Contract-Based Traffic Offloading over Delay Tolerant Networks

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***Abstract*—Traffic offloading over Delay Tolerant Networks (DTNs) is a promising paradigm to alleviate the network congestion caused by explosive traffic demands. As we all know, in mobile networks, the delay profile for traffic is remarkable due to user's mobility. How to exploit delay tolerance to improve the profit of the operator as well as mobile users becomes a big challenge. In this paper, we investigate the problem of the interrelation of delay and user QoS. Inspired by contract theory, we model the delayed offloading process as a monopoly market where the operator makes pricing by considering statistical information about user satisfaction. In addition, we propose an incentive framework to motivate users to leverage their delay and price sensitivity in exchange for service cost. To capture the heterogeneity of user satisfaction, we classify users into different types. Each user chooses an appropriate quality-price contract item according to its type. Moreover, we derive an optimal contract which is feasible and maximizes the operator's profit as well. Numerical results validate the effectiveness of our incentive framework for traffic offloading over DTNs.**

I. Introduction

Currently, a huge amount of cellular traffic has been generated, which is mainly due to the popularization of smart phones equipped with diverse applications. According to the Cisco Visual Networking Index [1], global mobile data traffic is expected to increase nearly tenfold between 2014 and 2019, reaching 24.3 exabytes per month by 2019. The continued growth of traffic is heavily pushing the capacity of cellular network and deteriorating the network quality.

To alleviate the overload problem caused by explosive traffic demands, offloading part of cellular traffic to other coexisting networks, such as Delay Tolerant Networks (DTNs) and WiFi Networks, would be a desirable approach [2]-[4]. On the other hand, due to user's mobility, these networks can only provide intermittent and opportunistic network connectivity, which results in non-negligible delay. With the increase of delay, users will become impatient, and hence their satisfaction will be greatly reduced [5]-[7]. In [8], the authors introduced satisfaction function to model user delay tolerance and obtained a tradeoff between delay and user Quality of Service (QoS) in DTN-based offloading. In recent years, traffic offloading over DTNs has gained a growing interest and is warmly welcomed by delay-tolerant applications, such as movie downloading and e-mail service, which can tolerate some delay and do not sacrifice too much user satisfaction as well [9][10].

Traffic offloading over DTNs is a promising paradigm to allow the traffic with diverse delay attributes and formulate the interrelation of delay and user QoS in a feasible way. The technology and economics issues behind it have exerted a tremendous fascination on many researchers. In [11], the authors proposed an analytical model to study the performance gains in DTNs. The coalitional game was used to analyze the cooperation decisions of multiple rational communities. Li *et al*. [12] developed a contact duration aware offloading scheme to address the problem of large-size multimedia contents. The scheme consisted of several designs specially tailored for DTNs to achieve the optimum dissemination.

Despite the distinct advantages over delay tolerance, there are still some problems remained for offloading over DTNs, especially incentive mechanism. Li *et al*. [13] established a framework to study offloading over DTNs and formulated it as a problem of Submodular Function Maximization. Traditionally, it is often supposed that users are willing to participate in delayed offloading. But in reality, delayed offloading may deteriorate user experience and make them reluctant to participate in it. Therefore, more attention should be given to incentive mechanism. In [14], the authors modeled the interactions among the operator and users as a Stackelberg game and devised an incentive mechanism to encourage user collaboration. However, these studies have not considered user satisfaction loss caused by longer delay. In order to obtain a tradeoff between delay and user satisfaction, Zhuo *et al*. [8] proposed an incentive mechanism to motivate users to leverage their delay tolerance based on reverse auction. Nevertheless, they depicted the characteristics of user QoS only by delay sensitivity and ignored price sensitivity, which also had a huge impact on QoS. In addition, reverse auction they used does not involve statistical information about user satisfaction which can assist the operator in making pricing effectively.

To this end, we are inspired to address the incentive issues about traffic offloading over DTNs. We model the delayed offloading process as a monopoly market based on contract theory, where an operator acts as monopolist who sets up the optimal quality-price contract. Each user chooses a contract item to maximize its utility according to its delay and price sensitivity. In this paper, we investigate the incomplete information scenario, where user type is private information and only known to user itself. The aim of this paper is to exploit the interaction between the operator and users and design an incentive framework for traffic offloading over DTNs. In addition, we derive an optimal contract which can maximize the operator's profit.

The contributions of this work are summarized as follows:

• To our knowledge, this is the first paper that introduces contract theory to assist the operator in making pricing and exploit the interaction between the operator and users in traffic offloading over DTNs. Specially, users with different delay and price sensitivity are classified into different types according to their satisfaction.

• We derive the optimal contract, which maximizes the operator's profit and guarantees the feasibility for users, under incomplete information and continuous-user-type model. Numerical results validate the effectiveness of our scheme in improving operator's profit.

The rest of this paper is organized as follows. First we introduce our system model in Section II. In Section III, we formulate the contract problem and derive the optimal contract under the asymmetric information scenario. In Section IV, we present the numerical results and discussions of our scheme. Finally, we conclude our work in Section V.

II. System model

In this section, we first model the offloading process as a monopoly market consisting of an operator and users. After that, we present their utility functions respectively.

A. Network and Service Model

Consider the offloading process over DTNs as a monopoly market consisting of a monopolist operator and a set $\mathcal{N} = \{1, \cdots, N\}$ of users who subscribe to the offloading service. We classify these users into different types θ according to their delay sensitivity. Each user not only requests the desired data, but also can provide its data to other users. In this paper, we design a contract-based incentive framework to investigate the interaction among the operator and users. Fig. 1 highlights the main idea of the network model.

For a given service, the operator offers users an optimal contract consisting of different quality-price contract items. Furthermore, we denote the sets of all possible qualities and prices as Ω and Π respectively. Note that each service quality $q \in \Omega$ corresponds to a price $\pi \in \Pi$. For each contract item, we denote the quality corresponding to user type θ as $q(\theta)$ and the price paid to the operator for the quality as $\pi(q(\theta))$. For simplicity, we write $\pi(q(\theta))$ as $\pi(\theta)$ since $q(\theta)$ is a single value function. When users make a request for this service, they will choose a contract item according to their types. In this paper, we focus on user delay tolerance and the quality mainly depends on the length of delay. The delay of contract items can be one minute, one hour, one day, etc. In addition, users will sign a contract with the operator and the operator will make commitments which are composed by two parts. The first part is that the user will receive a discount if it promises to delay up to a corresponding deadline. Second, before the deadline, the user can receive the data by contacting other users that cache the data. Once the deadline expires, the user will directly receive the date from cellular network.

As shown in Fig. 1, the operator first announces the contract to user 1. At 2:00 p.m., user 1 makes a request for the data delivery and chooses a corresponding contract item

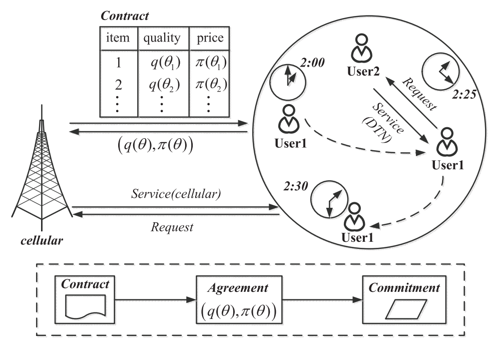

Fig. 1. Overview of the offloading scheme over DTNs.

$(q(\theta), \pi(\theta))$. In addition, user 1 signs a contract with the operator and receives the operator's commitment as mentioned before. Furthermore, before the deadline (i.e., 2:30 p.m.), user 1 will receive the data if it is able to contact user 2 who caches the data. Otherwise, if the deadline expires, use 1 will receive the date from cellular network immediately.

B. User Model

In general, users' willingness to delay the data service is mainly due to two factors: the length of delay and the discount to compensate for the delay. In order to quantify user satisfaction and economic gains behind delayed offloading, we introduce two following functions.

Quality Satisfaction Function:

In this paper, quality refers to the delay performance of offloading service. To depict the diversity of user delay sensitivity, we classify them into different types θ, i.e., the decrease of satisfaction given a unit delay. The user can obtain its own type by inferring from historical experiences. However the operator only knows the distribution of θ which is defined by the probability mass function $f(\theta)$ on $[\theta_l, \theta_u]$. Clearly, the larger user type is, the higher its requirement on quality will be. Accordingly, the user becomes more reluctant to delay. We denote $q(\theta)$ as service quality, which is a monotonically decreasing with delay. In view of the definitions of θ and $q(\theta)$, we can get $\theta q(\theta)$ indicates user satisfaction for this service. It is shown in [15] that logarithm utility functions lead to proportional fairness among users. Inspired by the quality discrimination in [16], we define quality satisfaction function as

$$V(\theta, q(\theta)) = \ln(1 + \theta q(\theta)). \tag{1}$$

Obviously, we obtain that $V_q(\theta, q)$[1] $> 0, V_\theta(\theta, q) > 0$ and $V_{qq}(\theta, q) < 0$. It means that users prefer higher quality, and for a given quality, a higher type user has a larger satisfaction than a lower one. Moreover, $V(\theta, q(\theta))$ increases more slowly with large quality than it does with small quality.

Price Satisfaction Function:

Users may have different requirements on price. We capture the dynamic characteristics of this diversity by price sensitivity. When user price sensitivity is high, e.g., students in

[1]For simplicity, we write $\partial f(\cdot)/\partial x$ as $f_x(\cdot)$ if $f(\cdot)$ is continuously differentiable with respect to x. Similarly, we write $\partial^2 f(\cdot)/\partial x^2$ as $f_{xx}(\cdot)$.

college, they are reluctant to request the service and prefer deferring the traffic when price is higher. Otherwise, when user price sensitivity is low, e.g., staff in stock markets, they don't care about whether the price is high or not.

If the price paid to the operator increases to infinity, users will refuse offloading and their price satisfaction, denoted by $G(\pi(\theta))$, will become zero, i.e., $\lim_{\pi(\theta)\to\infty} G(\pi(\theta)) = 0$. Clearly, price satisfaction is monotonically decreasing with price [17]. To guarantee proportional fairness among users, we also adopt the logarithm function as price satisfaction function, i.e.,

$$G(\pi(\theta)) = \ln\left(G_0 e^{-\alpha\pi(\theta)}\right) = \ln G_0 - \alpha\pi(\theta), \tag{2}$$

where α is price sensitivity and G_0 is the original price satisfaction. Without loss of generality, we assume that $\ln G_0 = 0$. Thus user price satisfaction function can be represented as

$$G(\pi(\theta)) = -\alpha\pi(\theta). \tag{3}$$

When type-θ user chooses the contract item $(q(\theta), \pi(\theta))$, we define its utility as the satisfaction function in terms of delay and price satisfaction, i.e.,

$$U(\theta, q(\theta)) = w_1 V(\theta, q(\theta)) + w_2 G(\pi(\theta)), \tag{4}$$

where w_1 is the conversion ratio between quality satisfaction and utility, and similarly w_2 is the conversion ratio between price satisfaction and utility. Without loss of generality, we suppose $w_1 = w_2 = 1$.

Substituting equation (1) and (3) into (4), we have

$$U(\theta, q(\theta)) = \ln(1 + \theta q(\theta)) - \alpha\pi(\theta). \tag{5}$$

C. Operator Model

Once the user subscribes to offloading service specified by contract item $(q(\theta), \pi(\theta))$, the operator will charge price $\pi(\theta))$ from the user. At the same time, providing this service for users will inevitably incur operation cost denoted by $c(q(\theta))$. From the view of the operator, the expected profit R is equal to revenue minus cost, i.e.,

$$R = \int_{\theta_l}^{\theta_u} (\pi(\theta) - c(q(\theta))) f(\theta) d\theta. \tag{6}$$

It is common to regard DTNs as free device-to-device networks, and the cost over DTNs is negligible compared with the operation cost over cellular network. Therefore, $c(q(\theta))$ mainly refers to the operation cost over cellular network. It is clear that operation cost $c(q(\theta))$ is proportional to service quality $q(\theta)$. We can consider it in two ways. First, when network congestion is heavy, quality $q(\theta)$ will experience a rapid decrease due to the increase of delay. In this case, the operator only needs to provide less cost to guarantee this negotiated quality. Second, as the delay increases, the user will have more chance to access DTNs. Thus operation cost will decrease accordingly.

III. Optimal contract design under strongly incomplete information

In this section, we first formulate the incentive framework as an optimal contract optimization problem. After that, we describe how to derive this optimal contract.

A. Contract Formulation

We investigate the delayed offloading under strongly incomplete information scenario, where user type θ is only known to itself and the operator does not know any user type. Instead, the operator only knows the distribution of θ which is defined by the probability mass function $f(\theta)$ on an interval $[\theta_l, \theta_u]$. Every participant is supposed to be rational and aims to maximize its own utility. After deriving the user's utility and operator's profit, we introduce contract theory to resolve the conflicting objectives between them.

In order to determine the optimal contract under asymmetric information, each contract item must satisfy the following two constraints according to revelation principle [18]-[21].

Definition 1: (IR: Individual Rationality): A contract satisfies the IR constraint if each type-θ user receives a non-negative utility by accepting the contract item for θ, i.e.,

$$\ln(1 + \theta q(\theta)) - \alpha\pi(\theta) \geq 0, \forall\theta \in [\theta_l, \theta_u]. \tag{7}$$

Definition 2: (IC: Incentive Compatibility): A contract satisfies the IC constraint if each type-θ user prefers to choose the contract item for θ rather than a contract item for $\hat{\theta}$, i.e.,

$$\ln(1+\theta q(\theta)) - \alpha\pi(\theta) \geq \ln(1+\theta q(\hat{\theta})) - \alpha\pi(\hat{\theta}), \forall\theta, \hat{\theta} \in [\theta_l, \theta_u]. \tag{8}$$

In a word, a feasible contract must satisfy the IR constraint in (7) and IC constraint in (8). Based on this, the ultimate goal of the operator is to establish an optimal contract which maximizes its profit under a feasible contract. Thus the operator's optimization problem can be formulated as

$$\begin{aligned} &\max_{\{(q(\theta),\pi(\theta)),\forall\theta\in[\theta_l,\theta_u]\}} \int_{\theta_l}^{\theta_u} (\pi(\theta) - c(q(\theta))) f(\theta) d\theta \\ &\text{subject to} \quad \text{IR constraint in (7)}, \\ &\qquad\qquad\quad\ \ \text{IC constraint in (8)}. \end{aligned} \tag{9}$$

Thus far, we have described the problem formulation for optimal contract design. Next we will interpret how to obtain this optimal contract.

B. Feasibility of Contract

The above problem in (9) is nontrivial to solve, since it involves optimization over a schedule $(q(\theta), \pi(\theta))$ under constraints that themselves involve other conflicting optimization problems. Such adverse selection problems can, however, still be solved step-by-step as follows [18]. Before that, we first simplify the IR and IC constraints.

Lemma 1: As for the optimal contract under incomplete information in (9), the IR constraint can be replaced by

$$\ln(1 + \theta_l q(\theta_l)) - \alpha\pi(\theta_l) \geq 0, \tag{10}$$

given that the IC constraint holds.

Proof: See Appendix A in our technical report [24]. ■

Definition 3: Spence-Mirrlees condition (SMC) [18]: The user's utility function satisfies the Spence-Mirrlees single-crossing condition if and only if

$$\frac{\partial}{\partial\theta}\left[-\frac{\partial U/\partial q}{\partial U/\partial\pi}\right] > 0. \tag{11}$$

This condition means that a more efficient type is also more efficient at the margin utility. We can easily find that user's utility, i.e., $U(q(\theta)) = \ln(1 + \hat{\theta} q(\theta)) - \alpha\pi(\theta)$, satisfies the SMC. According to [18], we can get the following Lemma.

Lemma 2: If the user's utility function satisfies the SMC, the IC constraint in (8) is equivalent to the following two constraints:

Monotonicity:

$$\frac{dq(\theta)}{d\theta} \geq 0, \tag{12}$$

Local incentive compatibility:

$$\frac{\theta q'(\theta)}{1+\theta q(\theta)} = \alpha\pi'(\theta). \tag{13}$$

Proof: See Appendix B in our technical report [24]. ■

C. Optimality of Contract

According to Lemma 1 and Lemma 2, the optimization problem in (9) can be simplified as

$$\begin{aligned} \max_{\{(q(\theta),\pi(\theta)),\forall\theta\in[\theta_l,\theta_u]\}} \ & \int_{\theta_l}^{\theta_u} (\pi(\theta) - c(q(\theta)))f(\theta)d\theta \\ \text{subject to} \quad & \ln(1+\theta_l q(\theta_l)) - \alpha\pi(\theta_l) \geq 0, \\ & \tfrac{dq(\theta)}{d\theta} \geq 0, \\ & \tfrac{\theta q'(\theta)}{1+\theta q(\theta)} = \alpha\pi'(\theta). \end{aligned} \tag{14}$$

In order to solve this optimization problem, one standard solution is first to solve the relaxed problem without the monotonicity condition and then to check whether the solution to this relaxed problem satisfies the monotonicity condition.

First, we define

$$\begin{aligned} W(\theta) &= \ln(1+\theta q(\theta)) - \alpha\pi(\theta) \\ &= \max_{\hat{\theta}} \left(\ln(1+\theta q(\hat{\theta})) - \alpha\pi(\hat{\theta})\right). \end{aligned} \tag{15}$$

According to the envelope theorem [18], we have

$$\frac{dW(\theta)}{d\theta} = \frac{\partial W(\theta)}{\partial\theta}\Big|_{\hat{\theta}=\theta} = \frac{q(\theta)}{1+\theta q(\theta)}. \tag{16}$$

Integrating the both sides of this equation, we can get

$$W(\theta) = \int_{\theta_l}^{\theta} \frac{q(x)}{1+xq(x)}dx + W(\theta_l). \tag{17}$$

At the optimal contract, the IR constraint of the lowest type is binding, so that $W(\theta_l) = 0$ and

$$W(\theta) = \int_{\theta_l}^{\theta} \frac{q(x)}{1+xq(x)}dx. \tag{18}$$

Since

$$\pi(\theta) = \frac{1}{\alpha}\left(\ln(1+\theta q(\theta)) - W(\theta)\right), \tag{19}$$

we rewrite the operator's profit as

$$\begin{aligned} R(q(\theta)) &= \textstyle\int_{\theta_l}^{\theta_u} \left(\frac{1}{\alpha}\left(\ln(1+\theta q(\theta)) - W(\theta)\right) - c(q(\theta))\right) f(\theta)d\theta \\ &= \textstyle\int_{\theta_l}^{\theta_u} \frac{1}{\alpha}\ln(1+\theta q(\theta))f(\theta)d\theta - \\ & \textstyle\int_{\theta_l}^{\theta_u}\int_{\theta_l}^{\theta} \frac{1}{\alpha}\frac{q(x)}{1+xq(x)}f(\theta)dxd\theta - \int_{\theta_l}^{\theta_u} c(q(\theta))f(\theta)d\theta. \end{aligned} \tag{20}$$

After integration by parts, we have

$$\begin{aligned} R(q(\theta)) \ &= \textstyle\int_{\theta_l}^{\theta_u} \left(\frac{1}{\alpha}\ln(1+\theta q(\theta)) - c(q(\theta))\right) f(\theta) \\ & \textstyle -\frac{1}{\alpha}\frac{q(\theta)}{1+\theta q(\theta)}\left(1-F(\theta)\right)d\theta. \end{aligned} \tag{21}$$

The maximization of R with respect to $q(\cdot)$ requires that the term under the integral be maximized with respect to $q(\cdot)$. Therefore, this relaxed problem can be further written as

$$\max_{q(\theta)} \left(\tfrac{1}{\alpha}\ln(1+\theta q(\theta)) - c(q(\theta)) - \tfrac{1}{\alpha}\tfrac{q(\theta)}{1+\theta q(\theta)}\tfrac{1-F(\theta)}{f(\theta)}\right) f(\theta). \tag{22}$$

By solving this optimization problem, we get optimal quality $\overline{q}^*(\theta)$ for the relaxed problem. In addition, we need to check whether this solution satisfies monotonicity condition. If $\overline{q}^*(\theta)$ satisfies this condition, we can consider it as our desired optimal quality $q^*(\theta)$. Otherwise, the solution that we obtained must be modified by "Bunching and Ironing" algorithm [22]. After that, we can work out optimal price $\pi^*(\theta)$, i.e.,

$$\pi^*(\theta) = \frac{1}{\alpha}\left(\ln(1+\theta q^*(\theta)) - \frac{q^*(\theta)}{1+\theta q^*(\theta)}\frac{1-F(\theta)}{f(\theta)}\right) f(\theta). \tag{23}$$

We conclude the detailed algorithm as follows:

Algorithm 1 Optimal contract algorithm

for $\theta \in \Theta$ **do**
  set $R_1(q(\theta)) = (\frac{1}{\alpha}\ln(1+\theta q(\theta)) - c(q(\theta)) - \frac{1}{\alpha}\frac{q(\theta)}{1+\theta q(\theta)}\frac{1-F(\theta)}{f(\theta)})f(\theta)$
  set $q^*(\theta) = \arg\max_q R_1(q(\theta))$
end for
while $q^*(\theta)$ is not feasible **do**
  find an infeasible region $[a, b] \subseteq \Theta$
  set $q^*(\theta) = \arg\max_q \int_a^b R_1(q(\theta))d\theta,\ \forall\theta \in [a, b]$
end while
for $\theta \in \Theta$ **do**
  set $\pi^*(\theta) = \frac{1}{\alpha}(\ln(1+\theta q^*(\theta)) - \frac{q^*(\theta)}{1+\theta q^*(\theta)}\frac{1-F(\theta)}{f(\theta)})f(\theta)$
  set $R = \int_{\theta\in\Theta}\left(\pi^*(\theta) - c(q^*(\theta))\right) f(\theta)d\theta$
end for

IV. Numerical Results and Discussions

In this section, we use numerical results to validate the performance of our proposed scheme and guide the operator how to devise the optimal contract under asymmetric information scenario. We assume that user type θ follows a uniform distribution on [0.1, 2]. As a reflection of requirement on delay, θ is defined as the decrease of user satisfaction given a unit time delay. The higher θ is, the higher user's requirement on delay will be.

It is common to consider the cellular cost as linearly increasing network cost [23]. We define the cellular cost as $c(q(\theta)) = k \cdot q(\theta)$, where cost parameter k is the cost of unit time delay. We investigate how the operator's profit R and optimal contract $(q^*(\theta), \pi^*(\theta))$ change with user type θ. Meanwhile, we show the impact of cost parameter k and price sensitivity α on these terms as well.

We capture the difference among operators carrying out cost management schemes by setting cost parameter k which reflects the impact of quality on cellular cost. Cost parameter is determined by the characteristics of network, and we set it to be 0.6, 0.8, 1.0, 1.2 and 1.4, respectively.

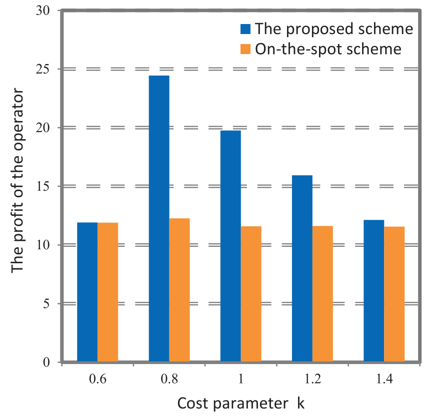

Fig. 2. The profit of the operator with respect to the cost parameter k. The price sensitivity α is set to be 0.03.

We compare the performance of the on-the-spot scheme and the proposed scheme in Fig. 2. In the on-the-spot scheme, there is no delay only if DTNs hotspot is available, indicating that quality is maximized. As we can see, the operator's profit in our scheme is larger than that in the on-the-spot scheme. In addition, the profit gap between these two schemes first increases with k and then decreases with k. When k is small (e.g., $k = 0.6$), the profit gap is pretty close since quality has little impact on operation cost. With the increase of k, quality has a growing impact on operation cost and the operator's profit in the on-the-spot scheme will decrease accordingly. However, in our scheme, users should pay much more money to the operator due to high quality. Accordingly, the operator's profit will increase. When k turns large (e.g., $k = 1.4$), quality has a huge impact on operation cost and user's payment is not enough to compensate for the cost. Thus the profit gap between these two schemes will decrease to zero.

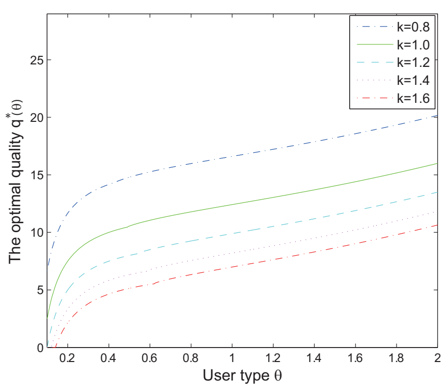

Fig. 3. The optimal quality $q^*(\theta)$ with respect to user type θ and the cost parameter k. The price sensitivity α is set to be 0.03.

Figure 3 shows that optimal quality $q^*(\theta)$ increases with θ, satisfying the monotonicity constraint defined in (12). When θ is small, the initial quality will decrease with k. Especially when k is very large, quality becomes zero to ensure IR constraint in (7) and users are totally unsatisfied at this time. With the increase of k, quality has a growing impact on operation cost. So the achievable quality becomes lower. Fig. 4 describes optimal price $\pi^*(\theta)$ with respect to θ. Since quality

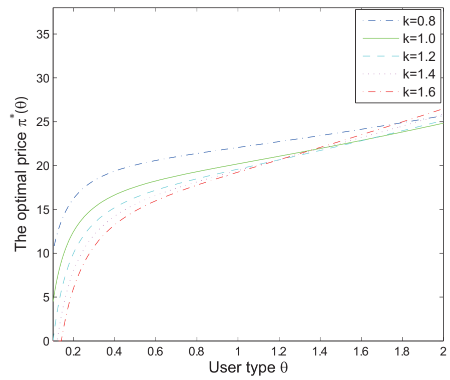

Fig. 4. The optimal price $\pi^*(\theta)$ with respect to user type θ and the cost parameter k. The price sensitivity α is set to be 0.03.

increases with θ, users need to pay much more money to the operator for high quality. When θ is small, quality has little impact on QoS and users only need to pay less money for the operator. With the increase of θ, quality and operation cost will increase accordingly. When θ increases to the maximum, quality becomes the highest and users should pay much more money. In addition, when k is large (e.g., $k = 1.4$), the operator should charge much more money to make up its operation cost since the impact of operation cost is large.

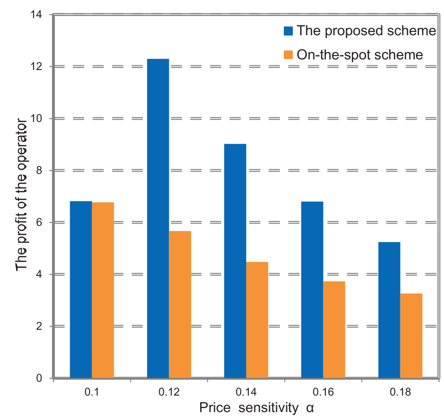

Fig. 5. The profit of the operator with respect to user price sensitivity α. The cost parameter k is set to be 0.25.

We depict the heterogeneity of user price sensitivity α by setting it to be 0.1, 0.12, 0.14, 0.16 and 0.18, respectively.

We compare the performance of the on-the-spot scheme and the proposed scheme in Fig. 5. As we can see, the proposed scheme outperforms the on-the-spot scheme. Moreover, the profit gap between them first increases with k and then decreases with k as well. When price sensitivity α is large or small, the profit gap is pretty small. On the one hand, when α is low, users don't care whether price is high or not and their satisfaction mainly depends on quality. Second, when α is high, users are inclined to delay if price is higher. Accordingly, they will receive more discount for the delay and the operator's profit will decrease. In the on-the-spot scheme, high price will greatly reduce users' satisfaction and they will pay less money to the operator, which decreases the operator's profit.

Figure 6 shows that optimal quality $q^*(\theta)$ is increasing with

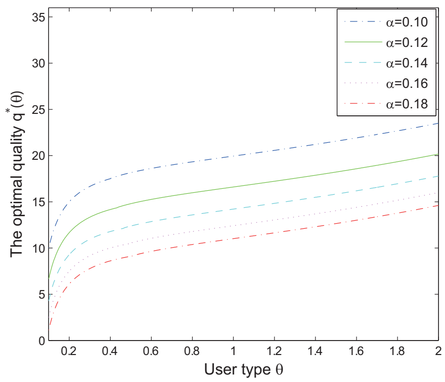

Fig. 6. The optimal quality $q^*(\theta)$ with respect to user type θ and price sensitivity α. The cost parameter k is set to be 0.25.

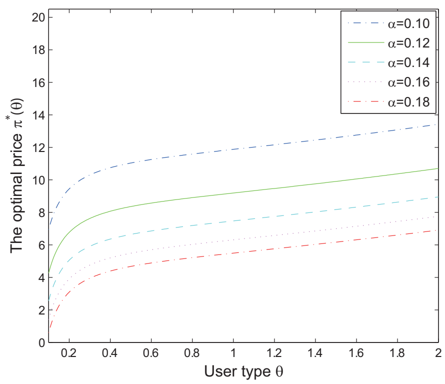

Fig. 7. The optimal price $\pi^*(\theta)$ with respect to user type θ and price sensitivity α. The cost parameter k is set to be 0.25.

θ, which is consistent with the monotonicity condition defined in (12). It means that high type users can obtain high quality and small delay. In addition, with the same type, the increase in price sensitivity α will result in lower quality and larger delay. With the increase of α, price has a growing impact on users and they are inclined to delay. Thus $q^*(\theta)$ will decrease accordingly. On the other hand, if users would like to wait for the access to DTNs, it is obvious that they only need to pay a little money to the operator since DTNs is nearly free compared with cellular network, just as shown in Fig. 7. We can easily find that $\pi^*(\theta)$ increases with θ, which is a necessary condition for the feasibility of optimal contract.

V. Conclusion

We propose a contract-based incentive framework to investigate how to design an optimal contract for traffic offloading over DTNs. The major focus is to motivate users to leverage their delay and price sensitivity in exchange for service cost. In addition, we model the delayed offloading process as a monopoly market where the operator makes pricing by considering statistical information about user satisfaction. Each user chooses the proper contract item according to its type. Furthermore, we derive the optimal contract which maximizes the operator's profit. Numerical results validate the efficiency of our scheme in improving operator's profit.

Acknowledgement

This work is supported by NSF China (No. 61325012, 61271219, 61221001, 61428205, 91438115); China Ministry of Education Doctor Program (No. 20130073110025); Shanghai Basic Research Key Project (12JC1405200).

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