial r} = \frac{\theta+\mu}{1-\mu\varphi}$.

Notice that the Hessian is $MN - L^2 = -\frac{(\theta-\mu)^2}{(1-\mu\varphi)^2}$, which is always negative when $\theta \neq \mu$. Therefore, the SP gets the maximal revenue at the boundary $r = 0$ and $r = P$, which correspond to the two possible optimal price schemes: contingent price with a full rebate and single price without any rebate, respectively.

By substituting $r = P$ into Eq. (10) and applying the first order condition with respect to P, we can get the corresponding optimal contingent price of the SP as Eq. (11). The optimal price under the single price contract can also be obtained as Eq. (12) by substituting $r = 0$ into Eq. (10) and applying the first order condition. □

The essential idea of Lemma 2 is that, if the SP is able to gain benefits by offering a rebate r when the EU underestimates the SP's QoS, a larger rebate will be offered by the SP since the SP's revenue increases with the increasing of r. The maximal possible rebate finally equals to the optimal price P^*, which induces the maximal revenue.

From Lemma 2, we show that the SP has two possible optimal contracts at the equilibrium state. We proceed to determine the conditions where the SP chooses the corresponding optimal contract. We find that the existence of the optimal contingent contract depends mainly on whether or not the SP has the private information about the performance of services. Especially, the SP will prefer to offer a full rebate contract when the EUS underestimates the performance of services, i.e., $\mu > \theta$. Otherwise, it is beneficial to the SP to offer a single price contract. We express this result in Proposition 2.

***Proposition** 2: The SP will prefer to offer a contingent contract when the EUS underestimates the performance of services, i.e., $\mu > \theta$; otherwise the SP will prefer to offer a single price contract.*

Proof: We first compute the SP's revenue in the presence of the two different optimal contracts. When the SP applies the full rebate payment scheme, i.e., $r = P$, the SP maximizes its revenue by setting a proper price P^*:

$$P^* \in \arg\max_P \{(P - \theta P - C - \theta c)D(P)\}. \tag{13}$$

By applying the first order condition of Eq. (13) with respect to P, we could get the optimal price P^* in the QoS contingent contract with a full rebate as follows:

$$P^* = \frac{1}{2}\left[\frac{1-\mu\varphi}{1-\mu} + (C+\theta c)\frac{1-\mu}{1-\theta}\right],$$

and the corresponding optimal revenue, denoted by $R^*_{SP_1}$, is as follows:

$$R^*_{SP_1} = \frac{(1-\mu\varphi)^2(1-\theta)^2 - (C+\theta c)^2(1-\mu)^2}{4(1-\mu\varphi)(1-\mu)(1-\theta)}. \tag{14}$$

Likewise, we can also obtain the corresponding revenue $R^*_{SP_2}$ when the SP applies the single price payment without any rebate (i.e., $r = 0$):

$$R^*_{SP_2} = \frac{(1-\mu\varphi)^2 - (C+\theta c)^2}{4(1-\mu\varphi)}. \tag{15}$$

By comparing the revenue of the SP under the two different payment schemes, we can verify that the profit difference between the two pricing schemes is a function of μ and θ:

$$R^*_{SP_1} - R^*_{SP_2} = \frac{(\mu-\theta)\left[(1-\mu\varphi)^2(1-\theta) + (C+\theta c)^2(1-\mu)\right]}{4(1-\mu\varphi)(1-\mu)(1-\theta)}. \tag{16}$$

Notice that $0 < \mu < 1$, $0 < \theta < 1$ and $0 < \varphi < 1$, we can see that $R^*_{SP_1} - R^*_{SP_2} > 0$ when $\mu > \theta$, thus the SP will prefer to choose the QoS contingent payment if the EUS underestimates the performance of services; otherwise, the SP will prefer to offer a single price contract. □

We can see that the SP's private information about its QoS plays a crucial role in making the contingent payment attractive, and the value of contingent payment increases when SP is more confident of the QoS, relative to EUS. Since MP2P streaming services are new and deployed rapidly, EUS may be unfamiliar with them. There may exist a significant gap in belief of QoS between SP and EUS, the contingent payment can serve as an effective signaling mechanism for new entrants.

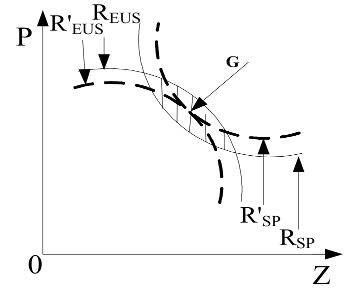


Fig. 2. Illustration of Pareto improvement. The solid lines represent the indifference curves of SP and EUS; the dashed lines represent the indifference curves of SP and EUS that reach Pareto efficiency. Point G indicates that the system achieves the Pareto optimum.

2.3 Pareto Improvement in Basic Contract

Up to now, we have obtained the equilibrium of the basic contract. However, it is shown that the equilibrium of a game may not achieve full efficiency in [14]. A classic concept in game theory quantifying the efficiency of a game is Pareto efficiency, which characterizes an efficient condition of the system in which no party in the system can be better off with no other parties being made worse off. We can verify that P^* is the equilibrium price of the basic contract, but it is not the Pareto efficient price. The implication of the analysis is that the SP non-cooperatively maximizing its own revenue will result in the corresponding loss of EUS' welfare. In fact, if the SP makes some compromise, for instance, the SP decreases its price and the EUS expands its service demand, i.e., increases its participating probability, both parties can derive better revenues. Conceptually, we can illustrate this in Fig. 2. In the shaded area enclosed by two indifferent curves R_{SP} and R_{EUS}[5], the revenues of the SP and EUS can both be improved to R'_{SP} and R'_{EUS} from R_{SP} and R_{EUS}, respectively. It should be noted that, in Fig. 2 the lower curve R'_{EUS} represents the higher revenue for the EUS, so the EUS attains a higher revenue through Pareto improvement.

Following the analysis in Subsection 2.2, our goal is to design an optimal basic contract so that the system consisting of the EU and SP can achieve Pareto efficiency. Notice that the revenue function of a single EU with type v is depicted in Eq. (3), thus the total revenue of the entire EUS can be represented as

$$R_{EUS} = \int_{v_d}^{1} [(1-\mu\varphi)v - (P-\mu r)]dv, \tag{17}$$

where v_d is the marginal type of EUs.

Let $Z = 1 - v_d$ denote the service demand of EUS, Eq. (17) can be further reduced to

$$R_{EUS} = \frac{1}{2}(1-\mu\varphi)(2-Z)Z - (P-\mu r)Z. \tag{18}$$

5. In microeconomic theory, an indifference curve shows that a consumer's preference is indifferent in the face of different bundles of goods. In the case of Fig. 2, the points on the curve represent the different combinations of the price P and the service demand Z, which render the same level of revenue for the SP or EUS.

Accordingly, the revenue of the SP can also be rewritten as

$$R_{SP} = (P - \theta r)Z - (C + \theta c)Z. \quad (19)$$

Note that the first item $(1 - \mu\varphi)(2 - Z)Z$ of Eq. (18) can be interpreted as the utility that the EUS gets from the service demand Z, the second item $(P - \mu r)Z$ is the total payment caused by the demand Z. Essentially, it can be observed that the payment $(P - \theta r)Z$ in Eq. (19) (or $(P - \mu r)Z$ in Eq. (18)) serves only to allocate the total revenue between the EU and SP. We may find an optimal basic contract that maximizes the total revenue through a bargain process, i.e., the SP sets the services' price to maximize its revenue, the EUS bargains with the SP by varying its service demand. With this concept, we can use the Nash Bargain Solution (NBS) [15] to get a Pareto efficient contract. Mathematically, we seek the optimal strategy profile $\{P^*, Z^*\}$ by solving the following problem:

$$\max_{P \geq 0, Z \geq 0} R_{EUS} \cdot R_{SP}. \quad (20)$$

***Proposition** 3: There exists an optimal Nash equilibrium with Pareto efficiency for the basic contract, and the equilibrium $\{P^*, Z^*\}$ satisfies:*

$$P^* = C + \theta(c + r),$$

$$Z^* = 1 - \frac{(C + \theta c) - (\mu - \theta)r}{1 - \mu\varphi}.$$

Proof: We use the Nash Bargain Solution (NBS) [15] to get a Pareto efficient contract. In fact, the Pareto efficiency is an outcome of the Nash Bargain Solution according to the conclusions of the work [16]. The optimal condition for the Pareto efficiency to occur in this Nash Bargain process is that EUS and SP reach a Nash equilibrium through negotiations. If they cannot reach an agreement, the utilities of EUS and SP become zero. Similar models are also used in some works of game theory [17].

The optimal solution can be uniquely determined by applying the first order condition of Eq. (20) with respect to P and Z:

$$\begin{aligned} \frac{\partial(R_{EUS} \cdot R_{SP})}{\partial P} &= 0, \\ \frac{\partial(R_{EUS} \cdot R_{SP})}{\partial Z} &= 0. \end{aligned} \quad (21)$$

Rearranging Eq. (21), we get

$$\frac{\partial R_{EUS}}{\partial Z} / \frac{\partial R_{EUS}}{\partial P} = \frac{\partial R_{SP}}{\partial Z} / \frac{\partial R_{SP}}{\partial P}. \quad (22)$$

Notice that $\frac{\partial R_{EUS}}{\partial Z} / \frac{\partial R_{EUS}}{\partial P}$ is the slope of EUS' indifference revenue curve and $\frac{\partial R_{SP}}{\partial Z} / \frac{\partial R_{SP}}{\partial P}$ is the slope of SP's indifference revenue curve. As shown in Fig. 2, the revenues of two parties R_{SP} and R_{EUS} (i.e., the solid lines) could be further improved by adjusting P and Z, until the curves of two parties R'_{SP} and R'_{EUS} (i.e., the dash lines) are tangent to each other at point G, which has optimal Z^* and P^*. Obviously, the solution of Eq. (22) is Pareto efficient, since the slope of EUS' indifference revenue curve is equal to the slope of SP's and neither of their revenues can be further improved. By substituting Eq. (18) and Eq. (19) into Eq. (22), Eq. (22) can be further reduced to

$$Z^* = 1 - \frac{(C + \theta c) - (\mu - \theta)r}{1 - \mu\varphi}. \quad (23)$$

The corresponding optimal price is $P^* = C + \theta(c + r)$. □

Proposition 3 shows that the basic contract could improve both parties' welfare and achieve Pareto efficiency by applying the Nash Bargain Solution. This bargain process possibly happens, especially under a competitive market with multiple SPs, where the EUS will obtain a certain bargain power and the SP cannot get a high revenue by setting an arbitrary price. Notice that the optimal price $P^* - \theta r = C + \theta c$, i.e., the expected marginal profit of the SP, $P^* - \theta r$, equals to its marginal cost $C + \theta c$, which indicates that the SP cannot further improve its revenue by reducing its price. From the optimal service demand of the NBS indicated in Eq. (23), we can see that the optimal EUS' service demand Z^* is related to the SP's marginal cost $C + \theta c$, and the less the SP's marginal cost, the larger the EUS' service demand. We can further verify that Z^* varies directly with the changing of $(\mu - \theta)r$, which implies that when the EUS underestimates the QoS of the SP, i.e., $(\mu - \theta) > 0$, the SP is able to extract a higher service demand by offering a larger rebate r, which verifies the result in Proposition 1.

3 Multi-agents QoS Subcontract

In this section, we describe the subcontract where the SP and multiple APs act as principal and agents, respectively. We first analyze the free-riding problem existed in the subcontract, which leads to an inefficient Nash equilibrium. Following this analysis, we propose a new profit allocation scheme with team penalty and show that a Pareto efficient optimal Nash equilibrium can be reached by setting a proper team penalty.

3.1 Economic Model for Subcontract

When the SP signs a basic QoS guarantee contract with an EU, the SP first needs to arrange its contracted task (i.e., providing streaming services to the EU with promised QoS) to the APs. Here the APs refer to the prospective peers within the coverage of the EU's Wi-Fi hotspot which reserve the cache and wish to make benefits from contributing their idle resources. The SP then initiates an auction process in order to select a proper number of APs to carry out the QoS task. The selected peers form a QoS work team and the SP will sign a bandwidth exporting subcontract with them, namely *multi-agents QoS subcontract*, where the SP and all AP members are principal and agents, respectively.

According to the multi-agents QoS subcontract, the work team should export a promised joint bandwidth output to a given EU which has reached a deal with the SP in the basic contract. In return, the team members will receive some monetary compensation from the SP in respect of the QoS output they have provided. The team profits will be distributed among team members based on the proportion of their contributions in the QoS work. We use the available bandwidth as the major measure of individual agent's contribution. The joint bandwidth of the work team directly determines the monetary profits of the whole QoS work.

Consider a subcontract between the SP and a work team of m agents. We assume the useful bandwidth supplying of the agents is $\{b_1, ...b_m\}$, the bandwidths provided by the whole team determine a joint bandwidth $B = \sum_{i=1}^{m} b_i$ that exports to the EU. We use monetary function $M(B)$ to indicate how much profit that the joint bandwidth contributed by APs could convert. Note that the team profits are closely related to the committed bandwidth to the EU. Here $M(B)$ can be considered as a utility function to capture the revenue that SP could collect from EU by providing a certain bandwidth. The revenue extracted from bandwidth may include multiple incomes, e.g., the traffic fee paid by EU and the incomes due to the network externality. As the primary contribution measure is the bandwidth, we assume that the joint bandwidth can be quantitatively evaluated by a monetary function $M(B)$, where $M(B)$ is strictly increasing, concave, and differentiable with b_i.

In the subcontract, the SP derives a monetary bandwidth output $M(B)$ from the QoS task, it should also pay some remuneration to the agents. Let the remuneration of agent i be $r_i(b_i)$, the revenue of the SP in this subcontract is $R_{SP} = M(B) - \sum_{i=1}^{m} r_i(b_i)$.

For agent i in the work team, its revenue comes from the remuneration $r_i(b_i)$ on a basis to its bandwidth providing. Generally, providing such bandwidth will generate a cost denoted by $c_i(b_i)$. Here we assume that the cost function $c_i(b_i)$ is differentiable and strictly convex as b_i increases. Hence, the revenue of agent i can be described as $R_i = r_i(b_i) - c_i(b_i)$.

For the subcontract that consists of the SP and multiple agents, there exists a noncooperative game where the agents always seek to maximize their own revenues by deciding how much bandwidth they will provide and the SP aims to obtain a desired team bandwidth output. What merits our concern is whether there exists a profit allocation scheme that leads to a Pareto optimal Nash equilibrium. Here, the Nash equilibrium implies that agents can satisfy their self-interests and none of them would violate this equilibrium. The Pareto optimality means that both the SP and agents can obtain a certain degree of revenue, and the aggregated revenue of the SP and all agents are maximal. Mathematically, the optimal bandwidth b_i^* provided by agent i that achieves the Pareto optimality should satisfy:

$$b_i^* \in \arg\max_{b_i} \left\{ M(B) - \sum_{i=1}^{m} c_i(b_i) \right\}, \tag{24}$$

where $B = \sum_{i=1}^{m} b_i$. However, such Pareto optimality is not easy to achieve. In the following subsection, we demonstrate that the free-riding problem always yields and leads to an inefficient Nash equilibrium due to the inadequate profit allocation scheme.

3.2 Free-riding Problem in Subcontract

Assume the work team has accomplished the contractual QoS work, SP needs to allocate the team profits among the agents. Note that the team profits are closely related to the committed bandwidth to EU. Hence we can use a monetary function $M(B)$ to denote the team profits, where B is the committed bandwidth provided by the whole team. A typical profit allocation scheme is full-sharing allocation, which is a common profit allocation scheme with budget-balance in economic studies. In this profit allocation scheme, SP distributes the profits collected from agents' bandwidth output among the agents according to a certain specification, e.g., the contributions of the team members. A full-sharing allocation scheme can be expressed as:

$$r_i(b_i) = s_i \cdot M(B), \quad s.t.: \sum_{i=1}^{m} s_i = 1, \tag{25}$$

where $B = \sum_{i=1}^{m} b_i$, $s_i \cdot M(B)$ stands for agent i's share ratio of the whole monetary profits. Thus, the revenue of agent i is rewritten as:

$$R_i = r_i(b_i) - c_i(b_i) = s_i \cdot M(B) - c_i(b_i). \tag{26}$$

Though the full-sharing allocation scheme might be the most generous allocation scheme that the SP can adopt, we show that in the following proposition, the system cannot achieve Pareto optimality even if the SP follows the full-sharing allocation scheme. The free-riding problem always occurs since the individual agent cannot satisfy its self-interest by performing the work of bandwidth providing.

***Proposition** 4: The full-sharing profit allocation scheme cannot result in an efficient Nash equilibrium with a desired bandwidth output.*

Proof: For individual agent i, the contributing bandwidth b_i^* that is a Nash equilibrium should maximize Eq. (26) to satisfy its condition of incentive compatibility. Differentiating Eq. (26) with respect to b_i, we have

$$\frac{\partial r_i}{\partial M}\frac{\partial M}{\partial b_i} - \frac{\partial c_i(b_i)}{\partial b_i} = 0.$$

Notice that Eq. (24) is a function of b_i, we can find the solution of Pareto optimality of Eq. (24) by differentiating it with respect to b_i, that is

$$\frac{\partial \left(M(B) - \sum_{i=1}^{m} c_i(b_i) \right)}{\partial b_i} = 0.$$

By taking consideration that $M(B)$ is also a function of b_i, above equation can be further reduced to

$$\frac{\partial M}{\partial b_i} - \frac{\partial c_i(b_i)}{\partial b_i} = 0.$$

Combining $\frac{\partial r_i}{\partial M}\frac{\partial M}{\partial b_i} - \frac{\partial c_i(b_i)}{\partial b_i} = 0$ and $\frac{\partial M}{\partial b_i} - \frac{\partial c_i(b_i)}{\partial b_i} = 0$, we can get the condition of Pareto optimality while satisfying the incentive compatibility of individual agent, i.e., $\frac{\partial r_i}{\partial M} = 1$, which implies that the marginal shared ratio should be 1 to meet individual agent's interest.

However, we can also differentiate Eq. (25) with respect to M, we then have: $\sum_{i=1}^{m} \frac{\partial r_i}{\partial M} = 1$ which suggests that the sum of agents' marginal shared ratio is equal to 1. It can be verified that $\sum_{i=1}^{m} \frac{\partial r_i}{\partial M} = 1$ is in conflict with the individual interest $\frac{\partial r_i}{\partial M} = 1$. Therefore, with the scheme of full-sharing allocation, all agents cannot make their revenues maximized and naturally have incentive to be slacking in the QoS work, which leads to an inefficient Nash equilibrium. □

Following Proposition 4, we can see that the free-riding problem always occurs in the multi-agents subcontract if the SP follows the full-sharing allocation scheme, since the individual agent cannot satisfy its self-interest by performing the work of bandwidth providing. This problem will become worse when the individual's QoS contribution cannot be measured accurately, e.g., the SP fails to distinguish the exact QoS contribution of an individual peer from a joint QoS output. This may happen, as the subcontract is signed between the SP and work team, but the joint QoS output is received by the third entity EU. Due to the lack of effective supervision, agents cannot be penalized sufficiently for the deviation of performing QoS task, some agents always have incentive to capitalize on this control deficiency, which finally leads to an inefficient bandwidth output. This kind of outcome should be avoided.

3.3 Profit Allocation Scheme with Team Penalty

From the previous analysis, we have known that the free-riding problem, which results in an inefficient equilibrium, is essentially due to the deficient profit allocation scheme. In this regard, we propose the following profit allocation scheme with team penalty, which is borrowed from economic literatures [18] [19], so as to assure a sufficient bandwidth output. The scheme is described as follows: *The SP sets a target of bandwidth output that the QoS work team should achieve. If the target is achieved, a monetary profit for the joint bandwidth output will be assigned to all of the team agents. Otherwise, each team agent will suffer a penalty.* The profit allocation scheme with team penalty can be mathematically formulated as

$$s_i \cdot M(B) = \begin{cases} s_i \cdot M(B) & , \quad B \geq \tilde{B}; \\ s_i \cdot M(B) - k_i & , \quad B < \tilde{B}. \end{cases} \tag{27}$$

Here, $M(B)$ is the monetary profit of the joint bandwidth, s_i is the shared ratio, $s_i \cdot M(B)$ represents the allocated profits of agent i, and $\sum_{i=1}^{m} s_i = 1$, $k_i > 0$ is the penalty of agent i, $\tilde{B}$ is the target bandwidth output that the SP expects. Note that as a special case, the SP can set $k_i = s_i \cdot M(B)$ so that agent i gains zero if the QoS work fails. The scheme in Eq. (27) prescribes a penalty k_i to each agent if the target bandwidth $\tilde{B}$ is not achieved. Otherwise, the entire profit is shared. Though $s_i M(b^*) - c(b_i^*)$ could be less than $s_i M(b_i, b_{-i}^*) - k_i - c(b_i)$ if we consider the cost of providing bandwidth to the APs, the SP could force $s_i M(b^*) - c(b_i^*)$ to be always larger than $s_i M(b_i, b_{-i}^*) - k_i - c(b_i)$ by setting a proper penalty value k_i based on the cost function. The efficient equilibrium is that the joint bandwidth output B achieves the target bandwidth $\tilde{B}$.

Next we will show that the profit allocation scheme with team penalty can lead to an efficient Nash equilibrium.

***Proposition** 5: In the multi-agents QoS contract, the profit allocation scheme with team penalty is able to lead to an efficient Nash equilibrium.*

Proof: Assume the bandwidth that agent i plans to provide is b_i and the bandwidth output of all other agents is denoted as b_{-i}. Let B' denote the joint bandwidth output of the work team that is not less than the target bandwidth output $\tilde{B}$, $B' = \sum_{i=1}^{m} b'_i \geq \tilde{B}$, where b'_i is the equilibrium bandwidth of agent i. Suppose agent i chooses to provide the bandwidth $b_i < b'_i$ while other agents choose b'_{-i}. According to the profit allocation depicted in Eq. (27), it will result in a pay $s_i \cdot M(b_i, b'_{-i}) - k_i$ since it will receive a penalty due to failing to achieve the target bandwidth output. Conversely, if agent i chooses the bandwidth b'_i, the corresponding revenue allocation is $s_i \cdot M(b'_i, b'_{-i}) > s_i \cdot M(b_i, b'_{-i}) - k_i$. It is clear that agent i will make its benefits maximized by providing bandwidth b'_i, and all the agents will choose the bandwidth providing $\{b'_1, ..., b'_m\}$ that leads to an efficient Nash equilibrium. □

By applying such profit allocation scheme, each team agent has incentive to provide bandwidth as the SP expects, and induces a positive bandwidth output. It can also be verified that the profit allocation scheme depicted in Eq. (27) does not violate self-interest of agents, and works well with the expansion of team size.

It is noted that the above profit allocation scheme assumes that all the APs participate the QoS work team for the QoS subcontract. For the scenario that the APs may dynamically quit the work team, the SP can use a simple mechanism to manage the list of the APs and adaptively adjust the expected payoff of each AP as well as the current penalty value of the subcontract based on the APs' current statuses. The SP monitors and updates the APs' statuses periodically. After each time slot elapses, the SP identifies the APs that have been out of touch and removes them from the list. Meanwhile, the current penalty value of the subcontract is recomputed. Specifically, if the list becomes empty, the SP will provide the entire bandwidth to the EU by itself through 3G connection. It should be noted that the mechanism focuses on dealing with the scenario that some APs quit the work team. A subcontract is frozen after it was built, which means that no new AP can join the subcontract at will.

3.4 Optimal Subcontract with Uncertainty

We have shown that the subcontract with team penalty is sufficient to regulate team agents' behavior, meanwhile the SP could obtain a desired bandwidth output at the state of Nash equilibrium. However, it should be noticed that such efficient Nash equilibrium can only be achieved under the certain condition where each agent in the work team is confident of accomplishing the target QoS output. In practice, agents may often work under uncertain conditions that are beyond the control of individual agent, e.g., high transmission noise. Obviously, on the condition of uncertainty, an excessive penalty k_i may hurt the benefit of agents and cannot result in Pareto efficiency, which is an optimal condition that maximizes the joint revenue of the SP and agents. In what follows, we investigate how to set team penalty k_i so as to achieve Pareto efficiency when the providing of target bandwidth output is uncertain.

We follow the same multi-agents model. Assume the expected bandwidth providing of agents is $\{b_1, ..., b_m\}$ and the corresponding expected joint bandwidth supplying is $B = \sum_{i=1}^{m} b_i$. Assume the target bandwidth output set by SP is $\tilde{B}$ where $\tilde{B} < B$. For ease of explanation, we use X to denote the joint bandwidth that the EU actually receives for a given expected joint bandwidth supplying B. X may be less than the target joint bandwidth supplying $\tilde{B}$ by taking account of network transmission noise, which may result in a team penalty for agents. We could define a conditional distribution function $F(\tilde{B}, B)$ to represent the failing probability, i.e., when given the expected joint bandwidth supplying B, the actual received joint bandwidth X does not meet the target joint bandwidth output $\tilde{B}$. $F(\tilde{B}, B)$ can be comprehended mathematically as a probability $F(\tilde{B}, B) = P\{X < \tilde{B}|B\}$. Note that X is embedded implicitly in $F(\tilde{B}, B)$ as an intermediate variable. For simplicity, we use $F(\tilde{B}, B)$ to denote the failing probability of agents in the following discussion.

It is easy to know that, when b_i increases, i.e., B increases, the actual joint bandwidth X received by the EU is likely increasing, and thus, the probability that the received bandwidth X is less than the target bandwidth $\tilde{B}$ is decreasing. For ease of analysis, we assume $F(\tilde{B}, B)$ is convex and denote the partial derivatives of $F(\tilde{B}, B)$ as $F'(\tilde{B}, B) = \frac{\partial F(\tilde{B}, B)}{\partial b_i}$ for all agents. Since $F(\tilde{B}, B)$ decreases as b_i increases, $F'(\tilde{B}, B)$ is always negative.

Therefore, in the subcontract with uncertainty, the probability agent i gets penalty k_i is $F(\tilde{B}, B)$ in the case that the joint bandwidth B is lower than the target bandwidth output level $\tilde{B}$. In particular, the expected remuneration agent i gets from bandwidth providing is $s_i \cdot M(B) - k_i \cdot F(\tilde{B}, B)$, so the expected revenue of agent i can be expressed as:

$$ER_i = s_i \cdot M(B) - k_i \cdot F(\tilde{B}, B) - c_i(b_i). \tag{28}$$

The following proposition extends the insights about team penalty k_i that achieves Pareto efficiency under the uncertain environment.

***Proposition** 6: In the multi-agents QoS contract, the profit allocation scheme with team penalty constitutes a Nash equilibrium with Pareto efficiency if k_i satisfies:*

$$k_i = \frac{(s_i - 1)\frac{\partial c_i(b_i)}{\partial b_i}}{F'(\tilde{B}, B)}. \tag{29}$$

Proof: For b_i^* is Pareto efficient, it should satisfy Eq. (24) which maximizes the sum of revenues of the SP and agents. We can find the corresponding b_i^* by applying the first-order necessary condition of it with respect to b_i

$$\frac{\partial M(B)}{\partial b_i} = \frac{\partial c_i(b_i)}{\partial b_i}. \tag{30}$$

Assume b_i^* is a Nash equilibrium, it should also satisfy the incentive compatible condition of agent i, which implies that b^* needs to maximize Eq. (28). Therefore, a necessary and sufficient condition of the Nash equilibrium to be held is:

$$s_i \frac{\partial M(B)}{\partial b_i} - k_i \cdot \frac{\partial F(\tilde{B}, B)}{\partial b_i} - \frac{\partial c_i(b_i)}{\partial b_i} = 0. \tag{31}$$

Recall that B can be considered as a function related to b_i, i.e., $B = \sum_{i=1}^{m} b_i$, rearranging Eq. (31) yields

$$k_i = \frac{s_i \frac{\partial M(B)}{\partial b_i} - \frac{\partial c_i(b_i)}{\partial b_i}}{F'(\tilde{B}, B)}. \tag{32}$$

Combining Eq. (30) with Eq. (32), we can get the condition of the Nash equilibrium with Pareto efficient

$$k_i = \frac{(s_i - 1)\frac{\partial c_i(b_i)}{\partial b_i}}{F'(\tilde{B}, B)}. \tag{33}$$

Remind that $F'(\tilde{B}, B)$ is negative, Eq. (33) can be satisfied by setting proper values of k_i and $\tilde{B}$. □

Particularly, if the actual joint bandwidth X follows a uniform distribution $X \in [0, B]$, i.e., the practical joint bandwidth output X cannot be larger than the sum of agents' bandwidth B by taking account of the influence of transmission noise. Note that X is an intermediate variable embedded implicitly in $F(\tilde{B}, B) = P\{X < \tilde{B}|B\}$, the corresponding distribution function can be represented as $F(\tilde{B}, B) = \frac{\tilde{B}}{B}$ and its first order condition with respect to B is $F'(\tilde{B}, B) = -\frac{\tilde{B}}{B^2}$. Assume the cost of agent i is a convex function such as $c_i(b_i) = \frac{\tau_i \cdot b_i^2}{p_i}$, where τ_i is a cost factor accounting for the heterogeneous roaming characteristics of an agent, i.e., an agent with higher τ enjoys more from roaming, and will cost comparative more for performing the subcontract, p_i is the residual power of the agent's handset, low p_i will bring comparative more cost to the agent. If the agents are homogeneous, which implies that both the bandwidth supplying b_i and the corresponding allocation ratio s_i of agent i are identical to other agents, we can rewrite Eq. (33) as

$$k_i = \frac{\left(\frac{2\tau_i b_i}{p_i} - \frac{2\tau_i b_i}{m p_i}\right)(m \cdot b_i)^2}{\tilde{B}}. \tag{34}$$

From Eq. (34), we conclude that, to achieve Pareto efficiency, the less the target bandwidth $\tilde{B}$ is, the larger the corresponding k_i should be. Meanwhile, the higher roaming characteristics τ_i the agent is, the larger k_i should be. The contrary result is suitable for p_i. Note that an AP with less residual power p_i is penalized more in our model, since we believe that an AP with less p_i has stronger incentive to escape the system. It is just like the bank's credit evaluation system in which a person with high income is more likely to get a higher credit limit than the one with low income. We also observe that the team penalty k_i increases with the increasing of the team member m. This is mainly due to the fact that the impact of penalty will be diffused as the team size increases. Thus it suggests that the SP should enhance the degree of penalty to get the desired QoS output when the team size increases.

4 The Equilibrium of Tripartite Game

In this section, we will take an overall view of the QoS trading that involves EU, SP and APs. We model the dynamic interactions among the three parties as a tripartite game.

In this tripartite game, the SP provides mobile streaming services to an EU and gets profits by setting proper service prices (P, r). The EU determines its subscribing probability by taking account of its price sensitivity and gets its revenue from the viewing experience, which can be interpreted as utility. When the SP signs a QoS guarantee contract (i.e., basic contract) with an EU, the SP needs to arrange its contracted task (i.e., providing streaming services to the EU with the promised QoS) to the APs. For ease of illustration, in this section, we consider all the APs as a single entity, namely work team, whose joint bandwidth output is B.

Thus, in addition to its operation cost, the SP should also undertake some extra cost, i.e., the wage of the APs denoted by $M(B)$. We can divide the tripartite game into two parts: leader-follower sub-game and non-cooperative sub-game. The leader-follower sub-game is introduced to model the interaction between the SP and EU, where the SP sets the prices (P, r) and the EU determines its bandwidth requirement. We apply the non-cooperative sub-game to model the interaction between the SP and work team, i.e., the work team seeks its revenue maximization by deciding its bandwidth output.

For the leader-follower sub-game, the SP sets the service prices (P, r). The EU determines its subscribing probability. As shown in Eq. (8), the probability that the EU has the willingness to subscribe the service is $D(P, r)$ in face of the given prices (P, r). Given the EU's subscribing probability and the wage of the work team $M(B)$, the goal of the SP is to decide how to carefully set the prices (P, r) so as to maximize its revenue:

$$R_{SP} = (P - \theta r - C - M(B) - \theta c) \cdot D(P, r). \quad (35)$$

That is, the optimal prices (P^*, r^*) should satisfy:

$$(P^*, r^*) \in \arg\max_{(P,r)} \{(P - \theta r - C - M(B) - \theta c) \cdot D(P, r)\}. \quad (36)$$

On the other hand, the work team derives a monetary bandwidth output $M(B)$ from accomplishing the QoS task successfully. Otherwise, the work team will suffer a penalty K. According to the discussion in Section 3.4, the probability that the work team gets the penalty is $F(\tilde{B}, B)$ due to the transmission uncertainty. We assume the joint cost of the work team as $C_a(B)$. As the APs get the revenue only under the condition that the EU chooses to subscribe the service, the revenue function of the work team can be represented as

$$R_{WT} = D(P, r) \cdot (M(B) - K \cdot F(\tilde{B}, B) - C_a(B)). \quad (37)$$

In this tripartite game, the work team of APs seeks its revenue maximization by providing an optimal bandwidth B^*. The following proposition shows the equilibrium of the tripartite game:

***Proposition** 7: There exists a Nash equilibrium in this tripartite game and the equilibrium strategy profile $\{P^*, B^*\}$ should satisfy:*

$$P^* = \begin{cases} \frac{1}{2}\left[\frac{1-\mu\varphi}{1-\mu} + (C + M(B^*) + \theta c)\frac{1-\mu}{1-\theta}\right] & , \quad r = P; \\ \frac{1}{2}(1 - \mu\varphi + C + M(B^*) + \theta c) & , \quad r = 0; \end{cases} \quad (38)$$

and

$$\frac{\partial M(B^*)}{\partial B} = K \cdot \frac{\partial F(\tilde{B}, B)}{\partial B} + \frac{\partial C_a(B)}{\partial B}. \quad (39)$$

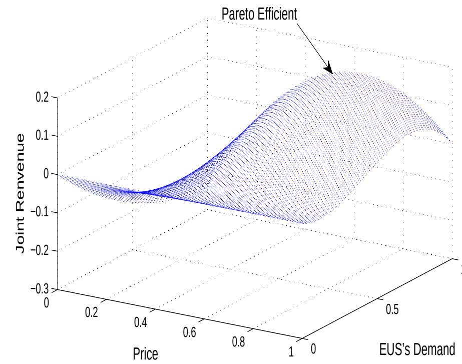


Fig. 3. The Illustration of Pareto Efficiency.

Proof: In this tripartite game, the APs provide a joint bandwidth to the EU and get profits from the SP, which are associated with their bandwidth contributions. The APs seek their revenue maximization by providing an optimal bandwidth B^*, i.e., for the APs, the contributing bandwidth B^* that achieves a Nash equilibrium should maximize Eq. (37) to satisfy its condition of incentive compatibility. Differentiating Eq. (37) with respect to B, we can get the optimal bandwidth of the APs as:

$$\frac{\partial M(B^*)}{\partial B} - K \cdot \frac{\partial F(\tilde{B}, B)}{\partial B} - \frac{\partial C_a(B)}{\partial B} = 0,$$

which leads to Eq. (39).

Given the optimal bandwidth B^* of APs, SP sets the service prices (P, r). EU determines its subscribing probability in face of the prices. As shown in Eq. (8), the probability that EU has the willingness to subscribe the service is $D(P, r)$. Given the EU's subscribing probability and the optimal bandwidth B^* of APs, the goal of SP is to decide how to carefully set the prices so as to maximize its revenue.

We substitute $M(B^*)$ into Eq. (35). The Nash equilibrium of the leader-follower sub-game can be solved by applying the first order condition of Eq. (35) with respect to P and r. Thus, we can get Eq. (38). The detailed derivation process is similar to Lemma 2. □

Proposition 7 shows the optimal prices of SP increase in this tripartite game, comparing with the result depicted in Lemma 2 for the game only between the SP and EU. This is mainly due to the increasing of SP's cost since SP should undertake some extra cost, i.e., the wage of the APs. We also notice that the optimal bandwidth providing of the APs has little connection with the prices (P, r). However, SP could control the bandwidth output of the peers by adjusting the penalty K.

5 Numerical Analysis

In this section, we provide numerical examples to illustrate the insight obtained from previous theoretical analysis. In particular, we concentrate on analyzing the changing of participants' revenues. We set up a virtual MP2P streaming system with 20 heterogeneous mobile peers and a SP. At the beginning of the simulation, an EU and several APs are selected from mobile peers randomly. We assume the costs of the APs fall equally within a certain range. The APs bid for the bandwidth providing according to their costs and each contracted agent has 0.01 possibility to run away.

We first investigate the Pareto efficiency of the EUS and SP. To illustrate the Pareto efficiency, we both increase the price of the SP and the service demand of the EUS from 0 to 1. The evolution of joint revenue of the SP and EUS is plotted in Fig. 3. The arrow indicates the Pareto efficient point, which is the maximum of joint revenue. At the point, no party in the system can be better off with no other parties being made worse off.

We next study the benefits of contingent contract. Fig. 4(a) shows the corresponding service demand of the EUs when the SP applies the QoS contingent contract and single price contract without any rebate. We can observe that the EUs' service demand in the case of the QoS contingent contract is always larger than that in the single price contract when the EUs underestimate the service quality of the SP, i.e., $\mu > \theta$. This illustrates that the QoS contingent contract can expand the SP's market coverage. On the other hand, the contingent contract results in less service demand comparing with a single price contract, when the EUs overestimate the performance of the SP's service, i.e., $\mu < \theta$, where it benefits for the SP to offer a single price contract.

We proceed to study the optimal contract of the SP. For ease of comparison, we investigate the optimal contract by relaxing the normal distribution of v for all EUs. We first investigate the optimal contract under the uniform distribution of v. We study two cases: $\mu < \theta$ and $\mu > \theta$. The evolution of the SP's revenue can be obtained by varying the price P and rebate r, which is illustrated in Fig. 4(b). As expected, the SP gets its highest revenue when $r = P$ in the case of $\mu > \theta$; on the contrary, the SP attains the highest revenue when $r = 0$ in the case of $\mu < \theta$. These results confirm the analysis in Section 2.2, the SP will prefer to offer a contingent contract when the EUs underestimate the performance of services, i.e., $\mu < \theta$; otherwise the SP will prefer to offer a single price contract. For ease of comparison, we also investigate the optimal contract by relaxing the uniform distribution of v to the normal distribution for all EUs, which is indicated in Fig. 4(c). We can observe similar results of SP's revenue under the normal distribution, which are consistent with the results under the uniform distribution. This suggests that the distribution of v has less impact on the strategy of SP.

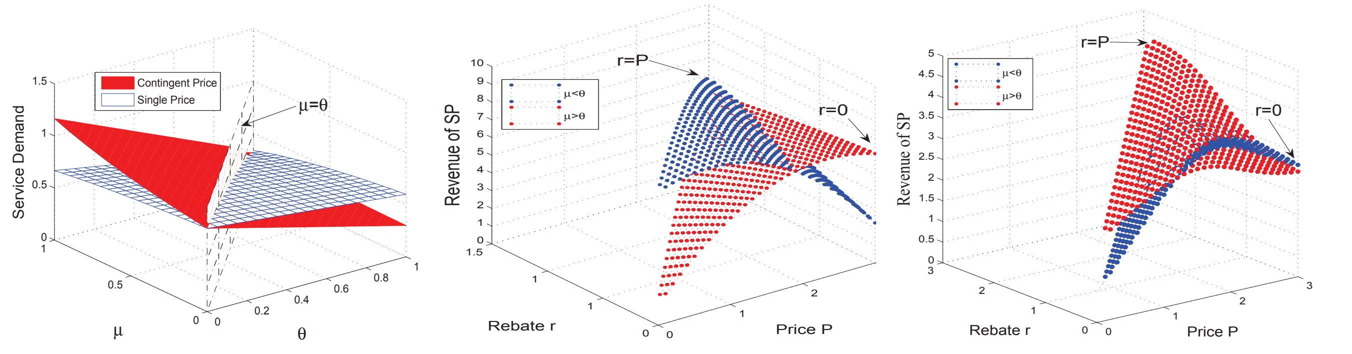
We now study the subcontract. The impact of team penalty on the revenue of the SP and agents is shown in Fig. 5(a). The revenue of the SP increases rapidly as team penalty increases at the initial range. It indicates that the team penalty is beneficial to regulate team agents' behavior and thus results in the desired SP's profit. As the team penalty continues increasing, the expected revenue of agents drops quickly. The reason is that the agents' expected revenues are very low when the team penalty is beyond a point. As a result, agents would have less incentive to join the system and the SP's revenue becomes almost unchanged. It shows that a heavy team penalty contributes little to improve the SP's revenue. Instead, it hurts the benefit of agents. These observations suggest that there may exist an optimal penalty that is sufficient to guarantee a relative high revenue for the SP while keeping agents' expected revenues in a relative high level. As indicated in Fig. 5(a), the optimal penalty is about 3.2, where the joint revenue of the SP and agents achieves maximum.

As the work team is composed of multiple agents, individual agent's revenue is associated with other agents' behavior. The team size will affect individual agent's revenue. As shown by Eq. (28), the individual revenue function of an agent consists of three parts: the remuneration obtained from SP $r_i(b_i)$, the cost function $c_i(b_i)$ and the expected penalty $k_i \cdot F(\tilde{B}, B)$. As mentioned in Section 3.1, the cost function $c_i(b_i)$ is differentiable and strictly convex as b_i increases. Note that the bandwidth output b_i, which the individual agent should provide, will decrease with the increasing of agents' number, resulting in the decreasing of agents' costs $c_i(b_i)$ and $r_i(b_i)$. The individual revenue will increase by taking the consideration that the decline of an agent's cost is faster than the decreasing of the agent's remuneration. Fig. 5(b) shows the impact of team size on individual agent's revenue. We can observe from Fig. 5(b)) that, when the team size is small, the individual agent's revenue increases as the team size increases. The agent's revenue reaches maximum when the team size is 3. It shows that the bandwidth provided by few agents is very costly. It calls for more mobile peers to engage in. As the number of agents continues increasing, the individual agent's revenue declines. It suggests that it is better to employ as less agents as possible if the team size is large enough to carry out the QoS work.

In practice, some agents may terminate the QoS work abruptly during the contract life, which may result in the failure of the QoS work, and decrease the expected revenue of agents. We have noticed that the churn rate of engaged agents play an important role in QoS work. We further discuss the impact of agent's churn rate on the revenues of SP and agents. We increase the agent's churn rate from 0 to 0.6 to illustrate the evolution of the revenues of SP and agents, which is indicated in Fig. 5(c). We can observe that the revenue of agents decreases significantly with the increasing of agent's churn rate. In contrast, the revenue of SP decreases much less. This phenomenon mainly due to the fact that SP shifts the risk of revenue decreasing to the agents by setting a proper penalty value. Furthermore, from Figs. 5(a) and 5(c), we can see that the collective revenue is increasing as the number of agents increases. This is because the expected penalty and individual cost will decrease with the increasing of agents' number if SP always adopts a constant penalty value.

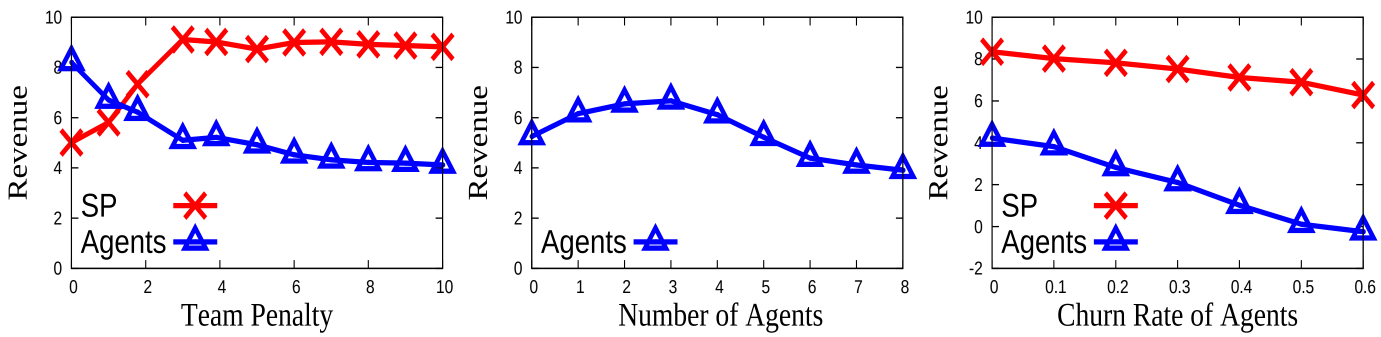
6 Prototype Implementation and Evaluation

To judge the general feasibility of the proposed system, we have implemented a peer-assisted mobile streaming prototype system and conducted a small-scale test to evaluate its performance. We have set up a data-source server that can be performed as a SP. The data-source server stores several popular videos and provides the internet-accessible HTTP streaming service. The dynamic APs management mechanism is also incorporated on the data-source server. Meanwhile, we have developed an Android application running on mobile



(a) Service demand (b) SP's revenue under the uniform distribution (c) SP's revenue under the normal distribution

Fig. 4. The benefit of contingent contract.



(a) Team penalty (b) Team size (c) Agent's churn rate

Fig. 5. The impact of various parameters on revenues of SP and agents.

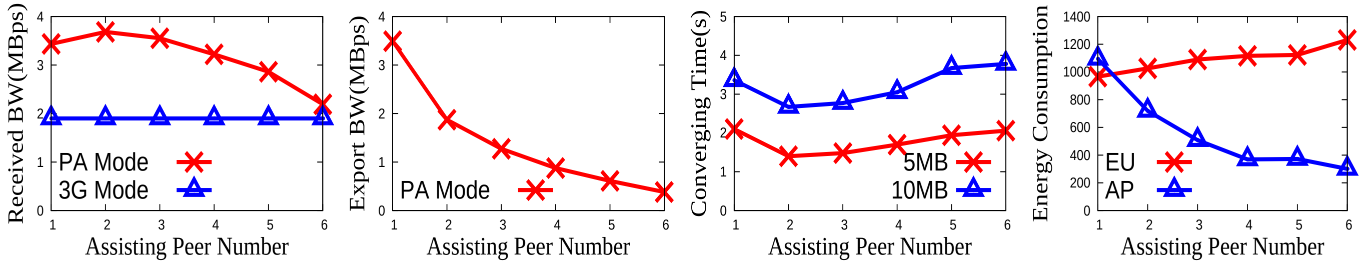
clients based on the Android multimedia framework. The Android application mainly includes three parts, (1) player module, which is a media player that allows EUs to request and play the videos provided by SP; (2) Wi-Fi hotspot module, which enables the EU's Android phone to initiate a wireless hotspot so that the nearby APs can join in the hotspot and provide their bandwidths to the EU; (3) AP module, which allows Android phones to act as APs, e.g., Android phones can detect the requests around themselves and decide whether or not to respond the requests for providing their bandwidths. The AP module also maintains a session with the SP to get the corresponding job schedule and current award/penalty.

The experiment set-up consists of one data-source server (IBM server System x3100 M4, running Ubuntu Linux) and seven identical mobile phones (Samsung GALAXY SIII I9300 with 16GB memory and Wi-Fi/3G connection). Each mobile node downloads and installs a test suite from the server. The test suite includes the Android application and a test video program. The video is encoded by H.264 with a resolution of 320x180 pixels and 24 frames per second. The video lasts for 15.56 minutes and its total volume is 107.6 MB. One mobile phone is selected to play as an EU and the others are candidate APs. The entire work flow of the prototype system is briefly described as follows: The EU sends a program request to the data-source server through 3G. On receiving the EU's request, the server indicates the EU to initiate a Wi-Fi hotspot. The Wi-Fi hotspot built by the EU has a special Service Set Identifier, SSID, so that nearby mobile phones, acting as APs, can join in the hotspot and provide their bandwidths to the EU. At the same time, each AP keeps a session with the data server to get the periodical updating information through 3G connection.

We evaluate the performance of the prototype system in terms of the following three metrics:

- Aggregating bandwidth, which indicates the aggregating bandwidth of EU provided by the APs;
- Converging time, which measures the time delay from the time the initial request of the video playback is sent to the time the video playback actually starts;
- Energy consumption, which indicates the corresponding battery drainage of the EU and APs during test run.

We first investigate how the aggregating bandwidth of the EU is affected by various number of APs. This metric can reveal the desired number of APs that able to provide a stable mobile streaming service. For ease of comparison, in this experiment we first let the EU access the streaming services through 3G (3G mode) and record its bandwidth as the benchmark, which is illustrated as a blue dashed line in Fig. 6(a). We further study the change of the aggregating bandwidth of the EU in the Pear-Assisted mode by increasing the number of APs. Fig. 6(a) shows that the aggregating bandwidth of the EU first increases when the number of APs increases from 1 to 2. After this, the aggregating bandwidth of the EU decreases as more APs participate in the system. We speculate the intuition behind the phenomenon is mainly



(a) The aggregating bandwidth of EU (b) The bandwidth output of AP (c) The converging time of EU (d) The energy consumption of EU and APs

Fig. 6. The impact of AP number on the EU and AP.

due to the co-channel interference. This observation implies that the aggregating bandwidth of the EU does not necessarily benefit from the increasing of the number of APs. We also observe that the aggregating bandwidth of the EU in the Pear-Assisted mode always exceeds the bandwidth provided by the 3G mode, even in the worst case that the system has six APs.

We also study the impact of the AP number on the bandwidth output distribution of individual AP. The experiment lasts six test rounds as we increase the engaged AP number from 1-6. We calculate the average bandwidth output of the APs that are involved in each test round. Fig. 6(b) shows the relationship between the number of engaged APs and the average bandwidth output of AP. We can see that the bandwidth output of each AP decreases as more APs participate in the system. This observation is consistent with our intuition, i.e., increasing the number of APs could ease the burden of each AP. However, from the previous experiment, we find that the system performance does not simply increase along with the increase of AP number.

We next investigate the impact of APs' number on the converging time of EU. In this experiment, the converge time is closely related to the startup buffer size, since EU has to buffer a specified size of streaming data before it could watch program fluently. To give a detailed comparison, we set the EU's buffer size to 5 MB and 10MB. Fig. 6(c) shows the changing of converge time while the participating APs' number increases from 1 to 6. As depicted in Fig. 6(c), the case of 5MB has a similar tendency with 10MB, so we take 10MB as a instance to illustrate. The converge time first decreases at the initial stage, i.e., the APs' number increases from 1 to 3. This tendency indicates that the increasing of APs' number certainly helps in reducing the converge time. However, the variation of converge time begins to rise, which implies that increasing APs' number has some negative impact on reducing the converge time. The intuition behind the phenomenon is that EU's available bandwidth does not continue increasing with the increasing of APs' number. In contrast, the co-channel interference increases with the increasing of participating mobile devices. In addition, EU has to more computing resources to handle the increasing sessions from APs, which result in the increasing of converge time consequently.

We also investigate the energy consumption of EU and APs under various AP numbers. Fig. 6(d) shows the changes of the energy consumption of EU and APs with the increasing size of AP number. We can observe that the energy consumption of EU continues to increase with the increasing of the AP number. This implies that the increased AP number has negative impact on EU's energy consumption. The intuition behind this phenomenon is that the energy consumption of EU is mainly caused by handling and receiving the aggregating bandwidth sent from APs, the more APs are, the larger EU's energy consumption is. On contrast, the energy consumption of each AP decreases with the increasing number of APs. This is consistent with the fact that the bandwidth contribution of each peer reduces as more APs participant in the system, which leads to the reductions of AP's energy consumption.

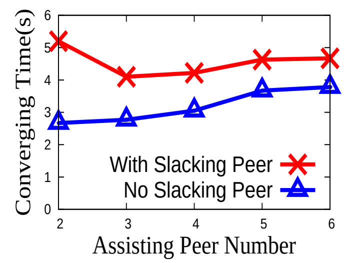


Fig. 7. The impact of slacking peer on the converging time of EU.

We further study how the existence of slacking APs affects the performance of the MP2P streaming system. Specifically, we consider the scenario that a slacking AP does not perform for the system. As the slacking AP does not provide any bandwidth to EU, the subcontract between the SP and the slacking AP has been violated. Fig. 7 shows the changes of EU's converging time when a slacking AP exists in the system under various number of APs. We can observe that, when there exists slacking APs in the system, the converging time of EU increases, comparing with the system without any slacking AP. This experiment shows that the existence of slacking APs would decrease the performance of the system. Especially, as indicated in Fig. 7, when the number of APs is 2, the EU's converging time increases about 80%. This suggests that the contract is necessary to rule the behaviors of APs.

From above experiments, we can conclude that, the peer-assisted mode could significantly improve the QoS of EU. However, the aggregating bandwidth does not often increase responding to the increasing of APs' number. As suggested in Fig. 6(a), two or three APs are preferable choices to satisfy the EU's demands by taking consideration of QoS improvement and energy consumption. We would like to state that the optimal AP's number is just derived from the experiments of our test runs. It may not be suitable for all MP2P environments.

7 Related Work

With the advancement in the pervasive use of mobile multimedia devices, MP2P technology has been employed in multimedia content distribution, such as PhotoChat [20], MobiTip [21], and mobile YouTube [22]. It can offer instant viewing instead of download-before-view in social community networks which exhibits high locality characteristics.

Many studies have also addressed system designs that leverage MP2P applications. In [23], Venot et al. introduced a JXTA based P2P video player that is able to operate on mobile devices. In [24], Eittenberger et al. presented a mobile P2P streaming prototype in the Android system. In [25], Stiemerling et al. proposed a scheme that allows several users to contribute their wireless Internet access resources for retrieving the content in a joint effort. Similar approaches were further explored in [26], [27]. More recently, in [2], Keller et al. implemented a novel system, MicroCast, that uses all the resources of a group of smartphones in a cooperative way so as to improve the streaming experience. Wei et al. designed a scheme for content sharing in a location preserving way [3]. In [4], Venkatramanan and Kumar studied the dissemination of a single item of content (e.g., a piece of news, a song or a video clip) in a mobile P2P environment. Each node in the environment is either a destination (interested in the content) or a potential relay (not yet interested in the content).

However, all of these MP2P studies have concentrated more on the technical implementation of MP2P systems. Moreover, most of the MP2P application prototypes are in an exploratory stage, which assume mobile peers are altruistic entities, without considering the free-riding problem that widely exists in P2P systems.

Different from the above MP2P studies, our work, which integrates mobile wireless devices into reputation or economic models, puts the focus on incentive schemes of MP2P systems. Incentives have been recently studied for MP2P systems in [28], [29]. These works mostly consider incentive mechanisms for resource information dissemination in transportation applications, where a mobile peer exchanges its information with the peers it encounters. The peers' contributions are mainly measured by reputation or virtual currency, which may not be attractive enough for peers to engage in information dissemination. Other incentive schemes in MP2P network are relevant to economic models [30]. They discuss utility functions to capture users' contributions, while trustworthiness issues are also studied. However, these schemes do not give any regulations on detailed QoS issues, and thus cannot achieve the purpose of QoS guarantee.

The contract model, as a typical economic model, has been employed in the networks [12], [31]–[33]. It can efficiently motivate as well as regulate the participants in the context of contracts to fulfil contractual obligations. In [12], a bandwidth contract integrating with a two-component spot pricing scheme was proposed for the sake of QoS guarantee. Cheliotis [31] proposed an economic model called plan contracts for better utilization of telecommunication network resources. In [32], contract model was introduced into large scale network applications to encourage cooperations. In [34], Duan et al. analyzed and compared different incentive mechanisms for a client to motivate the collaboration of smartphone users on both data acquisition and distributed computing applications. They used the contract theory to study how a client efficiently decides different task-reward combinations for different user types. Rebate pricing mechanisms are commonly used in many IT services, e.g., voice over IP or video streaming applications, owing to the factors such as unobservability of product, stochasticity in manufacturing or delivering process, lack of end-to-end control [8]. In [9], Bhargava et al. showed that the threshold-performance contingency contract can increase both profits and fairness relative to the standard pricing scheme.

Note that most of these contract models adopt the traditional MP2P architecture, i.e., the regular packet forwarding scheme under the ad hoc mode. However, in this paper we propose a peer-assisted system architecture, i.e., APs provides mobile streaming services through self-built Wi-Fi hotspots, for the purposes of enhancing programs' QoS and reducing operating cost. To the best of our knowledge, there is no previous work that applies the contract model to handle the problem of QoS guarantee in MP2P streaming applications.

8 Conclusions and Future Work

In this paper, we have developed a framework of QoS guarantee in mobile P2P streaming systems through a contract-ruled approach. We model the parties involved in the system as real economic entities, which are organized as a basic contract and a multi-agents subcontract. In the basic contract, we establish the business agreement between an interested EU and SP. We propose a QoS contingent payment to mitigate EUs' concern on the uncertainty of the services and derive the optimal price that achieves Pareto efficiency. In the subcontract, we model transactions between SP and contracted peers as a principal multi-agents problem which achieves a desired joint QoS output. We design a sharing scheme with team penalty to overcome the free-rider problem existing in the subcontract and show that Pareto efficiency can be achieved by setting proper team penalty. We believe that the proposed contracted-ruled framework can shed light on the deployment and evolution of practical mobile streaming markets.

An interesting future work worthy of attention is the hidden information problem which may exist in the subcontract, since the agents may exaggeratedly claim their transit costs for the remunerations. This opens the way to apply some strategy-proof methods like VCG to encourage the agents report their costs truthfully. The other interesting work is to investigate the dynamic changes of the system if the EUS' belief on the service changes based on the service they receive. The problem will become much difficult if we consider the EUS' belief to be changed over time. We would like to further study the mechanisms of eliciting the EUS' expectation value θ in the future work.

ACKNOWLEDGEMENT

This work was supported in part by grants from Hong Kong RGC (PolyU 523207, PolyU 521312), Hong Kong PolyU (A-PJ16, A-PL84, 1-VZ5N, 4-BCB6), and National Natural Science Foundation of China (No. 61272463, No. 61303226).

REFERENCES

[1] B. Li, Y. Qin, C. P. Low, and C. L. Gwee, "A survey on mobile WiMAX," *IEEE Commun. Mag.*, vol. 45, no. 12, pp. 70–75, 2007.

[2] L. Keller, A. Le, B. Cici, H. Seferoglu, C. Fragouli, and A. Markopoulou, "MicroCast: Cooperative video streaming on smartphones," in *Proc. ACM 10th Int. Conf. Mobile Syst., Appl., Serv.*, 2012, pp. 57–70.

[3] W. Wei, F. Xu, and Q. Li, "MobiShare: Flexible privacy-preserving location sharing in mobile online social networks," in *Proc. IEEE INFOCOM*, 2012, pp. 2616–2620.

[4] S. Venkatramanan and A. Kumar, "Co-evolution of content popularity and delivery in mobile P2P networks," in *Proc. IEEE INFOCOM*, 2012, pp. 3006–3010.

[5] Y. Liu, X. Liu, L. Xiao, L. M. Ni, and X. Zhang, "Location-aware topology matching in P2P systems," in *Proc. IEEE INFOCOM*, 2004, pp. 2220–2230.

[6] P. Golle, K. Leyton-Brown, and I. Mironov, "Incentives for sharing in peer-to-peer networks," in *Proc. 2nd Int. Workshop on Electron. Commerce*, 2001, pp. 264–267.

[7] R. Kumar, Y. Liu, and K. W. Ross, "Stochastic fluid theory for P2P streaming systems," in *Proc. IEEE INFOCOM*, 2007, pp. 919–927.

[8] H. K. Bhargava and S. Sundaresan, "Contingency pricing for information goods and services under industry-wide performance standard," *J. Manage. Inf. Syst.*, vol. 20, no. 2, pp. 113–136, 2003.

[9] H. K. Bhargava and S. Sundaresan, "Pricing under quality of service uncertainty: Market segmentation via statistical qos guarantees," *Eur. J. Oper. Res.*, vol. 191, no. 3, pp. 1189–1204, 2008.

[10] C. Aperjis, M. J. Freedman, and R. Johari, "Peer-assisted content distribution with prices," in *Proc. ACM CoNEXT Conf.*, 2008, Article No. 17.

[11] V. Misra, S. Ioannidis, and A. Chaintreau, "Incentivizing peer-assisted services: A fluid shapley value approach," *ACM SIGMETRICS Perform. Eval. Rev.*, vol. 38, no. 1, pp. 215–226, 2010.

[12] A. Gupta, S. Kalyanaraman, and L. Zhang, "Pricing of risk for loss guaranteed intra-domain internet service contracts," *Comput. Netw.*, vol. 50, no. 15, pp. 2787–2804, 2006.

[13] R. Gibbons, *A Primer in Game Theory*. London, UK: Financial Times Prentice Hal, 1992.

[14] P. Dubey, "Inefficiency of Nash equilibria," *Math. Oper. Res.*, vol. 11, no. 1, pp. 1–8, 1986.

[15] K. Binmore, A. Rubinstein, and A. Wolinsky, "The Nash bargaining solution in economic modelling," *The RAND J. Econ.*, vol. 17, no. 2, pp. 176–188, 1986.

[16] M. J. Osborne and A. Rubinstein, *A Course in Game Theory*. Combridge, MA, USA: MIT Press, 1994.

[17] Z. Han, Z. Ji, and R. Liu, "Fair multiuser channel allocation for OFDMA networks using Nash bargaining solutions and coalitions," *IEEE Trans. Commun.*, vol. 53, no. 8, pp. 1366–1376, 2005.

[18] B. Holmstrom and P. Milgrom, "Multitask principal-agent analyses: Incentive contracts, asset ownership, and job design," *J. Law Econ. Org.*, vol. 7, pp. 24–52, 1991.

[19] H. Itoh, "Incentives to help in multi-agent situations," *Econometrica*, vol. 59, no. 3, pp. 611–636, 1991.

[20] Y. Sumi, J. Ito, and T. Nishida, "PhotoChat: Communication support system based on sharing photos and notes," in *Proc. ACM CHI Extended Abstracts Human Factors Comput. Syst.*, 2008, pp. 3237–3242.

[21] A. Rudstrom, M. Svensson, R. Coster, and K. Hook, "MobiTip: Using bluetooth as a mediator of social context," in *ACM Ubicomp 2004 Adjunct Proceedings (demo)*, 2004.

[22] F. S. Tsai, W. Han, J. Xu, and H. C. Chua, "Design and development of a mobile peer-to-peer social networking application," *Expert Syst. Appl.: An Int. J.*, vol. 36, no. 8, pp. 11 077–11 087, 2009.

[23] S. Venot and L. Yan, "On-demand mobile peer-to-peer streaming over the JXTA overlay," in *Proc. Int. Conf. Mobile Ubiquitous Comput., Syst., Serv. Technol.*, 2007, pp. 131–136.

[24] P. M. Eittenberger, "RaptorStream: Boosting mobile peer-to-peer streaming with raptor codes," in *Proc. ACM Conf. Appl., Technol., Archit. Protocols Comput. Commun.*, 2012, pp. 291–292.

[25] M. Stiemerling and S. Kiesel, "Cooperative P2P video streaming for mobile peers," in *Proc. 19th Int. Conf. Comput. Commun. Netw.*, 2010, pp. 1–7.

[26] J. Noh, M. Makar, and B. Girod, "Streaming to mobile users in a P2P network," in *Proc. 5th Int. ICST Mobile Multimedia Commun. Conf.*, 2009, Article No. 24.

[27] P. M. Eittenberger, M. Herbst, and U. R. Krieger, "RapidStream: P2P streaming on android," in *Proc. 19th Int. Packet Video Workshop*, 2012, pp. 125–130.

[28] S. Gurun, P. Nagpurkar, and B. Y. Zhao, "Energy consumption and conservation in mobile P2P systems," in *Proc. 1st Int. Workshop Decentralized Resource Sharing Mobile Comput. Netw.*, 2006, pp. 18–23.

[29] B. Xu, O. Wolfson, and N. Rishe, "Benefit and pricing of spatio-temporal information in mobile peer-to-peer networks," in *Proc. 39th Annu. Hawaii Int. Conf. Syst. Sci.*, 2006, p. 223.

[30] S. Zhong, J. Chen, and R. Yang, "Sprite: A simple, cheat-proof, credit-based system for mobile ad-hoc networks," in *Proc. IEEE INFOCOM*, 2003, pp. 1987–1997.

[31] G. Cheliotis, "Structure and Dynamics of Bandwidth Markets," Ph.D. dissertation, Elect. Eng. and Comput. Sci. Dept., Nanyang Technological Univ., Singapore, 2001.

[32] B. Q. Zhao and J. C. S. Lui, "Cooperation via contracts: Stability and algorithms," in *Proc. IEEE INFOCOM*, 2010, pp. 26–30.

[33] M. Feldman and J. Chuang, "Overcoming free-riding behavior in peer-to-peer systems," vol. 5, no. 4, pp. 41–50, 2005.

[34] L. Duan, T. Kubo, K. Sugiyama, J. Huang, T. Hasegawa, and J. Walrand, "Incentive mechanisms for smartphone collaboration in data acquisition and distributed computing," in *Proc. IEEE INFOCOM*, 2012, pp. 1701–1709.