EFFICIENT DYNAMIC CELLULAR TRAFFIC OFFLOADING IN DELAY TOLERANT NETWORKS

D. Lakshmi, K. Manohari
1Department Of Computer Science, Theivanai Ammal College for Women Thiruvalluvar University, India.
2Department Of Computer Application, Theivanai Ammal College for Women Thiruvalluvar University, India.

Abstract
The explosive traffic demands and limited capacity provided by the current cellular networks, Delay Tolerant Networking (DTN) is used to migrate traffic from the cellular networks to the free and high capacity device-to-device networks. Since these networks can only provide intermittent connectivity to mobile users, utilizing them for cellular traffic offloading may result in a non-negligible delay. In this paper, we proposing a novel technique called dynamic cellular offloading to enable a cellular service provider to purchase and leverage third-party resources on demand through reverse auctions. Dynamic cellular offloading has several important features like explicit spatial coverage of different users, dynamic nature of traffic demands, effective truth valuation in bidding process. With this technique, we are using optimal algorithm to determine the optimal solution that minimizes the incentive cost during traffic offloading. Our trace-driven simulation shows that this method effectively reduces cost and is robust against collusion. Our prototype implementation demonstrates its feasibility.

Keywords—Cellular traffic offloading, Delay Tolerant Networking (DTN), WiFi hotspots.

1. INTRODUCTION

The recent popularization of cellular networks (e.g., 3G) 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 networks, and hence, deteriorates the network quality [1]. 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 [2]. 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 [3], [4], [5], 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 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 threefold:

1. We propose a novel incentive framework, WinCoupon, based on reverse auction, to motivate users leveraging their delay tolerance for cellular traffic offloading, which have three desirable properties: - truthfulness, - individual rationality, and - low computational complexity.

2. 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.

II. RELATED WORK

To deal with the problem of cellular traffic overload, some studies propose to utilize DTNs to conduct offloading. Ristanovic et al. [6] propose a simple algorithm, MixZones, 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. [7] 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. Han et al. [3] provide three simple algorithms to exploit DTNs to facilitate data dissemination among mobile users, to reduce the overall cellular traffic. Many research efforts have focused on how to improve the performance of data access in DTNs. In [8], the authors provide theoretical analysis to the stationary and transient regimes of data dissemination. Some later works [9], [10] 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.

This paper substantially extends the preliminary version of our results appeared in [18]. In [18], we mainly focused on how to stimulate users to offload cellular traffic via DTNs. In this paper, we propose a more general framework that 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.

III. OVERVIEW

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. Fig. 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.

During the delay period, u1 may retrieve some data pieces from other intermittently available networks, for example, by contacting other peers that 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 Fig. 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.

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 that 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] that 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 \( i \).
price cannot be less than the bids submitted by i. Utility\((u_i)\): It is the residual worth of the sold resource for bidder \(i\), namely the difference between \(i\)'s market-clearing price \(p_i\) and private value \(x_i\). 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.

3.4 Preliminaries on auction theory

In this section, we briefly overview the concept of auctions and some relevant terms and notations. In economics, an auction is a typical method to determine the value of a commodity that has a variable price. Most auctions are forward auctions which involves a single seller and multiple buyers. In this paper, we use a reverse auction in the Single MUE scenario, which involves a single buyer (MUE) and multiple sellers (femtocells). The sellers compete for selling the commodities by submitting bids, then the buyer decides on its purchase. In addition, we use a double auction in the MultiMUE scenario, where multiple buyers and sellers are included. They submit bids and asks to the auctioneer, who decides the result. The notation is introduced below. bid \((b_i)\): the valuation of the resource submitted by bidder \(i\), which is not necessarily true. An ask \((a_i)\) of a seller in a double auction is defined similarly. Private Value \((v_i)\): the true valuation for the resource by bidder \(i\). This value is only known by the bidder. Price \((p_i)\): the price actually paid by the buyer \(i\) (or paid to the seller \(i\)). Utility \((u_i)\): the residual value of the resource. For buyer \(i\), it is \(u_i = v_i - p_i\), while for seller \(i\), it is \(u_i = p_i - v_i\). Individual Rationality: An auction is individual rational if all buyers and sellers are guaranteed to obtain non-negative utility. It is a common requirement for auction designs.

A. Auction Mechanism Design for Single MUE

The Single MUE scenario involves one MUE and multiple neighboring femtocells, as shown in Figure 2. This scenario happens when the operator prefers to set up an auction for each MUE. The femtocells are sellers selling the access time units to the MUE, who can aggregate the data from multiple femtocells to achieve a larger rate. We will design a multiunit reverse auction framework with each time slot as a unit.

The MUE is both the buyer and auctioneer, it receives the bids submitted by the femtocells and determines the result.

We use \(I\) to represent the set of femtocells, and \(I = |I|\) the total number. There is a limit on the maximum number of timeslots that can be leased out, set by the owner for each femtocell. We denote it as \(N_i\). We further use \(R_i\) represent the datarate of the link between femtocell \(i\) and MUE. It is measured by the MUE and does not change during an auction round. In our framework, each femtocell \(i\) submits a bid vector.

Our auction mechanism design includes two parts, Winner Determination and Pricing. In the winner determination (W-D) part, the auctioneer, MUE, determines a set of femtocells as the winners according to the bid vectors they submitted. Following the VCG-based auction mechanisms, our winner determination aims to maximize the system efficiency, formulated as:

\[
\max_{n_i} U(\sum_{i \in I} \left(\frac{n_i R_i}{T}\right)) - \sum_{i \in I} b_i(n_i) - U(R^{true})
\]

\[
\sum_{i \in I} n_i \leq T,
\]

\[
n_i \leq N_i, \quad \forall i \in I.
\]

In the above formulation, \(U()\) is the utility of the MUE as a function of its data rate. \(n_i\) is the
number of time slots leased to the MUE from femtocell i. R
Macis MUE’s data rate with the macro base station (BS). System efficiency is represented by the difference of the utility gain. We assume the MUE’s utility function $U$ is concave in general, which reflects a wide range of applications. For instance, video quality follows a log-like function with the received videorate.

Next we focus on the pricing part. We have the following payment mechanism:

**Definition 1:** In SingleMUE auction, each winning femtocell $i$ receives a payment $p_i$ from the MUE as follows:

$$ p_i = b_i(n^*_i) + (Q^* - Q^* - b_i) $$

Based on the above pricing rule, we then prove some important properties of our auction.

**Theorem 1:** (Truthfulness) For each femtocell, setting its bid truthfully equal to its private valuation, $b_i = v_i$, is a weakly dominant strategy.

**Proof:** To prove the truthfulness, we compare two cases. One case is that the femtocell $i$ bids its true valuation as $b_i = v_i$. As shown from Equations (6) and (7), the resulting utility is $u_i = Q^* - Q^* - b_i$.

$$ \Delta u_i = u_i - u'_i = Q^* - (Q^* + b_i n^*_i - v_i n^*_i) $$

$$ = \left[ U\left( \sum_{i \in T} (n^*_i R_i/T) \right) - \sum_{i \in T} b_i(n^*_i) \right] $$

$$ - \left[ U\left( \sum_{i \in T} (n'_i R_i/T) \right) - \sum_{i \in T} b_i(n'_i) \right] $$

$$ = \left[ U\left( \sum_{i \in T} (n^*_i R_i/T) \right) - \sum_{i \in T} b_i(n^*_i) \right] $$

$$ - \left[ U\left( \sum_{i \in T} (n'_i R_i/T) \right) - \sum_{i \in T} b_i(n'_i) \right] $$

**B. Auction Mechanism Design for MultiMUE**

Another scenario we consider, MultiMUE, involves multiple MUEs and multiple femtocells coexisting in one area, as shown in Figure 3. This happens when the operator prefers to set up an auction covering multiple MUEs. Femtocells are still the resource holders selling their access time slots to the MUEs. The MUEs are buyers. We assume the macro cell covering the area is the auctioneer, who receives the bids/asks from all the agents and then performs winner determination and pricing. This characterizes a scenario similar to the exchange market and can be analyzed using multi-unit double auction.

![MultiMUE: auction with multiple MUEs and femtocells.](image)

With $a_i(k)$ representing the ask for leasing $k$ time units out. As in Section III-A, we aim to find a truthful double auction mechanism that drives both the buyers and
sellers to submit their bids and asks equivalent to their private values. To simplify the modeling, we restrict to the case that one MUE can only buy time slots from one femtocell, and one femtocell can only sell time slots to one MUE. We use $n_{ij}$ to denote the number of time slots bought from femtocell $j$ to MUE $i$. Then we can maximize the overall system efficiency as follows:

$$\max \sum_{i \in I} \sum_{j \in J} b_{ij}(n_{ij}) - \sum_{j \in J} \sum_{i \in I} a_{ij}(n_{ij})$$

subject to:

$$0 \leq n_{ij} \leq N_j, \forall j \in J,$$
$$\sum_i n_{ij} = \max_j \{n_{ij}\}, \forall j \in J,$$
$$\sum_j n_{ij} = \max_i \{n_{ij}\}, \forall i \in I,$$

where (12) follows the typical definition. Constraints (14) and (15) reflect the one-to-one mapping relationship. In the winner determination phase, we aim to solve the above problem in polynomial time. Fortunately, problem (12)-(15) can be converted into a max-weight bipartite matching problem.

**Algorithm 2: W-D Algorithm for MultiMUE Auction**

1. Construct the bipartite graph;
2. $w_{ij} \leftarrow \max_{n_{ij}, n_{ij} \leq N_j}(b_{ij}(n_{ij}) - a_{ij}(n_{ij}))$;
3. Find the optimal matching $\Phi$ using Hungarian Method. Nodes selected in $\Phi$ are the winners;
4. If $i$ and $j$ are a pair in $\Phi$, $i$ will lease $n_{ij} = \arg \max_{n_{ij}, n_{ij} \leq N_j}(b_{ij}(n_{ij}) - a_{ij}(n_{ij}))$ units from $j$;

C. System Performance

Next we evaluate the system performance of the two scenarios under the influence of several key parameters. All the points in the figures are the averages of 500 auction rounds. First, for the Single MUE scenario, we fix Max Demand $R_{max}$ of the FUEs to 6 Mb/s and increase Fem to Density from 0.1 to 1.0. We can see from that when the density of femtocells is close to 0, system efficiency is also close to 0, as few transactions happen.
Next, we examine the impact of traffic demand $R_{\text{dem}}$ of FUEs. We fix FemtoDensity to 1 and adjust $R_{\text{max dem}}$ in the range of $[1, 10]$ in the simulations. We deploy 10 MUEs in MultiMUE scenario. As shown in Figure 6(c), in both Single MUE and MultiMUE scenarios, as $R_{\text{max dem}}$ increases, the average utility of the MUEs drops. The reason is that when the traffic demand of FUEs gets higher, a femtocell’s private value on leasing one unit access time will increase, resulting in higher price. However, we can still see our framework leads to 150% improvement even when $R_{\text{max dem}} = 10$ Mb/s, which is significant. Note all the results are based on the truthfulness of the schemes.

IV. PERFORMANCE EVALUATION

In this section, we evaluate the performance of Win-Coupon through trace-driven simulations for both DTN and WiFi cases. For each case, we first introduce the simulation setup, and then evaluate the performance of Win-Coupon under various system parameters. In the evaluation, the following performance metrics are used:

. **Offloaded traffic.** The total amount of traffic that is actually offloaded.

. **Allocated coupon.** The total incentive cost spent by the network operator for offloading purpose.

. **Average downloading delay.** The average time a bidder spends to get the complete data after sending the request.

The DTN Case

DTN case is conducted on the UCSD trace [29], which records the contact history of 275 HP Jornada PDAs carried by students over 77 days. Based on the trace, we generate 50 data items, and each contains eight packets. The query rate $q_d$ for each data $d$ is generated following Zipf distribution, and the default skewness parameter $w$ is set to 1.5. The delete
rate \( d \) for each data \( d \) is randomly generated within the range of following the uniform distribution. When nodes request data, they can choose to attach bids with the request message based on their satisfaction function.

The scale of the trace, in terms of the number of users and their contact frequencies, is rather small. This results in long auction rounds for the network operator to collect enough bids, as well as long downloading delay experienced by the users. In a university there would probably be a larger number of users; thus, we further generate a large scale trace by replicating the nodes in the original trace 10 times, which seems like a more reasonable network scale.

Fig. 6. Impact of bidder number, reserve price, and delay tolerance—DTN.

4.2 The WiFi Case

To evaluate the performance of Win-Coupon in the WiFi case, we use the UMass DieselNet trace [30], which includes the mobility histories of 32 buses. In the trace, each bus is equipped with a GPS device, and periodically records its GPS location. To apply our prediction model, the map is divided into 10 - 15 uniform-sized geographical grids. Based on the mobility information provided by the trace, we further add synthetic WiFi information. We assume that some WiFi hotspots are distributed on the map. We preset a WiFi coverage rate, which represents the ratio of the number of grids with some WiFi hotspots to the total number of grids. The downlink data rate for those grids with WiFi hotspots are randomly generated within the range of 50 Kbps and 1 Mbps.

To derive the transition probability matrix and the corresponding sojourn time probability distributions for each node, we take two-week traces as the training data. We pick up one day trace (11-06-2007) which has relatively high network density to perform Win-Coupon. The first auction round begins at 8:30 AM and the auction is performed for 10 consecutive rounds with the interval of one hour. Since the total number of nodes in the trace is quite limited, we assume that each node will participate in the auction to increase the number of participants. The size of data requested by nodes are randomly generated within the range of 100 and 500 Mb.

Fig. 7. Impact of reserve price and delay tolerance—WiFi.
V. CONCLUSION

In this paper, we proposed an incentive framework to motivate femtocells to open their access to unregistered MUEs, which help increase network capacity and offload traffic. We carefully designed the VCG-based auction mechanisms to allocate access times and rigorously proved that all the participating agents can truthfully cooperate. Simulation results demonstrate that the performance of MUEs can be significantly improved, with system efficiency maximized in auctions. In the future, we plan to study the incentive issue of femtocells controlled by different operators. Hence, we need to design other offloading strategies and the prediction methods for the DTN case. For example, the uploading traffic can be offloaded by jointly using DTN and WiFi. Then, the node that generates data can transmit it via DTN to a contacted node which has large potential to have a WiFi connection in the near future, and upload the data through WiFi.

REFERENCES


