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Incentivize maximum continuous time interval coverage under budget constraint in mobile crowd sensing

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Abstract Mobile crowd sensing has become an effective approach to meet the demand in large scale sensing applications. In mobile crowd sensing applications, incentive mechanisms are necessary to compensate the resource consumptions and manual efforts of smartphone users. In this paper, we focus on exploring budget feasible frameworks for a novel and practical mobile crowd sensing scenario, where the platform expects to maximize the continuous time interval coverage under budget constraint. We present the system model and formulate the budget feasible maximum continuous time duration problem for this scenario. We design two budget feasible frameworks: BFF-STI and BFF-BTI, and integrate MST as the truthful mechanism to maximize the social efficiency. Then we extend the budget feasible frameworks to the general case, in which each user can bid multiple time intervals simultaneously. We show the proposed budget feasible frameworks are computationally efficient, individually rational, truthful and budget feasible. Through extensive simulations, we demonstrate that our budget feasible frameworks are efficient with different parameter settings. The simulation results also show that BFF-STI has superiority in large scale mobile crowd sensing applications, while BFF-STI is more suitable for long-term sensing applications.

Keywords Mobile crowd sensing · Incentive mechanism · Auction · Budget feasible

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1 Introduction

The smartphone has been developed as a powerful programmable mobile data collection device since it is integrated with many 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 [1]. The mobile crowd sensing has a huge potential due to the prominent advantages, such as wide spatiotemporal coverage, low cost, good scalability, pervasive application scenario, etc. As a novel sensing mode, mobile crowd sensing can enable attractive sensing applications in different domains, such as healthcare [2], social networking [3], environmental monitoring [4] and transportation [5, 6].

There are many applications and systems on mobile crowd sensing such as Co-evolution model for behavior and relationship discovery [7], SignalGuru [8] for providing traffic information, SmartTrace [9] for 3G/WiFi discovery, Frequent Trajectory Pattern Mining [10] for activity monitoring, LiFS [11] for indoor localization, etc. However, most of them are based on voluntary participation. In fact, incentivizing smartphone users is crucial to mobile crowd sensing system while smartphone users incure some cost (e.g., time and power consumption, memory, and data traffic for transmitting the data).

Moreover, there are potential privacy threats to smartphone users by sharing their sensed data with location tags, interests or identities. Incentive mechanisms also help to achieve good service quality since sensing services are dependent on quantity of users and quality of sensed data.

The problem of stimulating smartphone users in mobile crowd sensing is very difficult because strategic behaviors of smartphone users can seriously hinder the potential collaboration of smartphone users. There have been some research efforts on developing incentive mechanisms for mobile crowd sensing [12–21]. However, most of existing mechanisms cannot deal with the continuous time interval coverage tasks which require completing sensing data in the whole time interval publicized by the platform. For example, the tasks described in [12] and [13] are location dependent, and it may not necessary to make sure that all tasks are accomplished. There are some realistic examples of existing projects that fall into the continuous time interval coverage scenario: Bus Arrival Time Prediction System [22], Ear-Phone [23] and Haze Watch [24]. In aforementioned projects, the platform wants to collect sensing data over short time durations sent by participants, and then assembles pieces of incomplete information to reconstruct and represent the data over a long time interval. Obviously, the discontinuous sensing data is difficult to be assembled and is unvalued to the platform. However, most existing mechanisms consider there is no sequence between tasks, and the platform is indifferent to which task has been performed.

In this work, we focus on exploring truthful incentive mechanisms satisfying the desirable properties for maximum continuous time interval coverage under budget constraint in mobile crowd sensing. We present a universal system model for this novel mobile crowd sensing scenario. To stimulate smartphone users, the interactions between the platform and the smartphone users are modeled as a reverse auction mechanism. We propose two budget feasible frameworks: Sensing Time Interval based Budget Feasible Framework (BFF-STI) and Bidding Time Interval based Budget Feasible Framework (BFF-BTI). In proposed frameworks, the truthful mechanism MST [25] is introduced to maximize the social efficiency. Then we extend the budget feasible frameworks to the more general case, and a greedy approach based mechanism MMT [25] is applied in this case. We show that the designed incentive mechanisms satisfy the desirable properties in both cases.

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

- We focus on dealing with a category of time interval coverage task mobile crowd sensing, which is a novel and practical scenario. We present the universal system model and formulate the budget feasible maximum continuous time interval problem for this scenario.
- We design two budget feasible frameworks: BFF-STI and BFF-BTI. BFF-STI traverses all possible continuous time intervals in STI and chooses the best budget feasible outcome calculated by the truthful mechanism, while BFF-BTI traverses all possible continuous time intervals based on BTIs.
- We integrate MST as the truthful mechanism to maximize the social efficiency. Then we extend the proposed budget feasible frameworks to the general case, in which each user can bid multiple time intervals simultaneously and MMT is applied. We show the proposed budget feasible frameworks with MST or MMT are computationally efficient, individually rational, truthful and budget feasible.

The rest of the paper is organized as follows. Section 2 formulates the system model and problem. We present the budget feasible frameworks in Sect. 3. Section 4 integrates the MST into our frameworks, and analyzes the properties of budget feasible frameworks with MST. Section 5 extends the budget feasible frameworks to the multiple BTI case, and analyzes the properties of budget feasible frameworks with MMT. Performance evaluation is presented in Sect. 6. We review the related work in Sect. 7, and conclude this paper in Sect. 8.

2 System model and problem formulation

The system model can be briefly illustrated in Fig. 1. We consider a mobile crowd sensing system consisting of a platform and many smartphone users. The platform resides in the cloud and wants to collect the time continuous sensing data within a specific time interval. In detail, we consider the platform publicizes a Sensing Time Interval (STI)$\mathcal{W} = [T_S, T_E]$, where T_S and T_E are the start time and end time of STI, respectively. The platform has a strict budget constraint B for the time interval dependent tasks. We denote the length of $\mathcal{W}$, i.e., the number of time units of STI, 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 the time unit.

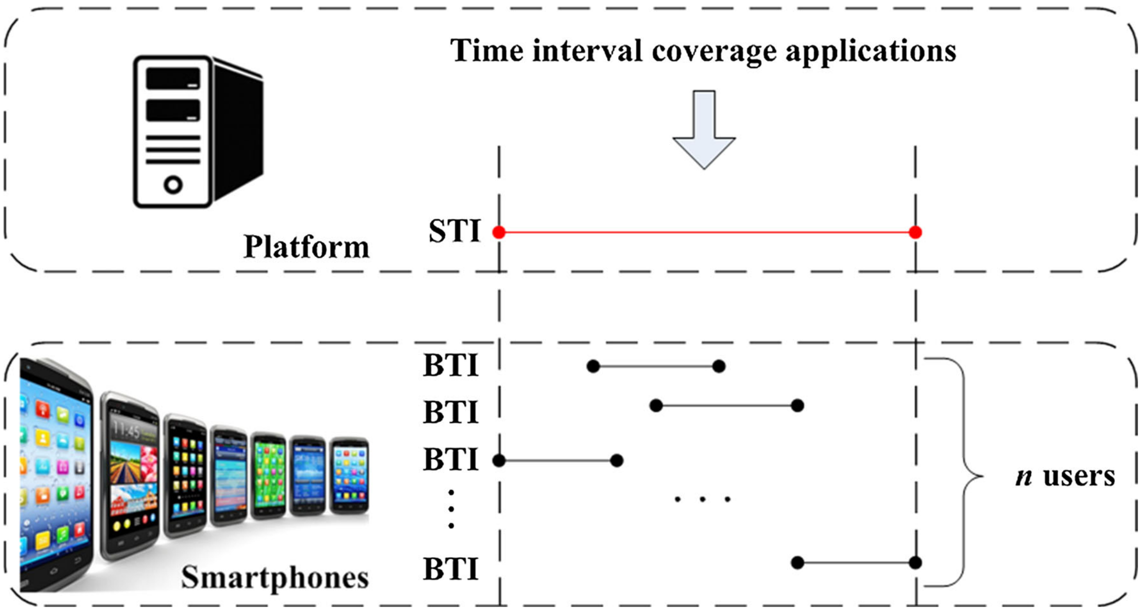


Fig. 1 Illustration of the time interval coverage mobile crowd sensing system

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 $A_i = ([s_i, e_i], b_i)$, in which $[s_i, e_i]$ is a Bidding Time Interval (BTI) the user i can perform. Each BTI is associated with the cost c_i. s_i and e_i are start time unit and end time unit of BTI, respectively, $\forall i \in U$. We also assume $s_i \geq T_S$ and $e_i \leq T_E$ since the users are rational and know that any $s_i < T_S$ or $e_i > T_E$ cannot bring extra benefit in our mechanisms. b_i is the claimed cost which is the bidding price that user i wants to charge for performing time continuous sensing from s_i to e_i. Note that the sensing data is processed by trusted time stamping such as *Public Key Infrastructure Time-Stamp Protocol* (*TSP*) [26] to prevent the users reporting the BTIs that are not real.

The platform selects a subset of users $S \subseteq U$, and notifies winners of the determination. The winners perform the sensing in their BTIs and send data back to the platform. Each user i is paid p_i, which is computed by the platform.

The above interactive process of our mobile crowd sensing system can be modeled as a reverse auction, which is illustrated by Fig. 2.

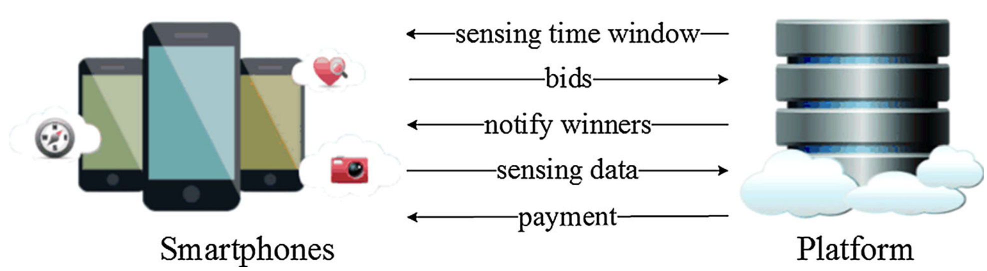
Table 1 Frequently used notations

Notation	Description
U, n	Set of users and number of users
$\mathcal{W}$, $\lvert\mathcal{W}\rvert$	Sensing time interval (STI) and the length of STI
T_S, T_E	Start time unit and end time unit of STI
t_i	Time unit in STI
BTI	Bidding time interval
s_i, e_i	Start time unit and end time unit of BTI
A, A_i	Set of bids and bid of user i
B	Budget constraint
b_i, c_i	Claimed cost and real cost of user i
S	Set of winners
u_i	Utility of user i
$v(S), v_{max}$	Total value over S and the maximum of value so far
$\mathbf{P}$, p_i	Payment to users and payment to user i

Table 1 lists frequently used notations.

We define the utility of user i as the difference between the payment and its real cost

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



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

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 BTI since we consider users are selfish and rational, 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.

We define the value function of the platform over the winners as the maximum continuous time duration the users in the winner set S can perform

$$v(S) = max_{i,j\in S, e_j \geq s_i} \left| \left[s_i, e_j \right] \right| \tag{2}$$

where $\left[s_i, e_j \right]$ is the continuous time duration which can be covered by the users in the winner set S.

The platform expects to obtain the maximum value from the winners under the budget constraint, i.e.,

$$\text{Maximize} v(S) \text{ s.t.} \sum_{i\in S} p_i \leq B \tag{3}$$

To prevent the monopoly, we exclude the situation where only one bid hits the arbitrary time unit in STI.

Our objective is to design the incentive mechanisms satisfying the following four desirable properties:

1. Computational Efficiency
   A mechanism is computationally efficient if the outcome 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 [27] for all users.
4. Budget Feasibility
   The total payment to winners is less than or equal to the budget, i.e., $\sum_{i\in S} p_i \leq B$.

The importance of the first two properties is obvious, because they together assure the feasibility of the incentive mechanism. The third property is indispensable for guaranteeing the compatibility. Being truthful, the incentive mechanism can eliminate the fear of market manipulation and the overhead of strategizing over others for the participating users. Budget feasibility guarantees that the mechanism is practical and satisfies the basic requirement.

3 Budget feasible framework design

In this section, we present the budget feasible frameworks for maximum continuous time interval coverage.

3.1 Design rationale

It is well known that the proportional share allocation rule [18] can be applied to design the budget feasible mechanism if the value function is submodular, monotone and non-negative. Unfortunately, the value function defined in formula (2) is not a submodular function. Another challenge is that the users can take a strategic behavior by reporting the bidding prices that are not real. A truthful mechanism is necessary for incentivizing the users to bid their real costs.

However, in our system model, traversing all possible continuous time intervals can be solved within polynomial time for arbitrary given finite STI or BTIs. Based on the observation, we develop the budget feasible frameworks which follow the exhaustive method. The basic idea is: run the truthful mechanism $\mathcal{M}(\mathcal{W}', A)$ for each possible continuous time interval $\mathcal{W}'$ iteratively. In each iteration, $\mathcal{M}(\mathcal{W}', A)$ returns the set of winners and the payment to the users. The budget feasible outcome with maximum continuous time interval is selected ultimately in our frameworks.

3.2 STI based budget feasible framework

In this subsection, we present a budget feasible framework by traversing all possible continuous time intervals in STI. We denote the maximum of value of the platform in current state as v_{max}. For each possible continuous time interval $\left[t_i, t_j\right]$ in STI, if the length of the interval is greater than v_{max}, the mechanism $\mathcal{M}\left(\left[t_i, t_j\right], A\right)$, which returns a subset of users $S' \subseteq U$ and a vector $\mathbf{P}'$ of payments to all the users, is carried out. Based on the outcome of the mechanism $\mathcal{M}\left(\left[t_i, t_j\right], A\right)$, if the summation of payments does not exceed the budget, we update the outcome of BFF-STI as that of $\mathcal{M}\left(\left[t_i, t_j\right], A\right)$. The whole process is illustrated in Algorithm 1.

Algorithm 1: STI based Budget Feasible Framework (BFF-STI)

Input: STI $\mathcal{W}$, Set of Users U, Budget B, Bids A

$v_{max} \leftarrow 0,\ S \leftarrow \emptyset,\ S' \leftarrow \emptyset,\ \mathbf{P} \leftarrow 0,\ \mathbf{P}' \leftarrow 0$;
for $t_i \leftarrow T_S$ to $T_E - 1$ **do**
  for $t_j \leftarrow T_E$ to $t_i + 1$ **do**
    if $\left|[t_i, t_j]\right| > v_{max}$ **then**
      $(S', \mathbf{P}') \leftarrow \mathcal{M}([t_i, t_j], A)$;
      if $\sum_{l \in S'} p_l \le B$ **then**
        $S \leftarrow S',\ v_{max} \leftarrow \left|[t_i, t_j]\right|,\ \mathbf{P} \leftarrow \mathbf{P}'$, **break**;
      end
    else
      break;
    end
  end
end
return(S, $\mathbf{P}$);

It is not difficult to analyze the computational efficiency of BFF-STI. We define $O(\mathcal{M})$ as the time complexity of $\mathcal{M}([t_i, t_j], A)$. The running time of BFF-STI is given in Lemma 1.

Lemma 1 *The running time of BFF-STI is* $O\left(|\mathcal{W}|^2 \cdot max(O(\mathcal{M}), n)\right)$.

Since we set the budget feasible outcome of mechanism $\mathcal{M}([t_i, t_j], A)$ as the outcome of BFF-STI, we can obtain the following Lemma.

Lemma 2 *BFF-STI is budget feasible.*

3.3 BTI based budget feasible framework

Since BFF-STI traverses all possible continuous time intervals in STI, it may take long time to compute the outcome if the length of STI is very long. In this subsection, we present a budget feasible framework by traversing all possible continuous time intervals based on BTIs.

In BFF-BTI, the BTIs are placed in the sequence Q and Q', respectively according to the left point of their time intervals such as $s_1 \le s_2 \le \ldots \le s_n$ and the right point of their time intervals such as $e_1 \ge e_2 \ge \ldots \ge e_n$. We scan Q and Q' respectively to find all possible continuous time intervals $[s_i, e_j]$, $i \in Q$, $j \in Q'$. We denote the left point of the continuous time interval in current state as s_0. In the ith iteration of Q, if $s_i \ne s_0$ and the length of interval $[s_i, e_q]$, where e_q is the greatest right point among all BTIs, is no more than v_{max}, BFF-BTI returns the current outcome as the ultimate outcome because the length of arbitrary time interval $[s_i, e_j]$, $j \in Q', j \ne q$, is less than the length of interval $[s_i, e_q]$. Moreover, the BTI j, which leads to $e_j \le s_i$, is removed from Q'. For each possible continuous time interval $[s_i, e_j]$, if the length of the interval is greater than v_{max}, the mechanism $\mathcal{M}([s_i, e_j], A)$ is carried out. If the summation of payments does not exceed the budget, we update the outcome of BFF-BTI as that of $\mathcal{M}([s_i, e_j], A)$. The whole process is illustrated in Algorithm 2.

Algorithm 2: BTI based Budget Feasible Framework (BFF-BTI)

Input: STI $\mathcal{W}$, Set of Users U, Budget B, Bids A

1 $v_{max} \leftarrow 0, s_0 \leftarrow -1$ $S \leftarrow \emptyset$, $S' \leftarrow \emptyset$, $\mathbf{P} \leftarrow 0$, $\mathbf{P}' \leftarrow 0$;
2 sort all BTIs based on the start time unit in nondecreasing order and the sequence is denoted by Q;
3 sort all BTIs based on the end time unit in nonincreasing order and the sequence is denoted by Q';
4 **foreach** $i \in Q$ in order **do**
5   **if** $s_i \neq s_0$ **then**
6     $s_0 \leftarrow s_i$;
7   let q be the head of Q';
8   **if** $\|[s_i, e_q]\| \leq v_{max}$ **then**
9   **break**;
10   **end**
11   **foreach** $j \in Q'$ **do**
12   **if** $e_j \leq s_i$ **then**
13   remove j from Q';
14   **end**
15   **end**
16   **foreach** $j \in Q'$ in order **do**
17   **if** $\|[s_i, e_j]\| > v_{max}$ **then**
18         $(S', \mathbf{P}') \leftarrow \mathcal{M}([s_i, e_j], A)$;
19   **if** $\sum_{l \in S'} p_l \leq B$ **then**
20           $S \leftarrow S'$, $v_{max} \leftarrow \|[s_i, e_j]\|$, $\mathbf{P} \leftarrow \mathbf{P}'$, **break**;
21   **end**
22   **end**
23   **end**
24   **end**
25 **end**
26 **return**(S, $\mathbf{P}$);

The properties of time complexity and budget feasibility of BFF-BTI are given in Lemma 3 and Lemma 4, respectively.

Lemma 3. *The running time of BFF-BTI is* $O(n^2 \cdot max(O(\mathcal{M}), n))$.

Proof The running time of the whole BFF-BTI is dominated by this for-loop (lines 4–25). Moreover, the running time of the for-loop (lines 4–25) is dominated by the for-loop (lines 16–23), which runs n^2 times. In each iteration of the for-loop (lines 16–23), the mechanism $\mathcal{M}([s_i, e_j], A)$ (line18) takes $O(\mathcal{M})$ time, and summating the payments (line19) takes $O(n)$ time. Hence the running time of BFF-BTI is bounded by $O(n^2 \cdot max(O(\mathcal{M}), n))$ ■.

Since we set the budget feasible outcome of the mechanism $\mathcal{M}([s_i, e_j], A)$ as the outcome of BFF-BTI, we can obtain the following Lemma.

Lemma 4. *BFF-BTI is budget feasible.*

4 Definition and integration of truthful mechanism

In this section, we aim to define and integrate the mechanism $\mathcal{M}(\mathcal{W}', A)$, which selects the winners to cover given continuous time interval $\mathcal{W}'$ and computes the payment for each user. The mechanism $\mathcal{M}(\mathcal{W}', A)$ is expected to satisfy the desirable properties of computational efficiency, individual rationality and truthfulness.

For the outcome $(S', \mathbf{P}')$ of $\mathcal{M}(\mathcal{W}', A)$, the utility of the platform is

$$u_0 = v(S') - \sum_{l \in S'} p_l \tag{4}$$

The objective function of $\mathcal{M}(\mathcal{W}', A)$ is maximizing the social efficiency, which is the total utility of all the participants. Hence, based on formula (1) and formula (4), the social efficiency is $v(S') - \sum_{l \in S'} c_l$. The value of $v(S')$ is constant since the winners can cover the given continuous time interval $\mathcal{W}'$. Thus we can maximize the social efficiency through minimizing the social cost, i.e. $\sum_{l \in S'} c_l$.

The problem can be formulated as follows:

$$min \sum_{l \in S'} c_l \tag{5}$$

$$s.t. \mathcal{W}' \subseteq \cup_{l \in S'} [s_l, e_l] \tag{6}$$

This problem is minimum weighted interval cover problem in essence, and can be solved in polynomial time. We can adopt the truthful mechanism MST [25], which uses dynamic programming to select the winners and computes payment based on the *VCG* payment rule.

We define the start time and the end time of $\mathcal{W}'$ as T'_S and T'_E, respectively. For applying MST, we remove the users who cannot sensing for $\mathcal{W}'$ (i.e., $s_i > T'_E$ or $e_i < T'_S$, $\forall i \in U$), and sort the rest of the users U' according to the right point of their BTIs such as $e_1 \leq e_2 \leq \ldots \leq e_n$. Then we compute $F(i)$ for U' in sequence with recurrence

$$F(i) = \begin{cases} min_{e_j \geq s_i} F(j) + b_i \ if \ T'_S \notin [s_i, e_i] \\ b_i \ if \ T'_S \in [s_i, e_i] \end{cases} \tag{7}$$

Then we get the minimum social cost

$$Cost(U') = min_{i \in U'} \left\{ F(i) | T'_E \in [s_i, e_i] \right\} \tag{8}$$

Finally, *VCG* based payment rule is applied to determine the payment for the users

$$p_i = \begin{cases} Cost(U' \setminus \{i\}) - (Cost(U') - b_i) \ if \ i \in U' \\ 0 \ if \ i \notin U' \end{cases} \tag{9}$$

We review the important and useful properties of MST here.

Lemma 5. ([25, Lemma 1]) *The running time of MST is* $O(n^2 \log n)$.

Lemma 6. ([25, Theorem 1]) *MST is individually rational and truthful.*

For convenience, we named the mechanism using BFF-STI and MST as BFF-STI-MST. Accordingly, the mechanism using BFF-BTI and MST is denoted as BFF-BTI-MST.

The above six lemmas together prove the following theorems.

Theorem 1 *The running time of BFF-STI-MST is* $O\left(|\mathcal{W}|^2 n^2 logn\right)$. *Furthermore, BFF-STI-MST is individually rational, truthful and budget feasible.*

Theorem 2 *The running time of BFF-BTI-MST is* $O(n^4 logn)$. *Furthermore, BFF-BTI-MST is individually rational, truthful and budget feasible.*

5 Extension to multiple bti case

In the previous section, we proposed the budget feasible frameworks for continuous time interval coverage tasks, in which the bid of each user only contain one BTI. As illustrated in Fig. 3, we extend them to a more practical scenario, in which the bid of each user can contain more than one BTI. In this case, the users can decide the set of time intervals by several ways in practice, such as future schedules, daily behaviors, habits or preferences. The users can predict the time intervals, within which they are in the specific locations to perform the sensing tasks based on their future schedules. Moreover, the users can decide time intervals according to their daily behaviors, habits or preferences with little effect on their daily life. The extended budget feasible frameworks are expected to achieve computational efficiency, individual rationality, truthfulness and budget feasibility.

Without loss of generality, we assume that each user i responds with a bid $A_i = (\Gamma_i, b_i)$, in which $\Gamma_i = \left\{ [s_i^1, e_i^1], \ldots, [s_i^{k_i}, e_i^{k_i}] \right\}$ is a set of k_i time intervals the user i can perform. Each Γ_i is associated with the cost c_i.

Hence the value function of the platform in the multiple BTI case can be formulated as follows

$$v(S) = max_{i,j \in S, 1 \leq f \leq k_i, 1 \leq g \leq k_j, e_j^g \geq s_i^f} \left| \left[s_i^f, e_j^g \right] \right| \tag{10}$$

Obviously, BFF-TSI illustrated in Algorithm 1 is also effective for the multiple BTI case. For BFF-BTI, we can index all BTIs as $[s_1, e_1]$, $[s_2, e_2], \ldots, [s_m, e_m]$, where $m = \sum_{i \in U} k_i$, then we run Algorithm 2 to obtain the budget feasible outcome.

The objective function of $\mathcal{M}(\mathcal{W}', A)$ is maximizing the social efficiency in multiple BTI case, which can be formulated as follows:

$$\begin{aligned} & min \sum_{l \in S'} c_l \\ & s.t. \mathcal{W}' \subseteq \cup_{l \in S', j \in \{1, \ldots, k_l\}} \left[s_l^j, e_l^j \right] \end{aligned} \tag{11}$$

This problem is essentially a modified minimum weighted set cover problem, which is an NP-complete problem [28]. We use the truthful mechanism MMT [25], which can approximate the optimal solution within a factor of $\ln|\mathcal{W}'| + 1$. MMT selects the winners through a greedy approach, which choose the user with minimum effective average cost iteratively. Specifically, in the ith iteration, given the uncovered time interval $\mathcal{W}'_{i-1} \subseteq \mathcal{W}'$, we select the user h with $\min_{h \in U \setminus S'} \frac{b_h}{\mathcal{W}'_{i-1} \cap \left(\cup_{\forall j \in \{1, \ldots, k_h\}} [s_h^j, e_h^j] \right)}$ as the winner. Repeat the selection until whole $\mathcal{W}'$ is covered. Finally, the critical payment [19] is calculated for each winner.

We review the important and useful properties of MMT here.

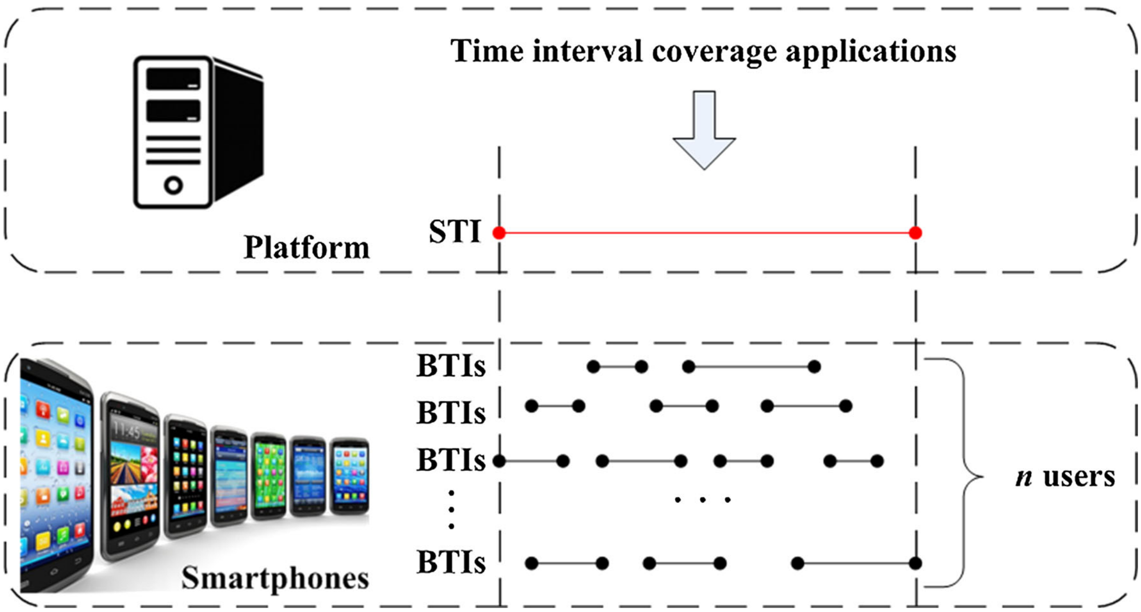


Fig. 3 Illustration of the time interval coverage mobile crowd sensing system with multiple BTIs

Lemma 7 ([25, *Lemma* 5]) *The running time of MMT is* $O\left(n^3 \cdot max_{i\in\{1,\ldots,n\}}k_i\right)$.

Lemma 8 ([25, *Theorem* 3]) *MMT is individually rational and truthful.*

For convenience, we named the mechanism using BFF-STI and MMT as BFF-STI-MMT. Accordingly, the mechanism using BFF-BTI and MMT is denoted as BFF-BTI-MMT.

Lemma 1 to Lemma 4 and Lemma 7 to Lemma 8 together prove the following theorems.

Theorem 3 *The running time of BFF-STI-MMT is* $O\left(|\mathcal{W}|^2 n^3 \cdot max_{i\in\{1,\ldots,n\}}k_i\right)$. *Furthermore, BFF-STI-MMT is individually rational, truthful and budget feasible.*

Theorem 4 *The running time of BFF-BTI-MMT is* $O\left(n^5 \cdot max_{i\in\{1,\ldots,n\}}k_i\right)$. *Furthermore, BFF-BTI-MMT is individually rational, truthful and budget feasible.*

6 Performance evaluation

In this section, we conduct thorough simulations to investigate the performance of our budget feasible frameworks. Firstly, we evaluate the budget feasible frameworks 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 value of the platform, the total payment and the running time. For our simulations, the cost of each bid is uniformly distributed in [1,100]. All the simulations were run on an Ubuntu 14.04.3 LTS machine with Intel Xeon CPU E5-2420 and 16 GB memory. Each measurement is averaged over 1000 instances. For convenience, we named the budget feasible framework in single BTI case as BFF-MST. Accordingly, the budget feasible framework in multiple BTI case is denoted as BFF-MMT.

6.1 Performance evaluation based on real traces

We use the real mobility traces of 370 taxi cabs that report their position every 15 s around the city of Rome during 2014-02-01 to 2014-03-02 [29]. For our simulations, we use the traces at the time snapshot in 2014-02-01. We consider the maximum continuous time interval coverage tasks are performed in the specific geographical areas under budget constraint. We choose three different places in the city of Rome: Piazza Colonna, Quirinal Palace and University of Arkansas Rome Center (UARC). The geographical areas are set as the circulars with the centers of the three 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 STIs for different geographical areas, and the bidders are taxis who are in the specific geographical areas during the STIs.

6.1.1 Evaluation of BFF-MST

We set the maximum STI of 15600 s for Piazza Colonna, 10800 s for Quirinal Palace and UARC, respectively, and measure the performance with different end time of STI. The time unit length is one second. We select the maximum length time interval in the STI of each taxi as the BTI in this single BTI case. Figure 4 depicts the performance of BFF under the budget 200. Since the start time is same, the different end time means different STI, which is an indication of workload for the crowd sensing application. As can be seen from the figure, the number of taxis increases when STI goes up. This is because more taxis pass through the pre-set geographical areas when there is more time for sensing. Given the same STI, the number of taxis depends on the taxi density in corresponding area. The value of the platform also increases because there are more taxis. Specifically, the value in Quirinal Palace area always equal to the length of STI. This means that the winning taxis selected by BFF can always complete the tasks in the whole STI under the budget in this setting. Moreover, the running time of BFF-STI increases severely with increasing STI since the running time largely depends on the length of STI and the number of taxis involved. However, the running time of BFF-BTI, which largely depends on the number of taxis, is much less than that of BFF-STI since the number of taxis is much fewer relative to the length of STI in the setting.

Then we fix the end time 3000 s of STI for all three geographical areas, and vary the budget. As can be seen from Fig. 5, the value of the platform increases when the budget goes up. This is because we can select more taxis or more valuable taxis to perform the tasks. The value in different geographical areas is quite different since the value also depends on the real mobility traces of taxis. The total payment also increases with the budget; moreover, the total payment is under the budget strictly.

6.1.2 *Evaluation of BFF-MMT*

In multiple BTI case, we use all time intervals of each taxi in the STI as the BTIs. We set the maximum STI of 520, 480 and 280 min for Piazza Colonna, Quirinal Palace and

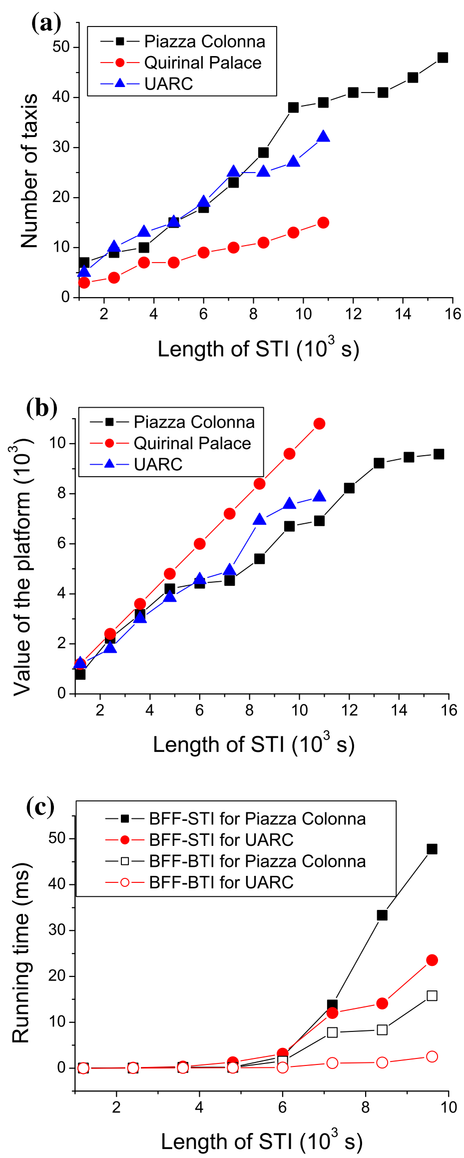


Fig. 4 Performance of BFF with various end time of the STI under budget = 200 in single BTI case **a** number of taxis, **b** value of the platform, **c** running time

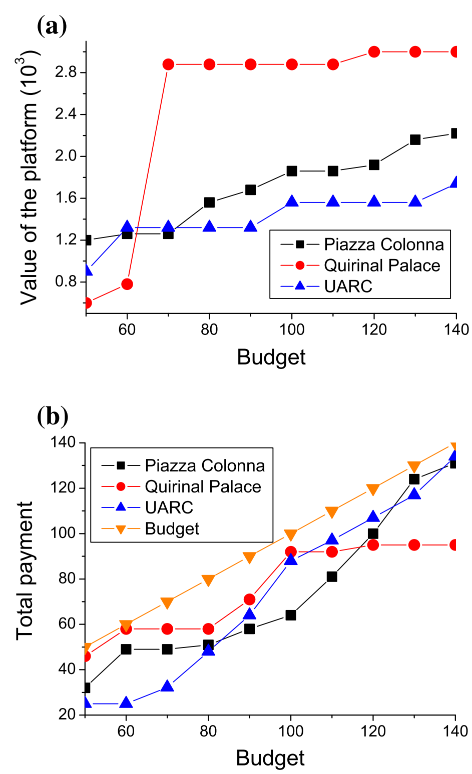


Fig. 5 Performance of BFF under various budgets in single BTI case **a** value of the platform, **b** total payment

UARC, respectively, and measure the performance with different end time. The time unit length is 1 min. In this setting, there are at most 26 BTIs in one bid. Figure 6 shows the performance of BFF with different end time under budget 200. The number of taxis increases when STI goes up. The value of the platform also increases because there are more taxis. Specifically, the value in UARC area is almost equal to the maximum value of the platform (i.e. the length of STI). This means that the winning taxis selected by BFF almost complete the tasks in the whole STI under such budget constraint. Moreover, the running time of BFF-STI increases with increasing STI. However, the running time of BFF-BTI is much less than that of BFF-STI since the number of taxis is much fewer relative to the length of STI in the setting.

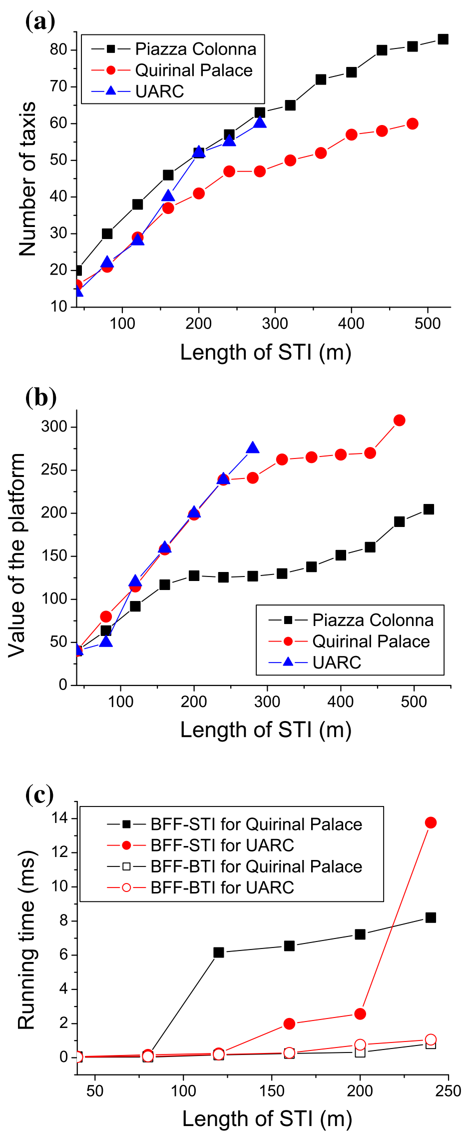


Fig. 6 Performance of BFF with various end time of the STI under budget = 200 in multiple BTI case **a** number of taxis, **b** value of the platform, **c** running time

We fix the end time 140 m of STI for all three geographical areas, and measure the performance with different budgets. As can be seen from Fig. 7, the value of the platform increases when the budget goes up. The value in Quirinal Palace is very close to the maximum value 140 when the budget is more than 100. However, the value also depends on the real mobility traces of taxis, and can be very different in different geographical areas. The total payment also increases with the budget, and the budget utilization ratio ($\sum_{i \in S} p_i / B$) is 89.6 % in average.

6.2 Revealing the impacts of the key parameters

There are four common key parameters: the upper limit ratio of BTI δ, the number of users n, the budget constraint B and the length of STI. There is a special parameter for BFF-MMT: the upper limit number of BTIs for each bid γ. For our simulations, the length of BTI is uniformly distributed in the interval $[1, \delta|\mathcal{W}|]$. Since the users are rational and know that any BTI out of STI cannot get the payoff, the start time of bid s_i is uniformly distributed in whole STI and satisfies $s_i \geq T_s$ and $e_i \leq T_E$. In BFF-MMT, each bid can contain more than one BTI. The number of BTIs for each bid in BFF-MMT is uniformly distributed in $[1,\gamma]$. We set $n = 180$, $|\mathcal{W}| = 100$, $\delta = 0.1$, $\gamma = 9$, $B = 30$ as the default setting, however we will vary them for exploring the impacts of these parameters respectively. The

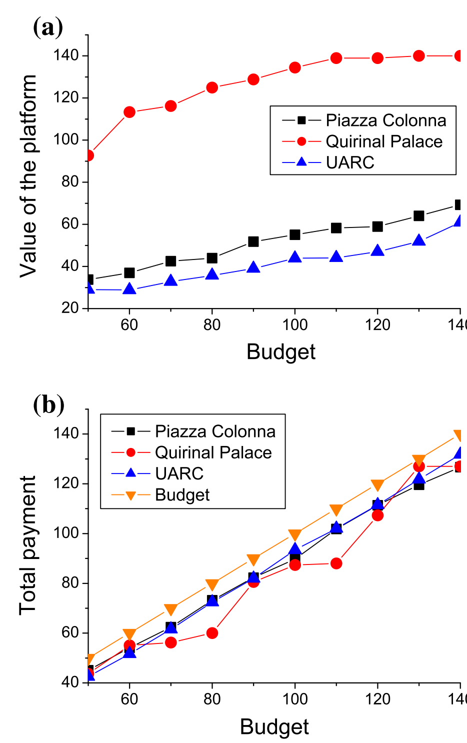


Fig. 7 Performance of BFF under various budgets in multiple BTI case **a** value of the platform, **b** total payment

impact of the length of STI has been investigated in Sect. 6.1. Thus we measure the impacts of other key parameters here.

6.2.1 Impact of δ

The BTI length of each bid responded by users can depict the interest and suitability of users for participating in mobile crowd sensing. We set the BTI length of each bid in $[1, \delta|\mathcal{W}|]$ with uniform distribution, and then vary δ from 0.08 to 0.26 to investigate the impact on BFF. As can be shown in Fig. 8, the value increases with increasing δ because each user can provide more value in average. Specifically, BFF-MMT can obtain 96.03 % of the maximum value when $\delta = 0.16$, while BFF-MST obtain 50.54 % of the maximum value even when $\delta = 0.26$. This is because the users in multiple BTI case are more powerful than that in single BTI case. Moreover, the running time decreases with increasing δ. In detail, given $|\mathcal{W}|$ and n, the running time of BFF is related to the current maximum of value v_{max} because each time interval $\mathcal{W}' \le v_{max}$ is not considered and is dropped directly in BFF (Line 10 of Algorithm 1 and Line 9 of Algorithm 2). Although there is no quantitative analysis, the simulation results indicate that the running time of BBF would decrease dramatically when BFF can obtain large value of the platform. On the other hand, BFF-BTI takes more time than BFF-STI in both single BTI case and multiple BTI case since the number of users is greater than the length of STI in the random user simulation setting.

6.2.2 Impact of n

To investigate the scalability of designed mechanisms, we fix the upper limit ratio of BTI $\delta = 0.1$, and vary the number of users from 180 to 270. Figure 9 shows the impact of user number on the performance of BFF. The value of the platform increases both in single BTI case and in multiple BTI case. The value from BFF-MST goes up slowly due to the limited budget, while BFF-MMT can obtain more than 90.46 % of maximum value when the number of users exceeds 240. Moreover, the running time of all mechanisms increase, which conforms to the expected running time properties of BFF proved in Theorem 1 to Theorem 4.

6.2.3 Impact of B

Then we fix the number of users $n = 180$, and vary the budget constraint from 20 to 110. Figure 10 depicts the performance of BFF in such setting. BFF can obtain more

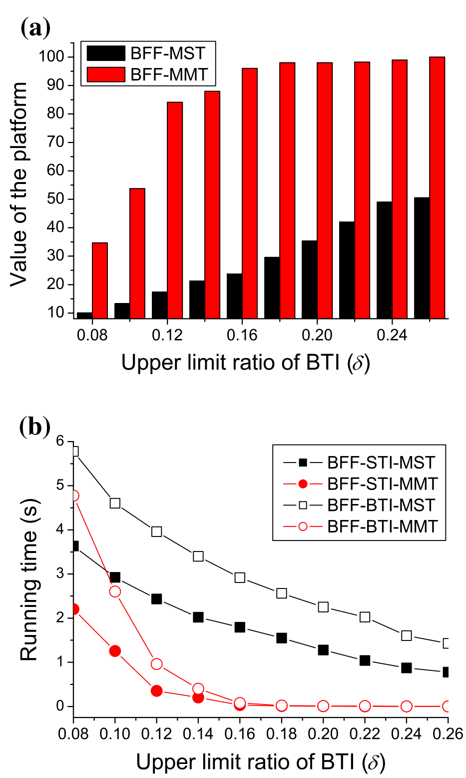


Fig. 8 Impact of the upper limit ratio of BTI δ **a** value of the platform, **b** running time

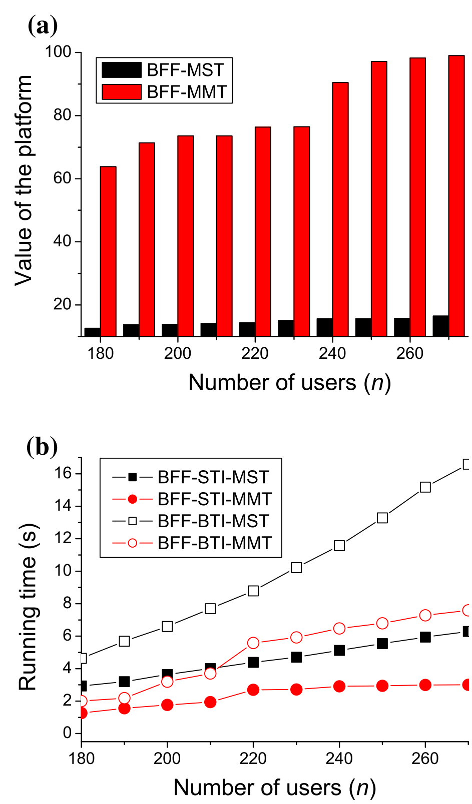


Fig. 9 Impact of the number of users n **a** value of the platform, **b** running time

value when the budget is relaxed. The total payment also increases with increasing budget with budget utilization ratio 91.31 and 91.36 % respectively in single BTI case and multiple BTI case in average. Moreover, all mechanisms can take less time when we increase the budget constraint.

6.2.4 Impact of γ in BFF-MMT

Since each user can respond with multiple BTIs in one bid in BFF-MMT, the number of BTIs for each bid is a key parameter which depends largely on users' movement habit in practice. Figure 11 depicts the performance of BFF-MMT with the upper limit number of BTIs for each bid γ being varied from 5 to 23. With more BTIs each user can provide, the value increases dramatically since each user can perform more tasks in STI. Meanwhile, the running time decreases severely when BFF can obtain larger value.

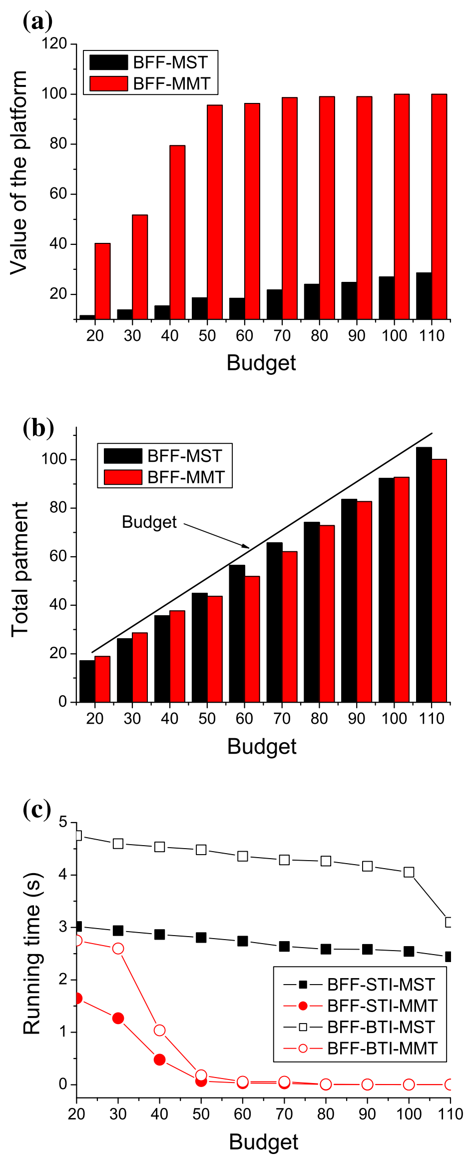


Fig. 10 Impact of the budget constraint B **a** value of the platform, **b** total payment, **c** running time

7 Related work

Many incentive mechanisms for mobile crowd sensing have been proposed thus far. Yang et al. [12] proposed two different models for smartphone crowdsourcing: 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 [20], they further extended the user-centric model to three cases: single requester with single bid, single requester with multiple bids and multiple requesters with multiple bids. Koutsopoulos [19] designed an optimal reverse auction, considering 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 historical information. In [15], Feng et al. formulated the location-aware collaborative sensing problem as the *winning bids determination problem*, and presented a truthful auction using the proportional share allocation rule proposed in [18].

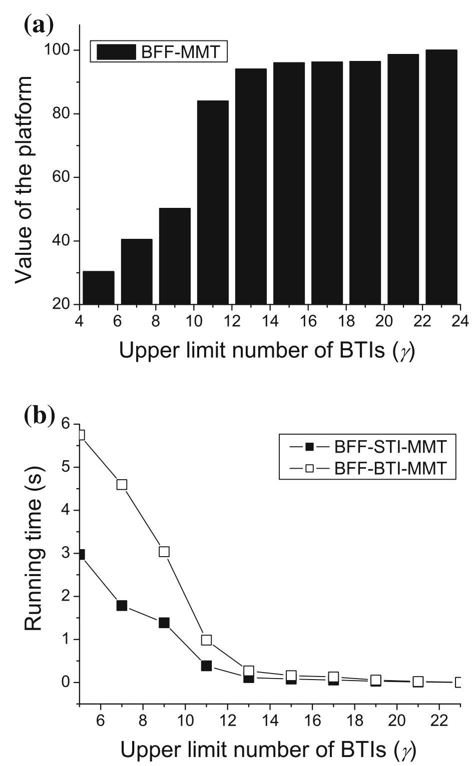


Fig. 11 Impact of the upper limit number of BTIs for each bid γ **a** value of the platform, **b** running time

However the mechanism is only effective to perform location-aware tasks. In [13], Zhao et al. investigated the online crowdsourcing scenario where the users submit their profiles to the crowdsourcer when they arrive. The objective is selecting a subset of users for maximizing the value of the crowdsourcer under the budget constraint. They designed two online mechanisms, *OMZ, OMG* for different user models. In [30], Peng et al. incorporate the consideration of data quality into the design of incentive mechanism for crowd sensing, and propose to pay the participants as how well they do, to motivate the rational participants to perform data sensing efficiently.

At present, there are some studies on budget feasible incentive mechanism design for mobile crowd sensing. Singer proposed a truthful budget feasible mechanism [18] based on the proportional share allocation rule. However, the designed mechanism was not established on any crowd sensing system model and only valid for submodular functions. Pricing mechanisms were also developed in [14] for the budget feasible maximizing task problem and the budget feasible minimizing payment problem based on the method proposed in [18]. Han et al. [31] proposed two truthful and budget feasible scheduling mechanisms with constant approximation ratio. In [32], Zhang et al. profiled the tasks' difficulty levels and workers' quality in crowdsourcing systems, where the collected labels are aggregated with sequential Bayesian approach, and proposed a budget feasible mechanism for incentivizing crowd labeling. In general, these existing incentive mechanisms have not considered the time interval coverage tasks.

8 Conclusion

In this paper, we have investigated budget feasible frameworks for maximum continuous time interval coverage under budget constraint in mobile crowd sensing. We have presented a system model based on reverse auction framework. The objective of our budget feasible frameworks is maximizing the value of the platform. We have designed two budget feasible frameworks, BFF-STI and BFF-BTI, and integrated MST as the truthful mechanism to maximize the social efficiency. Then we extend the proposed budget feasible frameworks to the multiple bidding time interval case. The truthful mechanism MMT was applied in this case. We show the proposed budget feasible frameworks with MST or MMT are computationally efficient, individually rational, truthful and budget feasible. The simulation results show that BFF-STI has superiority in large scale mobile crowd sensing applications, while BFF-STI is more suitable for long-term sensing applications.

In the future work, we will further extend the frameworks to multiple STI case. We consider there are several heterogeneous time interval coverage tasks which need to be performed simultaneously. Each task corresponds to a STI with independent budget. In the multiple STI case, if each user bids only for one of the tasks, we can apply our budget feasible frameworks for each STI. However, if the user can bid multiple BTIs for multiple STIs simultaneously, the problem can be very intractable.

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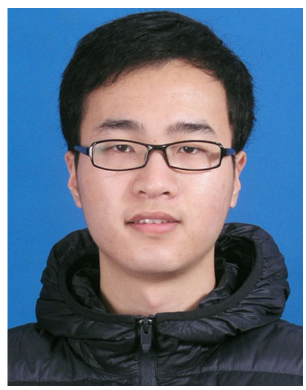

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