A Contract-Based Incentive Mechanism for Delayed Traffic Offloading in Cellular Networks

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***Abstract*— Delayed traffic offloading is a promising paradigm to alleviate the cellular network congestion caused by explosive traffic demands. As we all know, in mobile networks, the delay profile for traffic is remarkable due to users' mobility. How to exploit user delay tolerance to improve the profit of operator as well as mobile users becomes a big challenge. In this paper, we model this delayed offloading process as a monopoly market based on contract theory, where operator acts as the monopolist setting up the optimal contract by statistical information on user satisfaction. We propose an incentive mechanism 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 a proper quality–price contract item according to its type. More specifically, we investigate this delayed offloading scheme under strongly incomplete information scenario, where user type is private information. We derive an optimal contract, which maximizes operator's profit for both the continuous-user-type model and the discrete-user-type model. Numerical results validate the effectiveness of our incentive mechanism for delayed traffic offloading in cellular networks.**

***Index Terms*— Delayed offloading, incentive mechanism, contract theory, delay and price sensitivity.**

I. Introduction

With rapid popularization of smartphones and tablets equipped with diverse applications, a huge amount of cellular traffic is currently being generated. According to Cisco Visual Networking Index [1], global mobile data traffic is expected to grow to 24.3 exabytes per month by 2019, nearly a tenfold increase over 2014. This continued growth of traffic is heavily pushing the capacity of cellular networks and deteriorating the network service.

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To alleviate the serious overload problem caused by explosive traffic demands, increasing the capacity of cellular networks, e.g., widening the channel bandwith or upgrading to LTE (Long Term Evolution), may be the most straightforward solution. However, these approaches will inevitably incur soaring expenses and have been reported to face the overload issues as well [2]–[4]. Therefore, it is of great importance to seek more economical and efficient solutions to cope with this severe challenge. Offloading part of cellular traffic to other coexisting networks would be another desirable approach [5]–[9].

In view of users' mobility, these offloading networks can only provide intermittent and opportunistic network connectivity, which results in non-negligible delay. With the increase of delay, users become impatient gradually, and hence their satisfaction will be greatly reduced [10]–[12]. Delayed traffic offloading is a promising paradigm to allow the traffic with diverse delay attributes and formulate the interrelation of service delay and user satisfaction in a feasible way. Here offloading networks mainly refer to those available networks which can tolerant delay, such as Delay Tolerant Networks (DTNs) and delayed WiFi networks. Furthermore, delayed traffic offloading has attracted a growing interest in recent years 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 users' satisfaction too much. It is suggested in a recent survey [13] that more than 50% of the interviewed users would wait up to 10 minutes to stream YouTube videos and 3-5 hours for file downloads. Inspired by this, operators are seeking to provide users with this delayed offloading service to exploit user satisfaction and potential performance gains.

Despite the distinct advantages over delay tolerance, there are still some problems remained for delayed offloading, especially incentive mechanism. Traditionally, it is often supposed that users are willing to participate in delayed offloading scheme. 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 addition, most current studies have not considered user satisfaction loss caused by long delay. With the consideration of users' delay tolerance and offloading potential, Zhuo *et al*. [14] proposed a reverse auction-based incentive mechanism to motivate users to subscribe to offloading service. Nevertheless, reverse auction they used does not involve statistical information about user satisfaction which can assist operator in making pricing effectively. Moreover, they depicted the characteristics of user satisfaction only by delay sensitivity and ignored price sensitivity, which also has a huge impact on user satisfaction.

To this end, we are inspired to address the incentive issues about delayed traffic offloading in cellular networks. We model this delayed offloading process as a monopoly market based on contract theory, where operator acts as monopolist to set up optimal quality-price contract and offer it to users. Furthermore, we propose an incentive mechanism to motivate users to leverage their delay and price sensitivity in exchange for service cost. After being classified into different types, each user chooses a proper contract item to maximize its own utility by comparing the alternatives. In this paper, we exploit the interaction between operator and users under the strongly incomplete information scenario, where user type is private information and only known to user itself. Operator only knows some statistical information about user type,[1] such as probability distribution. In addition, we derive an optimal contract which can maximize operator's profit for both continuous-user-type model and discrete-user-type model.

The contributions of this work are summarized as follows.

- To our best knowledge, it is the first work that utilizes contract theory to exploit the interaction between operator and users in delayed traffic offloading. Specifically, we classify users with different delay and price sensitivity into different types to capture the heterogeneity of user satisfaction.
- We propose an incentive mechanism to motivate users to fully exert their advantages in delay tolerance under the strongly incomplete information scenario, where operator only knows some statistical information on user type.
- We derive the optimal contract, which maximizes operator's profit as well as guarantees the feasibility for users, for continuous-user-type model and discrete-user-type model respectively. Numerical results validate the effectiveness of our scheme in improving operator's profit.

The rest of this paper is organized as follows. First related works on delayed offloading and contract theory are given in Section II. In Section III, we provide the details of system model. We derive the optimal contract for continuous-user-type model and discrete-user-type model in Section IV and Section V. In Section VI, we present corresponding numerical results. Discussions and future work are shown in Section VII. Finally, we conclude our work in Section VIII.

II. Related Work

A. Delayed Traffic Offloading

With the rapid development of delay-tolerant applications, delayed offloading scheme has been extensively studied in recent years since it can alleviate increasing congestion effectively. The technology and economics issues behind it have exerted a tremendous fascination on many researchers [15]. Niyato *et al.* [16] developed an analytical model to study performance gains of data delivery in DTNs. And coalitional game was used to analyze the cooperation decisions of multiple rational communities. Cheung and Huang [17] investigated WiFi offloading problem for delay-tolerant applications and proposed a monotone Delay-Aware WiFi Offloading and Network Selection algorithm to solve the general offloading problem approximately.

However, these studies have not considered user satisfaction loss. As delay increases, users tend to be impatient, and their satisfaction will decrease accordingly. In [14], the authors introduced a satisfaction function to explore user delay tolerance in offloading networks including DTNs and WiFi networks. Based on two-stage game, Park *et al.* [18] proposed a theoretic framework to quantify the economic gains behind delayed offloading scheme.

In this paper, we investigate how to achieve a tradeoff between delay performance and user satisfaction. Compared with the studies above, the primary difference is that we take full account of the characteristics of user satisfaction in terms of not only delay sensitivity, but also price sensitivity, which captures users' response to payment and has a huge impact on user satisfaction.

B. Incentive Mechanism and Contract Theory

Another important issue that we want to emphasize is incentive mechanism [19]. Li *et al.* [20] supposed that both operator and users are willing to participate in delayed offloading scheme. But unfortunately, this is so far from the truth. With the increase of delay, this scheme may degrade user experience and then user satisfaction will decrease. In addition, operator may also hesitate to be involved in it due to the potential reduction in cellular usage and overall profit.

Based on the above analysis, it is urgent to provide participation incentive for both operator and users. Sugiyama *et al.* [21] modeled the interaction among operator and users as Stackelberg game and devised an incentive mechanism to encourage user collaboration. Ha *et al.* [22] developed a time-dependent pricing framework, i.e., TUBE, to stimulate users to delay their service from peak to off-peak times. And it was shown that TUBE can alleviate network congestion by creating a feedback loop between ISP's price computation and users' response to payment.

However, these incentive mechanisms do not involve statistical information about user satisfaction, which can assist operator in making pricing efficiently. Inspired by contract theory, we propose an incentive mechanism to motivate users to leverage their delay tolerance to improve the profit of operator and users. As a well-known market-driven mechanism, contract theory is effective to design incentive mechanisms under asymmetric information scenario [23]–[25]. There has been extensive research on it. In order to make dynamic pricing for idle spectrum resource, Gao *et al.* [26] modeled the spectrum trading process as monopoly market and devised optimal contract for primary user. Duan *et al.* [27] tackled the cooperative spectrum sharing between one PU and multiple SUs based on contract theory. In macrocell-WiFi/femtocell networks, Zhou *et al.* [28] classified users into different types according to their percentages of offloaded traffic and devised optimal volume-price contract for them.

[1]Operator can estimate statistical information about user type by leaning from user historical behavior or making a user survey.

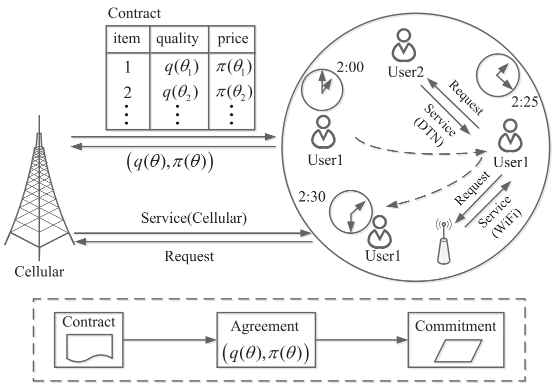


Fig. 1. Overview of delayed traffic offloading scheme in cellular networks.

In this paper, we adopt a similar methodology with [28] to obtain the optimal contract. However, the major difference is that we focus our research on how to motivate users to leverage their delay and price sensitivity in exchange for service cost. In addition, we further explore the offloading scheme under discrete-user-type model.

III. System Model

The details of delayed traffic offloading scheme are illustrated in this section. We first introduce the network and service model. Then the utility functions of operator and users are presented.

A. Network and Service Model

Consider this delayed offloading process as a monopoly market consisting of a monopolist operator and a set $\mathcal{N} = \{1, \cdots, N\}$ of mobile users. Users with different delay sensitivity are classified into different types θ according to their satisfaction. Mobile users can receive data service through offloading networks which can tolerant delay, such as DTNs[2] and WiFi networks. In this paper, our focus is to design an incentive mechanism to motivate users to fully leverage their delay tolerance in exchange for service cost.[3] Contract theory is utilized to investigate the interaction between operator and users. Fig. 1 highlights the main idea of system model.

We assume that users subscribe to delayed offloading service just for a specific piece of content, e.g., downloading one movie, and its transmission is completed instantly. For a given offloading service, operator offers users the optimal contract consisting of a set of quality-price contract items. Here quality mainly refers to the delay performance of this service. The delay of contract item can be one minute, one hour, one day, etc., characterizing the heterogeneity of service quality. The longer user can tolerate delaying service, the lower service quality it receives will be. Obviously, users would prefer to choose high-quality services given the payment. To motivate users to participate in this scheme, operator needs to offer users some discounts to compensate for delay. We further denote the sets of all possible qualities and prices as Ω and Π respectively. 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 operator as $\pi(q(\theta))$. For simplicity, we write $\pi(q(\theta))$ as $\pi(\theta)$ since $q(\theta)$ is a single value function of θ.

When making a request for delayed offloading service, the user first chooses a feasible contract item $(q(\theta), \pi(\theta))$ according to its type θ. After that, it signs a contract with operator, and the corresponding commitment made by both sides is composed of two parts. The first part is that the user will receive a discount if it promises to delay up to a deadline determined by $q(\theta)$. Second, before the deadline, the user can receive the desired service from offloading networks. Once the deadline expires, it will directly receive service through cellular network. Moreover, $q(\theta)$ specifies the maximum tolerable delay (i.e., deadline), and user may receive service earlier from this deadline. Thus the optimal contract item is only related to the maximum tolerable delay, rather than a specific delay.

As shown in Fig. 1, operator first announces the optimal quality-price contract to all users who subscribe to this service. At 2:00 p.m., User 1 makes a request for data delivery and then it chooses a feasible contract item $(q(\theta), \pi(\theta))$. In addition, User 1 signs a contract with operator and both of them will make the commitment as mentioned above accordingly. That is, before the deadline (e.g., 2:30 p.m.), User 1 will receive the desired service from offloading networks by its mobility. For example, it can contact other users (e.g., User 2) who cache the desired data in DTNs, or move into the wireless range of APs in WiFi networks. Otherwise, once the deadline expires, Use 1 will receive the date service from cellular network immediately.

B. User Model

In general, users' willingness to delay service is due to two main factors: the length of delay and the discount to compensate for delay. In order to quantify user satisfaction and economic gains behind delayed offloading scheme, we introduce two following satisfaction functions, which are based on the service commitment specified by the corresponding quality and price.

1) Quality Satisfaction Function: To depict the heterogeneity of user delay sensitivity, we classify users into different types θ. The set of all possible user types is denoted as Θ, which can be viewed as a continuous region or a discrete set. Both cases will be discussed exhaustively in the following parts. In continuous-user-type model, θ is defined as the reduction of user satisfaction for a unit delay increase. While in discrete-user-type model, we denote θ as the user's requirement on service quality, which can be represented by a set, e.g., $\{0.1, 0.2, \cdots\}$. In this paper, we investigate the strongly incomplete information scenario, where user type θ is private information and only known to user itself. However, operator can only obtain some statistical information about θ by inferring from historical experiences, such as its probability density or probability distribution.

Clearly, the larger user type is, the more sensitive to delay it will be. In other words, the user's requirement on quality

[2]In this delayed offloading scheme, every user is assumed to be willing to assist other users in forwarding cached packet.

[3]Users here refers to those who subscribe to delayed offloading service, rather than those who help others with data forwarding.

will be higher. We denote $q(\theta)$ as service quality, which is inversely proportional to delay. In view of the definitions of θ and $q(\theta)$, we obtain that the term $\theta \cdot q(\theta)$ can reflect user satisfaction about this offloading service. Inspired by the quality discrimination in [26], we define quality satisfaction function as

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

Accordingly, we can get $V_q(\theta, q)$[4]$> 0, V_\theta(\theta, q) > 0$ and $V_{qq}(\theta, q) < 0$. It means that users prefer high-quality services, and given a quality, a higher type user has larger satisfaction than a lower one. Moreover, $V(\theta, q(\theta))$ increases more slowly with high quality than it does with low quality.

2) Price Satisfaction Function: Users may have different views on the price paid to operator. We capture this heterogeneity by price sensitivity. Price sensitivity, denoted by α, is defined as the reduction of user satisfaction for a unit price increase. When α is low (e.g., staff in stock markets), users don't care about whether the price is high or not. On the other hand, when α is high (e.g., students in college), users are always reluctant to make a request for data delivery and would prefer to defer the offloading service in the case of high price.

Denote user price satisfaction as $G(\pi(\theta))$. Intuitively, $G(\pi(\theta))$ is monotonically decreasing with the price. And it will approach the maximum value when user payment approaches zero. This maximum value can be expressed as $G_0 = \lim_{\pi(\theta)\to 0} G(\pi(\theta))$. If the price increases to infinity, rational users always tends to refuse this offloading service since their price satisfaction becomes zero, i.e., $\lim_{\pi(\theta)\to\infty} G(\pi(\theta)) = 0$. Based on the above analysis, we are inspired to model user price satisfaction as exponential form, which is generally used in the economic literatures [30]. To prevent the difference in user satisfaction from being extremely obvious, we also adopt the logarithm function as price satisfaction function [26], [28], i.e.,

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

Without loss of generality, we assume $\ln G_0 = 0$. Thus user price satisfaction function can be represented as

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

If type-θ user chooses the contract item $(q(\theta), \pi(\theta))$, its utility can be defined 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 equations (1) and (3) into (4), we have

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

Throughout this paper, we assume that operator and users are all rational and both of them are trying to maximize their own utilities. Thus for each type-θ user, its optimal strategy for the utility maximization problem can be represented as

$$(q^*(\theta), \pi^*(\theta)) = \underset{\{(q(\theta),\pi(\theta)),\forall\theta\in\Theta\}}{\arg\max} U(\theta, q(\theta)). \tag{6}$$

As an important users' feature, price sensitivity α has a great impact on user utility. In this paper, however, we characterize the optimal contract mainly from the aspects of delay.[5] As for the heterogeneity of α, we will further explore its effect on the performance of our scheme by varying α in numerical simulations.

3) Examples and Illustrations: We illustrate the details about how to achieve the optimal strategy $(q^*(\theta), \pi^*(\theta))$ for two users with parameters $(\theta_1, \alpha_1) = (10, 0.5)$ and $(\theta_2, \alpha_2) = (20, 0.1)$. Given a movie downloading service, the type-θ_1 user subscribes to this service with low quality sensitivity and high price sensitivity. Thus when price is high, it will be reluctant to make a request for downloading service and would prefer to delay for a period of time. As for the type-θ_2 user, it subscribes to this service with high quality sensitivity and low price sensitivity. Thus it has a high demand for delay performance and does not care about whether the price is high or not. Suppose the optimal contract consists of the quality set $\Omega = \{1, 2.5\}$ and the corresponding price set $\Pi = \{2, 6\}$. Then the type-θ_1 user tends to choose the service with quality $q(\theta) = 1$ since $U(\theta_1, 1) = \ln(1 + 10) - 1 > U(\theta_1, 2.5) = \ln(1 + 25) - 3$, and the type-$\theta_2$ user prefers choosing the service with quality $q(\theta) = 2.5$ since $U(\theta_2, 2.5) = \ln(1 + 50) - 0.6 > U(\theta_2, 1) = \ln(1 + 20) - 0.2$. Therefore, the optimal strategy for these two users are $(q^*(\theta_1), \pi^*(\theta_1)) = (1, 2)$ and $(q^*(\theta_2), \pi^*(\theta_2)) = (2.5, 6)$, respectively.

C. Operator Model

When subscribing to the offloading service specified by contract item $(q(\theta), \pi(\theta))$, the user will pay the price $\pi(\theta)$ to operator. At the same time, providing this service for users will inevitably incur operation cost, which is directly related to service quality [10]. Accordingly, this incurred operation cost can be modeled as

$$C(q(\theta)) = c(q(\theta)) + c_0, \tag{7}$$

where $c_0 > 0$ is the fixed cost mainly including some necessary energy costs, infrastructure costs, etc. And $c(q(\theta))$ is quality-specific transmission cost, mainly consisting of data transmission cost through cellular network and traffic forwarding cost via offloading networks. Compared with cellular network, it is common to consider the service over offloading networks is relatively low-cost and low-quality for the intermittent and opportunistic network connectivity. Intuitively, $c(q(\theta))$ is monotonically increasing with quality $q(\theta)$. For example, when the network is heavily congested, quality will decrease rapidly due to delay increase. In this case, operator

[4]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 $f_{xx}(\cdot)$.

[5]The main reason is that if we characterize users in the form of two-tuple (θ, α), it is difficult to design an optimal contract which can combine the features of delay and price sensibility organically. In particular, computational complexity is an urgent issue that needs to be solved.

only needs to spend less money to guarantee such a negotiated quality.

From the operator's perspective, its expected profit R is equal to revenue minus cost, i.e.,

$$R = \sum_{\theta \in \Theta} N_\theta \left(\pi(\theta) - C(q(\theta))\right). \tag{8}$$

After deriving user's utility and operator's profit, we introduce contract theory to resolve the conflicting objectives between them. We next describe how to obtain the optimal quality-price contract for continuous-user-type model and discrete-user-type model, respectively.

IV. Optimal Contract Design in Continuous-User-Type Model

In this section, we investigate the delayed traffic offloading for continuous-user-type model. Particularly, we focus on the strongly incomplete information scenario, where user type θ is only known to user itself. Moreover, operator does not know any specific user type θ and only knows the distribution of θ determined by the probability density function $f(\theta)$ on an interval $[\theta_l, \theta_u]$.

A. Contract Formulation

According to equation (8), the expected profit of operator in this continuous-user-type model can be written as

$$R = \int_{\theta_l}^{\theta_u} \left(\pi(\theta) - C(q(\theta))\right) f(\theta) d\theta. \tag{9}$$

In order to determine the optimal contract under asymmetric information, each feasible contract item must satisfy the following two constraints according to revelation principle [23]–[25].

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

$$\ln(1 + \theta q(\theta)) - \alpha \pi(\theta) \geq 0, \forall \theta \in [\theta_l, \theta_u]. \tag{10}$$

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

$$\begin{aligned} &\ln(1 + \theta q(\theta)) - \alpha \pi(\theta) \\ &\quad \geq \ln(1 + \theta q(\hat{\theta})) - \alpha \pi(\hat{\theta}), \forall \theta, \hat{\theta} \in [\theta_l, \theta_u]. \end{aligned} \tag{11}$$

Remark: From the definition of IR constraint, we know that for any rational user, it always refuses the delayed offloading service which provides it with the negative utility. As for IC constraint, it is indicated that each type-θ user can achieve the highest utility once it chooses the contract item for θ. These two constraints guarantee that the optimal contract can provide participation incentive for users. That is, this contract is feasible for users.

In a word, a feasible contract must satisfy IR constraint in (10) and IC constraint in (11) simultaneously. Based on this, the goal of operator is to establish optimal contract $(q^*(\theta), \pi^*(\theta))$, which maximizes its profit under a feasible contract. Thus, the optimal contract design can be formulated as the operator's profit maximization problem, i.e.,

$$\begin{aligned} \max_{\{(q(\theta), \pi(\theta)), \forall \theta \in [\theta_l, \theta_u]\}} & \int_{\theta_l}^{\theta_u} \left(\pi(\theta) - C(q(\theta))\right) f(\theta) d\theta \\ \text{subject to} \;\; & \text{IR constraint in (10)}, \\ & \text{IC constraint in (11)}. \end{aligned} \tag{12}$$

B. Feasibility of Contract

The profit maximization problem in (12) is nontrivial to solve, since it involves the optimization over a schedule $(q(\theta), \pi(\theta))$ under the constraints, where other conflicting optimization problems are involved in themselves. Such adverse selection problem can, however, still be solved step-by-step as follows [23]. Before that, we simplify the IR and IC constraints.

Lemma 1: As for the optimal contract under the strongly incomplete information scenario in (12), IR constraint can be replaced by

$$\ln(1 + \theta_l q(\theta_l)) - \alpha \pi(\theta_l) \geq 0, \tag{13}$$

given that IC constraint is satisfied.

Proof: See Appendix A. ■

Definition 3 Spence-Mirrlees Condition (SMC) [23]: The user's utility function satisfies the Spence-Mirrlees single-crossing condition if and only if

$$\frac{\partial}{\partial \theta} \left[-\frac{\partial U / \partial q}{\partial U / \partial \pi} \right] > 0. \tag{14}$$

This condition indicates that a more efficient type is also efficient at the margin utility. We can easily find that the type-$\hat{\theta}$ user's utility function, i.e., $U(\hat{\theta}, q(\theta)) = \ln(1 + \hat{\theta} q(\theta)) - \alpha \pi(\theta)$, satisfies the SMC. According to [23], we can further get the following lemma.

Lemma 2: If the user's utility function satisfies the SMC, then IC constraint in (11) is equivalent to the following two constraints:

Monotonicity:

$$\frac{dq(\theta)}{d\theta} \geq 0, \tag{15}$$

Local Incentive Compatibility:

$$\frac{\theta q'(\theta)}{1 + \theta q(\theta)} = \alpha \pi'(\theta). \tag{16}$$

Proof: See Appendix B. ■

C. Optimality of Contract

By Lemma 1 and Lemma 2, we can simplify the profit maximization problem in (12) as

$$\begin{aligned} \max_{\{(q(\theta), \pi(\theta)), \forall \theta \in [\theta_l, \theta_u]\}} & \int_{\theta_l}^{\theta_u} \left(\pi(\theta) - C(q(\theta))\right) f(\theta) d\theta \\ \text{subject to} \;\; & \ln(1 + \theta_l q(\theta_l)) - \alpha \pi(\theta_l) \geq 0, \\ & \frac{dq(\theta)}{d\theta} \geq 0, \\ & \frac{\theta q'(\theta)}{1 + \theta q(\theta)} = \alpha \pi'(\theta). \end{aligned} \tag{17}$$

As for the above optimization problem, one standard solution is first to solve the relaxed problem, i.e., this problem without the monotonicity constraint, and then to check whether the solution to this relaxed problem satisfies the monotonicity condition.

First, we define

$$W(\theta) = \ln(1+\theta q(\theta)) - \alpha\pi(\theta) = \max_{\hat{\theta}} \left(\ln(1+\theta q(\hat{\theta})) - \alpha\pi(\hat{\theta})\right). \tag{18}$$

According to the envelope theorem [23], we have

$$\frac{dW(\theta)}{d\theta} = \frac{\partial W(\theta)}{\partial\theta}|_{\hat{\theta}=\theta} = \frac{q(\theta)}{1+\theta q(\theta)}. \tag{19}$$

Integrating both sides of this equation, we can get

$$W(\theta) = \int_{\theta_l}^{\theta} \frac{q(x)}{1+xq(x)}dx + W(\theta_l). \tag{20}$$

At the optimal contract, IR constraint of the lowest type is binding, i.e.,

$$W(\theta_l) = 0. \tag{21}$$

Substituting equation (21) into (20), we have

$$W(\theta) = \int_{\theta_l}^{\theta} \frac{q(x)}{1+xq(x)}dx. \tag{22}$$

Since

$$\pi(\theta) = \frac{1}{\alpha}\left(\ln(1+\theta q(\theta)) - W(\theta)\right), \tag{23}$$

operator's profit can be further rewritten as

$$\begin{aligned} R(q(\theta)) &= \int_{\theta_l}^{\theta_u} \left(\frac{\ln(1+\theta q(\theta)) - W(\theta)}{\alpha} - C(q(\theta))\right) f(\theta)d\theta \\ &= \int_{\theta_l}^{\theta_u} \left(\frac{\ln(1+\theta q(\theta))}{\alpha} - C(q(\theta))\right) f(\theta)d\theta \\ &\quad - \int_{\theta_l}^{\theta_u}\int_{\theta_l}^{\theta} \frac{1}{\alpha}\frac{q(x)}{1+xq(x)} f(\theta)d\theta. \end{aligned} \tag{24}$$

To facilitate the computation, we introduce the notation $L(q(x)) = \frac{q(x)}{1+xq(x)}dx$. Integrating the last term of equation (24) by parts, we have

$$\begin{aligned} &\int_{\theta_l}^{\theta_u}\int_{\theta_l}^{\theta} L(q(x))f(\theta)dxd\theta \\ &= \int_{\theta_l}^{\theta_u}\left(\int_{\theta_l}^{\theta} L(q(x))dx\right) f(\theta)d\theta \\ &= \int_{\theta_l}^{\theta} L(q(x))dxF(\theta)\Big|_{\theta_l}^{\theta_u} - \int_{\theta_l}^{\theta_u} L(q(x))F(\theta)d\theta \\ &= \int_{\theta_l}^{\theta_u} L(q(\theta))(1-F(\theta))d\theta. \end{aligned} \tag{25}$$

Substituting equation (25) into (24), we obtain

$$\begin{aligned} R(q(\theta)) = \int_{\theta_l}^{\theta_u} &\left(\frac{1}{\alpha}\ln(1+\theta q(\theta)) - C(q(\theta))\right) f(\theta) \\ &- \frac{1}{\alpha}\frac{q(\theta)}{1+\theta q(\theta)}(1-F(\theta))\,d\theta. \end{aligned} \tag{26}$$

Algorithm 1 Optimal Contract Algorithm in Continuous Model

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 $R = \int_{\theta\in\Theta}(\pi^*(\theta) - C(q^*(\theta)))f(\theta)d\theta$
end for

Clearly, the maximization of R with respect to $q(\cdot)$ requires the term under the integral be maximized with respect to $q(\cdot)$. Thus, the relaxed problem of (17) can be further replaced by

$$\max_{q(\theta)} \left(\frac{1}{\alpha}\ln(1+\theta q(\theta)) - C(q(\theta)) - \frac{1}{\alpha}\frac{q(\theta)}{1+\theta q(\theta)}\frac{1-F(\theta)}{f(\theta)}\right) f(\theta). \tag{27}$$

By solving the above maximization problem, we get the optimal quality $\overline{q}^*(\theta)$ for the relaxed problem of (17). In addition, we need to check whether this solution satisfies the monotonicity constraint, i.e., $\frac{dq(x)}{dx} \geq 0$. If $\overline{q}^*(\theta)$ satisfies this constraint, we can consider it as our desired optimal quality $q^*(\theta)$. Otherwise, the obtained solution $\overline{q}^*(\theta)$ must be adjusted by "Bunching and Ironing" algorithm [23]. To facilitate the understanding of this algorithm, we introduce a rather important lemma as follows.

Lemma 3: Suppose that $X(x_\theta)$ is the concave function about x_θ. We further let $x_\theta^* = \arg\max_{x_\theta} X(x_\theta)$. If x_θ^* is non-increasing with respect to θ, i.e., $dx_\theta^*/d\theta \leq 0$, then we obtain

$$\widetilde{x}_\theta = \widetilde{x}_a = \widetilde{x}_b, \forall\theta \in [a,b], \tag{28}$$

where $\widetilde{x}_\theta = \arg\max_{x_\theta} \int_a^b X(x_\theta)d\theta$ such that $dx_\theta/d\theta \geq 0$.

We can refer to [26] for the detailed proof of this lemma. We regard $\overline{q}^*(\theta)$, which violates the monotonicity constraint, as the infeasible solution to the operator's profit maximization problem in (17). Accordingly, an infeasible region can be defined as $[a,b] \subseteq \Theta$, satisfying $\frac{dq(x)}{dx} \geq 0, \forall x \in [a,b]$. By means of Lemma 3, we can adjust the infeasible region to be feasible.

The corresponding optimal price $\pi^*(\theta)$ for each optimal quality $q^*(\theta)$ can be obtained, i.e.,

$$\pi^*(\theta) = \frac{1}{\alpha}\left(\ln(1+\theta q^*(\theta)) - \frac{q^*(\theta)}{1+\theta q^*(\theta)}\frac{1-F(\theta)}{f(\theta)}\right) f(\theta). \tag{29}$$

We conclude the detailed algorithm as shown in Algorithm 1.

Remark: So far, we have derived optimal contract to maximize operator's profit, satisfying user IR and IC constraints simultaneously. According to Lemma 2, optimal quality $q^*(\theta)$ is a monotonous increasing function of user type θ. Moreover, local incentive compatibility ensures $\pi'(\theta) \geq 0$, indicating that optimal price $\pi^*(\theta)$ increases with θ.

V. Optimal Contract Design in Discrete-User-Type Model

Each user type specifies one quality-price contract item. Since operator may only provide a finite number of contract items, discrete-user-type model characterizes a more realistic scenario compared with continuous model. Here user type θ is not continuous any more, and takes a finite number of possible values instead. Suppose there are $n \geq 2$ different user types, indexed by $\theta_1, \theta_2, \cdots, \theta_n$, respectively. Without loss of generality, we assume $\theta_1 < \theta_2 < \cdots < \theta_n$.

Similar to continuous model, we utilize contract theory to explore delayed traffic offloading under the strongly incomplete information scenario as well, where user type $\theta_i, i \in \{1, 2, \cdots, n\}$ is private information. Operator only knows the distribution law of θ_i which is defined as p_i, the probability of the user's belonging to type θ_i, instead of the probability density function $f(\theta)$ in continuous model. It is obvious that $p_i \in [0, 1]$ and $\sum_{i=1}^{n} p_i = 1$. For the sake of brevity and readability, we rewrite $(q(\theta_i), \pi(\theta_i))$, i.e., the contract item assigned to the type-θ_i user, as (q_i, π_i). Thus the set of quality-price contract items can be denoted as $\{(q_i, \pi_i); i \in \{1, 2, \cdots, n\}\}$.

A. Contract Formulation

Based on equation (8), the expected profit of operator in discrete model can be rewritten as

$$R = \sum\nolimits_{i=1}^{n} \beta_i(\pi_i - C(q_i)). \tag{30}$$

Discrete model can be viewed as the discretization of continuous model with respect to user type when the amount of user type n is tending to infinite. That is, by dividing the continuous type $\theta \in [\theta_l, \theta_u]$ into n segments, we can get the desired types $\theta_i, i \in \{1, 2, \cdots, n\}$ defined in discrete model. The larger n is, the less the difference between these two models would be. Then IC and IR constraints in continuous model, to ensure the feasibility of contract, can be adapted to the discrete model as well. According to revelation principle, the ultimate goal of operator is to design optimal contract to maximize its expected profit subject to IC and IR constraints for all user types. Thus the operator's profit maximization problem can be written as

$$\begin{aligned} \max_{\{(q_i,\pi_i)\}} \quad & \sum\nolimits_{i=1}^{n} \beta_i(\pi_i - C(q_i)) \\ \text{subject to} \quad & \ln(1 + \theta_i q_i) - \alpha\pi_i \geq 0, \\ & \ln(1 + \theta_i q_i) - \alpha\pi_i \geq \ln(1 + \theta_i q_j) - \alpha\pi_j, \\ & \quad \text{for all } i, j \in \{1, 2, \cdots, n\}. \end{aligned} \tag{31}$$

B. Feasibility of Contract

Similarly, we need to simplify the IR and IC constraints before solving the problem in (31).

Lemma 4: As for the optimal contract under the strongly incomplete information scenario in (31), IR constraint can be replaced by

$$\ln(1 + \theta_1 q_1) - \alpha\pi_1 = 0, \tag{32}$$

given that IC constraint holds.

Proof: See Appendix C. ■

Remark: As shown in Lemma 4, we conclude that if only the user type θ_1 among all IR constraints binds, then the other types will automatically hold.

The above optimization problem in (31) includes $n(n-1)$ IC constraints. Inspired by SMC as well, we can further reduce them and obtain the following lemmas.

Lemma 5: If the user's utility function satisfies the SMC, then for any $\theta_m \geq \theta_n$ and $q_i \geq q_j$, user quality satisfaction function satisfies the following condition:

$$V(\theta_m, q_i) - V(\theta_m, q_j) \geq V(\theta_n, q_i) - V(\theta_n, q_j). \tag{33}$$

Proof: See Appendix D. ■

Lemma 6: If the contract satisfies IC constraint, then the monotonicity constraint will hold, i.e., $q_i \geq q_j$ if and only if $\theta_i \geq \theta_j$.

Proof: See Appendix E. ■

Remark: Lemma 6 presents the necessary condition for IC constraint. That is, service quality must be monotonically increasing with user type θ when IC constraint is satisfied. In addition, the corresponding sufficient conditions are shown in the following lemmas.

Lemma 7 (LDICs: Local Downward Incentive Constraints): As for the user's utility function satisfying the SMC, if the LDICs are satisfied for all user type $\theta_i, i \in \{1, 2, \cdots, n\}$, i.e.,

$$\ln(1 + \theta_i q_i) - \alpha\pi_i \geq \ln(1 + \theta_i q_{i-1}) - \alpha\pi_{i-1}, \tag{34}$$

then IC constraint will hold for any $j \leq i$, i.e.,

$$\ln(1 + \theta_i q_i) - \alpha\pi_i \geq \ln(1 + \theta_i q_j) - \alpha\pi_j. \tag{35}$$

Proof: See Appendix F. ■

Lemma 8 (LUICs: Local Upward Incentive Constraints): As for the user's utility function satisfying the SMC, if the LUICs hold for all user type $\theta_i, i \in \{1, 2, \cdots, n\}$, i.e.,

$$\ln(1 + \theta_i q_i) - \alpha\pi_i \geq \ln(1 + \theta_i q_{i+1}) - \alpha\pi_{i+1}, \tag{36}$$

then IC constraints will be satisfied, i.e.,

$$\ln(1 + \theta_i q_i) - \alpha\pi_i \geq \ln(1 + \theta_i q_j) - \alpha\pi_j, \tag{37}$$

for any $j \geq i$.

The proof of this lemma is similar to Lemma 7, and we omit it here for space constraint.

Remark: In discrete model, IC constraint can be reduced to the LDICs and LUICs by Lemma 7 and Lemma 8. Next, we continue studying the LDICs, and the LUICs are similar to the LDICs.

Lemma 9: If the operator's profit is maximized, i.e., the devised contract is at the optimum, then the LDICs must satisfy the following condition, i.e.,

$$\ln(1 + \theta_i q_i) - \alpha\pi_i = \ln(1 + \theta_i q_{i-1}) - \alpha\pi_{i-1}. \tag{38}$$

Proof: See Appendix G. ■

Remark: In fact, combining the LDICs in Lemma 9 and the monotonicity condition in Lemma 6, we can conclude that all the LUICs will hold. That is, $\ln(1+\theta_i q_i) - \alpha\pi_i = \ln(1+\theta_i q_{i-1}) - \alpha\pi_{i-1}$ implies that $\ln(1+\theta_{i-1} q_i) - \alpha\pi_i \le \ln(1+\theta_{i-1} q_{i-1}) - \alpha\pi_{i-1}$ given that $q_i \ge q_{i-1}$. Therefore, if user utility function satisfies the SMC condition, then IC constraint can be replaced by the LDICs in Lemma 9 and the monotonicity condition in Lemma 6.

C. Optimality of Contract

Based on the above lemmas, the operator's profit maximization problem in (31) can be further represented by

$$\begin{aligned} \max_{\{(q_i,\pi_i)\}} \quad & \sum\nolimits_{i=1}^{n} \beta_i(\pi_i - C(q_i)) \\ \text{subject to} \quad & \ln(1+\theta_1 q_1) - \alpha\pi_1 = 0, \\ & q_i \ge q_j \text{ if } \theta_i \ge \theta_j, \\ & \ln(1+\theta_i q_i) - \alpha\pi_i = \ln(1+\theta_i q_{i-1}) - \alpha\pi_{i-1}, \\ & \text{for all } i, j \in \{1, 2, \cdots, n\}. \end{aligned} \tag{39}$$

In order to solve this problem, one standard approach is to leave out the monotonicity condition at first and then to check whether the obtained solution satisfies this condition.

By iterating on the third condition of the problem in (39), we can conclude

$$\pi_i = \frac{1}{\alpha}\left(V(\theta_1, q_1) + \sum\nolimits_{k=1}^{i} \omega_k\right) \tag{40}$$

for any $i \in \{1, 2, \cdots, n\}$, where

$$\omega_k = \begin{cases} 0 & k = 1, \\ V(\theta_k, q_k) - V(\theta_k, q_{k-1}) & k = 2, \cdots, n. \end{cases} \tag{41}$$

Substitute (40) into (30), and we have

$$\begin{aligned} R &= \sum_{i=1}^{n} \beta_i \left(\frac{1}{\alpha}\left(V(\theta_1, q_1) + \sum_{k=1}^{i} \omega_k \right) - C(q_i) \right) \\ &= \sum_{i=1}^{n} \left(\frac{\beta_i}{\alpha} V(\theta_i, q_i) + \frac{\Lambda_i}{\alpha} \sum_{k=i+1}^{n} \beta_k - \beta_i C(q_i) \right), \end{aligned} \tag{42}$$

where

$$\Lambda_i = \begin{cases} V(\theta_i, q_i) - V(\theta_{i+1}, q_i) & \forall i < n, \\ 0 & i = n. \end{cases} \tag{43}$$

The second equation in (42) is obtained by putting the terms related to the same quality together. Using the notation $R_i = \frac{\beta_i}{\alpha} V(\theta_i, q_i) + \frac{\Lambda_i}{\alpha} \sum\limits_{k=i+1}^{n} \beta_k - \beta_i c(q_i)$, we can find that R_i is only related to q_i and independent of other quality $q_j, j \ne i$. Thus for any $i \in \{1, 2, \cdots, n\}$, the optimal quality q_i^* can be computed by maximizing each of R_i separately, that is,

$$\begin{aligned} q_i^* &= \arg\max_{q_i} R_i \\ &= \arg\max_{q_i} \left(\frac{\beta_i}{\alpha} V(\theta_i, q_i) + \frac{\Lambda_i(q_i)}{\alpha} \sum_{k=i+1}^{n} \beta_k - \beta_i C(q_i) \right). \end{aligned} \tag{44}$$

Algorithm 2 Optimal Contract Algorithm in Discrete Model

for $i = 1$ to n **do**
  set $R_i = \frac{\beta_i}{\alpha} V(\theta_i, q_i) + \frac{\Lambda_i(q_i)}{\alpha} \sum_{k=i+1}^{n} \beta_k - \beta_i C(q_i)$;
  set $q_i^* = \arg\max_{q_i} R_i$;
end for
while q_i^* is not feasible **do**
  find an infeasible subsequence $\{\hat{q}_m, \hat{q}_{m+1}, \cdots, \hat{q}_n\}$
  set $q_i^* = \arg\max_{q_i} \sum_{i=m}^{n} R_i, \ \forall i = m, m+1, \cdots, n$
end while
for $i = 1$ to n **do**
  set $\pi_i^* = \frac{1}{\alpha}\left(V(\theta_1, q_1^*) + \sum_{k=1}^{i} \omega_k^*\right)$
  set $R = \sum_{i=1}^{n} \beta_i(\pi_i^* - C(q_i^*))$
end for

By solving the above optimization problem, we can get the solution $\overline{q}_i^*, i \in \{1, 2, \cdots, n\}$ for the relaxation problem. Furthermore, we need to check whether these solutions satisfy the monotonicity condition. If $\overline{q}_i^*$ satisfies the monotonicity condition, it can be regarded as our desired optimal quality q_i^*. Otherwise, we need to make some adjustments for it according to "Bunching and Ironing" algorithm, which is similar to the continuous model.

Substituting equation (44) into (40), we obtain the corresponding optimal price π_i^* as follows:

$$\pi_i^* = \frac{1}{\alpha}\left(V(\theta_1, q_1^*) + \sum\nolimits_{k=1}^{i} \omega_k^*\right), \tag{45}$$

where

$$\omega_k^* = \begin{cases} 0 & k = 1, \\ V(\theta_k, q_k^*) - V(\theta_k, q_{k-1}^*) & k = 2, \cdots, n. \end{cases} \tag{46}$$

We design the optimal contract algorithm for discrete model as shown in Algorithm 2.

Remark: Similar to continuous model, the obtained optimal contract preserves the desired properties, i.e., maximizing operator's profit and providing user participation incentive. Intuitively, we can make a basic observation that both $q^*(\theta)$ and $\pi^*(\theta)$ increase with user type θ.

VI. Numerical Results

We conduct numerical simulations to validate the performance of our scheme and guide operator to offer optimal contract in continuous-user-type and discrete-user-type model. User type θ is assumed to follow uniform distribution over an interval [0.1, 2] in view of delay sensitivity and willingness to delay.[6] The higher θ is, the more sensitive to delay user would be.

Performance evaluation in [10] tells us that the incurred (energy or monetary) cost is inversely proportional to average delay for high cellular rate. Accordingly, we assume that operation cost grows incrementally with the increase of quality. Specifically, define operation cost is as

[6] We exclude [0, 0.1] for θ since user satisfaction always experiences non-ignorable reduction with the increase of delay. On the other hand, the interval[2, $+\infty$] is excluded so as to ensure users are willing to subscribe this delayed offloading service.

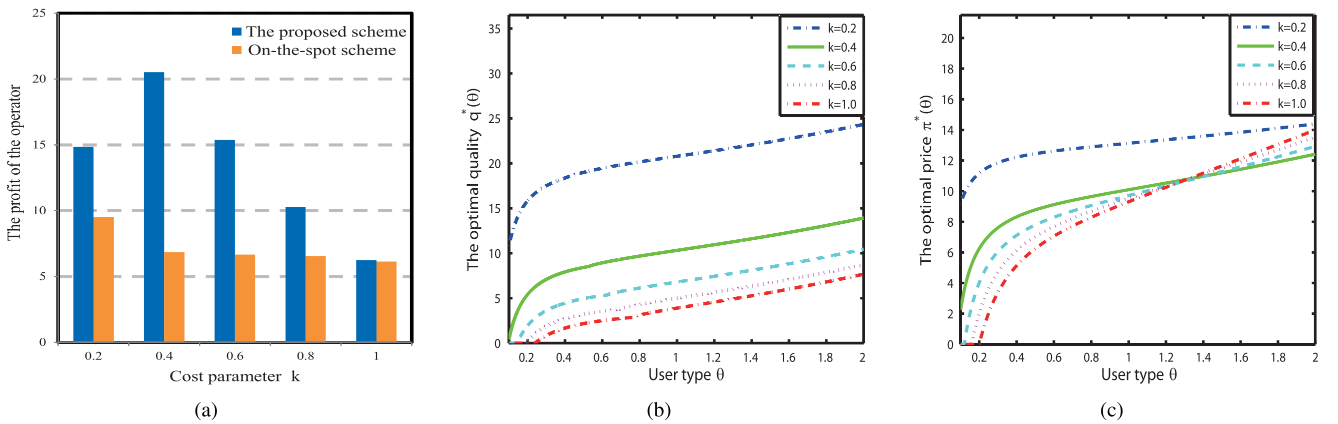


Fig. 2. Operator's profit R and optimal contract $(q^*(\theta), \pi^*(\theta))$ with respect to cost parameter k in continuous model.

$C(q(\theta)) = c(q(\theta)) + c_0 = kq(\theta) + c_0$, where cost parameter k is denoted as the increment of cost for a unit quality increase, reflecting the impact of quality on operation cost. To nicely demonstrate the trends in operator's profit gap, we set k to be 0.2, 0.4, 0.6, 0.8 and 1.0, respectively. Higher k (e.g., $k = 1.0$) indicates delay has great influence on operation cost, and lower k (e.g., $k = 0.2$) shows this influence is relatively small. In addition, users always have different responses to payment. Price sensitivity α is introduced to characterize users' requirement on price. To explore its effect on performance of our scheme, we set α to be 0.08, 0.10, 0.12, 0.14 and 0.16, respectively. Lower α represents that users are insensitive to price, and higher α mainly refers to those users who care about price and prefer low-price service.

We investigate how operator's profit R and optimal contract $(q^*(\theta), \pi^*(\theta))$ change with user type θ. The impact of k and α on these terms are shown as well. Note that our evaluations do not rely on particular parameter settings and we just try to demonstrate qualitative trends generally.

A. Continuous-User-Type Model

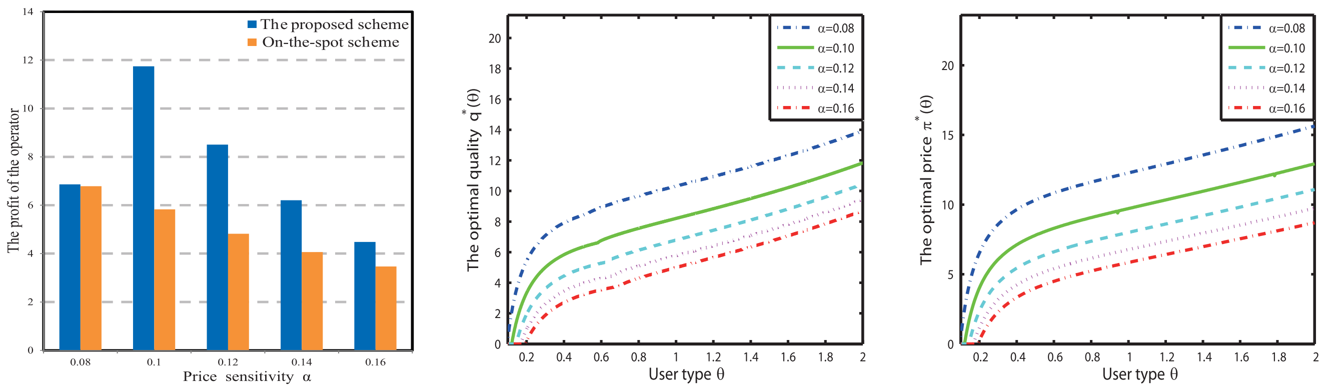
Figure 2 presents operator's profit and optimal contract with various k, where α is set to be 0.12. We compare the performance of the proposed scheme against the on-the-spot scheme[7] in Fig. 2(a). We observe that operator's profit in our scheme is larger than that in the on-the-spot scheme. And the profit gap between these two schemes first increases with k and then decreases with k. When k is small, quality has little impact on operation cost and thus profit gap is small. As k increases, this impact becomes larger, and operator's profit in the on-the-spot scheme decreases accordingly. In our scheme, however, under IC constraint, operator will charge more money from users subscribing to high-quality services. Thus operator's profit may not decrease too much. When k is large enough, user payment is not enough to compensate for cost due to the huge impact of quality, greatly reducing the profit gap. Figure 2(b) shows optimal quality increases with user type θ, satisfying the monotonicity constraint in (15). When θ is small, initial quality decreases with k. Especially when k is very large, quality decreases to zero, making users totally unsatisfied. As k increases, quality has a growing impact on cost, leading to a reduction of achievable quality. Figure 2(c) describes optimal price with various θ. Since $q^*(\theta)$ increases with θ, users need to pay much more money for high-quality service. When θ is small, users only need to pay less money in view of the little impact of quality on user satisfaction. As users have larger θ, quality and cost will increase accordingly. When k is large enough, operator will charge users much more money to compensate for the increased operation cost.

We illustrate how α affects operator's profit and optimal contract in Fig. 3, where k is set to be 0.6. Fig. 3(a) shows the proposed scheme outperforms the on-the-spot scheme. And the profit gap first increases with α and then decreases with α. Users with low α don't care about whether price is high or not and their satisfaction mainly depends on quality. Thus the difference of α has little impact on operator's profit, leading to a small profit gap. On the other hand, users with high α are always inclined to delay service when price is high. Accordingly, operator's profit will decrease since operator should provide users with some discount for delay. While in the on-the-spot scheme, plenty of high-price services result in a significant reduction in user satisfaction, making operator's profit decreased. From Fig. 3(b), we observe that optimal quality increases with θ as well, indicating high-type users may obtain high-quality and small-delay service. Moreover, as users have larger α, price has a growing impact on user satisfaction and users would prefer to delay service accordingly, leading to a reduction in quality. If users wait for the access to offloading networks, their received service is low-quality, i.e., user type is low. Thus users only need to pay a little money to operator since offloading service is relatively cheaper compared with cellular network service, as shown in Fig. 3(c). We can easily find that $\pi^*(\theta)$ increases with θ, which is a necessary condition for the feasibility of contract.

B. Discrete-User-Type Model

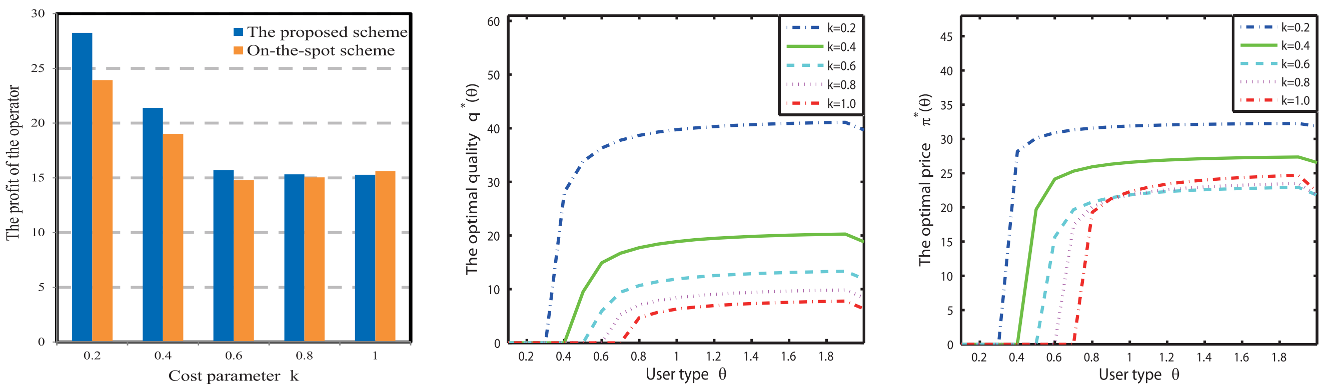
We further explore the proposed scheme in discrete-user-type model. More specifically, user type θ is chosen from

[7]In the on-the-spot scheme, users always offload cellular traffic immediately only if there exist available offloading networks, such as DTN hotspots or WiFi APs, indicating that service quality is maximized in this case.



(a) (b) (c)

Fig. 3. Operator's profit R and optimal contract $(q^*(\theta), \pi^*(\theta))$ with respect to price sensitivity α in continuous model



(a) (b) (c)

Fig. 4. Operator's profit R and optimal contract $(q^*(\theta), \pi^*(\theta))$ with respect to cost parameter k in discrete model.

the set $\{0.1, 0.2, \cdots, 2\}$ according to a uniform probability distribution.

Figure 4 demonstrates operator's profit and optimal contract with varying k, where α is 0.12. As expected, our scheme provides higher operator's profit than the on-the-spot scheme shown in Fig. 4(a), especially when k is small. Interestingly, the profit gap decreases with k, which is slightly different from continuous model. The intuitive is that as k increases, quality has a growing impact on cost. Given user payment, operator prefers offering low-quality service. Accordingly, operator's profit in the on-the-spot scheme decreases. To maintain IC constraint, however, operator in our scheme needs to provide discount for users and its profit experiences obvious decline. Thus the profit gap narrows. Figure 4(b) presents how optimal quality changes with θ and k. As users have higher θ, optimal quality increases, implying the monotonicity constraint in Lemma 6 holds. When θ is small, optimal quality tends to 0 since there is no feasible contract. As k increases, cost is greatly affected by quality, resulting in a reduction of achievable quality. As shown in Fig. 4(c), optimal price increases with θ since users need to pay more money for high-quality service. Obviously, optimal quality and payment will be maximized when θ is the highest. Moreover, as k increases, operator should charge users more money to ensure IC constraint. For example, when $k = 1.0$, optimal price exceeds that when $k = 0.6$.

We illustrate the effects of α on operator's profit and optimal contract in Fig. 5, where k is set to be 0.6. The results are consistent with our expectation: operator obtains more profit in our scheme compared with the on-the-spot scheme, shown in Fig. 5(a). As users have higher α, their demands for low-price service increase, and they are inclined to delay service when price is high. Operator's profit decreases accordingly for providing the discount. In the on-the-spot scheme, however, user satisfaction decreases rapidly for high-price services and then they only need to pay less money, leading to a reduction in operator's profit. As for optimal quality-price contract, we obtain similar results to continuous model, shown in Fig. 5(b) and Fig. 5(c). We find that optimal quality increases with θ as well. And similar things happen to optimal price. The intuitive is that operator should charge more money from high-quality service to guarantee contract's feasibility. As we discuss previously, with the increase of α, users are willing to delay service. Consequently, optimal quality and price will decrease greatly.

In the above scenarios, we suppose optimal contract consists of numerous contract items, covering all different user types. Indeed, however, operator may only offer limited contract items, indicating that some users have no choice but to choose the contract items specified for other user types. Accordingly, we investigate the effect of the number of contract items on the performance of our scheme, where k and α are

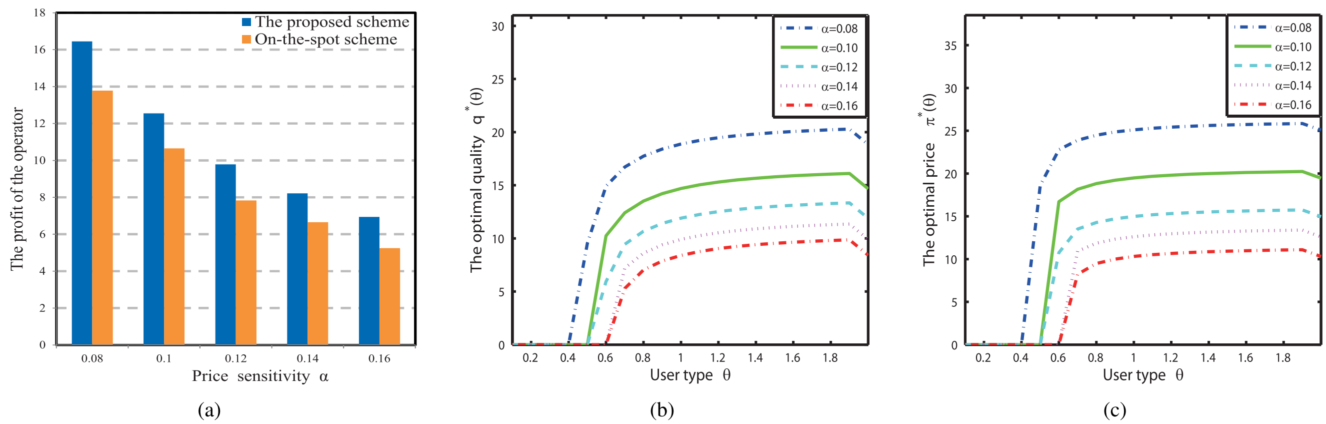


Fig. 5. Operator's profit R and optimal contract $(q^*(\theta), \pi^*(\theta))$ with respect to price sensitivity α in discrete model.

TABLE I
COMPARISON OF OPERATOR'S PROFIT AMONG NUMEROUS CONTRACT ITEMS AND ONLY ONE CONTRACT ITEM

	Numerous contract items	Only one contract item
Operator's profit	7.7891	5.9265

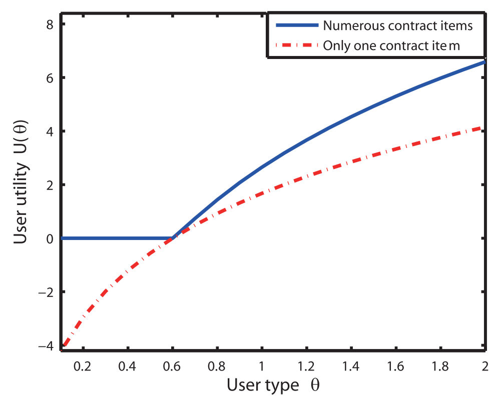


Fig. 6. Effects of the number of contract items on user utility.

set to 0.6 and 0.12. TABLE I presents the comparison of operator's profit among numerous contract items and only one contract item with $\theta = 0.6$. We find that operator will loss 23.9% profit if it only offers one contract items. Furthermore, we illustrate the effects of the number of contract items on user utility in Fig. 6. As expected, in the case of only one contract item, users except those with $\theta = 0.6$ obtain lower utility than numerous contract items. As for numerous contract items, user utility remains unchanged at 0 when θ is small to guarantee IR constraint. Therefore, it is suggested that operator should optimize the contract and offer as much contract items as possible to improve user satisfaction.

VII. DISCUSSIONS AND FUTURE WORK

This paper finishes a small step towards establishing a general incentive mechanism for delayed offloading. Despite this, there are several issues that deserve further discussion and study.

A. Discussions About User Mobility

In our scheme, operator offers optimal contract to users subscribing to delayed offloading service. Accordingly, there's a guarantee that users can receive service from offloading networks before their maximum tolerable delay (i.e., deadline); and once deadline expired, they will receive service via cellular network. Actually, our analysis is based on the service commitment specified by deadline and quality. However, our model can be applied to study opportunistic network connectivity in offloading networks, though we do not explicitly take into account user mobility.

As for mobile users, the chances to meet offloading networks depend on their mobility patterns and the distributions of DTN or WiFi hotspots. Inspired by [18], we introduce inter-hotspot meeting time to characterize this chance. As we all know, user satisfaction decreases with delay. Thus at meeting time t, the satisfaction of type-θ user can be modeled as

$$V(\theta, t) = \begin{cases} \theta(d - t) + V_0(\theta), & if \quad 0 \le t < d \\ V_0(\theta), & if \quad t \ge d, \end{cases} \tag{47}$$

where $V_0(\theta)$ is the minimum value of user satisfaction, determined by user type θ. Actually, in our proposed scheme, meeting time t is no larger than d.

Suppose inter-hotspot meeting time t is independent and exponentially distributed with rate λ, and we can obtain user expected satisfaction about delay, i.e.,

$$\begin{aligned} V(\theta) &= \int_0^d \lambda e^{-\lambda t} \left[\theta(d - t) + V_0(\theta)\right] dt + e^{-\lambda d} \cdot V_0(\theta) \\ &= V_0(\theta) + \theta \cdot \frac{\lambda d + e^{-\lambda d} - 1}{\lambda}. \end{aligned} \tag{48}$$

We can find $V_0(\theta)$ is inversely proportional to θ. To facilitate the analysis, we assume $V_0(\theta) = 2 - \theta$, $\theta \in [0.1, 2]$. Let $q = \frac{\lambda d + e^{-\lambda d} - \lambda - 1}{\lambda}$, and we can rewrite user expected satisfaction as

$$V(\theta) = 2 + \theta \cdot q, \tag{49}$$

which is consistent with quality satisfaction in our scheme after adopting the logarithm function about it. Hence, involving user's mobility does not affect the main results of our paper.

B. Future Work

1) Multi-Operator Market: Just as most previous research, we model this delayed offloading scheme as an oligopoly market, where there is a single operator dominating offloading process. In fact, however, more and more operators appear in mobile communication market. It is obvious that the competition among them has a huge impact on the behavior of users and operators, which cannot be neglected. As a future work, we are ready to extend our study into a multi-operator market with competition effects. That is, multiple operators may put forward some different discount programs so as to attract users' attention and preference.

2) Incomplete Information Scenarios: This paper focuses on the strongly incomplete information scenario, where operator only knows the statistical information on user type. Next, we will further study some more incomplete information structures, e.g., operator has no idea of any statistical information. Note that our contract-based delayed offloading scheme only involves user-sided private information. However, operator may also possess some private information, i.e., multi-sided private information case. The major difference between these two cases is that our optimal contract design can be reduced to a problem of controlling user's response. While in multi-sided case, it becomes one of controlling the strategic behaviors of operator and users. Thus it is interesting to explore game theory to cope with this incomplete information scenario.

VIII. Conclusion

We propose a contract-based incentive framework for delayed traffic offloading in cellular networks. The major focus is to motivate users to leverage their delay tolerance in exchange for service cost. Moreover, we model this delayed offloading process as a monopoly market where operator makes pricing with the consideration of statistical information on user satisfaction. Specifically, we investigate the strongly incomplete information scenario, where user type is private information depicting the heterogeneity of user satisfaction. Each user chooses the proper contract item according to its delay and price sensitivity. Furthermore, we derive optimal contract which maximizes operator's profit for both continuous model and discrete model. Numerical results validate the efficiency of our scheme in improving operator's profit.

Appendix A
Proof of Lemma 1

Proof: We assume that $\theta_l \le \theta_1 \le \theta_2 \le \theta_u$. According to the assumption, IC constraint holds for all types θ. Then we conclude that

$$\begin{aligned}\ln(1+\theta_2 q(\theta_2)) - \alpha\pi(\theta_2) &\ge \ln(1+\theta_2 q(\theta_1)) - \alpha\pi(\theta_1)\\ &\ge \ln(1+\theta_1 q(\theta_1)) - \alpha\pi(\theta_1). \quad (50)\end{aligned}$$

By iterating, we have $\ln(1+\theta_2 q(\theta_2)) - \alpha\pi(\theta_2) \ge \ln(1+\theta_l q(\theta_l)) - \alpha\pi(\theta_l)$. Due to the random selection of θ_2, we can further obtain $\ln(1+\theta q(\theta)) - \alpha\pi(\theta) \ge \ln(1+\theta_l q(\theta_l)) - \alpha\pi(\theta_l), \forall\theta \in [\theta_l, \theta_u]$.

In order to satisfy IR constraint for all contract items, we only need to guarantee $\ln(1+\theta_l q(\theta_l)) - \alpha\pi(\theta_l) \ge 0$. Thus we complete the proof of Lemma 1. ■

Appendix B
Proof of Lemma 2

Proof: We divide the proof into two parts. We first prove if IC constraint holds, the monotonicity constraint and local incentive compatibility constraint will hold. As we all know, satisfying IC constraint means that each type-θ user can maximize its utility by choosing the contract item for θ. Suppose $q(\theta)$ and $\pi(\theta)$ are all differentiable, then the following first- and second-order conditions for user's optimization problem are satisfied at $\hat{\theta} = \theta$, i.e.,

$$\frac{\hat{\theta} q'(\theta)}{1+\hat{\theta} q(\theta)} - \alpha\pi'(\theta) = 0, \quad (51)$$

$$\frac{\hat{\theta} q''(\theta)\left(1+\hat{\theta} q(\theta)\right) - \left(\hat{\theta} q'(\theta)\right)^2}{\left(1+\hat{\theta} q(\theta)\right)^2} - \alpha\pi''(\theta) \le 0. \quad (52)$$

The first-order condition of the user's optimization problem is the same as the local incentive compatibility constraint in (16). Differentiate (16) with respect to θ, and we obtain

$$\frac{q'(\theta)+\theta q''(\theta)}{1+\theta q(\theta)} - \frac{\theta q'(\theta)\left(q(\theta)+\theta q'(\theta)\right)}{(1+\theta q(\theta))^2} - \alpha\pi''(\theta) = 0. \quad (53)$$

Minus (53) by (52), we have $\frac{q'(\theta)}{1+\theta q(\theta)} \ge 0$. Therefore, we can conclude $q'(\theta) \ge 0$.

Next we utilize contradiction to prove if the monotonicity constraint and local incentive compatibility constraint hold, then IC constraint will hold. Suppose that for at least one user type θ, IC constraint is violated, i.e., for at least one $\hat{\theta} \ne \theta$,

$$\ln(1+\theta q(\theta)) - \alpha\pi(\theta) < \ln\left(1+\theta q(\hat{\theta})\right) - \alpha\pi(\hat{\theta}). \quad (54)$$

By integrating, we obtain

$$\int_{\theta}^{\hat{\theta}} \frac{\theta q'(x)}{1+\theta q(x)} - \alpha\pi'(x)\, dx > 0. \quad (55)$$

According to the assumption, the monotonicity constraint is satisfied, i.e., $q'(x) \ge 0$.

If $\hat{\theta} > \theta$, we have $\frac{\theta q'(x)}{1+\theta q(x)} < \frac{x q'(x)}{1+x q(x)}$. Since the local incentive compatibility constraint is supposed to be met, i.e., $\frac{x q'(x)}{1+x q(x)} = \alpha\pi'(x)$, we can get

$$\int_{\theta}^{\hat{\theta}} \frac{\theta q'(x)}{1+\theta q(x)} - \alpha\pi'(x)\, dx < 0, \quad (56)$$

which contradicts with (55). If $\hat{\theta} < \theta$, the same logic leads us to a similar contradiction.

Combining the above two cases, we have completed the proof of this lemma. ■

Appendix C
Proof of Lemma 4

Proof: User type in this discrete model satisfies $\theta_1 < \theta_2 < \cdots < \theta_n$. Since IC constraint holds for any type $\theta_i, i \in \{1, 2, \cdots, n\}$, we obtain

$$\begin{aligned}\ln(1+\theta_i q_i) - \alpha\pi_i &\ge \ln(1+\theta_i q_1) - \alpha\pi_1\\ &\ge \ln(1+\theta_1 q_1) - \alpha\pi_1. \quad (57)\end{aligned}$$

In order to satisfy IR constraint for all user type, we only need to guarantee

$$\ln(1+\theta_1 q_1) - \alpha\pi_1 \geq 0. \quad (58)$$

As mentioned in Section III, $c(q_i)$ increases q_i. To maximize its profit, operator will adapt its schedule by raising price π_i as much as possible, leading to the decrease of the left side of (58). Accordingly, the condition in (32) will be satisfied when contract is at the optimum. ∎

APPENDIX D
PROOF OF LEMMA 5

Proof: Similarly, we can easily prove that the user's utility function, i.e., $U(\theta_i, q_i) = V(\theta_i, q_i) + G(\pi_i) = \ln(1+\theta_i q_i) - \alpha\pi_i$, satisfies the SMC. Moreover, we can get $V_{\theta q}(\theta_i, q_i) > 0$.

By the fundamental theorem of calculus, we have

$$\begin{aligned} &V(\theta_m, q_i) - V(\theta_m, q_j) - V(\theta_n, q_i) + V(\theta_n, q_j) \\ &= \int_{q_j}^{q_i} V_q(\theta_m, y)\, dy - \int_{q_j}^{q_i} V_q(\theta_n, y)\, dy \\ &= \int_{\theta_n}^{\theta_m} \left(\int_{q_j}^{q_i} V_{\theta q}(x, y)\, dy \right) dx \\ &\geq 0. \end{aligned} \quad (59)$$

Through simple transforming, we have completed the proof of this lemma. ∎

APPENDIX E
PROOF OF LEMMA 6

Proof: Since IC constraint holds for any user type, we can get for $\theta_i \neq \theta_j$,

$$\ln(1+\theta_i q_i) - \alpha\pi_i \geq \ln(1+\theta_i q_j) - \alpha\pi_j, \quad (60)$$

and

$$\ln(1+\theta_j q_j) - \alpha\pi_j \geq \ln(1+\theta_j q_i) - \alpha\pi_i. \quad (61)$$

Adding (60) and (61) together, we obtain $(\theta_i - \theta_j)(q_i - q_j) \geq 0$. Therefore, if $\theta_i > \theta_j$, then $q_i \geq q_j$ holds for any incentive-compatible contract. If $\theta_i = \theta_j$, we have $q_i = q_j$ for the fairness of contract. Combining the above two cases, the proof of this lemma will be completed. ∎

APPENDIX F
PROOF OF LEMMA 7

Proof: Consider the LDICs for three types $\theta_{i-1} < \theta_i < \theta_{i+1}$, and we obtain

$$\ln(1+\theta_{i+1} q_{i+1}) - \alpha\pi_{i+1} \geq \ln(1+\theta_{i+1} q_i) - \alpha\pi_i, \quad (62)$$

and

$$\ln(1+\theta_i q_i) - \alpha\pi_i \geq \ln(1+\theta_i q_{i-1}) - \alpha\pi_{i-1}. \quad (63)$$

Since the SMC is satisfied, then according to Lemma 5, we can get

$$\begin{aligned} &\ln(1+\theta_{i+1} q_i) - \ln(1+\theta_{i+1} q_{i-1}) \\ &\quad \geq \ln(1+\theta_i q_i) - \ln(1+\theta_i q_{i-1}). \end{aligned} \quad (64)$$

Combining equations (63) and (64), we have $\ln(1+\theta_{i+1}q_i) - \alpha\pi_i \geq \ln(1+\theta_{i+1}q_{i-1}) - \alpha\pi_{i-1}$. Together with (62), we obtain $\ln(1+\theta_{i+1}q_{i+1}) - \alpha\pi_{i+1} \geq \ln(1+\theta_{i+1}q_{i-1}) - \alpha\pi_{i-1}$, implying that for user type θ_{i+1}, the LDIC is satisfied for contract item (q_{i-1}, π_{i-1}) besides (q_i, π_i). By iterating, we conclude the LDIC holds for all contract items (q_j, π_j), $j \leq i$, indicating that IC constraint is satisfied. In view of the random selection of θ_{i+1}, we have completed the proof. ∎

APPENDIX G
PROOF OF LEMMA 9

Proof: Suppose the LDICs hold for any user type $\theta_i, i \in \{1, 2, \cdots, n\}$, i.e., $\ln(1+\theta_i q_i) - \alpha\pi_i > \ln(1+\theta_i q_{i-1}) - \alpha\pi_{i-1}$. The LDICs will still be satisfied if both π_i and π_{i-1} are raised by the same positive amount. To maximize its profit, operator will try to raise all π_j for $j \geq i$ as much as possible until the following equation holds, i.e.,

$$\ln(1+\theta_i q_i) - \alpha\pi_i = \ln(1+\theta_i q_{i-1}) - \alpha\pi_{i-1}. \quad (65)$$

Note that this process will not impact on other LDICs. Therefore, if the contract is at the optimum, the condition in (38) will hold for all $\theta_i, i \in \{1, 2, \cdots, n\}$. ∎

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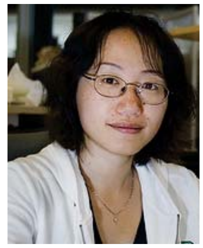

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