# Settling for Less - A QoS Compromise Mechanism For Opportunistic Mobile Networks

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## 1. INTRODUCTION

In recent years smartphones have become increasingly popular. In April 2011, Google claimed that around 350000 Android smartphones are being activated daily. A smartphone is a device equipped with a range of sensors, a gigahertz-range CPU, and high bandwidth wireless networking capabilities. The power and increasing prevalence of smartphones in combination with current research on opportunistic mobile networking have (1) increased the range of applications that could be supported on an opportunistic mobile network and (2) given birth to new fields of research such as mobile crowd computing [5] that are geared towards large-scale distributed computations.

An opportunistic network is created between mobile phones using local peer-to-peer connections. The nodes in such a network are mobile phones carried by human users on the move, and a link between two phones represent the fact that the corresponding phone users are within each other's wireless communication range. Opportunistic networks are usually intermittently connected and are characterized by social-based mobility and heterogeneous contact rate. Their basic principle of operation is based on the *store-and-forward* strategy [2].

Keeping in mind the fact that opportunistic networks in the near future will primarily comprise of smartphones as nodes, and would be geared towards servicing numerous applications of varied QoS demands, the opportunistic network research community today still face three basic hurdles to achieving good performance on most applications. User mobility is one such hurdle. In a relatively sparse network, user mobility might lead to network disconnectivity at times, which in turn increases response time of a user application. The second hurdle is the uncertainty in the quality of the wireless transmission channel. Effects like fading, shadowing, and interference might result in data packets being lost during transmission or being transmitted at a low speeds. Finally, individual user selfishness is a psychological hurdle which users in an opportunistic network face. A mobile user would be unwilling to forward packets for someone it does not know due to (1) individual security concerns and (2) it unnecessarily expending battery power and computation resources for an application it has no relation with. Under the above mentioned hurdles, it is not guaranteed that user QoS[1] demands could be satisfied to a certain degree at all times let alone guaranteeing complete user satisfaction. However, in practice, users are generally tolerant on accepting lesser QoS guarantees than what they demand, with the degree of tolerance varying from user to user. The latter fact has been taken into account in some sense in traditional opportunistic networks research, where the primary goal was to make sure that users can somehow get the information through data relaying without thinking of QoS. On the other hand, an opportunistic mobile network of the near future needs to focus on the user tolerance of QoS degradation in order to justify it handling varied applications of different QoS demands.

In this abstract we propose a market based mathematical framework that enables heterogenous mobile users in an opportunistic mobile network to *compromise* optimally and efficiently on their QoS demands in a manner such that each user is satisfied with its achieved (lesser) QoS, and at the same time the social welfare of users in the network is maximized. Our market based framework is practically implementable and is based on the concept of *parameterized supply function bidding* in traditional microeconomic theory [3][4]. *The contribution made in this abstract is important* because (1) the hurdles related to opportunistic mobile networks mentioned in the previous paragraph are not easy to get rid of in a practical sense, and as a result mobile users have to compromise with lesser QoS than they would have ideally liked (2) the mobile users would love to make sure that they can comprise in an optimal and efficient manner, given uncertain network conditions, and (3) In an opportunistic mobile network, the network conditions vary from time to time, and it may not be possible to conjure up network resources on demand to meet user QoS choices; thus there is the need of an efficient technique that matches user demand to supply rather than the other way round. Supply function bidding is one such technique specifically suited for this purpose. In the rest of the abstract we use the terms 'mobile user' and 'user' interchangeably.

[1]In general, QoS could be parameters such as response time, number of computations per unit time, allocated bandwidth, etc.

## 2. SYSTEM MODEL

We consider a mobile network system of $N_t$ mobile users in a time slot $t$. Each time slot $t$ lies within a total time period $T$ [2]and is of the form $[t-1, t]$. Within each time slot the total number of mobile users is assumed to be constant. We assume that the system is geared towards executing distributed computation tasks, in addition to regular data forwarding as in an opportunistic network. Each user in a time slot could either be (a) someone initiating a computation task, (b) someone doing computations for a task

[2]For example, the period $T$ could be a single day.

at hand, (c) someone just relaying information, or (d) someone doing all of (a), (b), and (c). In every time slot both the task initiators and task executors register with a central market agency. The agency could either be the one who develops the framework for efficient and optimal large-scale distributed computation or a third party. The agency has two functions in every time slot: (1) to accept user QoS demands and *supply functions* (QoS compromise functions) from task initiators and (2) to assess the aggregate service capacity of the task executors and enable market clearing, i.e., ensure aggregate user QoS compromise equals aggregate service capacity deficit. We also assume that the agency is connected to the mobile users via a control channel for signaling purposes (e.g., via a 3G connection).

## 2.1 The Basic Idea in a Nutshell

In every time slot the task initiators 'supply' (via an *iterative bidding process [4]* between themselves and the central agency) their supply functions to the central agency. A supply function is a measure of the amount of QoS a user is willing to compromise in return for a certain amount of benefit the agency would provide to the mobile user for making the compromise[3]. The agency estimates [4] the deficit in the aggregate service capacity (if there is any) that prevents the network from servicing ideal user QoS demands, and chooses a common benefit value that clears the market. This benefit value is passed on to all the task initiators in the time slot who in turn settle for the corresponding compromise level based on their compromise (supply) functions. In this abstract we consider two ways in which mobile users could choose their supply functions: (1) it chooses an optimal function in a 'price taking' (competitive) [6] market[5] of task initiators and (2) it chooses an optimal function in an 'price anticipating' (oligopolistic) [6] market of task initiators.

## 2.2 QoS Compromise Function

Let $c_{it}(k_{it}, b_t)$ be the QoS compromise function for user $i$ in time slot $t$. We parameterize user $i$'s compromise function in each time $t$ as follows.

$$c_{it}(k_{it}, b_t) = k_{it}b_t,\ \forall i \,\epsilon\, N_t^{init} \subseteq N_t, \tag{1}$$

where $N_t^{init}$ consists of those users in time slot $t$ who initiate the execution of a task. The function $c_{it}(\cdot)$ is the 'supply' function for user $i$ and gives the amount of QoS it is committed to compromise. In this abstract we treat QoS as the reciprocal of response time of an application initiated by a user. For example, if a user expects to ideally achieve a response time of 2 time units, its QoS metric would have a value of $\frac{1}{2}$. However, it could compromise[6] say a response time of 3 additional seconds in which case its achieved QoS is $\frac{1}{5}$. Thus, it makes a compromise of $\frac{3}{10}$ QoS units. $k_{it} \geq 0$ is the supply function profile [4] for user $i$ in time slot $t$. It is a scalar quantity that determines the supply function of a user in time slot $t$, and is known to the central agency. $b_t$ is the benefit that the central agency provides to all the task initiators.

## 2.3 Clearing the Market

The central agency clears the market in every time slot by solving the following equation.

$$\sum_i c_{it}(k_{it}, b_t) = \sum_i k_{it}b_t = d_t, \tag{2}$$

where $d_t$ is the aggregate service capacity deficit in time slot $t$. Solving the latter equation we get the value of $b_t$ as

$$b_t(\overrightarrow{k_t}) = \frac{d_t}{\sum_i k_{it}},\ \forall t, \tag{3}$$

where $\overrightarrow{k_t} = (k_{1t}, k_{2t}, ......, k_{|N_t^{init}|})$ is the vector of support profiles for the task initiators in time slot $t$.

# 3. COMPETITIVE MARKET ANALYSIS

We consider a competitive market of task initiators where the latter are 'benefit' taking. Given a benefit value $b_t$ in time slot $t$, each user $i$ maximizes its profit according to the following optimization problem.

$$argmax_{k_{it}} b_t c_{it}(k_{it}, b_t) - C_{it}(c_{it}(k_{it}, b_t)),$$

where $C_{it}(c_{it}(\cdot))$ is the disutility or cost incurred by user $i$ in time slot $t$ when it compromises $c_{it}(\dot{)}$ QoS units. We assume that $C_{it}(\cdot)$ is continuous, increasing, and strictly convex with $C_{it}(0) = 0$.

In every time slot $t$, a competitive (Walrasian) equilibrium amongst the task initiators and the central agency is defined as a tuple $\{(k_{it}^{eq})_{i \,\epsilon\, N_t^{init}}, b_t^{eq}\}$ that satisfies the following conditions:

$$C'_{it}(c_{it}(k_{it}^{eq}, b_t^{eq})) - b_t^{eq})(b_t - b_t^{eq}) \geq 0,\ \forall b_t \geq 0 \tag{4}$$

$$\sum_i c_{it}(k_{it}^{eq}, b_t^{eq}) = d_t \tag{5}$$

**Theorem 1.** *There exists a competitive equilibrium in the market of task initiators in every time slot, t that maximizes the following:*

$$argmax_{c_{it}} \sum_i -C_{it}(c_{it})$$

subject to $\quad \sum_i c_{it} = d_t.$

***Proof Sketch.*** We get the optimality conditions of the optimization problem in Theorem 1 from equations (4) and (5). The uniqueness of the optimal solution, i.e., the equilibrium solution, follows from the fact that the optimization problem and its dual are strictly convex.

***Theorem Implications.*** The equilibrium solution *maximizes the social welfare*, i.e., minimizes the sum of the disutility of the task initiators, via the optimization problem in the theorem. Thus in every time slot, the central agency is able to clear the market by enabling optimal user QoS compromises as well as by ensuring social welfare.

***The Iterative Bidding Process.*** We provide a *distributed iterative bidding* scheme based on the dual gradient

[3]The benefit provided also incentivizes users to compromise. Benefits could be in the form of reduction of prices charged for service.

[4]Message passing between the agency and task executors could be one way of estimating service capacity deficits.

[5]We note here that the market is jointly run by the central agency and the task initiators.

[6]To decide on its amount of compromise, a user, amongst other factors, may account for the delay due to computation information percolating through relay nodes before it reaches the intended recipient. In this abstract we do not explicitly model the role that relay nodes have on the optimal supply function of a user.

algorithm in [1] that achieves the market equilibrium in each time slot $t$.
At the $j$-th iteration in time slot $t$, we execute the following steps:

1. Upon receiving benefit $b_t(j)$ announced by the central agency, task initiator $i$ updates its supply function profile, $k_{it}(j)$ as

$$k_{it}(j) = \left\{ \frac{(C'_{it})^{-1}(b_t(j))}{b_t(j)} \right\}^+, \quad (6)$$

   and supplies it to the central agency. Here '+' denotes the projection onto $\mathbb{R}^+$, the set of non-negative real numbers.

2. The central agency updates its benefit according to the following equation

$$b_t(j+1) = [b_t(j) - \rho(\sum_i k_{it}(j)b_t(j) - d_t]^+, \quad (7)$$

   and announces the new benefit to the task initiators.

The above distributed bidding process converges for small enough values of step size, $\rho$ [1].

# 4. OLIGOPOLISTIC MARKET ANALYSIS

We consider an oligopolistic market of task initiators where the latter are 'benefit' anticipating. The initiators are strategic in the sense that they know that benefit $b_t$ in each time slot $t$ is computed according to equation (3) and as a result choose their supply function profile in a manner so as to maximize their net utility functions. The net utility function for each user $i$ in time slot $t$ is represented by $U_{it}(k_{it}, k_{(-i)t})$ and is given as

$$U_{it}(k_{it}, k_{(-i)t}) = b_t c_{it}(k_{it}, b_t(\overrightarrow{k_t})) - C_{it}(c_{it}(k_{it}, b_t(\overrightarrow{k_t}))), \quad (8)$$

where $k_{(-i)t} = (k_{1t}, ...., k_{i-1}t, k_{i+1}t....., k_{|N_t^{init}|})$ is the vector of supply function profile of users other than $i$. Each user participates in a non-cooperative game of selecting $k_{it}$'s, with other task initiators in time slot $t$, in order to maximize its net utility function. The intersection of the best responses of all the task initiators results in a Nash equilibrium [6].

**Lemma 1.** *If $(\overrightarrow{k_t^{neq}})$ is a Nash equilibrium of the non-cooperative game at time slot t, then (1) $\sum_{j \neq i} k_{jt}^{neq} > 0$ for any $i \epsilon N_t^{init}$, (2) $k_{it}^{neq} < K_{(-i)t}^{neq}$ for any $i \epsilon N_t^{init}$, and (3) No Nash equilibrium exists when $|N_t^{init}| = 2$, where $K_{(-i)t}^{neq} = \sum_{j \neq i} k_{jt}^{neq}$.*
We omit the proof of the lemma due to lack of space.

***Lemma Implications.*** At Nash equilibrium in every time slot, each task initiator compromises at most $\frac{d_t}{2}$ amount of QoS units, and at least two task initiators are necessary to reach a Nash equilibrium.

**Theorem 2.** *There exists a Nash equilibrium, $(\overrightarrow{k_t^{neq}})$, in the market of task initiators in every time slot, t that maximizes the following:*

$$argmax_{0 \leq c_{it} < \frac{d_t}{2}} \sum_i -H_{it}(c_{it})$$

subject to $\sum_i c_{it} = d_t$, where

$$H_{it}(c_{it}) = \left(1 + \frac{c_{it}}{d_t - 2c_{it}}\right) C_{it}(c_{it}) - \int_0^{c_{it}} \frac{d_t}{(d_t - 2x_{it})^2} C_{it}(x_{it}) dx_{it}$$

***Proof Sketch.*** The uniqueness of the Nash equilibrium (optimal) solution follows from the fact that the optimization problem and its dual are strictly convex.

***Theorem Implications.*** The equilibrium solution *maximizes the social welfare*, i.e., minimizes the sum of the disutility of the task initiators, via the optimization problem in the theorem. Thus in every time slot, the central agency is able to clear the market by enabling optimal user QoS compromises, reaching a unique Nash equilibria, as well as ensuring social welfare.

**Proposition 1.** *The Nash equilibrium benefit $b_t^{neq}$ is bounded within a factor $(1 + \frac{r_t}{d_t - 2r_t})$ of $b_t^{eq}$, the Walrasian equilibrium benefit where $r_t = max_i(H'_{it})^{-1}(Y_t)$ and $Y_t = max_i H'_{it}(\frac{d_t}{|N_t^{init}|})$.*

Proposition 1 *is an important result* and implies that the benefit anticipating and *mutually* competitive nature of task initiators in an oligopoly market leads to the Nash equilibrium benefit being bounded by the Walrasian equilibrium benefit as Walrasian markets are benefit taking. We omit the proof of the proposition due to lack of space.

***The Iterative Bidding Process.*** At the $j$-th iteration in time slot $t$, we execute the following steps:

1. Upon receiving benefit $b_t(j)$ announced by the central agency, task initiator $i$ updates its supply function profile, $k_{it}(j)$ as

$$k_{it}(j) = \left\{ \frac{(H'_{it})^{-1}(b_t(j))}{b_t(j)} \right\}^+, \quad (9)$$

   and supplies it to the central agency.

2. The central agency updates its benefit according to the following equation

$$b_t(j+1) = [b_t(j) - \rho(\sum_i k_{it}(j)b_t(j) - d_t]^+, \quad (10)$$

   and announces the new benefit to the task initiators.

# 5. CONCLUSION

In this abstract we studied ways to optimally and efficiently entail user QoS compromises in opportunistic mobile networks via market mechanisms. As part of future work, we plan to conduct a simulation study of our proposed theory, and extend our theory to include different forms of parameterized supply functions.

# 6. REFERENCES


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