Budget-Feasible Sybil-Proof Mechanisms for Crowdsensing

Xiang Liu[1], Weiwei Wu[1(✉)], Wanyuan Wang[1], Yuhang Xu[1], Xiumin Wang[2], and Helei Cui[3]

[1] School of Computer Science and Engineering, Southeast University, Nanjing, China
{xiangliu,weiweiwu,wywang,yuhang_xu}@seu.edu.cn

[2] School of Computer Science and Engineering, South China University of Technology, Guangzhou, China
xmwang@scut.edu.cn

[3] School of Computer Science, Northwestern Polytechnical University, Xi'an 710129, China
chl@nwpu.edu.cn

Abstract. The rapid use of smartphones and devices leads to the development of crowdsensing (CS) systems where a large crowd of participants can take part in performing data collecting tasks in large-scale distributed networks. Participants/users in such systems are usually selfish and have private information, such as costs and identities. Budget-feasible mechanism design, as a sub-field of auction theory, is a useful paradigm for crowdsensing, which naturally formulates the procurement scenario with buyers' budgets being considered and allows the users to bid their private costs. Although the bidding behavior is well-regulated, budget-feasible mechanisms are still vulnerable to the Sybil attack where users may generate multiple fake identities to manipulate the system. Thus, it is vital to provide Sybil-proof budget-feasible mechanisms for crowdsensing. In this paper, we design a budget-feasible incentive mechanism which can guarantee truthfulness and deter Sybil attack. We prove that the proposed mechanism achieves individual rationality, truthfulness, budget feasibility, and Sybil-proofness. Extensive simulation results further validate the efficiency of the proposed mechanism.

Keywords: Crowdsensing · Budget feasibility · Sybil-proofness · Mechanism design · Auction

1 Introduction

The proliferation of smart mobile devices, such as phones, tablets and smartwatch, which are installed with rich sensors (*e.g.*, camera, light sensor, and GPS), has made crowdsensing a new popular economic paradigm which provides the crowd of users with mobile devices chances accomplishing large-scale distributed tasks, like collecting and sharing environmental information. Crowdsensing (CS) systems usually consists of a platform and a collection of users. The platform

M. Li and X. Sun (Eds.): IJTCS-FAW 2022, LNCS 13461, pp. 269–288, 2022.
https://doi.org/10.1007/978-3-031-20796-9_19

acts as a data requester who posts a set of tasks need to be finished and smartphone users provide services by performing assigned tasks. Applications like reCAPTCHA [18], Amazon Mechanical Turks (AMT) and oDesk have made it possible to exploit human resources solving crowdsensing problems.

Most of smartphone users are not voluntary to work on the tasks since they consume their own resources, *e.g.*, battery, computing power, time, cellular data traffic, and expose private information with potential privacy. Furthermore, the system can be more effective with more users' participation. Thus a good incentive mechanism is vitally important to stimulate users to contribute to the platform. Many works [5,9,21,25] model the crowdsourcing/crowdsensing problems as reverse auctions where the requester works as a buyer and the users act as service sellers who bid for performing tasks. Users achieve monetary reward after submitting results of assigned tasks. Auction-based systems often face the strategic scenario where the participants may take strategic behaviors to obtain more utilities, *e.g.*, bidding false private information. Sufficient works thus make the effort to design truthful mechanisms so that users have no incentive to bid dishonestly [4–6,8,12,15,20,21,25]. Apart from false bidding behaviors, there is another kind of strategic behavior called Sybil attack, also known as false-name attack, that users may generate fake identities to manipulate the system for more utilities. The detection methods for Sybil attack have been considered in various research areas such as combinatorial auctions [16,17,24], spectrum auctions [19], and social networks [2]. Unfortunately, Lin *et al.* [10] show that many existing truthful mechanisms in crowdsourcing are vulnerable to Sybil attack, *e.g.*, by taking Sybil attack, users in [5,25] can increase her payment by reporting false information, and the user in [27] can change from a loser to a winner with a positive utility. Lin *et al.* [10] and Zhang *et al.* [26] are the first to propose incentive mechanisms guaranteeing truthfulness and Sybil-proofness in the auction-based crowdsourcing systems.

However, in the procurement scenario, the requester often comes with budget and the designed procurement mechanism should satisfy the budget constraint that the total payment from the requester cannot exceed a given budget. The goal of requester in this scenario is to maximize total value of assigned tasks finished by users within the budget constraint. This problem falls into research of budget-feasible mechanism design problem first studied in [13] which proposes the first budget-feasible truthful mechanism in the procurement scenarios. After that, many works [1,7,14,28] extend the budget-feasible mechanism design into the crowdsourcing systems. Although the truthfulness/bidding behavior is well regulated in these mechanisms, budget-feasible mechanisms in crowdsourcing systems yet consider the Sybil-proofness and are still vulnerable to Sybil attack of users. And existing Sybil-proof mechanisms proposed for the auction-based systems [10,26] also cannot be applied to the procurement scenario as an unlimited payment is even allowed if necessary to elicit the incentive behaviors.

Therefore, in this paper, we focus on designing a budget-feasible Sybil-proof mechanism for CS systems to deter the untruthful bidding behaviors and Sybil attack. The designed mechanism should guarantee various desired properties like, *individual rationality* that the payment to each seller covers at least (but not necessarily equals) her private cost, *budget feasibility* that the total payment of the requester does not exceed her budget, *truthfulness* that no sellers have incentive to bid dishonestly, and *Sybil-proofness* that users cannot increase their utilities by launching Sybil attack. The main contributions of this paper are as follows:

(1) We are the first to address Sybil attack in procurement scenarios for CSs, and propose a corresponding budget-feasible Sybil-proof mechanism, which moves a step forward to robust budget-feasible mechanisms in crowdsensing.
(2) We design a Mechanism TBS (**T**ruthful **B**udget-feasible and **S**ybil-proof mechanism) and prove that the proposed mechanism achieves computational efficiency, individual rationality, truthfulness, budget feasibility and Sybil-proofness.
(3) We evaluate the performance and validate the desired properties by extensive simulations. Furthermore, it shows that the proposed mechanism spends less when procuring fixed value from users than previous Sybil-proof mechanisms, while ensuring the budget feasibility.

The rest of paper is organized as follows. In Sect. 2, we briefly review the works in truthful auctions, budget-feasible mechanisms in crowdsensing and Sybil-proof mechanisms. In Sect. 3, we introduce the system model and problem formulation. We discuss the vulnerability to Sybil attack in traditional budget-feasible mechanisms in Sect. 4. In Sect. 5, we propose a mechanism TBS and prove the desired properties. The performance evaluation is presented in Sect. 6. Finally, we conclude this paper in Sect. 7.

2 Related Work

Many works consider incentive mechanisms in crowdsensing/crowdsourcing systems. Yang *et al.* [21] compute the unique Stackelberg Equilibrium for the platform-centric crowdsensing model and designed truthful mechanism for the user-centric crowdsourcing model. Feng *et al.* [5] further take the location information into consideration when assigning sensing tasks to smartphones. Zhang *et al.* [25] study three models of crowdsourcing which consider the cooperation and competition among the service and propose incentive mechanisms for each of them. Zhu *et al.* [29] design incentive mechanisms based on the combination of a reverse auction and a Vickrey auction to address malicious competition behavior in price bidding. Huang *et al.* [8] design a truthful double auction mechanism which takes max-min fairness into consideration. Cui *et al.* [4] propose an incentive mechanism for task allocation problem in crowdsourcing systems by designing a bid-independent payment calculation scheme.

Budget-feasible mechanism was first studied in [13] which addresses the procurement scenarios where buyers have budgets and the payment scheme should be carefully designed. After that, Singer and Mittal [14] present constant-competitive truthful mechanisms for maximizing the number of tasks under a budget. Some works [7,28] focus on budget-feasible mechanisms in online scenario where users arrive online and the requester wants to select users for maximizing the value of services under a budget constraint. Singla *et al.* [15] use the approach of regret minimization by combining multi-armed bandits to design budget-feasible mechanisms that achieve near-optimal utility for the requester.

Although Sybil attack has been addressed in some auction scenarios, it has rarely been studied in budget-feasible mechanisms. For example, Terada and Yokoo [16] propose a false-name-proof multi-unit auction protocol. The works [4,17,24] focus on truthful and Sybil-proof mechanisms in combinatorial auctions. Wang *et al.* [19] design mechanisms that detect Sybil attack in dynamic spectrum auctions. Brill *et al.* [2] consider Sybil-proofness for users who may manipulate the recommendation by performing a false-name manipulation in social networks. Yao *et al.* [23] propose a novel Sybil attack detection method based on Received Signal Strength Indicator (RSSI) for Vehicular Ad Hoc Networks (VANETs). For crowdsourcing systems, Lin *et al.* [10] and Zhang *et al.* [26] investigate truthful and Sybil-proof mechanisms in auction-based systems. However, these mechanisms do not take into account the budget constraints of requesters, thus cannot be applied to the procurement scenarios in crowdsourcing systems.

In summary, although the bidding behaviors are well regulated, existing budget-feasible mechanisms in crowdsourcing systems are still vulnerable to Sybil attack. Therefore, it is vital to design budget-feasible mechanisms that are robust in truthfulness and Sybil-proofness.

3 Preliminaries

We consider a crowdsensing system that consists of a platform and n users denoted by $u = \{1, 2, \ldots, n\}$. Users may participate in this system to finish crowdsensing tasks. Denote by T_i the task set user i wants to finish. Let $T = \bigcup_{i \in u} T_i$ denote the whole tasks that can be finished by all users. In addition, each task $t_l \in T$ has a value $v_l > 0$ to the platform. The platform gains value v_l when task t_l is completed.

3.1 Reverse Auction Model

We model the interaction between the platform and users as a reverse auction, where the platform acts as a requester/buyer and users serve as sellers. We take into account the procurement scenario in the crowdsensing systems where the requester wants to procure service from users (sellers) within budget $\mathbb{B}$. We assume that each user i has a cost function $c_i(\mathcal{B})$ to show the cost of finishing all tasks in a bundle $\mathcal{B} \subseteq T$. Following the assumption in [10], the cost function $c_i(\cdot)$ of user i satisfies the following properties:

- $c_i(\emptyset) = 0$ and $c_i(\{t_l\}) = \infty, \forall t_l \in T \backslash T_i$;
- $c_i(\mathcal{B}') \leq c_i(\mathcal{B}''), \forall \mathcal{B}', \mathcal{B}'' \subseteq T$ with $\mathcal{B}' \subseteq \mathcal{B}''$;

– $c_i(\mathcal{B}) \leq c_i(\mathcal{B}') + c_i(\mathcal{B}''), \forall \mathcal{B}', \mathcal{B}'' \subseteq T$ and $\mathcal{B} = \mathcal{B}' \cup \mathcal{B}''$.

These four properties characterize the cost of performing tasks in practice.

Meanwhile, we consider the scenario of *incomplete information* auction where only user herself knows her private information, *e.g.*, task sets and cost function. The budget and value function of the requester, as an auctioneer, are common knowledge. Let $(T_i, c_i(\cdot))$ denote the *task-cost pair* of each user i. Initially, all users would bid their costs. In the auction model, we consider the strategic scenario where each user is selfish and rational and she may misreport her cost for more utilities denoted by $\tilde{c}_i \neq c_i$ or her task set denoted by $\tilde{T}_i \neq T_i$. Similarly, let $(\tilde{T}_i, \tilde{c}_i(\cdot))$ denote the reported *task-cost pair* of each user i and $\vec{\beta} = \{(\tilde{T}_1, \tilde{c}_1), (\tilde{T}_i, \tilde{c}_i), \cdots, (\tilde{T}_i, \tilde{c}_i)\}$ denote the bid profile of all users. Specifically, denote by $\vec{\beta}_{-i}$ the bid profile of all users except user i.

After receiving the bids from users, the requester/buyer selects a subset of users $u_w \subseteq u$ called winners and assign each winner $i \in u_w$ a task set $A_i = T_i$ to finish, and, $A_i = \emptyset$ if $i \notin u_w$. Let $\vec{A} = (A_1, A_2, \ldots, A_n)$ denotes the assignment profile. To stimulate users to participate in the auction, the platform gives payment p_i to each winner i. Note that $p_i = 0$ if $i \notin u_w$. Let $\vec{p} = (p_1, p_2, \ldots, p_n)$ denote the payment profile. We further consider the *budget feasibility* on the buyer's side which requires that the total payments paid to the sellers cannot exceed the budget, *i.e.*, $\sum_{i \in u} p_i \leq \mathbb{B}$. We assume that each user is willing to perform only the whole set T_i following the assumption in [10,22]. We thus define user i's *utility* as the payment minus her cost, *i.e.*,

$$u_i((\tilde{T}_i, \tilde{c}_i(\cdot)), \vec{\beta}_{-i}) = \begin{cases} p_i - c_i(T_i), \; if \;\; A_i = T_i \\ \qquad 0, \qquad otherwise \end{cases} \tag{1}$$

The platform adopts value function $\mathcal{V}(\cdot)$ to calculate the total value over a subset of users. We define the utility of platform as total value procured from winners, *i.e.*, $\mathcal{V}(u_w)$, which is the sum of value of all tasks in the union set of assigned task sets of winners, *i.e.*, $u_b = \mathcal{V}(u_w) = V(\cup_{i \in u_w} T_i) = \sum_{t_i \in \cup_{i \in u_w} T_i} v_i$, where function $V(\cdot)$ denotes the sum of value of all tasks in the subset of T. It is easy to show that the value function $\mathcal{V}(\cdot)$ is a monotone submodular function by the following definition.

Definition 1 *(Monotone Submodular Function): Let G be a finite set. For any $X \subseteq Y \subseteq G$ and $x \in G$, a function $f : 2^G \leftarrow R$ is called submodular if and only if $f(X \cup \{x\}) - f(X) \geq f(Y \cup \{x\}) - f(Y)$ and it is monotone (increasing) if and only if $f(X) \leq f(Y)$.*

3.2 Sybil Attack

We further consider the Sybil attack where a user could submit multiple fictitious identities. As a simple case, user i could submit two task-cost pairs $(\tilde{T}_{i'}, \tilde{c}_{i'})$ and $(\tilde{T}_{i''}, \tilde{c}_{i''}))$ under two identities i' and i'', respectively. This case is sufficient to represent the general Sybil attack.

Assume that user i submits $(\tilde{T}_{i'}, \tilde{c}_{i'})$ and $(\tilde{T}_{i''}, \tilde{c}_{i''})$ under two identities i' and i'', where $\tilde{T}_{i'} \cup \tilde{T}_{i''} = T_i$. Let $A_{i'}$ and $A_{i''}$ denote the assigned task set for user i' and i'', respectively. Similarly, denote by $p_{i'}$ and $p_{i''}$ the corresponding payments for them. As user i is willing to perform only the whole set T_i, her utility $\tilde{u}_i$ under Sybil attack will be zero if the union assigned task set among generated identities is not equal to T_i. Thus, $\tilde{u}_i = p_{i'} + p_{i''} - c_i(T_i)$ if $A_{i'} \cup A_{i''} = T_i$ and otherwise $\tilde{u}_i = 0$. When $\tilde{u}_i > u_i$, user i has an incentive to conduct Sybil attack.

3.3 Properties

The goal of this paper is to design a budget-feasible and Sybil-proof mechanism maximizing the utility of platform under the crowdsensing model above and guaranteeing the following desired properties:

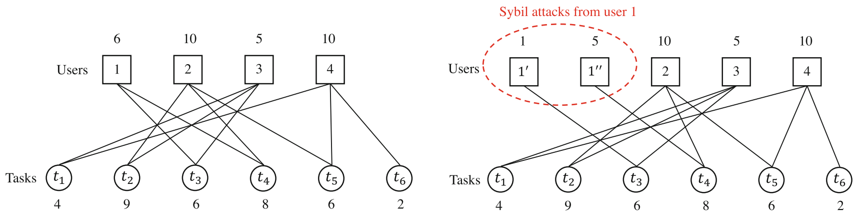
(1) **Individual Rationality:** Each user i has a non-negative utility when bidding her true task-cost pair, *i.e.*, $u_i((T_i, c_i(\cdot)), \vec{\beta}_{-i}) \geq 0$.
(2) **Truthfulness:** Reporting true cost function is user i's dominant strategy, *i.e.*, $u_i((T_i, c_i(\cdot)), \vec{\beta}_{-i}) \geq u_i((\tilde{T}_i, \tilde{c}_i(\cdot)), \vec{\beta}_{-i})$.
(3) **Budget Feasibility:** The total payment cannot exceed the budget of requester, *i.e.*, $\sum_{i \in u} p_i \leq \mathbb{B}$.
(4) **Sybil-proofness:** Any user's utility is maximized when bidding her true task-cost pair using a single identity, *i.e.*, $\tilde{u}_i \leq u_i$.
(5) **Computational Efficiency:** The mechanism terminates in polynomial time.

4 Sybil Attack on Budget-Feasible Mechanisms

In this section, we discuss the vulnerability to Sybil attack in truthful incentive mechanisms. As discussed in Sect. 2, many existing budget-feasible mechanisms do not take into account the threat of Sybil attack. Thus, we present a detailed example showing how Sybil attack increases a dishonest user's utility.

In budget-feasible mechanisms [3,13], the proportional share allocation rule is widely used to generate budget-feasible allocations and elicit the truthfulness. Denoted by m_i or $m_i(S) = \mathcal{V}(S \cup \{i\}) - \mathcal{V}(S)$ the marginal value of a user i with respect to set S, users are sorted according to their non-decreasing order of the cost relative to marginal contributions, *i.e.*, $i + 1 = \text{argmin}_{j \in u} \frac{c_j}{m_j(S_i)}$ where $S_i = \{1, 2, \ldots, i\}$, and selected as winners if $\frac{c_i}{m_i(S_{i-1})} \leq \frac{\mathbb{B}/2}{\mathcal{V}(S_i)}$. In addition, user i in the winner set is rewarded $m_i(S_{i-1}) \cdot \frac{\mathbb{B}}{\mathcal{V}(u_w)}$ to guarantee the truthfulness.

Proportional share allocation rule: (1) Sort all the users according to their non-decreasing costs relative to marginal contribution. (2) Allocate user i to winner set u_w if $\frac{c_i}{m_i(S_{i-1})} \leq \frac{\mathbb{B}/2}{\mathcal{V}(S_i)}$.



(a) Example of budget-feasible mechanisms. (b) Example of Sybil attack in budget-feasible mechanisms.

Fig. 1. Example of the sybil-attack.

Next, we illustrate an example to show Sybil attack in Fig. 1. In this example, we set the budget of the requester (buyer) at $\mathbb{B} = 50$. We use squares to denote users (sellers) while circles represent tasks. The edge between a user and a task means that this task is in this user's task set. Each user owns a task set T_i and the number above user i is her cost for task set T_i. The number below task t_j is her value v_j to the buyer. There are four users $u = \{1, 2, 3, 4\}$, and corresponding task sets: $T_1 = \{t_3, t_4\}, T_2 = \{t_2, t_4, t_5\}, T_3 = \{t_1, t_2, t_3\}, T_4 = \{t_1, t_5, t_6\}$. In addition, their costs are $c_1 = 6, c_2 = 10, c_3 = 5, c_4 = 10$, and the value of these tasks are $v_1 = 4, v_2 = 9, v_3 = 6, v_4 = 8, v_5 = 6, v_6 = 2$, respectively. Let $\mathcal{V}(S) = \sum_{t_j \in \cup_{i \in S} T_i} v_j$ denote the value function given the user subset S.

According to proportional share allocation rule, user 3 with the minimum cost per marginal value $\frac{c_3}{V(T_3)} = \frac{c_3}{v_1+v_2+v_3} = \frac{5}{19} \leq \frac{\mathbb{B}/2}{\mathcal{V}(\{3\})} = \frac{25}{19}$ is first selected as a winner. Then, user 2 with the minimum cost per marginal value among remaining users $\{1, 2, 4\}$ is selected as the second winner, *i.e.*, $\frac{c_2}{V(T_2 \setminus T_3)} = \frac{c_2}{v_4+v_5} = \frac{10}{14} \leq \frac{\mathbb{B}/2}{\mathcal{V}(\{3,2\})} = \frac{25}{33}$. Last, user 4 has the minimum cost per marginal value $\frac{c_4}{V(T_4 \setminus (T_2 \cup T_3))} = \frac{c_4}{v_6} = \frac{10}{2}$, but exceeds the threshold $\frac{\mathbb{B}/2}{\mathcal{V}(\{3,2,4\})} = \frac{25}{35}$. Thus, we have the winner set $\{3, 2\}$. According to the payment scheme, we have the payment $p_1 = 0, p_2 = (v_4 + v_5) \cdot \frac{\mathbb{B}}{\mathcal{V}(\{3,2\})} \approx 21.21, p_3 = (v_1 + v_2 + v_3) \cdot \frac{\mathbb{B}}{\mathcal{V}(\{3,2\})} \approx 28.79, p_4 = 0$. The utilities of these four users are $u_1 = 0, u_2 = 11.21, u_3 = 23.79, u_4 = 0$, respectively.

Now, we assume that user 1 generates two identities: user $1'$ with task set $T_{1'} = \{t_3\}$ and cost $c_{1'} = 1$, and user $1''$ with task set $T_{1''} = \{t_4\}$ and cost $c_{1''} = 5$, as shown in Fig. 1(b).

In such a scenario, user $1'$ is selected as the first winner with the minimum cost per marginal value $\frac{c_{1'}}{v_3} = \frac{1}{6} \leq \frac{\mathbb{B}/2}{\mathcal{V}(\{1'\})} = \frac{25}{6}$. Then, user 3 is selected as the second winner since $\frac{c_3}{v_1+v_2} = \frac{5}{13} \leq \frac{\mathbb{B}/2}{\mathcal{V}(\{1',3\})} = \frac{25}{19}$. After that, user $1''$ is selected as the third winner by $\frac{c_{1'}}{v_4} = \frac{5}{8} \leq \frac{\mathbb{B}/2}{\mathcal{V}(\{1',3,1''\})} = \frac{25}{27}$. Last, user 4 has the minimum cost per marginal value $\frac{c_4}{v_6} = \frac{10}{8}$ which exceeds $\frac{\mathbb{B}/2}{\mathcal{V}(\{1',3,1'',4\})} = \frac{25}{35}$. Thus, we have the winner set $\{1', 3, 1''\}$. According to the payment scheme, we have the payment $p_{1'} = 11.11, p_{1''} = 14.81, p_2 = 0, p_3 = 24.07, p_4 = 0$. The utilities of these four users in this case are $u_1 = 19.92, u_2 = 0, u_3 = 19.07, u_4 = 0$, respectively. Therefore, we can find that user 1 gains higher utility of 19.92 by launching Sybil attack.

This demonstrates that the traditional budget-feasible mechanisms are vulnerable to Sybil attack. We can also find that Sybil attack may impact the auctions from two aspects: First, a user launching Sybil attack may increase her utility, at the cost of effecting the profits of other users, *e.g.*, user 1' utility increases while the utilities of user 2 and 3 decrease when user 1 generates fake identities. This behaviour may hinder the willingness of other users to participate in the system. Second, Sybil attack can also hurt the platform's utility, *e.g.*, the platform can only achieve utility 27 in Fig. 1(b) rather than 33 in Fig. 1(a). Therefore, this motivates us to design an incentive budget-feasible mechanism that is robust against Sybil attack.

5 Mechanism TBS

In this section, we propose a budget-feasible Sybil-proof mechanism **TBS** (**T**ruthful **B**udget-feasible and **S**ybil-proof mechanism).

The main idea of Mechanism TBS is as follows. In order to detect Sybil attack, we first group all the users by the task size and sort all the groups in the decreasing order of their users' task size. Mechanism TBS consists of two phases: winner selection and payment determination. In winner selection scheme, we scan these groups to select winners starting from the group with largest task size. Within each group, we iteratively select the user with the lowest bid per marginal value until the specified threshold set to guarantee budget feasibility and truthfulness is violated. In payment determination scheme, we find a threshold payment, above which bids cannot be selected as winners.

Next, we introduce more details of Mechanism TBS as shown in Algorithm 1. Considering the budget constraint, we use $B = \frac{\mathbb{B}}{2}$ as virtual budget to select winners. We first group all the users by the task size $|T_i|$, *i.e.*, users in the same group have the same task size, and sort these groups in the decreasing order of task size, *i.e.*, $\mathcal{G}_1, \mathcal{G}_2, \ldots, \mathcal{G}_l$, and start from the largest task size group. Assume that we are now considering group $\mathcal{G}_h$. We find the user with the lowest bid per marginal value $i = \text{argmin}_{j \in \mathcal{G}_h} \frac{b_j}{v_j(R_j)}$ where set R_j denotes the union set of all assigned task sets before j and $v_j(R_j)$ denotes the marginal value of user j given the task set R_j, *i.e.*, $v_j(R_j) = V(R_j \cup T_j) - V(R_j)$. Suppose that i is the i-th lowest user in this group. Let q denote the *maximum bid per marginal value* among winners in the previous groups, *i.e.*, $q = \max_{j \in \mathcal{G}_l \cap u_w, \forall l < h} \frac{b_j}{v_j(R_j)}$. User i will be selected as a winner if it satisfies

$$\frac{b_i}{v_i(R_i)} \le \frac{B}{V(R_i \cup T_i)}, q \le \frac{B}{V(R_i \cup T_i)} \tag{2}$$

and

$$b_i \le v_i(R_i), V(R_i) + v_i(R_i) \le \mathbb{B}. \tag{3}$$

Based on the strategies above, the mechanism can control winners' cost per marginal value and elicit the budget-feasibility as well as the Sybil-proofness.

Algorithm 1: Mechanism **TBS**

Input: Sensing task set T, budget $\mathbb{B}$, user set u, bidding profile $\vec{\beta}$.
Output: Assignment profile $\vec{A}$, payment profile $\vec{p}$.

$R \leftarrow \emptyset, q \leftarrow 0, p_i \leftarrow 0, A_i \leftarrow \emptyset, u_w \leftarrow \emptyset$;
Group users by the task set size, and sort these groups according to the decreasing order of task size, *i.e.*, $\mathcal{G}_1, \mathcal{G}_2, ..., \mathcal{G}_l$;
$k \leftarrow 1, q \leftarrow 0, B \leftarrow \mathbb{B}/2,\ q_0 \leftarrow 0, R_0 \leftarrow \emptyset$;
while $k \leq l$ **do**
  // **Winner Selection**;
  $\mathcal{G}' \leftarrow \mathcal{G}_k,\ i \leftarrow \text{argmax}_{j \in \mathcal{G}'} \frac{b_j}{v_j(R)}$;
  while $\frac{b_i}{v_i(R)} \leq \frac{B}{V(R \cup T_i)}$ **and** $q \leq \frac{B}{V(R \cup T_i)}$ **and** $b_i \leq v_i(R)$ **and** $\mathcal{V}(R) \leq \mathbb{B}$ **and** $\mathcal{G}' \neq \emptyset$ **do**
    $\mathcal{G}' \leftarrow \mathcal{G}' \setminus \{i\}, q \leftarrow \max\{q, \frac{b_i}{v_i(R)}\},\ A_i \leftarrow T_i, R \leftarrow R \cup T_i, u_w \leftarrow u_w \cup \{i\}$;
    $i \leftarrow \text{argmax}_{j \in \mathcal{G}'} \frac{b_j}{v_j(R)}$;
  end
  $q_k \leftarrow q, R_k \leftarrow R$
  // **Payment Determination**;
  for $i \in \mathcal{G}_k, A_i \neq \emptyset$ **do**
    $\mathcal{G}' \leftarrow \mathcal{G}' \setminus \{i\}, R' \leftarrow R_{k-1}, q' \leftarrow q_{k-1}$;
    $i_j \leftarrow \text{argmax}_{j \in \mathcal{G}'} \frac{b_j}{v_j(R)}$;
    while $\frac{b_{i_j}}{v_{i_j}(R')} \leq \frac{B}{V(R' \cup T_{i_j})}$ **and** $q' \leq \frac{B}{V(R' \cup T_{i_j})}$ **and** $b_{i_j} \leq v_{i_j}(R')$ **and** $V(R') \leq \mathbb{B}$ **and** $\mathcal{G}' \neq \emptyset$ **do**
      $p_i \leftarrow \max\{p_i, \min\{v_i(R') \cdot \min\{\frac{b_{i_j}}{v_{i_j}(R')}, \frac{B}{V(R' \cup T_i)}\}, v_i(R')\}\}$;
      $\mathcal{G}' \leftarrow \mathcal{G}' \setminus \{i\}, q' \leftarrow \max\{q', \frac{b_i}{v_i(R')}\},\ R' \leftarrow R' \cup T_{i_j}$;
      $i_j \leftarrow \text{argmax}_{j \in \mathcal{G}'} \frac{b_j}{v_j(R')}$;
    end
  end
  $k \leftarrow k + 1$;
end
return $u_w, \vec{A}, \vec{p}$

The process repeats until the bid per marginal value of user $\frac{b_i}{v_i(R_i)}$ or the value of q exceeds the threshold $\frac{B}{V(R_i \cup T_i)}$, or the total value is higher than the budget in this group $V(R_i) + v_i(R_i) > \mathbb{B}$, or user's submitted cost is higher than the marginal value $b_i > v_i(R_i)$.

Then we calculate the payment p_i for each winner i in this group $\mathcal{G}_h$. Following the general rule in [11,13], to elicit the truthfulness, the payment should be set as the *threshold payment* by bidding which the winner can replace one of the virtual winners as the winner. Thus, to find the threshold payment, we select virtual winners from the same group without the winner herself using the same winner selection scheme as follow. Given users $\mathcal{G}_h \setminus \{i\}$, we similarly execute the winner selection scheme to select new virtual winning users denoted by $u^h_{w,-i}$ and we assume that $|u^h_{w,-i}| = K_i$. Let i_j denote the selected user in the j-th iteration. User i can be selected as a winner instead of user i_j when her reported cost $\tilde{c}_i(T_i)$ satisfies:

$$\frac{\tilde{c}_i(T_i)}{v_i(R_{i_j})} \leq \frac{b_{i_j}}{v_{i_j}(R_{i_j})}, \frac{\tilde{c}_i(T_i)}{v_i(R_{i_j})} \leq \frac{B}{V(R_{i_j} \cup T_i)}, \tilde{c}_i(T_i) \leq v_i(R_{i_j}), \tag{4}$$

simultaneously. Thus, to replace the virtual winner $i_j \in u^h_{w,-i}$, the bid of user i is at most the minimum of three values: $\theta_{i(j)} = \min\{\delta_{i(j)}, \rho_{i(j)}, v_i(R_{i_j})\}$ where $\delta_{i(j)} = v_i(R_{i_j}) \cdot \frac{b_{i_j}}{v_{i_j}(R_{i_j})}$ and $\rho_{i(j)} = v_i(R_{i_j}) \cdot \frac{B}{V(R_{i_j} \cup T_i)}$. Moreover, we have K_i bids since the size of set $u^h_{w,-i}$ is K_i and the last virtual winner is i_{K_i}. To replace one of these virtual winners, user i should report at most the maximum among these values and the marginal value of user i after K_i iteration:

$$p_i = \max\left\{\max_{i_j \in u^h_{w,-i}} \theta_{i(j)}, v_i(R_{i_{K_i}} \cup T_{i_{K_i}})\right\} \tag{5}$$

which will be set as the final payment for winner i in this group.

After considering the current group, we process the next group $\mathcal{G}_{h+1}$. This will repeat until no users can be selected as winners.

5.1 Theoretical Analysis on Desired Properties

Next, we analyze the properties of mechanism TBS.

Lemma 1. *Mechanism TBS is computationally efficient.*

Proof. The running time of Mechanism TBS is dominated by the loop in the winner selection phase (lines 8–12) and payment determination phase (lines 18–31). In the winner selection process, the running time is at most $O(n^2)$ because finding the minimum price-per-value user will take $O(n)$ time and the number of winners is at most n. In the payment scheme phase, the running time is $O(n^3)$ since the select scheme will be executed n times. Therefore, the total computational complexity of Mechanism TBS is $O(n^4)$ since at most n groups need to be processed.

Lemma 2. *Mechanism TBS is individually rational.*

Proof. To simplify the notation, we neglect the label of group and let user i denote the i-th winner in group $\mathcal{G}_h$. Recall that user i_j is the j-th virtual winner in payment determination phase which selects virtual winners by excluding user i herself. We assume that the order of virtual winners in the payment determination phase is $i_1, i_2, \ldots, i_{[i]}, \ldots, i_{K_i}$ where $[i]$ denotes the place where user i should be selected in the winner selection phase if it was involved. It is obvious that previous $i-1$ sellers, *i.e.*, from i_1 to $i_{[i]-1}$, are still selected as winners in the winner selection phase. According to (2), we have

$$\begin{cases} \frac{c_i}{v_i(R_i)} \leq \frac{B}{V(R_i \cup \{T_i\})} \\ c_i \leq v_i(R_i) \end{cases} \tag{6}$$

since user i is the winner in the truthful case. For the virtual winner $i_{[i]}$, we have

$$\frac{c_i}{v_i(R_i)} \leq \frac{c_{i_{[i]}}}{v_{i_{[i]}}(R_{i_{[i]}})} \tag{7}$$

since user i is selected as winner rather than user $i_{[i]}$ in the winner selection phase. Recall that $\delta_{i_{[i]}} = v_i(R_{i_{[i]}}) \cdot \frac{c_{i_{[i]}}}{v_{i_{[i]}}(R_{i_{[i]}})}$ and $\rho_{i_{[i]}} = v_i(R_{i_{[i]}}) \cdot \frac{B}{V(R_{i_{[i]}} \cup \{T_i\})}$. By combining (6) and (7), we have

$$\begin{cases} c_i \leq \frac{v_i(R_i) \cdot c_{i_{[i]}}}{v_{i_{[i]}}(R_i)} = \frac{v_i(R_{i_{[i]}}) \cdot c_{i_{[i]}}}{v_{i_{[i]}}(R_{i_{[i]}})} = \delta_{i_{[i]}} \\ c_i \leq \frac{v_i(R_i) \cdot B}{V(R_i \cup T_i)} = \frac{v_i(R_{i_{[i]}}) \cdot B}{V(R_{i_{[i]}} \cup T_i)} = \rho_{i_{[i]}} \\ c_i \leq v_i(R_i) = v_i(R_{i_{[i]}}). \end{cases}$$

Thus, it is obvious that $c_i \leq \theta_{i([i])}$. According to Eq. (5), we have $p_i \geq \max \theta_{i(j)} \geq \theta_{i([i])} \geq c_i$. Therefore, TBS guarantees the individual rationality.

Before analyzing Mechanism TBS's truthfulness, we first introduce a general rule for verifying truthfulness:

Theorem 1 *(Monotone theorem, [11,13]). In single parameter domains, an auction mechanism is truthful iff:*

- *The selection rule is monotone: If user i wins the auction by bidding b_i, it also wins by bidding $b_i' \leq b_i$;*
- *Each winner is paid the critical value, which is the smallest value such that user i would lose the auction if it bids higher than this value.*

Lemma 3. *Mechanism TBS is truthful.*

Proof. We first prove that user i cannot improve her utility by submitting a false task set. We assume that user i submits a false task set $\tilde{T}_i \neq T_i$. If $\tilde{T}_i \subset T_i$, the utility of i is zero according to Eq. (1). If $T_i \subset \tilde{T}_i$, user i can not finish all the tasks as a winner, thus fails to get payment. Therefore, users have to submit her true task set for utility maximization.

Next, we prove that user i cannot improve her utility by bidding a false cost. Following the general rule in Theorem 1, we show that the designed mechanism is monotone and the payment to each winning seller is the critical value.

Monotonicity: Assume that a winner user i in group $\mathcal{G}_h$ bids a lower cost $b_i' < c_i$. Since user i is a winner, we have

$$\begin{cases} \frac{c_i}{v_i(R_i)} \leq \frac{B}{V(R_i \cup T_i)} \\ q \leq \frac{B}{V(R_i \cup T_i)} \\ c_i \leq v_i(R_i) \end{cases} \tag{8}$$

Suppose that user i converts to the j-th ($j < i$) lowest price per marginal value after bidding the lower bid. Recall that R_i denotes the total value of winners before user i. It is obvious that the total value of winners before i and j satisfies $R_j \leq R_i$. Thus, we have $\frac{b_i'}{v_i(R_j)} \leq \frac{c_i}{v_i(R_i)}$ due to $b_i' \leq c_i \leq v_i(R_i) \leq v_i(R_j)$. In addition, we have $\frac{b_i'}{v_i(R_j)} \leq \frac{B}{V(R_j \cup T_i)}$ since $\frac{c_i}{v_i(R_i)} \leq \frac{B}{V(R_i \cup T_i)} \leq \frac{B}{V(R_j \cup T_i)}$. Additionally, note that $q \leq \frac{B}{V(R_i \cup T_i)} \leq \frac{B}{V(R_j \cup T_i)}$. According to (2) and (3), user i is still selected as a winner. Thus, mechanism guarantees monotonicity.

Threshold Payments: Now we consider each winner's payment. Assume that user i_{K_i} is the last winner in the payment determination scheme which processes the users without i herself. Recall that

$$p_i = \max\left\{\max_{1 \leq j \leq K_i}\{\theta_{i(j)}\}, v_i(R_{i_{K_i}} \cup T_{i_{K_i}})\right\} \tag{9}$$

If user i bids a higher cost $b_i > p_i$, we have $b_i > \max_{1 \leq j \leq K_i}\{\theta_{i(j)}\}$ which means that user i will not be selected as a winner before K_i iterations in this group. We also have $p_i > v_i(R_{i_K} \cup T_{i_{K_i}})$, thus i will not be selected after K_i iterations since any user will not be selected as winners if her bid is higher than it marginal value due to (3). Thus, p_i is the threshold payment and any winner will not be selected as winner if her bid is higher than the payment p_i. Therefore, users have no incentive to submit false bid.

In summary, no sellers can increase her utility by submitting a false task-cost pair. Therefore, Mechanism TBS guarantees truthfulness.

Before starting to consider budget feasibility, we first introduce a useful lemma inspired by [3].

Lemma 4. *Consider any set* $S \subset T \subseteq \mathcal{G}_h$ *in one group and* $i = \operatorname{argmin}_{j \in T \setminus S} \frac{c_j}{v_j(S)}$. *Then*

$$\frac{c(T) - c(S)}{V(T) - V(S)} \geq \frac{c_i}{v_i(S)}. \tag{10}$$

Proof. Assume that $\frac{c(T)-c(S)}{V(T)-V(S)} < \frac{c_i}{v_i(S)}$ which implies $\frac{c(T)-c(S)}{V(T)-V(S)} < \frac{c_t}{v_t(S)}$ for any $t \in T \setminus S$. After adding all inequalities, we have

$$\begin{aligned} \frac{c(T) - c(S)}{V(T) - V(S)} &< \frac{\sum_{t \in T \setminus S} c_t}{\sum_{t \in T \setminus S} v_t(S)} \\ &= \frac{c(T) - c(S)}{\sum_{t \in T \setminus S} v_t(S)} \end{aligned}$$

which means $V(T) - V(S) > \sum_{t \in T \setminus S} v_t(S)$ contradicting to the submodularity.

Lemma 5. *Mechanism TBS is budget-feasible.*

Proof. We prove the budget feasibility by showing that Mechanism TBS satisfies two properties: $\sum_{i \in u_w} \max_{1 \leq j \leq K} \theta_{i(j)} \leq \mathbb{B}$ and $\sum_{i \in u_w} v_i(R_{i_{K_i}} \cup T_{i_{K_i}}) \leq \mathbb{B}$. Assume that user K in group k is the last winner in mechanism TBS. We focus on payment determination phase and let i_j denote j-th user in the group $e(e \leq k)$ without user i. We consider two cases:

(1) Consider $\theta_{i(j)}$: Recall that $\theta_{i(j)} = \min\{\delta_{i(j)}, \rho_{i(j)}, v_i(R_{i_j})\}$ and $\delta_{i(j)} = v_i(R_{i_j}) \cdot \frac{c_{i_j}}{v_{i_j}(R_{i_j})}$. For each user $i_j < i_{[i]}$, we have $\frac{c_{i_j}}{v_{i_j}(R_{i_j})} \leq \frac{c_i}{v_i(R_{i_j})}$ since user i_j is selected as winner instead of user i. Thus $\delta_{i(j)} \leq c_i$ which means $\theta_{i(j)} \leq c_i$.

In group $\mathcal{G}_h$, for each user $i_j \geq i_{[i]}$, we assume that the set of winners we have chosen before i_j is $\mathcal{S}$. Suppose user i replaces i_j as a winner by bidding $\theta_{i(j)}$. Thus we have $\mathcal{S} \cup \{i\} \subset u_w \cup \mathcal{S}$. In addition, we have

$$\frac{\theta_{i_j}}{v_i(\mathcal{S})} \leq \frac{c(u_w \cup \mathcal{S}) - c(\mathcal{S} \cup \{i\})}{V(u_w \cup \mathcal{S}) - V(\mathcal{S} \cup \{i\})} \tag{11}$$

Recall that $\frac{c_i}{v_i(R_i)} \leq \frac{B}{V(u_w)}$ which means that $\sum_{i \in u_w} c_i \leq B$. Thus, we have

$$\begin{aligned} \frac{V(u_w) - V(\mathcal{S} \cup \{i\})}{B} &\leq \frac{V(u_w) - V(\mathcal{S} \cup \{i\})}{\sum_{i \in u_w} c_i} \\ &\leq \frac{V(u_w \cup \mathcal{S}) - V(\mathcal{S} \cup \{i\})}{c(u_w \cup \mathcal{S}) - c(\mathcal{S} \cup \{i\})} \end{aligned} \tag{12}$$

Assume that $\theta_{i(j)} > v_i(R_i) \cdot \frac{\mathbb{B}}{V(u_w)}$, we have

$$\frac{v_i(\mathcal{S})}{\theta_{i(j)}} < \frac{v_i(\mathcal{S})}{v_i(R_i)} \cdot \frac{V(u_w)}{\mathbb{B}} \leq \frac{V(u_w)}{\mathbb{B}} \tag{13}$$

where the second inequality is due to $R_i \subseteq \mathcal{S}$. By combining (11) and (13), we have

$$\frac{\mathbb{B}}{V(u_w)} < \frac{c(u_w \cup \mathcal{S}) - c(\mathcal{S} \cup \{j\})}{V(u_w \cup \mathcal{S}) - V(\mathcal{S} \cup \{j\})} \tag{14}$$

According to (12) and (14), we have $V(u_w) < 2V(\mathcal{S} \cup \{i\})$ due to $\mathbb{B} = 2B$. However, since $\frac{b_{i_j}}{v_{i_j}(R_{i_j})} \leq \frac{B}{V(\mathcal{S} \cup \{i_j\})}$, we have

$$\begin{aligned} \theta_{i(j)} \leq \delta_{i(j)} = \frac{v_i(R_{i_j}) \cdot b_{i_j}}{v_{i_j}(R_{i_j})} &\leq \frac{v_i(R_{i_j}) \cdot B}{V(\mathcal{S} \cup \{i_j\})} \\ &\leq v_i(R_i) \cdot \frac{\mathbb{B}}{V(u_w)} \end{aligned} \tag{15}$$

which contradicts to the assumption $\theta_{i(j)} > v_i(R_i) \cdot \frac{B}{V(u_w)}$. Thus, we have $\theta_{i(j)} \leq v_i(R_i) \cdot \frac{\mathbb{B}}{V(u_w)}$.

(2) Consider $v_i(R_{i_K})$: It is obvious that $v_i(R_{i_K}) \leq v_i(R_i)$. Thus, we have $v_i(R_{i_K}) \leq v_i(R_i) \leq v_i(R_i) \cdot \frac{\mathbb{B}}{V(u_w)}$ since $V(u_w) \leq \mathbb{B}$ due to (3).

Therefore, Mechanism TBS guarantees budget feasibility.

Before proving Sybil-proofness of Mechanism TBS, we introduce the following general rules introduced by [10]:

Theorem 2. *A mechanism is Sybil-proof if it satisfies the following two conditions:*

- *If any user i pretends two identities i' and i'', and both i' and i'' are selected as winners, then i should be selected as a winner while using only one identity;*
- *If any user i pretends two identities i' and i'', the payment to i should not be less than the summation of the payments to i' and i''.*

Lemma 6. *Mechanism TBS is Sybil-proof.*

Proof. We first prove TBS satisfies the first condition. Assume that user i generate two identities i' and i'' which implies that $T_{i'} \subset T_i$ and $T_{i''} \subset T_i$, and both of them are selected as winners. Let $\mathcal{R}', \mathcal{R}''$ denote the union assigned task set before i', i'' are selected as winners respectively. Similarly, denote by $\mathcal{R}$ the union assigned task set before user i is selected as the winner. W.l.o.g, suppose the group of i' is ahead of the group of i''. Since user i' and i'' are all winners, according to conditions of being winners in (2) and (3), we have

$$b_{i'} \leq v_{i'}(\mathcal{R}'), b_{i''} \leq v_{i''}(\mathcal{R}'') \tag{16}$$

and

$$\begin{aligned} \frac{b_{i'}}{v_{i'}(\mathcal{R}')} &\leq \frac{B}{V(\mathcal{R}' \cup T_{i'})} \\ \frac{b_{i''}}{v_{i''}(\mathcal{R}'')} &\leq \frac{B}{V(\mathcal{R}'' \cup T_{i''})} \\ \frac{b_{i'}}{v_{i'}(\mathcal{R}')} &\leq \frac{B}{V(\mathcal{R}'' \cup T_{i''})} \end{aligned} \tag{17}$$

where the reason for the third inequality is that the maximum bid per marginal value q among winners before i'' is higher than $\frac{b_{i'}}{v_{i'}(\mathcal{R}')}$ and it must be not higher than the current average price-per-value $\frac{B}{V(\mathcal{R}'' \cup T_{i''})}$ according to the selection rule (2). Also note that

$$v_{i'}(\mathcal{R}') \leq v_{i'}(\mathcal{R}), v_{i''}(\mathcal{R}'') \leq v_{i''}(\mathcal{R}) \tag{18}$$

since the groups of user i', i'' will follow the groups of user i. Combining (16) and (18), we have

$$\begin{aligned} b_i = c_i \leq c_{i'} + c_{i''} &= b_{i'} + b_{i''} \\ &\leq v_{i'}(\mathcal{R}') + v_{i''}(\mathcal{R}'') \\ &\leq v_{i'}(\mathcal{R}) + v_{i''}(\mathcal{R}) \\ &\leq v_i(\mathcal{R}) \end{aligned} \tag{19}$$

where the reason for the first and last inequality is because $T_i = T_{i'} \cup T_{i''}$. By combining (17) and (19), it holds that

$$\begin{aligned} \frac{c_i}{v_i(\mathcal{R})} &\leq \frac{b_{i'} + b_{i''}}{v_{i'}(\mathcal{R}') + v_{i''}(\mathcal{R}'')} \leq \frac{B}{V(\mathcal{R}'' \cup T_{i''})} \\ &\leq \frac{B}{V(R \cup T_i)}. \end{aligned} \tag{20}$$

Thus user i will still be selected as a winner without generating multiple identities.

Next, we consider the second condition. It is obvious that the payment of user i is at least $v_i(R_{i_{K_i}})$ according to (5). Recall that the order of winning seller in the payment determination phase is $i_1, i_2, \ldots, i_{[i]}, \ldots, i_{K_i}$ and $[i]$ denotes the place where user i should be selected in the winner selection phase if it was involved. Thus, we have $b_{i_j} \leq v_{i_j}(R_{i_j})$ where i_j is selected in K_i iterations. For the user after $i_{[i]}$, we have $\min\{\delta_{i(r)}, \rho_{i(r)}, v_i(R_{i_r})\} \leq v_i(R_{i_r}) \leq v_i(R_i)$ where $i_r \geq i_{[i]}$. For the user i_j before $i_{[i]}$, we have

$$\begin{aligned} \min\{\delta_{i(j)}, \rho_{i(j)}, v_i(R_{i_r})\} \leq \delta_{i(j)} &= v_i(R_{i_j}) \cdot \frac{b_{i_j}}{v_{i_j}(R_{i_j})} \\ &\leq v_i(R_{i_j}) \cdot \frac{b_i}{v_i(R_{i_j})} = b_i \\ &\leq v_i(R_i) \end{aligned} \tag{21}$$

where the reason for the second inequality is that user i_j is selected as winner instead of user i. Furthermore, after K_i iterations, we have $v_i(\mathcal{R}_{K_i}) \leq v_i(R_i)$. Hence, we have $p_i \leq v_i(R_i)$. Similarly, we have $p_{i'} \leq v_{i'}(R_{i'})$ and $p_{i''} \leq v_{i''}(R_{i''})$. Thus we have

$$\begin{aligned} p_{i'} + p_{i''} &\leq v_{i'}(R_{i'}) + v_{i''}(R_{i''}) \\ &\leq v_{i'}(\mathcal{R}_{i_{k'}}) + v_{i'}(\mathcal{R}_{i_{k'}}) \\ &\leq v_i(\mathcal{R}_{i_{K'}}) \leq p_i \end{aligned} \tag{22}$$

Hence, the second condition is satisfied.

Therefore, Mechanism TBS guarantees Sybil-proofness.

6 Performance Evaluation

In this section, we conduct extensive simulations to validate the performance of Mechanism TBS. We first verify the desired properties (truthfulness and robustness against Sybil attack) of Mechanism TBS. Then, we validate the performance of Mechanism TBS in terms of various optimization metrics, *e.g.*, *payment* (the payment for target value), *platform utility* (the total value procured from users), and *average user utility* (the sum of users' utilities over the number of sellers). Under these metrics, we take the Sybil-proof Mechanism SPIM-S proposed in [10] as the benchmark algorithm. Although Mechanism SPIM-S cannot work in the procurement scenario with budget constraint, we can achieve the comparison by enumerating the inputs of Mechanism SPIM-S.

Simulation Setup. In our evaluation, we assume that the task size of each user is uniformly distributed over [1, 5], and value of each task is uniformly distributed over [1, 20]. The users' costs for each task is uniformly distributed over [1,10]. In default, we set the number of users, the number of tasks and budget at 150, 200 and 200, respectively. To evaluate the impact of number of total users on the performance of platform utility and average user utility, we

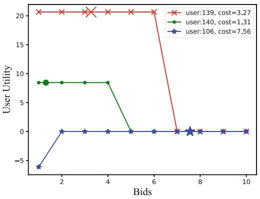


Fig. 2. The impact of untruthful bids on TBS.

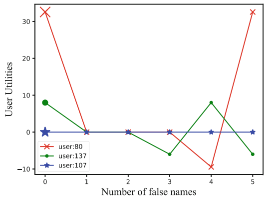


Fig. 3. The impact of Sybil attack on TBS.

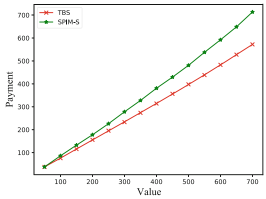


Fig. 4. The impact of Sybil attack on TBS.

vary the number of users from 40 to 140 with the increment of 20. Similarly, to evaluate the impact of number of total tasks on the performance of platform utility and average user utility, we let the number of tasks vary from 80 to 200 in increment of 20. Furthermore, to evaluate the impact of total budget on the performance of platform utility and average user utility, we change the budget from 120 to 400 with the increment of 40. All the results are averaged over 100 instances.

6.1 Evaluation of Desired Properties

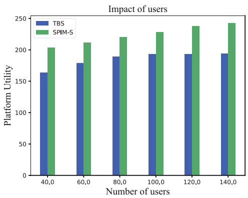
The properties like individual rationality and budget feasibility of Mechanism TBS can be easily verified. In this part, we mainly validate the truthfulness and Sybil-proofness of Mechanism TBS by letting users submit false bids or launch Sybil attack unilaterally, and monitoring the corresponding utilities. In the simulation, we fix the number of tasks at 150 and the number of users at 200, respectively.

Figure 2 shows the impact of (untruthful) bids on user utilities for Mechanism TBS. To validate truthfulness, we let each of these users unilaterally change her bid in $[1, 10]$. We randomly select three users: 139, 140, and 106 of TBS. User 106 is a loser with real cost 7.56 while users 139 and 140 are winners with real costs 3.27 and 1.31, respectively. Specifically, in Fig. 2, we use larger markers to indicate the utilities for truthful bids and the smaller ones to indicate those of untruthful bids. We observe that these users cannot achieve more utilities after bidding false costs, *e.g.*, user 139 obtains less utilities if her bid is not equal to her real cost 3.27. Therefore, users obtain the maximum utility when bidding real cost, which validates the truthfulness of Mechanism TBS.

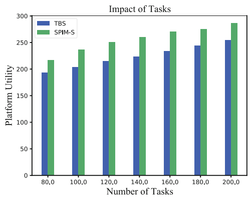
Figure 3 shows the impact of Sybil attack on user utilities of Mechanism TBS. To validate Sybil-proofness, we let each of these users create up to 5 false names. For each false name, the submitted task set is a subset of the submitted tasks of the user. We select three users: 80, 137, and 107 of TBS. User 80 and 137 are winners while user 107 is a loser. Moreover, in Fig. 3, we also use larger markers to indicate the utilities when users do not launch Sybil attack. We observe that these users achieve the highest utilities without generating fake identities, *e.g.*, user 137 obtains less utilities after creating more false names. Therefore, a user cannot increase her utility by unilaterally launching Sybil attack which validates the Sybil-proofness of Mechanism TBS.

6.2 Evaluation of Optimization Metrics

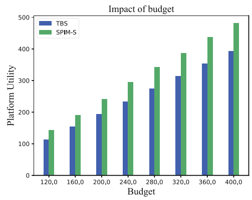
Next, we compare Mechanism TBS with Mechanism SPIM-S using aforementioned metrics. Since Mechanism SPIM-S actually cannot be applied to procurement scenarios with budget constraint, we use enumeration method when conducting the comparison. Specifically, to evaluate the platform utility and average user utility, we enumerate the possible outputs of SPIM-S by running multiple rounds of auctions to find the one that uses up the given budget. To evaluate the payment, we enumerate possible outputs until a target total value is procured.



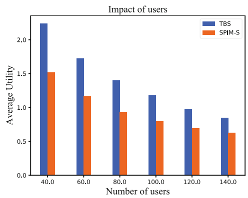
(a) Impact of users on platform utility



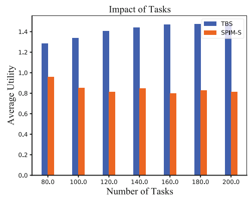
(b) Impact of tasks on platform utility



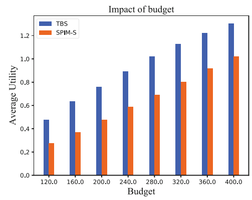
(c) Impact of budgets on platform utility



(d) Impact of users on average user utility



(e) Impact of tasks on average user utility



(f) Impact of budgets on average user utility

Fig. 5. (a)–(c) show the impact of users, tasks and budget on platform utility, while (d)–(f) on average user utility.

Evaluation of Platform Utility. The top part of Fig. 5 shows the impact of users, tasks and budget on platform utility for Mechanism TBS and Mechanism SPIM-S. In Fig. 5(a), Fig. 5(b) and Fig. 5(c), we see that while preserving the budget feasibility, Mechanism TBS can achieve similar platform utility to that of the Mechanism SPIM-S. This demonstrates that a small loss of overall platform utility might be needed to guarantee budget constraint in the procurement scenario. Furthermore, in both Fig. 5(a) and Fig. 5(b), the platform utility increases in all these two mechanisms. The respective reasons are that competition among users has become more fierce which leads to more users with lower costs being winners, and more users can be selected as winners with increments of tasks. However, as a constant budget is set in the experiment, the platform utility is growing slowly in both figures. In addition, the platform utility grows steadily with the increments of budget as shown in Fig. 5(c).

Evaluation of Average User Utility. The bottom part of Fig. 5 shows the performance of user average utility, defined as the total utilities of all uses over the number of users, for Mechanism TBS, and Mechanism SPIM-S. In Fig. 5(d), Fig. 5(e) and Fig. 5(f), we can see that the average user utility of Mechanism TBS is higher than Mechanism SPIM-S. This is because TBS can select the user with smaller cost which improves winner's utility. As shown in Fig. 5(d) and Fig. 5(f), average user utility decreases as the number of users increases, while it rises as budgets increase. This is because 1) as the number of users increases the competition among users become more fierce resulting in lower payments, 2) as budget increases more users can participate in the system.

Evaluation of Payment. Figure 4 compares payments at various target values. We fix the number of tasks and the number of users at 150 and 200, respectively, and set budget at 600 for Mechanism TBS. We vary the target value from 50 to 700 with increment of 50. We can see that Mechanism SPIM-S spends higher payments when procuring the same value from users than Mechanism TBS. The reason is Mechanism TBS considers each user's cost per marginal value below the defined threshold in the selection phase, while Mechanism SPIM-S only considers the costs which may lead to a user with higher cost per marginal value also being selected as a winner, and further result in a increment of total payment. Therefore, our proposed mechanism will spend less for unit value while guaranteeing budget-feasibility.

In summary, our proposed Mechanism TBS can guarantee budget feasibility, truthfulness and Sybil-proofness. More importantly, it spends less on procuring a target value than previous Sybil-proof mechanisms.

7 Conclusion

In this paper, we study Sybil-proof and budget-feasible incentive mechanisms for crowdsensing systems. We design an incentive mechanism TBS and prove that the designed mechanism guarantees the individual rationality, truthfulness, budget-feasibility and Sybil-proofness. We validate the desired properties of the designed mechanism through extensive simulations.

Acknowledgements. The work is supported in part by the National Key Research and Development Program of China under grant No. 2019YFB2102200, National Natural Science Foundation of China under Grant No. 61672154, 61672370, 61972086 and the Postgraduate Research & Practice Innovation Program of Jiangsu Province under grant No. KYCX19_0089.

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