AN INCENTIVE FRAMEWORK FOR CELLULAR TRAFFIC OFFLOADING

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ABSTRACT - Cellular networks (e.g., 4G) are currently facing severe traffic overload problems caused by excessive traffic demands. Offloading part of the cellular traffic through other forms of networks, such as Delay Tolerant Networks (DTNs) and WiFi hotspots, is a promising solution. However, since these networks can only provide intermittent connectivity to mobile users, utilizing them for cellular traffic offloading may result in a non-negligible delay. As the delay increases, the users' satisfaction decreases. In this paper, we investigate the tradeoff between the amount of traffic being offloaded and the users' satisfaction. We provide a novel incentive framework to motivate users to leverage their delay tolerance for cellular traffic offloading. To minimize the incentive cost given an offloading target, users with high delay tolerance and large offloading potential should be prioritized for traffic offloading. To effectively capture the dynamic characteristics of users' delay tolerance, our incentive framework is based on reverse auction to let users proactively express their delay tolerance by submitting bids. We further illustrate how to predict the offloading potential of the users by using stochastic analysis for both DTN and WiFi cases. Extensive trace-driven simulations verify the efficiency of our incentive framework for cellular traffic offloading.

1. INTRODUCTION

The recent popularization of cellular networks (e.g., 4G) provide mobile users with ubiquitous Internet access. However, the explosive growth of user population and their demands for bandwidth-eager multimedia content raise big challenges to the cellular networks. A huge amount of cellular data traffic has been generated by mobile users, which exceeds the capacity of cellular network and hence deteriorates the network quality. To address such challenges, the most straightforward solution is to increase the capacity of cellular networks, which however is expensive and inefficient. Some researchers studied on how to select a small part of key locations to realize capacity upgrade, and shift traffic to them by exploiting user delay tolerance. Remaining the capacity of cellular networks unchanged, offloading part of cellular traffic to other coexisting networks would be another desirable and promising approach to solve the overload problem. Some recent research efforts have been focusing on offloading cellular traffic to other forms of networks, such as DTNs and WiFi hotspots, and they generally focus on maximizing the amount of cellular traffic that can be offloaded. In most cases, due to user mobility, these networks available for cellular traffic offloading only provide intermittent and opportunistic network connectivity to the users, and the traffic offloading hence results in non-negligible data downloading delay. In general, more offloading opportunities may appear by requesting the mobile users to wait for a longer time before actually downloading the data from the cellular networks, but this will also make the users become more impatient and hence reduce their satisfaction.

In this paper, we focus on investigating the tradeoff between the amount of traffic being offloaded and the users' satisfaction, and propose a novel incentive framework to motivate users to leverage their delay tolerance for traffic offloading. Users are provided with incentives; i.e., receiving discount for their service charge if they are willing to wait longer for data downloading. During the delay, part of the cellular data traffic may be opportunistically offloaded to other networks mentioned above, and the user is assured to receive the remaining part of the data via cellular network when the delay period ends.

The major challenge of designing such an incentive framework is to minimize the incentive cost of cellular network operator which includes the total discount provided to the mobile users, subject to an expected amount of traffic being offloaded. To achieve this goal, two important factors should be taken into account; i.e., the *delay tolerance* and *offloading potential* of the users. The users with high delay tolerance and large offloading potential should be prioritized in cellular traffic offloading.

First, with the same period of delay, the users with higher delay tolerance require less discount to compensate their satisfaction loss. To effectively capture the dynamic characteristics of the users' delay tolerance, we propose an incentive mechanism based on reverse auc- tion which is proved to conduct a justified pricing. In our mechanism, the users act as sellers to send bids, which include the delay that they are willing to experience and the discount that they want to obtain for this delay. Such discount requested by users is called "*coupon*" in the rest of the paper. The network operator then acts as the buyer to buy the delay tolerance from the users.

Second, with the same period of delay, users with larger offloading potential are able to offload more data traffic. For example, the offloading potential of a user who requests popular data is large, because it can easily retrieve the data pieces from other contacted peer users during the delay period. Also, if a user has high probability to pass by some WiFi hotspots, its offloading potential is large. To effectively capture the offloading potential of the users, we propose two accurate prediction models for DTN and WiFi case respectively.

The optimal auction outcome is determined by considering both the delay tolerance and offloading potential of the users to achieve the minimum incentive cost, given an offloading target. The auction winners set up contracts with the network operator for the delay they wait and the coupon they earn, and other users directly download data via cellular network at the original price. More specifically, the contribution of the paper is three-fold:

We propose a novel incentive framework, *Win-Coupon*, based on reverse auction, to motivate users leveraging their delay tolerance for cellular traffic offloading, which have three desirable properties: 1) truthfulness, 2) individual rationality, 3) low computational complexity.We provide an accurate model using stochastic analysis to predict users' offloading potential based on their data access and mobility patterns in the DTN case. We provide an accurate Semi Markov based prediction model to predict users' offloading potential based on their mobility patterns and the geographical distribution of WiFi hotspots in the WiFi case.

The rest of the paper is organized as follows. In Section 2 we briefly review the existing work. Section 3 provides an overview of our approach and the related background. Section 4 describes the details of our incentive framework, and proves its desirable properties. Section 5 evaluates the performance of Win Coupon through trace-driven simulations and Section 6 discusses further research issues. Section 7 concludes the paper.

2. RELATED WORK

To deal with the problem of cellular traffic overload, some studies propose to utilize DTNs to conduct offloading. Ristanovic et al. propose a simple algorithm, Mix-Zones, to let the operator notify users to switch their interfaces for data fetching from other peers when the opportunistic DTN connections occur. Whitbeck et al design a framework, called Push-and-Track, which includes multiple strategies to determine how many copies should be injected by cellular network and to whom, and then leverages DTNs to offload the traffic. provide three simple algorithms to exploit DTNs to facilitate data dissemination among mobile users, in order to reduce the overall cellular traffic. Many research efforts have focused on how to improve the performance of data access in DTNs. In the authors provide theoretical analysis to the stationary and transient regimes of data dissemination. Some later works disseminate data among mobile users by exploiting their social relations. Being orthogonal with how to improve the performance of data access in DTNs, in this paper, we propose an accurate model to capture the expected traffic that can be offloaded to DTNs to facilitate our framework design.

Public WiFi can also be utilized for cellular traffic offloading. In the authors design HotZones to enable users turning on WiFi interfaces when a WiFi connection is expected to occur based on the user mobility profile and location information of hot zones covered by WiFi. In the authors measure the availability and the offloading performance of public WiFi based on vehicular traces. Lee et al. consider a more general mobile scenario, and present a quantitative study on delayed and on-the-spot offloading by using WiFi. The prediction of future WiFi availability is important to the offloading scheme design, and has been studied i. In the authors propose to enable mobile users to schedule their data transfers when higher WiFi transmission rate can be achieved based on the prediction. In a Lyapunov framework based algorithm, called SALSA, is proposed to optimize the energy-delay tradeoff of the mobile devices with both cellular network and WiFi interfaces. Different from the existing work, in this paper, we propose an accurate model to predict how much traffic that can be offloaded via WiFi hotspots if a mobile user is willing to wait for certain delay time.

All the existing offloading studies have not considered the satisfaction loss of the users when a longer delay is caused by traffic offloading. To motivate users to leverage their delay tolerance for cellular traffic offloading, we propose an auction based incentive framework. Auction has been widely used in network design. Applying auc-tion in the spectrum leasing is one of the most practi-cal applications. Federal Communications Commission (FCC) has already auctioned the unused spectrum in the past decade, and there are a large amount of works on wireless spectrum auctions. Moreover, auction has also been applied for designing incentive mechanism to motivate selfish nodes to forward data for others. However, none of them has applied auction techniques to cellular traffic offloading.

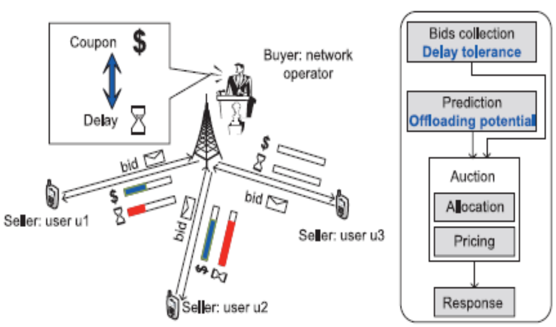
This paper substantially extends the preliminary version of our results appeared in we mainly focused on how to stimulate users to offload cellular traffic via DTNs. In this paper, we propose a more general framework which considers both DTNs and WiFi case. We provide an accurate model to predict users' offloading potential in the WiFi case and perform trace-driven simulations to evaluate its performance. In addition, we change the data query model in [18] to more realistic Zipf-like distribution to evaluate our framework.

Fig. 1. The main idea of Win-Coupon.

3. OVERWIEW

3.1 The Big Picture

In this section, we give an overview of the Win-Coupon framework. By considering the users' delay tolerance and offloading potential, Win-Coupon uses a reverse auction based incentive mechanism to motivate users to help cellular traffic offloading. Figure 1 illustrates the main idea. The network operator acts as the buyer, who offers coupons to users in exchange for them to wait for some time and opportunistically offload the traffic. When users request data, they are motivated to send bids along with their request messages to the network operator. Each bid includes the information of how long the user is willing to wait and how much coupon he wants to obtain as a return for the extra delay. Then, the network operator infers users' delay tolerance. In addition, users' offloading potential should also be considered when deciding the auction outcome. Based on the historical system parameters collected, such as users' data access and mobility patterns, their future value can be predicted by conducting network modeling, and then based on the information, users' offloading potential can be predicted. e.g., by contacting other peers which cache the data or moves into the wireless range of APs. Once delay t passes, the cellular network pushes the remaining data pieces to $u1$ to assure the promised delay. The losing bidders (e.g. user $u3$ shown in Figure 1) immediately download data via cellular network at the original price.



3.2 User Delay Tolerance

With the increase of downloading delay, the user's satisfaction decreases accordingly, the rate of which reflects the user's delay tolerance. To flexibly model users' delay tolerance, we introduce a *satisfaction function* $S(t)$, which is a monotonically decreasing function of delay t, and represents the price that the user is willing to pay for the data service with the delay. The satisfaction function is determined by the user himself, his requested data, and various environmental factors. We assume that each user has an upper bound of delay tolerance for each data. Once the delay reaches the bound, the user's satisfaction becomes zero, indicating that the user is not willing to pay for the data service. Figure 2 shows an example of the satisfaction function $S(t)$ of a specific user for a specific

data, where t_{bound} is the upper bound of the user's delay tolerance. p is the original charge for the data service, and the satisfaction curve represents the user's expected price for the data as the delay increases. For example, with delay t_1 the user is only willing to pay p_1 instead of p. $p - p_1$ is the satisfaction loss caused by delay t_1.

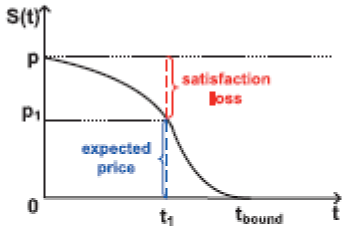


Fig. 2. Satisfaction function.

3.3 Auctions

In economics, auction is a typical method to determine the value of a commodity that has an undetermined and variable price. It has been widely applied to many fields. Most auctions are *forward auction* which involves a single seller and multiple buyers, and the buyers send bids to compete for obtaining the commodities sold by the seller. In this paper, we use *reverse auction* [19] which involves a single buyer and multiple sellers, and the buyer decides its purchase based on the bids sent by the sellers. To begin with, we introduce some notations. *Bid* (*bi*): It is submitted by bidder *i* to express *i*'s valuation on the resource for sale, which is not necessarily true. *Private value* (*xi*): It is the true valuation made by bidder *I* for the resources; i.e., the true price that *i* wants to obtain for selling the resource. This value is only known by *i*. *Market-clearing price* (*pi*): It is the price actually paid by the buyer to bidder *i*. This price cannot be less than the bids submitted by *i*.

Utility (*ui*): It is the residual worth of the sold resource for bidder *i*, namely the difference between *i*'s marketclearing price *pi* and private value *xi*. The bidders in the auction are assumed to be rational and risk neutral. A common requirement for auction design is the so-called *individual rationality*. ***Definition 1:*** *An auction is with individual rationality if all bidders are guaranteed to obtain non-negative utility.* The rational bidders decide their bidding strategy to maximize their utility. Let *N* denote the set of all bidders. The concept of *weakly dominant strategy* is defined as:

Definition 2: *bi = βi is a weakly dominant strategy for user i if and only if: ui(βi, β−i) ≥ ui(β_i, β−i), □β_i_= βi.*

Here *β−i = {β1, β2, · · · , βi−1, βi+1, · · · , β|N|}* denotes the set of strategies of all other bidders except for bidder *i*. We can see a weakly dominant strategy maximizes *i*'s utility regardless of the strategies chosen by all other bidders. If for every bidder, truthfully setting its bid to its private value is a weakly dominant strategy, the auction is *truthful* (strategyproof).

Definition 3: *An auction is truthful if each bidder, say i, has a weakly dominant strategy, in which bi = xi.* The truthfulness eliminates the expensive overhead for bidders to strategize against other bidders and prevents the market manipulation. Also, it assures the efficient allocation by encouraging bidders to reveal their true private values. Vickrey-Clarke-Groves (VCG) is the most well-studied auction format, due to its truthful property. However, VCG only ensures truthfulness when the optimal allocation can be found, and it usually cannot assure the truthfulness when applied to the approximation algorithms. Unfortunately, the allocation problem in Win-Coupon is NP-hard. It is known that an allocation algorithm leads to be truthful if and only if it is monotone. In order to maintain the truthfulness property, we design an approximation algorithm and make it monotone in a deterministic sense. Therefore, our incentive mechanism possesses three important properties: 1) truthfulness, 2) individual rationality, and 3) low computational complexity.

4. MAIN APPROACH OF WIN-CUPON

In this section, we illustrate the details of Win-Coupon. In the reverse auction based Win-Coupon, the buyer is the network operator who pays coupon in exchange for longer delay of the users. The sellers are the cellular users who sell their delay tolerance to win coupon. The right side of Figure 1 shows the flow chart of Win-Coupon. At first, the network operator collects the bids to derive the delay tolerance of the bidders, and predicts their offloading potential. Then, based on the derived information, a reverse auction is conducted, which includes two main steps: allocation and pricing. Finally, the network operator returns the auction outcome to the bidders. In the rest of this section, we first introduce the bidding. Then, we present auction mechanism and prove its properties. Finally, we illustrate how to predict bidders' offloading potential for both DTN and WiFi cases.

4.1 Bidding

To obtain coupon, the users attach bids with their data requests to reveal their delay tolerance. For each user, the upper bound *tbound* of its delay tolerance can be viewed as the resources that it wants to sell. The user can divide *tbound* into multiple time units, and submit multiple bids **b** = *{b*1*, b*2*, ……… , bl}* to indicate the value of coupon it wants to obtain for each additional time unit ofdelay, where *l* equals *tbound* , and *e* is the length of one time unit. By receiving these bids, the network operator knows that the user wants to obtain coupon with value no less than _*ki k*=1 *bk* by waiting for *ki* time units. The length of time unit *e* can be flexibly determined by the network operator. Shorter time unit results in larger bids with more information, which increases the performance of the auction, but it also induces more communication overhead and higher computational complexity. To simplify the presentation, in the rest of the paper delay *t* is normalized by time unit *e*. As shown in Figure 2, $p - S(t)$ is the

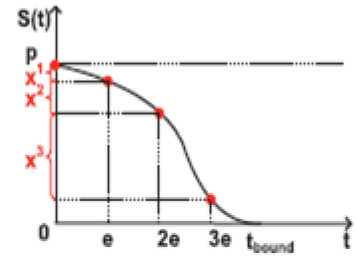


Fig. 3. Private value.

satisfaction loss of the user due to delay *t*. Then, $p - S(t)$ represents the private value of the user to the delay, namely the user wants to obtain the coupon with value no less than $p-S(t)$ for delay *t*. Thus, the private value of the user to each additional time unit of delay is **x** = *{x*1*, x*2*, · · · , xl}*, where *xk* (*k* ⊠ *{*1*, · · · , l}*), equals $S(k - 1) - S(k)$. For example, as shown in Figure 3, the user wants to obtain the coupon with value no less than *x*1 if it waits for one time unit, *x*1 + *x*2 for two time units, and *x*1 + *x*2 + *x*3 for three time units. Generally, the user can set its bids with any value at will, however we will prove that the auction in Win-Coupon is truthful, which guarantees that the users would bid their private value; that is, *bk* = *xk,* for all *k*.

4.2 Auction Algorithms

Win-Coupon is run periodically in each auction round. Usually, the auction would result in an extra delay for the bidders to wait for the auction outcome. However, different from other long-term auctions, such as the FCC-style spectrum leasing, the auction round in our scenario is very short, since hundreds of users may request cellular data service at the same time. Also, because the bidders who are willing to submit bids are supposed to have a certain degree of delay tolerance, the extra delay caused by auction can be neglected. Next, we describe two main steps of the auction: allocation and pricing.

4.2.1 Allocation

In traditional reverse auction, the allocation solution is purely decided by the bids; i.e., the bidders who bid the lowest price win the game. However, in our scenario, besides the bids which express the bidders' delay tolerance, the offloading potential of the bidders should also be considered. Let *{t1, t2,……..,t|N|}* represent the allocation solution, where *ti* denotes the length of delay that network operator wants to buy from bidder *i*.

Note that since each bidder is asked to wait for integer multiples of time unit, *ti* is an integer. If *ti* equals zero, bidder *i* loses the game. The allocation problem in Win- Coupon can be formulated as follows: ***Definition 4:*** *The allocation problem is to determine the optimal solution {t1, t2, · · · , t|N|} which minimizes the total incentive cost, subject to a given offloading target.*

$$\min_{t_i} \sum_{i \in \mathcal{N}} \sum_{k=1}^{t_i} b_i^k \qquad (1)$$

$$s.t. \sum_{i \in \mathcal{N}} V_i^d(t_i) \geq v_0 \qquad (2)$$

$$\forall i,\ t_i \in \{0, 1, 2, \ldots, l_i\}. \qquad (3)$$

In Eq.(1), $\sum_{k=1}^{t_i} b_i^k$ denotes the value of the coupon that the network operator needs to pay bidder *i* in exchange for its delay *ti*. *V di* (*t*) in Eq.(2) denotes the expected traffic that can be offloaded, if bidder *i* downloads data *d* and is willing to wait for delay *t*. We will provide the details on how to predict *V di* (*t*) in Section 4.3 and 4.4 for both DTN and WiFi cases respectively. We assume that within a short auction round, each bidder only requests one data item, so that each *i* is mapped to a single *d*. Thus, this constraint ensures that the total expected offloaded traffic is no less than the offloading target *v*0. Eq.(3) ensures that the delay that each bidder *i* waits does not exceed *li*, the maximum number of time units that *i* is willing to wait. It is easy to prove that our allocation problem can be reduced to the 0-1 knapsack problem, under the assumption that *li* = 1, for all *i*. The 0-1 knapsack problem is proved to be NP-hard, and thus our problem is also NP-hard. Next, we transform the original problem, and derive the optimal solution of the new problem by dynamic programming (DP).

```
Perform initialization phase of algorithm 2 (lines 1–4);
ξ ← 4; θ ← 16;
δ ← ⌊min{N/ξ, n_B/θ}⌋;                ▷ Initialize threshold δ
while |I| > 0 do
    ε ← θ/(n_B+1);
    while |I| > δ do
        Perform bidding and assignment phase of algorithm 2 (lines 9–15);
        ε ← ε · ξ;
    end while
    δ ← δ/ξ; θ ← θ · ξ;
end while
```

4.2.1 Auction algorithm

To develop an intuitive understanding of the auction algorithm, it is helpful to introduce an economic equilibrium problem that turns out to be equivalent to the assignment problem. Let us consider the possibility of matching then objects with then persons through a market mechanism, viewing each person as an economic agent acting in his own best interest. Suppose that object j has a price p j and that the person who receives the object must pay the price pj. Then, the (net) value of object j for person I is aij− pj and each person I would logically want to be assigned to an object ji with maximal value, that is, with

aiji−pji = maxj=1 ,...,n { aij −pj }

We will say that a person I is happy if this condition holds and we will say that an assignment and a set of prices are at equilibrium when all persons are happy. Equilibrium assignments and prices are naturally of great interest to economists, but there is also a fundamental relation with the assignment problem; it turns out that an equilibrium assignment offers maximum total benefit (and thus solves the assignment problem), while the corresponding set of prices solves an associated dual optimization problem. This is a consequence of the celebrated duality theorem of linear programming. Let us consider now a natural process for finding an equilibrium assignment. I will call this process the naive auction algorithm because it has a serious flaw, as will be seen shortly. Nonetheless, this flaw will help motivate a more sophisticated and correct algorithm.

The naive auction algorithm proceeds in "rounds" (or "iterations") starting with any assignment and any set of prices. There is an assignment and a set of prices at the beginning of each round, and if all persons are happy with these, the process terminates. Otherwise some person who is not happy is selected. This person, call him i, finds an object ji which offers maximal value, that is,

$$ji \in \arg \max j = 1, \ldots, n \{ aij - pj \}$$

and then:

(a) Exchanges objects with the person assigned to ji at the beginning of the round,

(b) Sets the price of the best object jI to the level at which he is indifferent between ji and the second best object, that is, he sets pji to

$$Pji \text{ to } pji + \gamma i ,$$

Where $\gamma i = vi - wi$

Vi is the best object value, $vi = \max j \{ aij - pj \}$ and wi is the second best object value

$$wi = \max j6 = ji \{ aij - pj \}$$

that is, the best value over objects other than ji (Note that γi is the largest increment by which the best object price pji can be increased, with ji still being the best object for person I)In traditional reverse auction, the allocation solution is purely decided by the bids; i.e., the bidders who bid the lowest price win the game in our scenario, besides the bids that express the bidders' delay tolerance, the offloading potential of the bidders should also be considered. Let ft1; t2; .....; tjN jg represent the allocation solution, where ti denotes the length of delay that network operator wants to buy from bidder i. Note that because each bidder is asked to wait for integer multiples of time unit, ti is an integer. If ti equals zero, bidder [8] loses the game. The allocation problem in Win-Coupon can be formulated

4.2.2. Pricing

The VCG-style pricing is generally used in forward auction, which involves single seller with limited resources [8] for sale, and multiple buyers. The bidders who have the highest bid win the game, and each winning bidder pays the "opportunity cost" that its presence introduces to [5] others it is proved that this pricing algorithm provides bidders with the incentives to set their bids truthfully. Based on the basic idea, in our pricing algorithm [9], the network operator also pays bidder i the coupon with value equal to the "opportunity cost" exerted to all the other bidders due to presence.

5. DISCUSSIONS

In this paper, we mainly focused on the downloading scenario since the majority of cellular traffic is on the downlink [31]. We also separate WiFi and DTN when discussing Win-Coupon design. Actually, our framework is very general, and can be extended to fit many other scenarios. Win-Coupon consists of two parts: auction based incentive mechanism and prediction. As long as the volume of offloaded traffic $V\ di\ (t)$ can be predicted, the incentive mechanism can be adopted for coupon allocation and pricing under various scenarios such as uploading, downloading, DTN only, WiFi only, or hybrid of DTN and WiFi. The only difference under various scenarios is in the prediction part.

6. CONCLUSION

In this paper, we proposed a novel incentive framework for cellular traffic offloading. The basic idea is to motivate the mobile users with high delay tolerance and large offloading potential to offload their traffic to other intermittently connected networks such as DTN or WiFi hotspots. To capture the dynamic characteristics of users' delay tolerance, we design an incentive mechanism based on reverse auction. Our mechanism has been proved to guarantee truthfulness, individual rationality, and low computational complexity. Moreover, we design two accurate models to predict the offloading potential of the users for both DTN and WiFi cases. Extensive tracedriven simulations validate the efficiency and practical use of our incentive framework.

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