Incentive Mechanisms for Time Window Dependent Tasks in Mobile Crowdsensing

Jia Xu, *Member, IEEE*, Jinxin Xiang, and Dejun Yang, *Member, IEEE*

***Abstract*—Mobile crowdsensing can enable numerous attractive novel sensing applications due to the prominent advantages such as wide spatiotemporal coverage, low cost, good scalability, pervasive application scenarios, etc. In mobile crowdsensing applications, incentive mechanisms are necessary to stimulate more potential smartphone users and to achieve good service quality. In this paper, we focus on exploring truthful incentive mechanisms for a novel and practical scenario where the tasks are time window dependent, and the platform has strong requirement of data integrity. We present a universal system model for this scenario based on reverse auction framework and formulate the problem as the *Social Optimization User Selection (SOUS)* problem. We design two incentive mechanisms, *MST* and *MMT*. In single time window case, we design an optimal algorithm based on dynamic programming to select users. Then we determine the payment for each user by *VCG* auction; while in multiple time window case, we show the general *SOUS* problem is NP-hard, and we design *MMT* based on greedy approach, which approximates the optimal solution within a factor of $\ln|\mathcal{W}|+1$, where $|\mathcal{W}|$ is the length of sensing time window defined by the platform. Through both rigorous theoretical analysis and extensive simulations, we demonstrate that the proposed mechanisms achieve high computation efficiency, individual rationality and truthfulness.**

***Index Terms*—Mobile crowdsensing, incentive mechanism, auction, strategic behavior, optimal algorithm, approximation ratio.**

I. Introduction

In the past few years, the market of smartphone has proliferated rapidly and continues to expand. According to the mobile phone forecast from the International Data Corporation (IDC) Worldwide Quarterly Mobile Phone Tracker, worldwide smartphone shipments will reach a total of nearly 1.3 billion units in 2014, representing an increase of 26.3% over 2013. Looking ahead, IDC expects 1.4 billion smartphones to be shipped worldwide in 2015 [1]. With the technological advances of 4G/5G networks and embedded sensors, the smartphone has been developed as a powerful programmable mobile data interface since it is integrated with a set of sensors such as camera, light sensor, GPS, accelerometer, digital compass, gyroscope, microphone, and proximity sensor. Other types of sensors, such as sleep sensor, EEG earphone, barometer, heart rate monitoring sensor, chemical sensor are expected to be available in smartphones in the near future [2]. These sensors can sense various human activities and the surrounding environment cooperatively. It will be an efficient approach to meet the demand in large scale sensing applications if we take advantage of pervasive smartphones to collect data.

Manuscript received January 21, 2015; revised April 23, 2015; accepted June 17, 2015. Date of publication July 6, 2015; date of current version November 9, 2015. This work is sponsored in part by NSF Grant (No. 1444059, 1420881), NSFC (No. 61472193, 61472192, 61373139), the Natural Science Foundation of Jiangsu Province (No. BK20141429), Scientific and Technological Support Project (Society) of Jiangsu Province (No. BE2013666), China Postdoctoral Science Foundation (No. 2014M562662, 2013T60553), Jiangsu Postdoctoral Science Foundation (No. 1402223C). The associate editor coordinating the review of this paper and approving it for publication was J. Huang.

J. Xu and J. Xiang are with the School of Computer Science and Technology, Institute of Computer technology, Nanjing University of Posts and Telecommunications, Nanjing 210003, China (e-mail: xujia@njupt.edu.cn).

D. Yang is with the Department of Electrical Engineering and Computer Science, Colorado School of Mines, Golden, CO 80401 USA.

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TWC.2015.2452923

Comparing with the traditional sensor networks, mobile crowdsensing has a huge potential due to the prominent advantages [2], such as wide spatiotemporal coverage, low cost, good scalability, pervasive application scenario, etc. As a novel sensing mode, mobile crowdsensing can enable attractive sensing applications in different domains, such as healthcare [3], social networking [4], environmental monitoring [5] and transportation [6], [7].

Realizing the great potential of the mobile crowdsensing, many researchers have developed numerous applications and systems, such as DietSense [8] and BikeNet [9] for healthcare, CenceMe [10] and Co-evolution model [11] for behavior and relationship discovery, PIER [12] for calculating personalized environmental impact and exposure, Haze Watch [13] for pollution monitoring, Ear-Phone [14] and NoiseTube [15] for creating noise maps, Nericell [16], SignalGuru [17] and VTrack [18] for providing traffic information, SmartTrace [19], City-Explorer [20], Sensorly [21] for 3G/WiFi discovery, Frequent Trajectory Pattern Mining [22] for activity monitoring, LiFS [23] for indoor localization, crowd-participated system [24] for bus arrival time prediction, etc.

Although there are many applications and systems on mobile crowdsensing, most of them are based on voluntary participation. In fact, incentive mechanisms are crucial to mobile crowdsensing while smartphone users spend their time and consume battery, memory, computing power and data traffic of device to sense, store and transmit the data. Moreover, there are potential privacy threats to smartphone users by sharing their sensed data with location tags, interests or identities. Therefore the incentive mechanism, which computes payoff for users to compensate their resource consumption and potential privacy breach, is a necessary component of mobile crowdsensing systems. Incentive mechanisms also help to achieve good service quality since sensing services are truly dependent on quantity of users and quality of sensed data.

Exploring the incentive mechanism for stimulating smartphone users in mobile crowdsensing is very difficult because smartphone users would adopt strategic behaviors to maximize their own payoffs. Strategic behaviors of smartphone users can seriously hinder the potential collaboration of smartphone users. Thus it is essential to develop effective incentive mechanisms, which can guarantee the compatibility and fairness of mobile crowdsensing systems.

There have been some research efforts on developing incentive mechanisms for mobile crowdsensing, which can generally be divided into two categories: offline mechanisms [25]–[27] and online mechanisms [28]–[30]. In offline mechanisms, the concurrent presence of numerous smartphone candidates is required. These offline schemes assume that all users will stay from the beginning of one round of task distribution for bidding, while online mechanisms aim to deal with the case where users submit their profiles when they arrive.

In practice, many mobile crowdsensing applications have strong requirement of data integrity. It is important in many scenarios to accomplish all tasks publicized by the platform since the fragmented data may not meet the requirements of the applications, and the value of the fragmented data may decrease significantly. There are some realistic examples of existing projects with strong requirement of data integrity:

Project 1: The crowd-participated bus arrival time prediction system [24]

In this work, the sharing users sample the cell tower sequences and send the sequences to the backend server. Then the backend server uses the cell tower sequences to match the bus route stored in the database and predicts bus arrival time at various bus stops. One of the challenges of this system is called information assembling: One sharing user may not stay on one bus to collect adequate time period of information. Insufficient amount of uploaded information may result in inaccuracy in matching the bus route. An effective information assembling strategy is required to solve the jigsaw puzzle of combining pieces of incomplete information from multiple users to picture the intact bus route status. There is a strong requirement of data integrity in this application scenario since only continuous cell tower sequences can be used to predict realtime bus arrival time accurately.

Project 2: Ear-Phone [14]

Ear-Phone is an end-to-end participatory urban noise mapping system, which consists of a mobile phone component and a central server component. Noise levels are assessed on the mobile phones before being transmitted to the central server. The central server reconstructs the noise map based on the partial noise measurements. When the mobile phone is not used for conversation, the *MobSLM* on the phone is turned on. When turned on, the signal processing module starts computing a loudness characteristic known as the equivalent noise level over a time interval T from the raw acoustic samples collected by the microphone over the corresponding time interval. There is a component for computing long-term equivalent noise level in central server. This component computes the long-term equivalent noise level over the duration $N \cdot T$ (where $N > 1$ and N is an integer) from the equivalent noise levels measured over shorter time durations T. There is a strong requirement of data integrity in this application since the equivalent noise levels measured over shorter time durations are necessary to compute long-term equivalent noise level.

Project 3: Haze Watch [13]

The members of the Haze Watch project are developing a mobile air pollution sensor which will be attached to motor vehicles and used for gathering air pollution readings. These devices will measure Carbon Monoxide, Ozone, Sulphur Dioxide and Nitrogen Dioxide. Using Bluetooth, these measurements will be sent to an iPhone within the car where both time and GPS coordinates are recorded and sent to a server. Haze Watch has also developed an effective form of displaying pollution readings on visual maps to reflect the levels of concentrations of particulate pollutants. There is also a strong requirement of data integrity in this application scenario since the pollution readings are required to cover whole time line.

However, the existing mechanisms consider the applications with weak requirement of data integrity. For example, the tasks described in [25] or [29] are location dependent, and it may not necessary to make sure that all tasks are accomplished. The existing mechanisms cannot be applied to the mobile crowdsensing applications with strong requirement of data integrity since these mechanisms aim to optimize the payoff of the platform [25] or the value from the selected *users′* services under the budget constraint [29], [33] no matter whether all tasks are performed.

In this work, we focus on exploring truthful incentive mechanisms satisfying the desirable properties for time window dependent tasks in mobile crowdsensing. We present a universal system model for this novel mobile crowdsensing scenario. To stimulate smartphone users, the interactions between the platform and the smartphone users are modeled as a reverse auction mechanism. We formulate the *Social Optimization User Selection (SOUS)* problem and propose two incentive mechanisms, *MST* and *MMT* to solve the *SOUS* problem in single time window case and multiple time window case, respectively. In *MST*, we design a dynamic programming algorithm to select users and determine the payment by Vickrey-Clarke-Groves (*VCG*) auction. Since the general *SOUS* problem is NP-hard, we design *MMT* based on approximation algorithm, which follows a greedy approach. We show that both two designed incentive mechanisms satisfy the desirable properties.

The key contributions of our work are summarized in the following:

- To the best of our knowledge, this is the first work on incentive mechanism design for the mobile crowdsensing applications with strong requirement of data integrity. In this paper, we focus on dealing with a category of time window dependent task mobile crowdsensing, which is a novel and practical scenario. We present the universal system model for this scenario and formulate the *Social Optimization User Selection (SOUS)* problem.
- In single time window case, we design an optimal algorithm based on dynamic programming to solve the *SOUS* problem. We design a *VCG* auction based incentive mechanism, which is computationally efficient, individually rational and truthful.

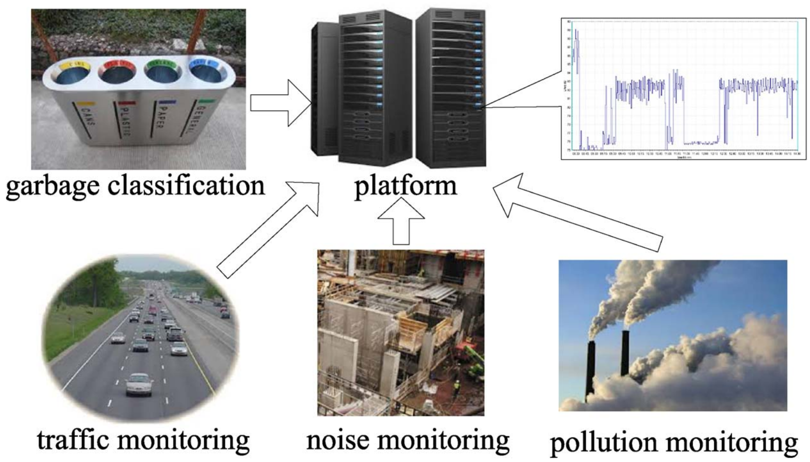


Fig. 1. Examples of time window dependent task crowdsensing paradigm.

- In multiple time window case, we show the general *SOUS* problem is NP-hard, and we develop an approximation algorithm, which follows a greedy approach to select users and determine payment. Moreover, we show the proposed incentive mechanism in such case is computationally efficient, individually rational and truthful with low approximation ratio.

The rest of the paper is organized as follows. Section II formulates the system model and problem. We present incentive mechanism, *MST*, in single time window case in Section III. The incentive mechanism, *MMT*, in multiple time window case is described in Section IV. Performance evaluation is presented in Section V. We review the related work in Section VI, and conclude this paper in Section VII.

II. System Model and Problem Formulation

A. System Model

We consider a mobile crowdsensing system consisting of a platform and many smartphone users. The platform resides in the cloud. Different from most crowdsensing systems, we consider a time window dependent task crowdsensing scenario, i.e., the platform wants to collect the continuous data in a specific time interval.

This scenario is very practical and pervasive. As shown in Fig. 1, there are many time window dependent applications in crowdsensing with strong requirement of data integrity, such as continuous measure of trace, traffic condition, noise, air pollution and continuous observation of garbage classification, etc. These tasks can be regarded as a big task, which lasts in whole time window and is unlikely to be accomplished by single human being, such as sampling the cell tower sequences on whole bus route [24], measuring the long-term equivalent noise levels [14], and gathering the air pollution readings all the time [13]. These projects all fall into the time window dependent task crowdsensing scenario.

We consider the platform publicizes a sensing time window $\mathcal{W} = [T_S, T_E]$, where T_S and T_E are the start time and end time respectively. In other words, the platform requests the sensing data in the period from T_S to T_E. We denote the length of time window $\mathcal{W}$, i.e., the number of time units, as $|\mathcal{W}|$. The time unit, which is closely bound up with the application scenarios, is determined by the sampling frequency of sensing data in practice. It is reasonable that the sensing data is valid if a user submits it in arbitrary point-in-time within time unit.

Assume that a crowd of smartphone users $U = \{1, 2, \ldots, n\}$ are interested in participating sensing tasks. Each user i responds with a bid $B_i = (\Gamma_i, b_i)$, in which $\Gamma_i = \{[s_i^1 e_i^1], \ldots, [s_i^{k_i}, e_i^{k_i}]\}$ is a set of k_i time windows the user i can perform. Each Γ_i is associated with the cost c_i. s_i^j and e_i^j, $\forall\, i \in U,\ \forall\, j \in \{1, \ldots, k_i\}$ can be any point-in-time, although any $s_i^j < T_S$ or $e_i^j > T_E$ cannot bring extra benefit for user i in our mechanisms. b_i is the claimed cost which is the bid price that user i wants to charge for performing Γ_i.

The platform selects a subset of users $S \subseteq U$, and notifies winners of the determination. The winners perform the sensing in their submitted time windows and send data back to the platform. Each user i is paid p_i, which is computed by the platform. The above interactive process can be illustrated by Fig. 2.

We define the utility of user i as the difference between the payment and its real cost. Then the utility of user i can be computed as follows

$$u_i = p_i - c_i. \tag{1}$$

Specially, the utility of the losers would be zero because they are paid nothing in our designed mechanisms and there is no cost for sensing.

Note that b_i can be different from the real cost c_i of performing Γ_i since we consider users are selfish individuals, and the real cost is private and unknown to other users and the platform. So the users may take a strategic behavior by claiming cost to maximize their own utility.

The users can also take a strategic behavior by reporting the set of time windows that are not real. The time window truthfulness can be achieved if the platform can verify whether all sensing data in announced time windows is submitted and whether the sensing data is generated at the announced time. For this purpose, we assume the sensing data is processed by trusted time stamping such as *Public Key Infrastructure Time-Stamp Protocol (TSP)* [39], which is based on digital signatures and

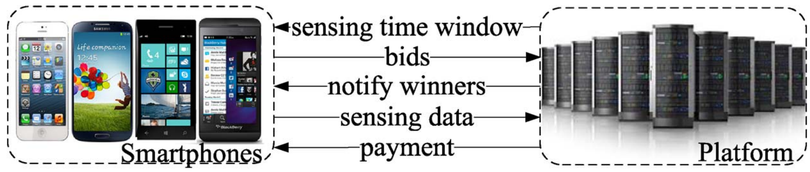


Fig. 2. Illustration of a mobile crowdsensing system as a reverse auction framework.

hash functions. By using *TSP*, it is not difficult to verify that the timestamp of sensing data is unaltered and was issued by the *Time Stamping Authority* (*TSA*, a trusted third party).

The utility of the platform is

$$u_0 = v(\mathcal{W}) - \sum_{i \in s} p_i \tag{2}$$

where $v(\mathcal{W})$ is the value to the platform when it obtained all data in whole $\mathcal{W}$.

Note that "continuous sensing data" is defined by the specific requirement of the platform. Specifically, the sensing data is not only the data with continuous time line, but also discrete sampling data abide by the certain time distribution required by the platform. For example, the platform wants to collect photos per minute in continuous sixty minutes.

B. Problem Formulation

We consider an incentive mechanism $\mathcal{M}(f, p)$ consisting of a user selection function f and a payment decision function p. For any time window $\mathcal{W}$ and a set of strategy bids $B = (B_1, \ldots, B_n)$, the function $f(\mathcal{W}, B)$ computes a subset of users $S \subseteq U$, and the function $p(\mathcal{W}, B)$ returns a vector $(p_1, \ldots, p_n)$ of payments to all the users. The objective function is minimizing the social cost which is the sum of the real costs of selected users for completing the sensing in whole time window. The problem can be formulated as follows:

$$min \sum_{i \in S} b_i \tag{3}$$

$$\text{s.t.} \quad \mathcal{W} \subseteq \cup_{i \in S, j \in \{1,\ldots,k\}} \left[s_i^j, e_i^j \right] \tag{4}$$

The problem of minimizing the social cost is equivalent to the problem of maximizing social efficiency. In our system model, the social efficiency is $v(\mathcal{W}) - \Sigma_{i \in S} b_i$. The value of $v(\mathcal{W})$ is constant since $\mathcal{W}$ is publicized by the platform at the beginning of the auction, and all tasks in $\mathcal{W}$ are performed. Thus the objective of the problem presented in formula (3) and formula (4) is maximizing social efficiency in essence. We call this problem as *Social Optimization User Selection (SOUS)* problem.

The constraint means the time windows submitted by selected users should cover the required time window, i.e., the mechanisms should make sure that the sensing data submitted by the winners can meet the requirement of data integrity from T_S to T_E. We assume that there are enough users who can satisfy the constraint naturally. We also exclude the situation where only one bid hits the arbitrary time slot in $[T_S, T_E]$ in order to prevent the monopoly.

Although the real cost c_i is only known by user i, we will prove that claiming a different cost b_i cannot help to increase the utility of user i in our designed mechanisms. So we still use b_i when we attempt to maximize social efficiency in the mechanisms designed below.

We consider two types of user bids in our system model: bids with single time window and bids with multiple time windows.

In the multiple time window case, the users can submit multiple time windows in one bid. For example, the equivalent noise levels [14] or the air pollution readings [13] can be submitted with multiple time windows. The participants can decide the set of time windows by several ways, such as future schedules, daily behaviors, habits or preferences. The participants can predict the time windows, within which they are in the specific locations to perform the sensing tasks based on their future schedules. Moreover, the participants can decide time windows according to their daily behaviors, habits or preferences with little effect on their daily life. A large body of research has demonstrated that people show striking persistence in their mobility profiles. For example, in [36], the authors state that the similarity of the mobility profile of a given user to its future profile is high, above 0.75 for eight days and remains above 0.6 for five weeks. The observations demonstrate that the mobility profile is indeed an intrinsic property and a valid representation of the user, even if only a short history of mobility profile is used.

Specially, in single time window case, each user only bids one time window, and the constraint of the *SOUS* problem can be relaxed as

$$\text{s.t.} \quad \mathcal{W} \subseteq \cup_{i \in S} [s_i, e_i] \tag{5}$$

Our objective is to design the incentive mechanisms satisfying the following four desirable properties to solve *SOUS* problem:

(1) Computational Efficiency

A mechanism $\mathcal{M}(f, p)$ is computationally efficient if both user selection function f and payment decision function p can be computed in polynomial time.

(2) Individual Rationality

Each user will have a non-negative utility, i.e., $p_i \geq c_i, \ \forall i \in U$.

(3) Truthfulness

A mechanism is truthful if no user can improve its utility by submitting a bid different from its real cost, no matter what others submit. In other words, reporting the real cost is a dominant strategy [31] for all users.

(4) Social Optimization

The objective function is maximizing the social efficiency. We attempt to find optimal solution or approximation algorithm with low approximation ratio when there is no optimal solution computed in polynomial time. For the latter, the approximation ratio, $O(g(n))$, is the ratio between approximation solution and the optimal solution.

The importance of the first two properties is obvious, because they together assure the feasibility of the incentive mechanism. The last two properties are indispensable for guaranteeing the compatibility and high performance. Being truthful, the incentive mechanism can eliminate the fear of market manipulation and the overhead of strategizing over others for the participating users.

III. Incentive Mechanism in Single Time Window Case

In this section, we consider the special case where each user bids with only one time window. We present an incentive mechanism *MST* in this single time window case.

A. Mechanism Design

We design an auction mechanism consisting of user selection phase and payment determination phase. In user selection phase, we propose an optimal algorithm based on dynamic programming to solve *SOUS* problem. In payment determination phase, we compute payment based on the *VCG* auction [31]. The whole process is illustrated in Algorithm 1.

Algorithm 1 Incentive Mechanism in Single Time Window Case (*MST*)

Input: Time Window $\mathcal{W}$, Set of Bids B, Set of Users U
//Phase 1: Selection
1: $S \leftarrow \phi$;
2: **for all** $i \in U$ **do**
3: $F(i) = \infty$;
4: **end for**
5: Sort Γ_i based on e_i for $\forall\, i \in U$ in the nondecreasing order and the sequence is denoted by $\{\Gamma_1, \Gamma_2, \ldots, \Gamma_n\}$;
6: **for** $i = 1$ to n **do**
7: **if** $T_S \in [s_i, e_i]$ **then**
8: $pre(i) \leftarrow (-1), F(i) = b_i$;
9: **else**
10: $pre(i) \leftarrow (arg\ min_{e_j \geq s_i, j<i} F(j))$;
11: $F(i) \leftarrow F(pre(i)) + b_i$;
12: **end if**
13: **end for**
14: $i \leftarrow arg\ min_{T_E \in [s_j, e_j], j \in U} F(j)$;
15: $cost \leftarrow F(i)$;
16: **while** $i \neq -1$
17: $S \leftarrow S \cup \{i\}, i \leftarrow pre(i)$;
18: **end while**
//Phase 2: Payment
19: **for all** $i \in U$ **do** $p_i \leftarrow 0$;
20: **end for**
21: **for all** $i \in S$ **do** $p_i \leftarrow Cost(U \backslash \{i\}) - (Cost(U) - b_i)$;
22: **end for**
23: **return** $(cost, S, \mathbf{P})$;

The user selection phase follows a dynamic programming approach: Users are sorted according to the right point of their time windows such as $e_1 \leq e_2 \leq \ldots \leq e_n$. Then we compute $F(i)$, for $\forall\, i \in U$ in sequence, where $F(i)$ is the minimum social cost covering time window $[T_S, e_i]$. Considering all $F(j), j < i$, in above order have been computed, $F(i)$ is determined by the sum of minimum $F(j)$ satisfying $e_j \geq s_i$ and b_i. So our recurrence is

$$F(i) = \begin{cases} min_{e_j \geq s_i} F(j) + b_i & \text{if} \quad T_S \notin [s_i, e_i] \\ b_i & \text{if} \quad T_S \in [s_i, e_i] \end{cases} \tag{6}$$

Then we get the minimum social cost

$$min_{i \in U} \{F(i) \mid T_E \in [s_i, e_i]\} \tag{7}$$

In payment phase, we apply *VCG* based payment rule to determine the payment function. A winner will be paid an amount equal to the benefit it introduces to the system, i.e., the difference between others user's minimum social cost with and without it. The payment scheme is

$$p_i = Cost\,(U \backslash \{i\}) - (Cost(U) - b_i)\,, \qquad \forall_i \in U \tag{8}$$

Here function $Cost()$ means the minimum social cost computed by selection phase.

B. Mechanism Analysis

In the following, we analyze the properties of the *MST* from four aspects mentioned in Section II-B.

Lemma 1: *MST* is computationally efficient.

Proof: Initializing $F(i)$ takes $O(nlogn)$ time. Sorting time windows takes $O(nlogn)$ when we use computationally efficient sorting algorithm such as quick sorting. The recurrence of dynamic programming (Lines 6–13) runs n times. Finding minimum $F(j)$ (line10) takes $O(n)$ time. So the recurrence of dynamic programming takes $O(n^2)$ time.

In fact, we can further improve the computational efficiency of finding minimum $F(j)$ as follows. When computing $F(i)$, we can maintain a stack to store every $F(i)$ which has been computed. Before pushing $F(i)$ into stack, we pop the top element of stack until $F(stack(top)) < F(i)$. Since we push and pop each time window once at most, the complexity of maintaining the stack in whole recurrence is $O(n)$. When $F(j)$ in the stack has been sorted, we can use binary search algorithm to finding minimum $F(j)$ (line10), which takes $O(logn)$ time. So the recurrence of dynamic programming (Lines 6–13) can take only $O(nlogn)$ time.

Finding the minimum social cost (Lines 14–15) takes $O(n)$ time. Finding the solution (Line 16–18) takes $O(n)$ time. Hence the running time of the selection phase is $O(nlogn)$. In payment phase, we call selection phase to compute Cost() for each winner, thus the time for computing payment takes $O(n^2logn)$ time. Hence the running time of *MST* is bounded by $O(n^2logn)$. □

Note that the running time of *MST*, $O(n^2logn)$, is very conservative since the number of winner is much less than n in practice.

Lemma 2: *MST* is individually rational.

Proof: We denote ω^* and ω^*_{-i} as the optimal social cost of *SOUS* problem in single time window case with and without user i respectively. Then $p_i = \omega^*_{-i} - (\omega^* - b_i)$ based on line 21 in Algorithm 1. Since ω^* is the optimal social cost, we have $\omega^* \leq \omega^*_{-i}$, and it is easy to deduce $p_i \geq b_i$. If user i is not chosen, its utility $u_i = 0$. □

Lemma 3: MST is truthful.

Proof: Since *MST* is based on *VCG* auction, which is known as a truthful auction [31], *MST* is truthful. □

Lemma 4: MST is an optimal algorithm of SOUS problem in single time window case.

Proof: Since *MST* follows a dynamic programming approach, we need prove the recurrence relationship is correct to minimize the social cost. Considering $F(i)$ is the minimum social cost covering time window $[T_S, e_i]$, if $T_S \in [s_i, e_i]$, $[s_i, e_i]$ can be a candidate for the first time window in whole solution, then the minimum social cost for interval $[s_i, e_i]$ is equal to the cost itself. In case $T_S \notin [s_i, e_i]$, $F(i)$ should be the sum of minimum cumulative cost covering $[T_S, s_i]$ and b_i in order to cover the time window $[s_i, e_i]$. Since we have sorted all users based on the right point of their time windows, $[T_s, e_j]$ has been covered by $F(j),\ \forall j < i$, which has been computed previously. Thus $F_i = min_{e_j \geq s_i} F_j + b_i$ is a correct recurrence relationship to find the optimal solution. □

The above four lemmas together prove the following theorem.

Theorem 1: MST is computationally efficient, individually rational, truthful and an optimal algorithm of SOUS problem in single time window case.

IV. Incentive Mechanism in Multiple Time Window Case

In this section, we consider the general case where each user can bid more than one time window. We present an incentive mechanism in this multiple time window case (*MMT*).

A. Mechanism Design

First of all, we attempt to find an efficient algorithm for the original form of *SOUS* problem presented in formula (3) and formula (4), called general *SOUS* conveniently. Unfortunately, as the following theorem shows, it is NP-hard to find the optimal solution.

Theorem 2: The general *SOUS* problem is NP-hard.

Proof: We will prove this theorem in the Appendix. □

Since the general *SOUS* problem is NP-hard, we turn our attention to develop an approximation algorithm in user selection phase. In addition, the *VCG* mechanism [31], which requires the optimal set of winning bids, does not work for our problem. We design our auction mechanism in this multiple time window case (*MMT*), which follows a greedy approach. Illustrated in Algorithm 2, *MMT* still consists of user selection phase and payment determination phase.

Algorithm 2 Incentive Mechanism in Multiple Time Window Case (*MMT*)

Input: Time Window $\mathcal{W}$, Set of Bids B
//Phase 1: Selection
$\mathcal{W}' \leftarrow \mathcal{W}, S \leftarrow \emptyset$;
while $\mathcal{W}' \neq \emptyset$
  $i \leftarrow arg\ min_{h \in U \backslash S} \frac{b_h}{v_h(\mathcal{W}')}$;
  $\mathcal{W}' \leftarrow \mathcal{W}' - v_i(\mathcal{W}')$;
  $S \leftarrow S \cup \{i\}$;
end while
//Phase 2: Payment
for all $i \in U$ **do** $p_i = 0$;
end for
for all $i \in S$ **do**
  $U' \leftarrow U \backslash \{i\}, \mathcal{T} \leftarrow \emptyset, \mathcal{W}' \leftarrow \mathcal{W}$;
  while $\mathcal{W}' \neq \emptyset$ **do**
    $i_h \leftarrow arg\ min_{h \in U' \backslash \mathcal{T}} \frac{b_h}{v'_h(\mathcal{W}')}$;
    $p_i \leftarrow max\left\{p_i, \frac{v'_i(\mathcal{W}')}{v'_{i_h}(\mathcal{W}')} b_{i_h}\right\}$;
    $\mathcal{T} \leftarrow \mathcal{T} \cup \{i\}$;
    $\mathcal{W}' \leftarrow \mathcal{W}' - v'_{i_h}(\mathcal{W}')$;
  end while
end for
return $(S, \mathbf{P})$;

In user selection phase, users are essentially sorted according to the effective average cost. Given the remaining required coverage time window, denoted by $\mathcal{W}'_{S_{i-1}}$, the effective coverage of user i is $v_i(\mathcal{W}'_{S_{i-1}}) = \mathcal{W}'_{S_{i-1}} \cap (\cup_{\forall j \in \{1,\ldots,k\}} [s_i^j, e_i^j])$. The effective average cost of user i is defined to be $\frac{b_i}{v_i(\mathcal{W}'_{S_{i-1}})}$. In this sorting, the ith user is the user h such that $\frac{b_h}{v_h(\mathcal{W}'_{S_{i-1}})}$ is minimum over $U \backslash S_{i-1}$, where $S_{i-1} = \{1, 2, \ldots, i-1\}$, $S_0 = \emptyset$, and $\mathcal{W}'_{S_0} = \mathcal{W}$. Considering $v_i(\mathcal{W}'_{S_{i-1}}) \geq v_i(\mathcal{W}'_{S_j})$ for any $j \geq i-1$, this sorting implies that

$$\frac{b_1}{v_1\left(\mathcal{W}'_{s_0}\right)} \leq \frac{b_2}{v_2\left(\mathcal{W}'_{s_1}\right)} \leq \ldots \leq \frac{b_n}{v_n\left(\mathcal{W}'_{s_{n-1}}\right)} \tag{9}$$

The set of winners is $S_L = \{1, 2, \ldots, L\}$, where $L \leq n$ is the largest index such that results in $\mathcal{W}' = \emptyset$. We use $v_i(\mathcal{W}')$ instead of $v_i(\mathcal{W}'_{s_{i-1}})$ to simplify the notation in Algorithm 2.

In the payment determination phase, we sort the users in $U \backslash \{i\}$ similarly,

$$\frac{b_{i_1}}{v'_{i_1}\left(\mathcal{W}'_{\mathcal{T}_0}\right)} \leq \frac{b_{i_2}}{v'_{i_2}\left(\mathcal{W}'_{\mathcal{T}_1}\right)} \leq \ldots \leq \frac{b_{i_n}}{v'_{i_n}\left(\mathcal{W}'_{\mathcal{T}_{n-1}}\right)} \tag{10}$$

where $v'_{i_h}(\mathcal{W}'_{\mathcal{T}_{h-1}}) = \mathcal{W}'_{\mathcal{T}_{h-1}} \cap (\cup_{\forall j \in \{1,\ldots,k_{i_h}\}} [s_{i_h}^j, f_{i_h}^j])$ denotes the effective coverage of the hth user and $\mathcal{T}_h$ denotes the first h users according to this sorting over $U \backslash \{i\}$, $\mathcal{T}_0 = 0$ and $\mathcal{W}'_{\mathcal{T}_0} = \mathcal{W}$. The effective coverage of user i is $v'_i(\mathcal{W}'_{\mathcal{T}_{h-1}}) = \mathcal{W}'_{\mathcal{T}_{h-1}} \cap (\cup_{\forall j \in \{1,\ldots,k_i\}} [s_i^j, e_i^j])$. For each position h in the sorting, we compute the maximum price that user i can be selected instead of user at hth place. We will prove that this price is a critical payment for user i later. We also use $v'_i(\mathcal{W}')$ instead of $v'_i(\mathcal{W}'_{\mathcal{T}_{h-1}})$ to simplify the notation in Algorithm 2.

B. Mechanism Analysis

In the following, we present theoretical analysis, demonstrating that *MMT* achieves the desired properties of computational efficiency, individual rationality, truthfulness and low approximation ratio.

Lemma 5: MMT is computationally efficient.

Proof: Finding the user with minimum effective average cost takes $O(n \cdot max_{i\in\{1,\ldots,n\}}k_i)$, where computing the value of $v_i(\mathcal{W}')$ takes $O(k_i)$ time. Hence, the while-loop (Lines 2–6) takes $O(n^2 \cdot max_{i\in\{1,\ldots,n\}}k_i)$. In each iteration of the for-loop (Lines 9–17), a process similar to Lines 2–6 is executed. Hence the running time of the whole auction is dominated by this for-loop, which is bounded by $O(n^3 \cdot max_{i\in\{1,\ldots,n\}}k_i)$. □

Note that the running time of *MMT*, $O(n^3 \cdot max_{i\in\{1,\ldots,n\}}k_i)$, is very conservative since the number of winners is much less than n in practice.

Lemma 6: MMT is individually rational.

Proof: Let i_h be user i's replacement which appears in the ith place in the sorting over $U\backslash\{i\}$. Since user i_h would not be at ith place if i is considered, we have $\frac{b_i}{v_i(\mathcal{W}'_{s_{i-1}})} \le \frac{b_{i_h}}{v_{i_h}(\mathcal{W}'_{s_{i-1}})}$. Hence we have $b_i \le \frac{v_i(\mathcal{W}'_{s_{i-1}})}{v_{i_h}(\mathcal{W}'_{s_{i-1}})} b_{i_h} = \frac{v'_i(\mathcal{W}'_{\mathcal{T}_{h-1}})}{v'_{i_h}(\mathcal{W}'_{\mathcal{T}_{h-1}})} b_{i_h} \le p_i$, where the equality relies on the observation that $v_i(W'_{s_{i-1}}) = v'_i(\mathcal{W}'_{\mathcal{T}_{h-1}})$ for every $h \le i$, which is due to the fact that $s_{i-1} = \mathcal{T}_{h-1}$ for $h \le i$. This is sufficient to get $b_i \le max_{h\in U'\backslash\mathcal{T}} \frac{v'_i(\mathcal{W}')}{v'_{i_h}(\mathcal{W}')} b_{i_h} = p_i$. □

Before analyzing the truthfulness of *MMT*, we firstly introduce the Myerson's Theorem [32].

Theorem 2 [34, Theorem 2.1]: An auction mechanism is truthful if and only if:

- The selection rule is monotone: If user i wins the auction by bidding b_i, it also wins by bidding $b'_i \le b_i$;
- Each winner is paid the critical value: User i would not win the auction if it bids higher than this value.

Lemma 7: MMT is truthful.

Proof: Based on Theorem 2, it suffices to prove that the selection rule of *MMT* is monotone and the payment p_i for each i is the critical value. The monotonicity of the selection rule is obvious as bidding a smaller value cannot push user i backwards in the sorting. We next show that p_i is the critical value for i in the sense that bidding higher p_i could prevent i from winning the auction. Note that $p_i = max_{h\in\{1,\ldots,q\}} \frac{v'_i(\mathcal{W}')}{v'_{i_h}(\mathcal{W}')} b_{i_h}$. If user i bids $b_i \ge p_i$, it will be placed after q since $b_i \ge \frac{v'_i(\mathcal{W}')}{v'_{i_q}(\mathcal{W}')} b_{i_q}$ implies $\frac{b_i}{v'_i(\mathcal{W}')} \ge \frac{b_{i_q}}{v'_{i_q}(\mathcal{W}^1)}$. Hence, user i would not win the auction because the first q users have covered the time window $\mathcal{W}$. □

Lemma 8: MMT can approximate the optimal solution within a factor of $In|\mathcal{W}| + 1$.

Proof: We rank each time unit by sequence when it is firstly covered in *MMT*. The time units covered simultaneously can be ranked arbitrarily. We assume that this rank is $s_1, s_2, \ldots, s_{|\mathcal{W}|}$. Considering the beginning of $i + 1$th iteration in while-loop (Lines 2–6) of *MMT*, if the number of time units covered by previous i users is $X_i = |\cup_{j\in\{1,\ldots,i\},m\in\{1,\ldots,k_j\}} [s_j^m, e_j^m]|$, the number of uncovered time units will be $|\mathcal{W} - X_i|$. Now we denote the minimum social cost computed by optimal algorithm as *OPT*. Since the optimal algorithm can cover all time units in $\mathcal{W}$, the uncovered time units can be covered with cost at most *OPT*, where the effective average cost is $\frac{OPT}{|\mathcal{W}-X_i|}$. When *MMT* covers s_r in $i + 1$th iteration, the number of uncovered time unit is at least $|\mathcal{W}| - r + 1$, i.e., $|\mathcal{W} - X_i| \ge |\mathcal{W}| - r + 1$. While covering s_r, we denote the effective average cost as $cost(s_r)$. Since *MMT* selects the user with the minimum effective average cost to cover s_r, we have $cost(s_r) \le \frac{OPT}{|\mathcal{W}-X_i|} \le \frac{OPT}{|\mathcal{W}|-r+1}$. Hence the total cost of *MMT* for covering all time units is $\Sigma_{r=1}^{|\mathcal{W}|} cost(s_r) \le \left(1 + \frac{1}{2} + \ldots + \frac{1}{|\mathcal{W}|}\right) OPT = H_{|\mathcal{W}|}OPT \le (In|\mathcal{W}| + 1)OPT$. □

The above four lemmas together prove the following theorem.

Theorem 3: MMT is computationally efficient, individually rational, truthful and $In|\mathcal{W}| + 1$ approximate in multiple time window case.

Remark: Our *MMT* auction mechanism can be applied to many other problems since the general *SOUS* is a weighted set cover problem in essence. The data integrity and four desirable properties still hold.

V. Performance Evaluation

In this section, we conduct thorough simulations to investigate the performance of the *MST* and *MMT*. Firstly, we evaluate both *MST* and *MMT* based on real word experience data traces. Then we conduct the simulations based on random users in order to reveal the impacts of the key parameters. The performance metrics include the social cost, the number of winners, the running time, and the payment cost ratio η, where $\eta = \frac{\Sigma_{i\in S} p_i}{Cost(S)}$. For our simulations, the cost of each bid is uniformly distributed in [1,100]. All the simulations were run on a windows machine with Intel Core i5-4210U CUP and 4 GB memory. Each measurement is averaged over 100 instances.

A. Performance Evaluation Based on Real Traces

1) Scenario Settings: We use the real mobility traces of 370 taxi cabs that report their position every 15 seconds around the city of Rome during 2014-02-01 to 2014-03-02 [38]. For our simulations, we use the traces at the time snapshot in 2014-02-01. We consider the mobile crowdsensing applications are performed in the specific geographical areas with strong requirement of data integrity such as noise mapping in [14] or sensing pollution in [13]. We choose five different places in the city of Rome: Piazza Colonna, Quirinal Palace, University of Arkansas Rome Center (UARC), Basilica of Our Lady and Marcello Theater. The geographical areas are set as the circulars with the centers of the five places respectively, and the radius for each circular is 1 km. We assume that a smartphone is carried by the passenger or the driver of each taxi. The platform publicizes different sensing time windows for different geographical areas, and the bidders are taxis who are in the specific geographical areas during the time interval. For each geographical area, we set the maximum sensing time window, and measure the performance with different end time. The maximum sensing time window for each geographical area is shown in Table I.

2) Evaluation of MST: Firstly, we investigate the performance of *MST*. We select the maximum length time interval in the sensing time window of each taxi as the user time window in this case. Fig. 3 depicts the performance of *MST* with different end time. Since the start time is same, the different end time means different $|\mathcal{W}|$, which is an indication of workload for the crowdsensing application. As can be seen from the figure, the

TABLE I
THE MAXIMUM SENSING TIME WINDOWS FOR DIFFERENT GEOGRAPHICAL AREAS

The geographical area	The maximum sensing time window	
	MST	*MMT*
Piazza Colonna	[19:13:48, 23:57:08]	[14:44:02, 23:59:59]
Quirinal Palace	[05:38:54, 08:58:54]	[05:27:13, 13:47:13]
UARC	[20:20:22, 23:40:22]	[14:58:37, 17:58:37]
Basilica of Our Lady	[00:34:35, 02:14:35]	[19:20:49, 22:40:49]
Marcello Theater	[18:32:08, 19:22:08]	[18:28:01, 21:14:41]

number of taxis increases when $|\mathcal{W}|$ goes up. This is because more taxis pass through the pre-set geographical areas when there is more time for sensing. Given the same $|\mathcal{W}|$, the number of taxis depends on the taxi density in corresponding area. The number of winning taxis also increases because the platform has to recruit more participators to accomplish the tasks in large sensing time window. Accordingly, higher social cost is incurred since we randomize the cost of each bid. The payment cost ratio fluctuates with increasing $|\mathcal{W}|$. In most cases, the payment cost ratio is lower than 3. However, in specific cases, the payment cost ratio will be very high if specific taxis stay in these geographical areas for a long time and make momentous hurt to other taxis. For example, the payment cost ratio reaches to 4.1 in Piazza Colonna area with sensing time window [19:13:48, 19:30:28]. This is because the taxi with ID 187 can perform all tasks in this sensing time window. Moreover, the running time of *MST* increases with increasing $|\mathcal{W}|$ since the running time depends on the number of taxis, which also increases when $|\mathcal{W}|$ goes up. However, the running time of *MST* is bounded by 1.34 ms in all cases.

3) Evaluation of MMT: In multiple time window case, we use all time intervals of each taxi in the sensing time window as the user time windows. As shown in Table I, we set five long-term applications in different geographical areas. The length of sensing time windows is from 10000 s to 34000 s, where there are at most 26 time windows in one bid. Fig. 4 shows the performance of *MMT* with different end time. Both the number of taxis and the number of winning taxis increase when $|\mathcal{W}|$ goes up. For the long-term application, the number of taxis increases gently after 20 000 s due to the limited total number of taxis. Another reason may be that the drivers have preferences in geographical areas especially in large city of Rome which covers an area of 1285 km^2. The social cost also increases when the number of winning taxis goes up. In most cases, the payment cost ratio is lower than 2.2. However, there are some specific cases such as the area of UARC. We can see from the Fig. 4(e) that the running time increases severely with the increasing number of taxis. However, the running time of *MMT* is bounded by 308.51 ms in the sensing time window with the maximum length of 34 000 s.

B. Revealing the Impacts of the Key Parameters

1) Simulation Setup: There are three common key parameters: the number of users n, the length of sensing time window $|\mathcal{W}|$ and the upper limit ratio of user time window δ. There is a special parameter for *MMT*: the upper limit number of time windows for each bid γ. For our simulations, the time window length of each bid is uniformly distributed in the interval $[1, \delta|\mathcal{W}|]$. Since the users are rational and know that any user time window out of W cannot get the payoff, the start time of bid s_i is uniformly distributed in whole $\mathcal{W}$ and satisfies $s_i \geq T_S$ and $e_i \leq T_E$. In *MMT*, each bid can contain more than one time window. The number of time windows for each bid in *MMT* is uniformly distributed in $[1, \gamma]$. We set $n = 1800$, $|\mathcal{W}| = 1000$, $\delta = 0.1$, $\gamma = 9$ as the default values, however we will vary them for exploring the impacts of these parameters respectively. The impact of $|\mathcal{W}|$ has been investigated in Section V-A. Thus we measure the impacts of other key parameters here.

2) Impact of δ: The time window length of each bid responded by users can depict the interest and suitability of users for participating in mobile crowdsensing. We set the time window length of each bid in $[1, \delta|\mathcal{W}|]$ with uniform distribution, and then vary δ from 0.04 to 0.22 to investigate the impact on *MST* and *MMT*. As can be shown in Fig. 5, the number of winners and the social cost also decrease severely both in *MST* and *MMT* with increasing δ. This is because the platform can select fewer users to perform the tasks when each user can sense more data within time window $\mathcal{W}$ on average. The winners of *MMT* are fewer than that of *MST* since the users with multiple time windows can contribute more than the users with single time window. Accordingly, the social cost of *MMT* is lower than that of *MST*. The payment cost ratio is lower than 3.75 in *MST* and 2.73 in *MMT* with different values of δ.

3) Impact of n: To investigate the scalability of designed mechanisms, we fix the upper limit ratio of user time window $\delta = 0.1$, and vary the number of users from 1800 to 2700. Fig. 6 shows the impact of user number on the performance of *MST* and *MMT*. The winner number of *MST* and *MMT* distribute between 17.1 to 21.1 and 10.9 to 13.4 respectively. Both of them do not change much when user number goes up. This is because that increasing user number cannot help to cover the time window W since the time window length of each bid is fixed. The social cost decreases with increasing user number since the platform can find more cheap users to perform the sensing tasks. However, the decreasing of social cost of *MST* and *MMT* is slight because in our system model, the user number needs to be large enough in order to guarantee the coverage of time window $\mathcal{W}$. The payment cost ratio is lower than 2.0 in *MST* and 2.2 in *MMT* with different user number. Moreover, the running time of both mechanisms increase, which conforms to the expected running time properties of *MST* and *MMT* proved in lemma 1 and lemma 5 respectively. However, the designed mechanisms are computational efficient since the running time of *MST* and *MMT* is bounded by 0.5 s and 1 s respectively when user number increases severely from 1800 to 2700.

4) Impact of γ in MMT: Since each user can respond with multiple time windows in one bid in *MMT*, the number of time windows for each bid is a key parameter which depends largely on users' movement habit in practice. Fig. 7 depicts the performance of *MMT* with the upper limit number of time windows for each bid γ being varied from 5 to 23. With more time windows each user can provide, the number of winners decreases severely from 15.9 to 7.4, and the social cost decreases from 54.2 to 11.3 accordingly. The payment cost ratio fluctuates between 1.47 and 2.1 with different values of γ. In

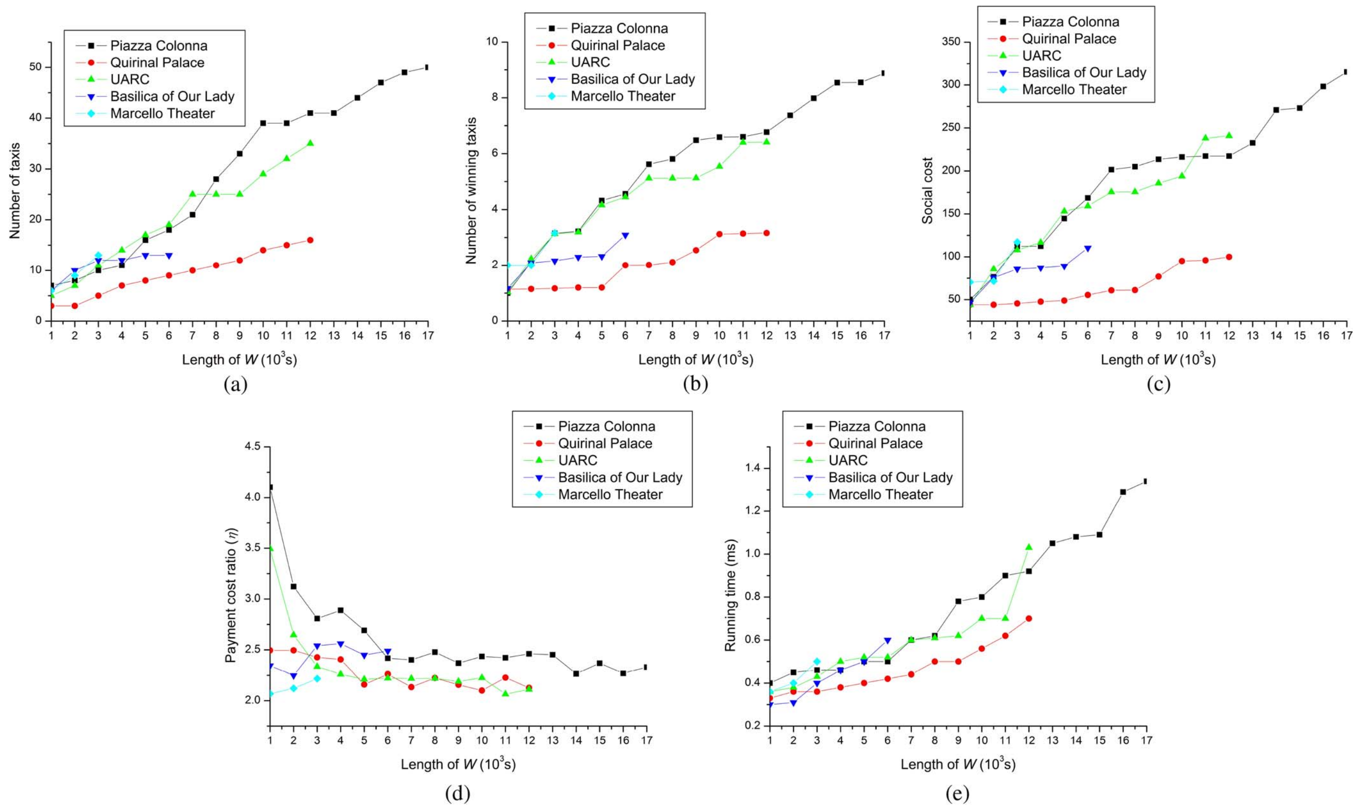


Fig. 3. Performance of *MST* with various end time of the sensing time window. (a) The number of taxis. (b) The number of winning taxis. (c) The social cost. (d) The payment cost ratio. (e) The running time.

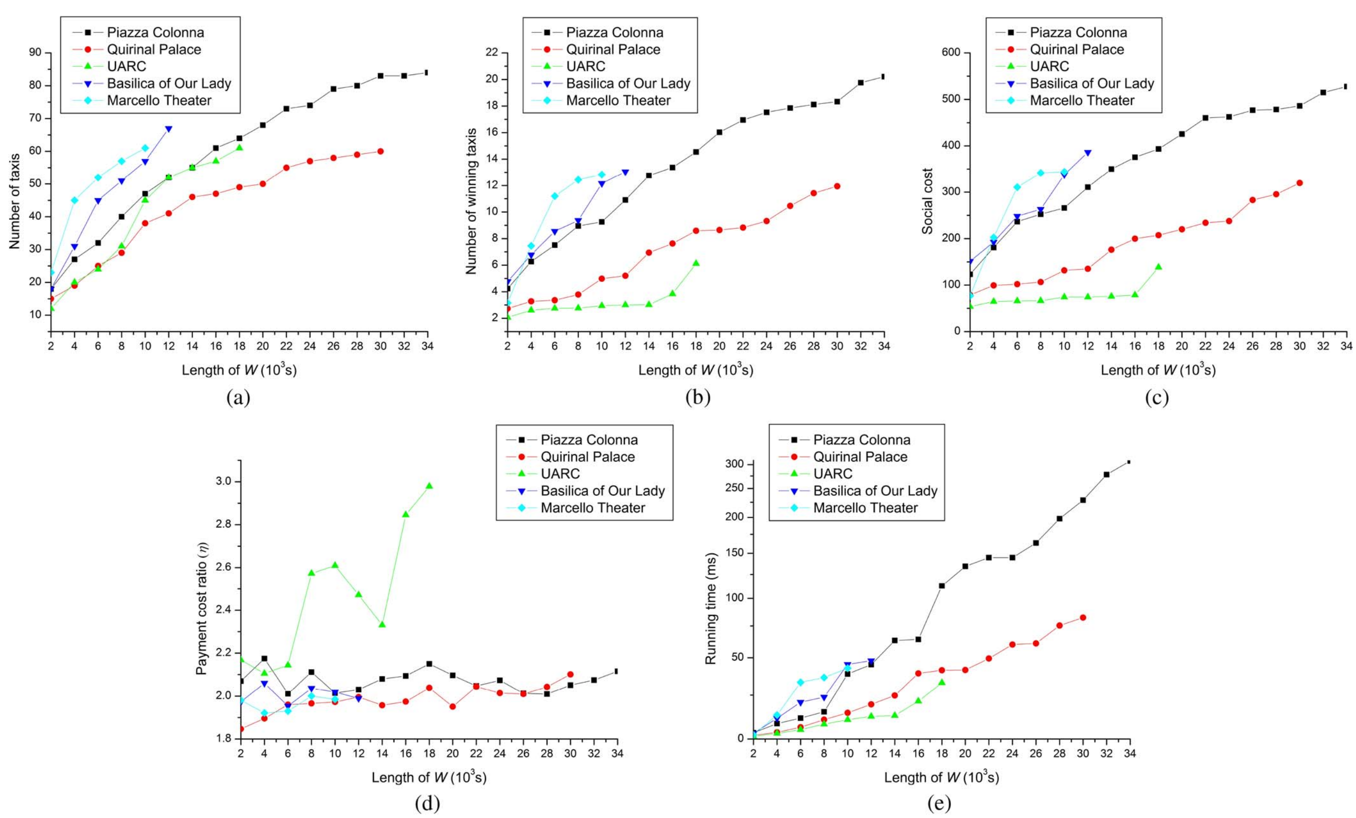


Fig. 4. Performance of *MMT* with various end time of the sensing time window. (a) The number of taxis. (b) The number of winning taxis. (c) The social cost. (d) The payment cost ratio. (e) The running time.

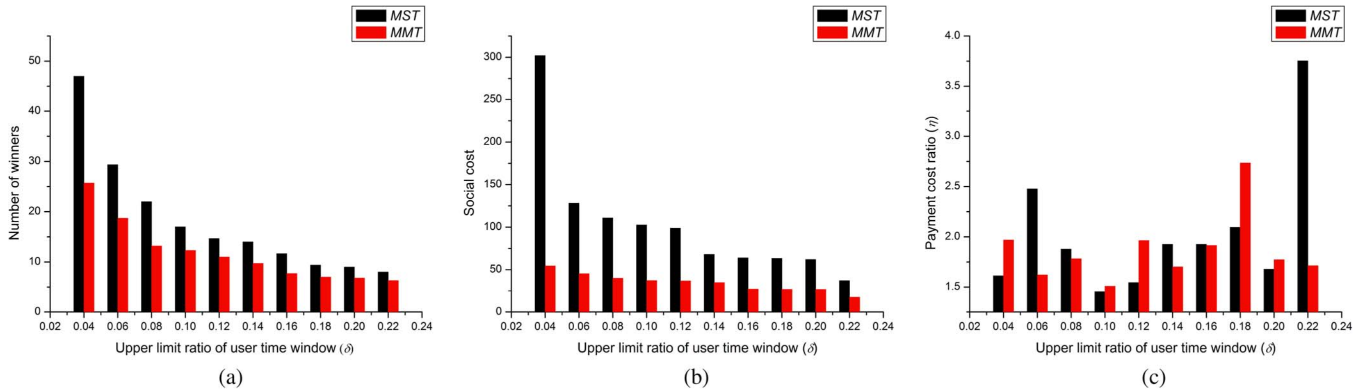


Fig. 5. Impact of the upper limit ratio of user time window δ. (a) The number of winners. (b) The social cost. (c) The payment cost ratio.

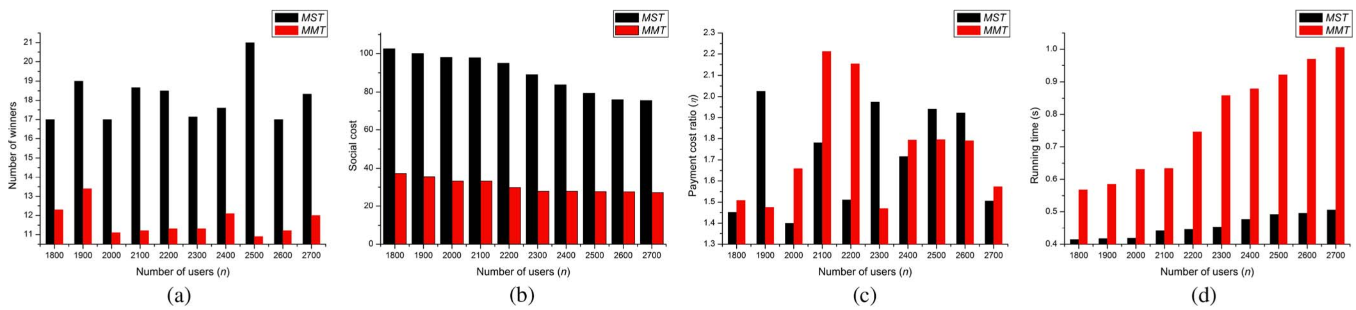


Fig. 6. Impact of the number of users n. (a) The number of winners. (b) The social cost. (c) The payment cost ratio. (d) The running time.

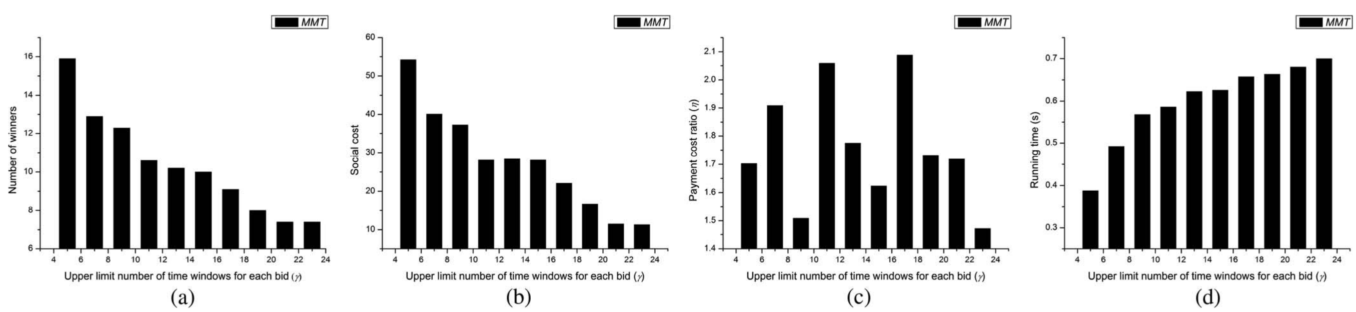


Fig. 7. Impact of the upper limit number of time windows for each bid γ. (a) The number of winners. (b) The social cost. (c) The payment cost ratio. (d) The running time.

addition, the running time of *MMT* increases with increasing γ. This is a reasonable phenomena since the running time of *MMT* is related to the maximum of time windows of users. However the running time of *MMT* is still lower than 0.7 s when there are 1800 users with 12 time windows on average.

VI. Related Work

At present, there are some studies on incentive mechanism design for mobile crowdsensing. Lee *et al.* proposed a Reverse Auction based Dynamic Price incentive mechanism with Virtual Participation Credit (RADP-VPC) [37] for collecting user sensing data with weak data integrity requirement. The service provider publicized the time period in each round r for the time sensitive property of the application. However, RADP-VPC is not truthful. Singer proposed a budget feasible mechanism [33], which is truthful and computationally efficient based on proportional share allocation rule. However, the designed mechanism was not established on any explicit crowdsensing system model. To overcome this drawback, they develop pricing mechanisms [26] for budget feasible maximizing task problem and budget feasible minimizing payment problem based on the method proposed in [33]. Yang *et al.* consider two system models of smartphone crowdsourcing [25]: the platform-centric model where the platform provides a reward shared by participating users, and the user-centric model where users have more control over the payment they will receive. In [35], they further investigate the user-centric model with three scenarios: single requester with single bid, single requester with multiple bids and multiple requesters with multiple bids. Koutsopoulos designed an optimal reverse auction [34], which considered the data quality as *user participation level*. However, the *quality indicator*, which essentially measures the relevance or usefulness of information is empirical and relies on user's information in the past. It is not reasonable to assume that the historical information can be obtained in advance. In [27], Feng *et al.*

presented a truthful auction, which was formulated as *winning bids determination problem*, for collaborative sensing in mobile crowdsourcing. However the mechanism is only effective to perform location-aware tasks. In [29], Zhao *et al.* investigated the problem that users submit their private profiles to the crowdsourcer when they arrive, and the crowdsourcer aims at selecting a subset of users before a specified deadline for minimizing the total payment while a specific number of tasks can be completed. They designed three online mechanisms, *Homo-OMZ, Hetero-OMZ* and *Hetero-OMG* for different user models.

VII. Conclusion

In this paper, we have investigated truthful incentive mechanisms for time window dependent tasks in mobile crowdsensing with strong requirement of data integrity. We have presented a universal system model based on reverse auction framework and formulated the problem as the *Social Optimization User Selection (SOUS)* problem. The objective function of *SOUS* problem is maximizing the social efficiency while the whole time window publicized by the platform can be covered. We have designed two incentive mechanisms, *MST* and *MMT*, to solve the *SOUS* problem in different cases. In single time window case, we designed an optimal algorithm based on dynamic programming to select users. The determination phase of *MST* is inspired by the *VCG* mechanism that is known to be truthful. While in multiple time window case, we have shown the general *SOUS* problem is NP-hard. We designed *MMT* based on greedy approach, which approximates the optimal solution within a factor of $In|\mathcal{W}| + 1$. Through both rigorous theoretical analysis and extensive simulations, we demonstrated that the proposed mechanisms achieve high computation efficiency, individual rationality and truthfulness. In the future work, we will further explore the incentive mechanisms for time window dependent tasks in more complex scenarios. For example, the time window dependent tasks in mobile crowdsensing applications are associated with specific locations.

Appendix

A. Proof of Theorem 2

We demonstrate that general *SOUS* belongs to NP firstly. Given an instance of general *SOUS*, we can check whether the winners cover the time window $\mathcal{W}$ and check whether the social cost is at most k. This process can be end up in polynomial time.

Next, we prove general *SOUS* is NP-hard by giving a polynomial time reduction from the NP-hard weighted set cover problem, *WSC*.

Instance of *WSC* (denoted by A): For an universe set $Z = \{z_1, z_2, \ldots, z_n\}$ of n elements, a family of sets $G = \{g_1, g_2, \ldots, g_n\}$ and a positive real v, each $g_i \subseteq G$ has its weight c'_{g_i} for $i \in \{1, \ldots, m\}$. The question is whether exists a set $G' \subseteq G$ with $\Sigma_{g_i \in G'} c'_{g_i} \leq v$, such that every element in Z belongs to at least one member in G'?

We consider a corresponding instance of general *SOUS* (denoted by B): We identify the time units in time window $\mathcal{W}$ and the sequence is denoted by $\{t_1, t_2, \ldots, t_n\}$, where t_i means the ith time unit. For an universe set $\mathcal{W} = \{t_1, t_2, \ldots, t_n\}$ of n time units and a family of time window sets $U = \{u_1, u_2, \ldots, u_n\}$, each user i is associated with a time window set u_i and a cost $c(u_i)$.

This reduction from A to B ends in polynomial time. We can simply see that q is a solution of A if and only if q is a solution of B.

References

[1] Worldwide Smartphone Forecast by Shipments and Value, 2014. [Online]. Available: http://www.idc.com/getdoc.jsp?containerId=prUS25282214

[2] R. K. Ganti, F. Ye, and H. Lei, "Mobile crowdsensing: Current state and future challenges," *IEEE Commun. Mag.*, vol. 49, no. 11, pp. 32–39, Nov. 2011.

[3] S. Consolvo *et al.*, "Activity sensing in the wild: A field trial of ubifit garden," in *Proc. 26th Annu. ACM SIGCHI Conf.*, Apr. 2008, pp. 1797–1806.

[4] E. Miluzzo *et al.*, "Sensing meets mobile social networks: The design, implementation, and evaluation of the CenceMe application," in *Proc. 6th ACM SenSys*, Nov. 2008, pp. 337–350.

[5] M. Mun *et al.*, "Peir, the personal environmental impact report, as a platform for participatory sensing systems research," in *Proc. 7th ACM MobiSys*, Jun. 2009, pp. 55–68.

[6] A. Thiagarajan *et al.*, "VTrack: Accurate, energy-aware traffic delay estimation using mobile phones," in *Proc. 7th ACM SenSys*, Nov. 2009, pp. 85–98.

[7] "Mobile millennium," UC Berkeley/Nokia/NAVTEQ, Berkeley, CA, USA. [Online]. Available: http://traffic.berkeley.edu/

[8] S. Reddy *et al.*, "Image browsing, processing and clustering for participatory sensing:lessons from a dietsense prototype," in *Proc. Workshop EmNetS*, Jun. 2007, pp. 13–17.

[9] S. Eisenman *et al.*, "The bikenet mobile sensing system for cyclist experience mapping," in *Proc. 5th ACM SenSys*, Nov. 2007, pp. 87–101.

[10] E. Miluzzo *et al.*, "Sensing meets mobile social networks: The design, implementation and evaluation of the CenceMe application," in *Proc. 6th ACM SenSys*, Nov. 2008, pp. 337–350.

[11] W. Dong, B. Lepri, and S. Pentland, "Tracking co-evolution of behavior and relationships with mobile phones," *Tsinghua Sci. Technol.*, vol. 17, no. 2, pp. 136–151, Apr. 2012.

[12] M. Mun *et al.*, "PIER, the personal environmental impact report, as a platform for participatory sensing systems research," in *Proc. ACM MobiSys*, Jun. 2009, pp. 55–68,

[13] J. Carrapetta, N. Youdale, A. Chow, and V. Sivaraman, Haze Watch Project. [Online]. Available: http://www.hazewatch.unsw.edu.au/

[14] R. Rana, C. Chou, S. Kanhere, N. Bulusu, and W. Hu, "Earphone: An end-to-end participatory urban noise mapping," in *Proc. ACM/IEEE IPSN*, Apr. 2010, pp. 105–116.

[15] N. Maisonneuve, M. Stevens, M. Niessen, and L. Steels, "Noisetube: Measuring and mapping noise pollution with mobile phones," in *Proc. ITEE*, May 2009, pp. 215–228.

[16] P. Mohan, V. Padmanabhan, and R. Ramjee, "Nericell: Rich monitoring of road and traffic conditions using mobile smartphones," in *Proc. 6th ACM SenSys*, Nov. 2008, pp. 323–336.

[17] E. Koukoumidis, L. Peh, and M. Martonosi, "SignalGuru: Leveraging mobile phones for collaborative traffic signal schedule advisory," in *Proc. ACM 9th Int. Conf. MobiSys*, Jun. 2011, pp. 127–140.

[18] A. Thiagarajan *et al.*, "Vtrack: Accurate, energy-aware road traffic delay estimation using mobile phones," in *Proc. 7th ACM SenSys*, Nov. 2009, pp. 85–98.

[19] C. Costa, C. Laoudias, D. Zeinalipour-Yazti, and D. Gunopulos, "Smarttrace: Finding similar trajectories in smartphone networks without disclosing the traces," in *Proc. IEEE 27th ICDE*, Apr. 2011, pp. 1288–1291.

[20] S. Matyas *et al.*, "Designing location-based mobile games with a purpose: Collecting geospatial data with city explorer," in *Proc. ACM Int. Conf. Adv. Comput. Entertain. Technol.*, Dec. 2008, pp. 244–247.

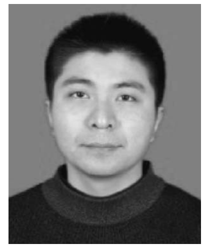
[21] Sensorly, 2014. [Online]. Available: http://www.sensorly.com

[22] Y. Liu, Y. Zhao, L. Chen, J. Pei, and J. Han, "Mining frequent trajectory patterns for activity monitoring using radio frequency tag arrays," *IEEE Trans. Parallel Distrib. Syst.*, vol. 23, no. 11, pp. 2138–2149, Nov. 2012.

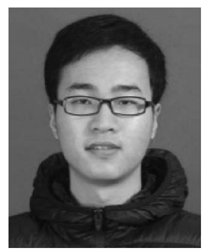
[23] Z. Yang, C. Wu, and Y. Liu, "Locating in fingerprint space: Wireless indoor localization with little human intervention," in *Proc. ACM MobiCom*, Aug. 2012, pp. 269–280.

[24] P. Zhou, Y. Zheng, and M. Li, "How long to wait?: Predicting bus arrival time with mobile phone based participatory sensing," in *Proc. ACM MobiSys*, Jun. 2012, pp. 1228–1240.

[25] D. Yang, G. Xue, X. Fang, and J. Tang, "Crowdsourcing to smartphones: Incentive mechanism design for mobile phone sensing," in *Proc. ACM MobiCom*, Aug. 2012, pp. 173–184.
[26] Y. Singer and M. Mittal, "Pricing mechanisms for crowdsourcing markets," in *Proc. 22nd Int. Conf. World Wide Web*, Apr. 2013, pp. 1157–1166.
[27] Z. Feng, Y. Zhu, Q. Zhang, L. M. Ni, and A. V. Vasilakos, "TRAC: Truthful auction for location-aware collaborative sensing in mobile crowdsourcing," in *Proc. IEEE INFOCOM*, Apr. 2014, pp. 1231–1239.
[28] A. Subramanian, G. S. Kanth, and R. Vaze, "Offline and online incentive mechanism design for smart-phone crowd-sourcing," *arXiv Preprint arXiv: 1310.1746*, 2013.
[29] D. Zhao, X. Li, and H. Ma, "How to crowdsource tasks truthfully without sacrificing utility: Online incentive mechanisms with budget constraint," in *Proc. IEEE INFOCOM*, Apr. 2014, pp. 1213–1221.
[30] X. Zhang *et al.*, "Free market of crowdsourcing: Incentive mechanism design for mobile sensing," *IEEE Trans. Parallel Distrib. Syst.*, vol. 25, no. 12, pp. 3190–3200, Dec. 2014.
[31] L. Blumrosen and N. Nisan, "*Combinatorial auctions (a survey)*," in *Algorithmic Game Theory*, N. Nisan, T. Roughgarden, E. Tardos, and V. Vazirani, Eds. Cambridge, U.K.: Cambridge Univ. Press, 2007.
[32] R. Myerson, "Optimal auction design," *Math. Oper. Res.*, vol. 6, no. 1, pp. 58–73, Feb. 1981.
[33] Y. Singer, "Budget feasible mechanisms," in *Proc. IEEE FOCS*, Oct. 2010, pp. 765–774.
[34] I. Koutsopoulos, "Optimal incentive-driven design of participatory sensing systems," in *Proc. IEEE INFOCOM*, Apr. 2013, pp. 1402–1410.
[35] X. Zhang, G. Xue, R. Yu, D. Yang, and J. Tang, "Truthful incentive mechanisms for crowdsourcing," in *Proc. INFOCOM*, Apr. 2015, pp. 2830–2838.
[36] W. Hsu, D. Dutta, and A. Helmy, "CSI: A paradigm for behavior-oriented profile-cast services in mobile networks," *Ad Hoc Netw.*, vol. 10, no. 8, pp. 1586–1602, Nov. 2012.
[37] J. Lee and B. Hoh, "Sell your experiences: A market mechanism based incentive for participatory sensing," in *Proc. IEEE PerCom*, Mar. 2010, pp. 60–68.
[38] R. Amicia *et al.*, "Performance assessment of an epidemic protocol in VANET using real traces," *Procedia Comput. Sci.*, vol. 40, pp. 92–99, 2014.
[39] C. Adams, P. Cain, D. Pinkas, and R. Zuccherato, "Internet X.509 public key infrastructure Time-Stamp Protocol (TSP)," Internet Eng. Task Force (IETF), Fremont, CA, USA, IETF RFC3161, Aug. 2001. [Online]. Available: http://tools.ietf.org/pdf/rfc3161.pdf



Jia Xu (M'15) received the M.S. degree from the School of Information and Engineering, Yangzhou University, Jiangsu, China, in 2006 and the PhD. degree from the School of Computer Science and Engineering, Nanjing University of Science and Technology, Jiangsu, China, in 2010. He is currently an Associate Professor at Nanjing University of Posts and Telecommunications. He was a visiting Scholar in the Department of Electrical Engineering and Computer Science, Colorado School of Mines from November 2014 to May 2015. His main research interests include crowdsourcing, opportunistic networks and wireless sensor networks.



Jinxin Xiang received the bachelor's degree in computer science and technology from Nanjing University of Posts and Telecommunications, Nanjing, China, in 2014. He is currently working toward the master's degree in the same university. His research interests are mainly in the area of the mobile crowdsensing, wireless sensor networks and wireless ad-hoc networks.

Dejun Yang (M'13) received the B.S. degree in computer science from Peking University, Beijing, China, in 2007 and the Ph.D. degree in computer science from Arizona State University, Tempe, AZ, USA, in 2013. He is currently the Ben L. Fryrear Assistant Professor of Computer Science in the Department of Electrical Engineering and Computer Science, Colorado School of Mines. His main research interests include economic and optimization approaches to networks, crowdsourcing, smart grid, big data, and cloud computing. He has received Best Paper awards at IEEE MASS 2011 and IEEE ICC 2011 and 2012, and was a Best Paper Award runner-up at IEEE ICNP 2010.