Incentive Mechanisms for Crowdsensing: Motivating Users to Preprocess Data for the Crowdsourcer

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Crowdsensing is a popular method that leverages a crowd of sensor users to collect data. For many crowdsensing applications, the collected raw data need to be preprocessed before further analysis, and the preprocessing work is mainly done by the crowdsourcer. However, as the amount of collected data increases, this type of preprocessing approach has many disadvantages. In this article, we construct monetary-based incentive mechanisms to motivate users to preprocess the collected raw data for the crowdsourcer. For two common crowdsensing scenarios, we propose two system models, which are the single-task-multiple-participants (STMP) model and the multiple-tasks-multiple-participants (MTMP) model. In the STMP model, we design an incentive mechanism based on game theory and prove that there is a Nash equilibrium. In the MTMP model, we develop an incentive mechanism based on an auction and demonstrate that the incentive mechanism has the desirable properties of truthfulness, individual rationality, profitability, and computational efficiency. Furthermore, the utility maximization problems of the crowdsourcer and users are simultaneously considered in our incentive mechanisms. Through theoretical analysis and extensive experiments, we evaluate the performance of our incentive mechanisms.

CCS Concepts: • **Human-centered computing** → **Mobile computing**; • **Networks** → *Mobile networks*;

Additional Key Words and Phrases: Crowdsensing, efficiency, incentive mechanism, utility

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1 INTRODUCTION

Crowdsensing is a product of the development of the Internet of Things (IoT) [48], and it includes the properties of flexibility, wide coverage, and scalability. Due to the great characteristics of crowdsensing, various applications have been designed [22], such as collecting healthy data [3, 9], sensing environment information [15, 25, 28], and monitoring traffic flows [36, 37, 39].

Many crowdsensing applications can directly analyze the collected raw data without any preprocessing, such as noise monitoring [35] and Wi-Fi measurement [8]. However, other crowdsensing applications, due to their own needs and the nature of the raw data, cannot directly consume the collected raw data [24]. Therefore, before further analysis, preprocessing, such as the filtering and denoising of the collected raw data, needs to be performed.

As mentioned in Reference [1], the preprocessing work is mainly completed by the crowdsourcer, i.e., the cloud or edge server, as shown in Figure 1. However, with the explosive growth of data in various industries [27], this type of preprocessing will face many challenges. First, a large amount of raw data will overwhelm the storage space of the crowdsourcer. Second, a large amount of redundant data will consume the bandwidth, which can cause network congestion. Finally, for delay-sensitive applications, crowdsourcers with limited computing power may not complete the data analysis in time, thereby affecting people's experiences.

For example, in Reference [23], the authors mentioned that many crowdsenisng-based multimedia applications require a lot of resources in terms of transmission bandwidth, computing power, and storage resources, such as the Twitch TV platform, which attracts over 44M visitors per month and every second its servers are loaded with thousands of live channels, which means large-scale resources are needed to handle online video synchronization, processing, and transcoding; even though the cloud-computing technology has been applied by crowdsourcers, however, simultaneous bursts of multimedia data access, processing, and transmissions in the cloud may cause bottlenecks, which have been highlighted in Reference [2] using real-world measurement.

In view of the above situation, and considering the popularization and enhancement of intelligent sensing devices, in this article, we construct monetary-based incentive mechanisms to motivate users to preprocess the collected raw data for the crowdsourcer. In this way, the crowdsensing system can reduce the workload of the crowdsourcer, lower the transmission energy costs, and improve the efficiency. Especially with the development of 5G and the pervasion and enhancement of mobile devices, users' computing power should receive more attention in crowdsensing systems.

For instance, in the crowdsensing-based automatic recognition system of human activities [5, 45]. To train a machine learning model for human activity recognition, if users only do the work of data collection and submission, then all the remaining work should be done by the crowdsourcer, such as the classification, annotation, and model training. Therefore, when the computing power and storage space of the crowdsourcer are limited, massive data from different sources and formats will complicate classification and annotation, thus affecting the efficiency of the system. Thereby, the model cannot be updated in time, which reduces the accuracy of recognition. If we can motivate users to classify the collected data and do some annotation work in advance, the workload of the crowdsourcer can be relieved and the efficiency of the crowdsensing system will be significantly improved. Moreover, if we can also encourage users to make redundant judgment on the collected data and motivate users to upload data that help to improve the accuracy of model recognition, then the required communication bandwidth can be decreased.

Although many incentive mechanisms have been designed for various crowdsensing applications, most of these mechanisms are either based on the assumption that users directly submit the collected raw data to the crowdsourcer or they do not consider some critical properties [6, 11, 13, 16, 39, 46]. Unlike these traditional incentive mechanisms, to design an incentive mechanism to

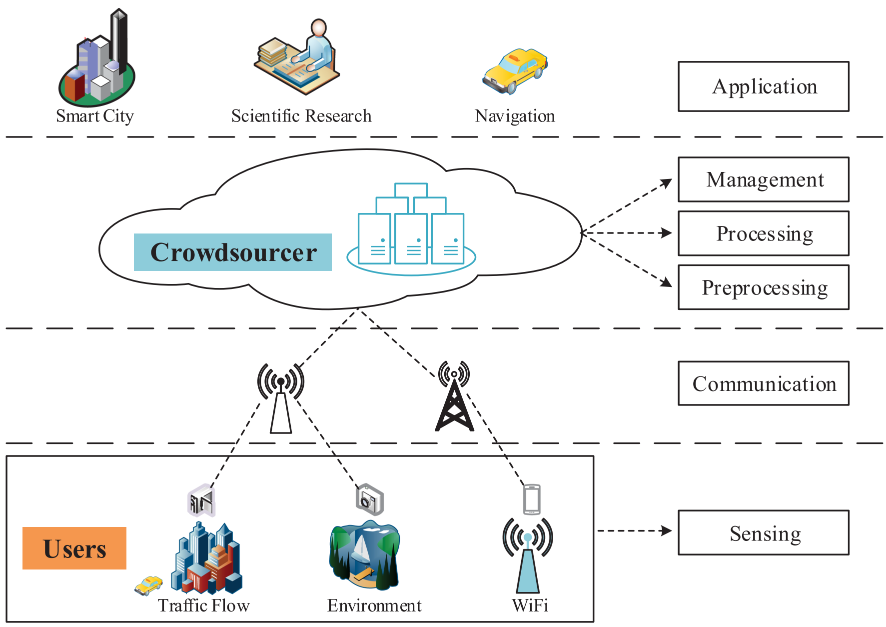


Fig. 1. Crowdsensing system.

motivate users to preprocess the collected data for the crowdsourcer, we should consider some challenges:

- Consider the differences in users' preprocessing abilities. To design an incentive mechanism to motivate users to preprocess the collected raw data, we should consider the differences in users' preprocessing abilities, which directly affect the quality of the sensing service. Moreover, if a user does not have the ability to preprocess the collected data, the crowdsourcer will not recruit him.
- Simultaneously consider the utility maximization problems of the crowdsourcer and users. The purposes of both the crowdsourcer and users are to maximize their own utilities, and they can make their strategies independently. Therefore, it is a challenge to design an incentive mechanism that can simultaneously consider the utility maximization problems of both the crowdsourcer and users.
- Guarantee the number of participants. The number of participants is a requirement of a crowdsensing system achieving high-quality sensing services. In addition, we also know that the more participants there are, the more efficient the system will be. Therefore, we are required to reasonably allocate tasks to ensure the number of participants. However, due to the limited budget of the crowdsourcer, it is also a challenge to design incentive mechanisms to balance the number of participants and the crowdsourcer's budget.
- Meet the desirable properties. Since our incentive mechanisms are based on an auction mechanism, another challenge is to design an incentive mechanism to meet the four desirable properties: truthfulness, individual rationality, profitability, and computational efficiency.

In this article, for two common crowdsensing scenarios, we propose two system models and design the corresponding incentive mechanisms to motivate users to preprocess the collected raw data. For the single-task-multiple-participants model, we create an incentive mechanism named the IMSTMP. For the multiple-tasks-multiple-participants model, we develop an incentive mechanism called the IMMTMP. Both the IMSTMP and IMMTMP mechanisms are user-centric incentive mechanisms, where users can make reasonable strategies independently, and the crowdsourcer selects the optimal users for the crowdsensing system. These mechanisms are different from crowdsourcer-centric incentive mechanisms, where the crowdsourcer completely controls the rewards for users, and users can only change their sensing service time to cater to the crowdsourcer.

The contributions of this article can be summarized as follows:

- For different crowdsensing system models, we propose monetary-based incentive mechanisms to motivate users to preprocess the collected data for the crowdsourcer.
- We present utility functions and formulate utility maximization problems for the crowdsourcer and users. Moreover, in our incentive mechanisms, we simultaneously consider the utility maximization problems of the crowdsourcer and users.
- We model our incentive mechanism as a game, where the crowdsourcer and users can make their strategies independently. In addition, we prove that the game has a Nash equilibrium.
- We design incentive mechanisms based on an auction mechanism, which satisfies four desirable properties: truthfulness, individual rationality, profitability, and computational efficiency.

The organization of the remainder of this article is outlined as follows: We first review the related work in Section 2. We describe the system models in Section 3. In Section 4, we present the incentive mechanisms for two different models. The experimental analysis is discussed in Section 5. We conclude the article in Section 6.

2 RELATED WORK

Participants are the foundation of a crowdsensing system, and without a certain number of participants, the service quality of the crowdsensing system cannot be guaranteed. As users will consume resources to provide sensing services, various types of incentive mechanisms have been designed to compensate users, such as monetary-based incentive mechanisms [49], entertainment-based incentive mechanisms [40], social-based incentive mechanisms [7], and virtual credit-based incentive mechanisms [34]. Monetary-based incentive mechanisms are mainly applied in auction mechanisms and game theory [4, 20, 29, 31, 43]. For example, to address the sensor selection problem under different scenarios, the authors designed an incentive for long-term user participation based on a VCG auction policy in Reference [18]. In Reference [32], to take into account the uncertain mobility of participants, the authors designed a framework that leverages game theory and reverse auction mechanism. In this article, we propose monetary-based incentive mechanisms by combining auction mechanism and game theory, in which both the crowdsourcer and users are players. Moreover, our incentive mechanisms can guarantee the number of participants by selecting all users who meet the winner conditions as participants, which is different from the RADP-VPC method [16], which only selects the lowest bidders as participants.

Crowdsensing has been applied to various scenarios, and many corresponding incentive mechanisms have been designed [33]. In Reference [39], the authors designed a mechanism to motivate vehicles to provide real-time information for a traffic management system. Han et al. designed a game-based incentive mechanism to motivate users to observe and collect data for an environmental monitoring project in Reference [11]. Jin et al. proposed INCEPTION to motivate users to provide reliable data in Reference [13]. However, these works were based on the situation that users directly submit the collected data to the crowdsourcer and ignored the fact that users' computing power can also be utilized to preprocess the collected raw data for the crowdsourcer.

In Reference [6], Danezis et al. focused on motivating users to participate in a crowdsensing system but ignored the utility of the crowdsourcer. In Reference [23], the authors motivated smartphone users to participate in a cloud-enabled multimedia crowdsensing system, where users can only choose the duration of its service to maximize their payoffs. In Reference [46], Yang et al. first proposed a crowdsourcer-centric incentive mechanism where the task reward was given by the crowdsourcer, and users need to change their service time to cater to the crowdsourcer. Then, the authors designed a user-centric incentive mechanism but only discussed the utility of the crowdsourcer. In other words, these above incentive mechanisms either fail to simultaneously consider the utility maximization problems of the crowdsourcer and users or do not take into account the fact that users can bid their sensing services independently.

Many incentive mechanisms have been designed to meet the different goals of crowdsensing systems. The problem of how to ensure the quality of a sensing service has been studied in References [30, 42, 47]. For example, in Reference [10], Gao et al. utilized the reputation value to measure the probability of users providing high-quality data, and users were motivated to maintain high-quality sensing services in the next stage by adapting an extra bonus. In Reference [47], to guarantee the quality of users' contributed data, Yu et al. designed an incentive mechanism to motivate participants to provide accurate data, and the incentive mechanism can motivate and guide participants to contribute accurate data over time. The issue of privacy protection has been studied in Reference [38]. In Reference [19], to jointly consider the privacy and the social cost, the authors designed and proposed two frameworks that implement incentive mechanisms for privacy protection, which can also achieve approximate social cost minimization. In addition to the above-mentioned issues, many other issues have been studied. In Reference [21], the object of energy consumption fairness among participants was considered. In Reference [44], Xu et al. proposed a crowdsourcing mechanism to align the incentives of the requester, worker, and platform together, which can improve the four key evaluation indices. In Reference [14], budget constraints, privacy protection, and service accuracy were all taken into consideration. In this article, we focus on designing incentive mechanisms that are brief and scalable and satisfy four desirable properties: computational efficiency, individual rationality, profitability, and truthfulness.

3 SYSTEM ARCHITECTURE AND UTILITY FUNCTIONS

In this section, we first describe the system architecture. Then, we formulate the utility functions of the crowdsourcer and users. Finally, we present four desirable properties as the performance metrics of our incentive mechanisms.

The architecture of our crowdsensing system is described in Figure 2, which includes one crowdsourcer and many users. Unlike the traditional system architecture, in our system, users will be motivated to perform data preprocessing on the local devices. The workflow of the system is described as follows: First, the crowdsourcer publishes sensing tasks. Second, the crowdsourcer and users conduct multiple strategy bidding rounds. In each round of bidding, users bid their strategies for their interested tasks in turn, and then the crowdsourcer selects the user strategies for each task. Note that, after each round, the users who are not selected by the crowdsourcer will not be able to continue bidding for the task. After multiple rounds of bidding, the crowdsourcer and users will reach an equilibrium in which no user is willing to unilaterally change its strategy. Third, the selected users will complete the data collection work, preprocess the collected data on the local devices, and then submit the result to the crowdsourcer. Finally, the crowdsourcer will pay the selected users and conduct further data analysis.

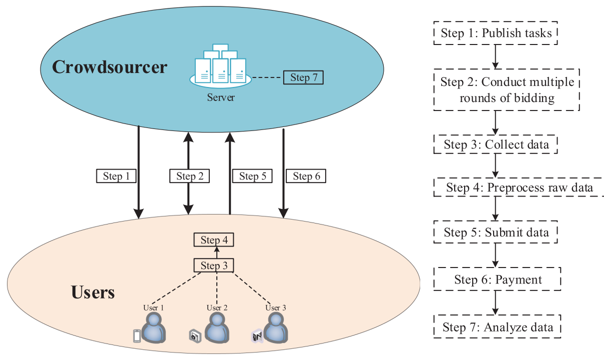


Fig. 2. The architecture of the crowdsensing system.

3.1 System Architecture

A few comments are in order. First, we assume that the tasks are data partitioned–oriented applications, which can be partitioned into subtasks of any size [41]. Second, we assume that the users can collect enough data if requested, and they also have different professional abilities to preprocess the collected raw data. Specifically, a user who does not have a sufficient preprocessing ability will not be selected as a participant in our crowdsensing system. Finally, the utility of the crowdsourcer is related to the final preprocessed data, so the sensing service addressed in this article includes two processes: data collection and data preprocessing.

The crowdsourcer publishes N tasks, $\tau = (\tau_1, \ldots, \tau_i, \ldots, \tau_N)$, and provides a reward, R, to motivate users to accomplish these tasks. For a task $\tau_i = (v_i, c_i, p_i)$, v_i denotes the amount of data to be collected and preprocessed. c_i indicates the importance of the task in τ, which is determined by the needs of the crowdsourcer. p_i is a reward to motivate users to complete the task, where $R = \sum_{i=1}^{N}(p_i)$. In addition, it is obvious that the higher the values of v_i and c_i are, the more important task i is to the crowdsourcer. Therefore, the reward p_i can be calculated by

$$p_i = R \times \frac{v_i c_i}{\sum_{k \in N}(v_k c_k)}. \tag{1}$$

Assume that there are M users, $\varphi = (\varphi_1, \ldots, \varphi_j, \ldots, \varphi_M)$, interested in participating in the crowdsensing system after receiving the task information. Since users need to consume resources to complete tasks, they will bid on their sensing services to receive compensation. For task i, user φ_j's bidding strategy can be described as $s_i^j = (b_{j,i}, q_j)$. $b_{j,i}$ represents the bidding price for completing the unit data amount of task i. q_j denotes the ability to preprocess collected data, and each user performs data preprocessing in strict accordance with his/her ability.

The frequently used notations are summarized in Table 1.

3.2 Utility Functions

3.2.1 Utility Functions in STMP. For the scenario where the crowdsourcer only publishes one task, τ_i, and there are M users interested in providing sensing services for the task, we propose the single-task-multiple-participants (STMP) model. In each round of bidding, user φ_j sets his/her bidding strategy $s_i^j = (b_{j,i}, q_j)$, and the bidding strategy set of user φ_j is denoted by S_i^j, where $s_i^j \in S_i^j$. After each user has sets his/her bidding strategy, the crowdsourcer will select a subset of users ϕ_i to participate in the next round of bidding. The crowdsourcer's selection strategy set is $\Phi = 2^M$, where $\phi_i \in \Phi$. If user φ_j is selected, we describe it as $j \in \phi_i$ or $\varphi_j \in \phi_i$; otherwise, $j \notin \phi_i$

Table 1. List of Notations

Notation	Explantation
$\tau_i,\ \tau,\ v_i,\ c_i$	Task i, a set of tasks, the amount of data that needs to be preprocessed in task i, and the importance of task i, respectively.
$p_i,\ o_i$	The reward to motivate users to complete task i and the value that user φ_j brings to the crowdsourcer by completing the unit data amount of task i, respectively.
$R,\ \varphi_j,\ \varphi$	The reward for completing all tasks, user j, and a set of users, respectively.
$q_j,\ d_j,\ b_{j,i}$	User φ_j's ability to preprocess collected data, the resource consumption required by user φ_j for completing unit data amount of the task, and user φ_j's bidding price completing unit data amount of task i, respectively.
$s_i^j,\ s_i^{-j},\ S_i^j$	The bidding strategy of user φ_j for task i, the bidding strategy profile of users except for user φ_j, and the bidding strategy set of user φ_j for task i, respectively.
$\phi_i,\ \Phi,\ m_{j,i}$	A selection strategy of the crowdsourcer for task i, the selection strategy set of the crowdsourcer for all tasks, and the workload that user φ_j needs to complete in task i, respectively.
$e_{j,i},\ \gamma_{j,i}$	The resource consumption required by user φ_j to complete $m_{j,i}$ and the consumption required for preparation, respectively.
$u_{j,i},\ u_j$	the utility that user φ_j receives from providing sensing service for task i and the utility that user φ_j receives from providing sensing service for all tasks, respectively.
$g_i,\ g$	The utility of the crowdsourcer obtained from task i and the utility of the crowdsourcer obtained from all tasks, respectively.

or $\varphi_j \notin \phi_i$. After multiple rounds of bidding, the strategies of the crowdsourcer and users will not change.

In each round of bidding, if user φ_j is selected, then the workload that he/she needs to complete is denoted as $m_{j,i}$. As we all know, among the set of selected users, ϕ_i, those who have high preprocessing abilities and low bidding prices will be more favored by the crowdsourcer. Therefore, $m_{j,i}$ can be calculated by

$$m_{j,i}\left(s_i^j, s_i^{-j}, q_j\right) = v_i \frac{q_j/b_{j,i}}{\sum_{l\in\phi_i} q_l/b_{l,i}}. \tag{2}$$

Here, the joint bidding strategy s_i^{-j} is for the users except for user φ_j. According to Equation (2), we can also observe that a user without any data preprocessing ability will not be selected to participate in the crowdsensing system.

As a user will consume resources to complete $m_{j,i}$, we assume that d_j denotes the resource consumption required by user φ_j for completing the unit data amount of the task, and $\gamma_{j,i}$ denotes the consumption required for preparation. For each user, d_j and $\gamma_{j,i}$ are constants in this article. Therefore, the resource consumption required by user φ_j to complete $m_{j,i}$ is

$$e_{j,i} = m_{j,i} d_j + \gamma_{j,i}. \tag{3}$$

Thereby, according to Equation (2) and Equation (3), we can determine that the utility that user φ_j receives from providing sensing service for task i is

$$\begin{aligned} u_{j,i}\left(s_i^j, s_i^{-j}, \phi_i\right) &= m_{j,i} b_{j,i} - e_{j,i} \\ &= v_i \frac{q_j/b_{j,i}}{\sum_{l\in\phi_i} \frac{q_l}{b_{l,i}}} (b_{j,i} - d_j) - \gamma_{j,i}. \end{aligned} \tag{4}$$

The case of $j \notin \phi_i$ means that user φ_j is not selected to participate in the next round of bidding, and we can get $m_{j,i} = 0$, $e_{j,i} = 0$, and $u_{j,i} = 0$.

The crowdsourcer's utility is denoted as g_i, which is related to the workload completed by each user and the rewards paid to users. Thereby, we can calculate g_i as

$$\begin{aligned} g_i\left(s_i^j, s_i^{-j}, \phi_i\right) &= \sum_{k \in \phi_i} \left(m_{k,i}\left(o_i^j - b_{k,i}\right)\right) \\ &= \sum_{k \in \phi_i} \left(v_i \frac{q_k / b_{k,i}}{\sum_{l \in \phi_i} \frac{q_l}{b_{l,i}}} \left(o_i^j - b_{k,i}\right)\right). \end{aligned} \tag{5}$$

Here, o_i^j represents the value that user φ_j brings to the crowdsourcer by completing the unit data amount of task i. In addition, o_i^j is related to c_i and q_j, and we assume that $o_i^j = ac_i q_j$, a is a parameter.

3.2.2 Utility Functions in MTMP. For the scenario where the crowdsourcer publishes N tasks, and there are M users interested in participating in the system, we propose the multiple-tasks-multiple-participants (MTMP) model. For user φ_j, in each round of bidding, his/her strategy for N tasks is $s^j = (s_1^j, \ldots, s_i^j, \ldots, s_N^j)$. After each user has set his/her bidding strategy, the crowdsourcer will select users for each task $\phi = (\phi_1, \ldots, \phi_i, \ldots, \phi_N)$ to participate in the next round of bidding.

The utility of user φ_j is u_j, which is obtained by providing sensing services for N tasks, is calculated by

$$u_j(s^j, s^{-j}, \phi) = \sum_{i=1}^{N} (u_{j,i}), \tag{6}$$

where

$$u_{j,i} = \begin{cases} v_i \frac{q_j / b_{j,i}}{\sum_{l \in \phi_i} \frac{q_l}{b_{l,i}}} (b_{j,i} - d_j) - \gamma_{j,i}, & \text{if } j \in \phi_i, \\ 0, & otherwise. \end{cases}$$

The crowdsourcer's utility is denoted by g. According to Equation (5), we calculate g as

$$\begin{aligned} g(s^j, s^{-j}, \phi) &= \sum_{i=1}^{N} (g_i) \\ &= \sum_{i=1}^{N} \left(\sum_{k \in \phi_i} \left(v_i \frac{q_k / b_{k,i}}{\sum_{l \in \phi_i} \frac{q_l}{b_{l,i}}} \left(o_i^j - b_{k,i}\right)\right)\right). \end{aligned} \tag{7}$$

3.3 Desirable Properties

As Yang et al. mentioned in Reference [46], for the STMP model and the MTMP model, we use the following four characters as the performance metrics for our incentive mechanisms:

- **Rationality:** Each participant will get utility by completing the tasks in our crowdsensing system.
- **Truthfulness:** No participant can improve his/her utility by providing a bidding price different from its true valuation. In other words, the selection rule needs to be monotonic, and the winners are paid the critical value.
- **Profitability:** The value brought by the winners should be more than the rewards paid to them.
- **Computation efficiency:** The final result of the bidding should be computed in polynomial time.

4 INCENTIVE MECHANISMS

In this section, we introduce the incentive mechanisms for the STMP model and the MTMP model. In addition, we analyze the incentive mechanisms by using the four desirable properties as performance metrics.

4.1 Incentive Mechanism for the STMP Model

4.1.1 Problem Formulation of the STMP Model. For the STMP model, in each round of bidding, the crowdsourcer's purpose is to maximize the utility g_i, and its strategy is making a selection ϕ_i. User φ_j ($1 \le j \le M$) aims to maximize his/her own utility $u_{j,i}$ by providing a bidding strategy s_i^j.

Based on Equation (4) and Equation (5), the purposes of both the users and the crowdsourcer can be formulated as utility maximization problems:

$$\begin{aligned} &\text{maximize} \quad u_{j,i}\left(s_i^j, s_i^{-j}, \phi_i\right),\\ &\text{s.t.} \quad \phi_i \subseteq \Phi, \left\langle s_i^j, s_i^{-j}\right\rangle \in S_i^j; \end{aligned} \tag{8}$$

and

$$\begin{aligned} &\text{maximize} \quad g_i\left(s_i^j, s_i^{-j}, \phi_i\right),\\ &\text{s.t.} \quad \phi_i \subseteq \Phi, \left\langle s_i^j, s_i^{-j}\right\rangle \in S_i^j. \end{aligned} \tag{9}$$

Before solving the utility maximization problems, we need to discuss the conditions that allow users to win in each round of bidding.

First, a user needs to consume resources to provide sensing services for a task; thereby, users will not participate in crowdsensing unless they can make a profit. Therefore, if user φ_j is selected, $j \in \phi_i$, his/her utility must satisfy

$$\begin{aligned} & u_{j,i} > 0 \\ & \Rightarrow v_i \times \frac{q_j/b_{j,i}}{\sum_{l\in\phi_i}\frac{q_l}{b_{l,i}}} \times (b_{j,i} - d_j) - \gamma_{j,i} > 0 \\ & \Rightarrow b_{j,i} \times \left(v_i q_j - \gamma_{j,i}\sum_{l\in\phi_i\setminus j}\frac{q_l}{b_{l,i}}\right) > v_i q_j d_j + \gamma_{j,i} q_j. \end{aligned}$$

According to the above inequality, we can determine that user φ_j's bidding strategy must satisfy

$$q_j > \frac{\gamma_{j,i}}{v_i}\sum_{l\in\phi_i\setminus j}\frac{q_l}{b_{l,i}}, \tag{10}$$

$$b_{j,i} > \frac{\gamma_{j,i} q_j + v_i q_j d_j}{v_i q_j - \gamma_{j,i}\sum_{l\in\phi_i\setminus j}\frac{q_l}{b_{l,i}}}. \tag{11}$$

If $u_{j,i} \le 0$, then user φ_j will not provide sensing services for task i.

Second, since the reward to motivate users to complete task i is given as $p_i = R$, the bidding price of user φ_j must satisfy

$$b_{j,i} \le p_i/v_i. \tag{12}$$

However, users are selfish and need to make profits; therefore, their bidding prices may not meet Inequality (12). When $b_{j,i} > p_i/v_i$, the crowdsourcer views it as $b_{j,i} = p_i/v_i$.

According to Inequality (11) and Inequality (12), if user φ_j is a winner, his/her bidding price must satisfy

$$\frac{\gamma_{j,i} q_j + v_i q_j d_j}{v_i q_j - \gamma_{j,i}\sum_{l\in\phi_i\setminus j}\frac{q_l}{b_{l,i}}} < b_{j,i} \le \frac{p_i}{v_i}. \tag{13}$$

Third, from the perspective of the crowdsourcer, in each round of bidding, the purpose is to maximize its utility g_i by selecting a subset of users ϕ_i. Therefore, if user φ_j wants to win in each round of bidding, his/her bidding strategy should satisfy $g_i(s_i^j, s_i^{-j}) > g_i(s_i^{-j})$, where $g_i(s_i^{-j})$ represents the utility of the crowdsourcer without selecting user φ_j. In addition, we can deduce that

$$
\begin{aligned}
& g_i\left(s_i^j, s_i^{-j}\right) > g_i\left(s_i^{-j}\right) \\
& \Rightarrow \sum_{k\in\phi_i}\left(v_i \frac{q_k/b_{k,i}}{\sum_{l\in\phi_i}\frac{q_l}{b_{l,i}}}\left(o_i^k - b_{k,i}\right)\right) > \sum_{k\in\phi_i\setminus j}\left(v_i \frac{q_k/b_{k,i}}{\sum_{l\in\phi_i\setminus j}\frac{q_l}{b_{l,i}}}\left(o_i^k - b_{k,i}\right)\right) \\
& \Rightarrow \frac{q_j\left(o_i^j - b_{j,i}\right)}{b_{j,i}\sum_{l\in\phi_i}\frac{q_l}{b_{l,i}}} > \sum_{k\in\phi_i\setminus j}\left(\frac{q_k\left(o_i^k - b_{k,i}\right)}{b_{k,i}}\left(\frac{1}{\sum_{l\in\phi_i\setminus j}\frac{q_l}{b_{l,i}}} - \frac{1}{\sum_{l\in\phi_i}\frac{q_l}{b_{l,i}}}\right)\right) \\
& \Rightarrow \frac{q_j\left(o_i^j - b_{j,i}\right)}{b_{j,i}\sum_{l\in\phi_i}\frac{q_l}{b_{l,i}}} > \frac{q_j/b_{j,i}}{(\sum_{l\in\phi_i\setminus j}\frac{q_l}{b_{l,i}})(\sum_{l\in\phi_i}\frac{q_l}{b_{l,i}})} \times \sum_{k\in\phi_i\setminus j}\left(\frac{q_k\left(o_i^k - b_{k,i}\right)}{b_{k,i}}\right) \\
& \Rightarrow \left(o_i^j - b_{j,i}\right)\sum_{l\in\phi_i\setminus j}\frac{q_l}{b_{l,i}} > \sum_{k\in\phi_i\setminus j}\left(\frac{q_k\left(o_i^k - b_{k,i}\right)}{b_{k,i}}\right) \\
& \Rightarrow b_{j,i}\sum_{l\in\phi_i\setminus j}\frac{q_l}{b_{l,i}} < \sum_{k\in\phi_i\setminus j} q_k.
\end{aligned}
$$

Finally, we get that

$$
b_{j,i} \leq \frac{\sum_{l\in\phi_i\setminus j} q_l}{\sum_{l\in\phi_i\setminus j} q_l/b_{l,i}}. \tag{14}
$$

According to Inequality (12), if $j\in\phi_i$, then we have

$$
\begin{aligned}
& b_{j,i} \leq p_i/v_i \\
& \Rightarrow \frac{q_j}{b_{j,i}} \geq \frac{q_j v_i}{p_i} \\
& \Rightarrow \sum_{l\in\phi_i\setminus j}\frac{q_l}{b_{l,i}} \geq \sum_{l\in\phi_i\setminus j}\frac{q_l v_i}{p_i},
\end{aligned}
$$

and we can deduce that

$$
\frac{p_i}{v_i} \geq \frac{\sum_{l\in\phi_i\setminus j} q_l}{\sum_{l\in\phi_i\setminus j} q_l/b_{l,i}}. \tag{15}
$$

In other words, the conditions for user φ_j to win each round of bidding can be summarized as follows: the preprocessing ability q_j should satisfy

$$
q_j > \frac{\gamma_{j,i}}{v_i}\sum_{l\in\phi_i\setminus j}\frac{q_l}{b_{l,i}},
$$

while the bidding price $b_{j,i}$ should satisfy

$$
b_{j,i} > b_{min} = \frac{\gamma_{j,i} q_j + v_i q_j d_j}{v_i q_j - \gamma_{j,i}\sum_{l\in\phi_i\setminus j}\frac{q_l}{b_{l,i}}}, \tag{16}
$$

and

$$
b_{j,i} \leq b_{max} = \frac{\sum_{l\in\phi_i\setminus j} q_l}{\sum_{l\in\phi_i\setminus j}\frac{q_l}{b_{l,i}}}. \tag{17}
$$

4.1.2 IMSTMP. In this section, we propose an incentive mechanism, namely, the IMSTMP, for the STMP model and model it as a dynamic game, which we call the IMSTMP game.

The crowdsourcer and users are players in this game. In each round of bidding, the strategy of the crowdsourcer is ϕ_i, where $\phi_i \in \Phi$. The strategy of user φ_j is s_i^j, where $s_i^j \in S_i^j$; and the *strategy profile* consisting of all users is $s_i = (s_i^1, \ldots, s_i^j, \ldots, s_i^M)$, where $s_i \in S_i$ and $S_i = S_i^1 \times S_i^2 \times \cdots \times S_i^M$. In addition, $u_i = (u_{1,i}, \ldots, u_{j,i}, \ldots, u_{m,i})$ denotes the *utility profile* consisting of all users.

According to Equation (8) and Equation (9), the IMSTMP game can be represented by $G = (\Phi, S_i, g_i, u_i)$, and the purpose of the game is to find the equilibrium where the point (ϕ_i^*, s_i^*) satisfies

$$\begin{aligned} s_i^* &\in \arg\max_{s_i^j \in S_i^j} u_{j,i}\left(s_i^j, s_i^{-j}, \phi_i\right), \quad s_i^* \in S_i, \\ \phi_i^* &\in \arg\max_{\phi_i \in \Phi_i} g_i\left(s_i^j, s_i^{-j}, \phi_i\right), \quad \phi_i^* \in \Phi. \end{aligned} \tag{18}$$

In the IMSTMP game, we would like to emphasize the following points: In a dynamic game with complete information, each player can get the other players' bidding strategies. In addition, in each round of bidding, those unselected users will not be able to continue bidding for the task.

Before we solve the IMSTMP game, we will introduce the background of convex optimization and Nash equilibrium [12, 26].

Given a convex set S and an objective function $f(x)$, which is convex and continuously differentiable on S, the convex optimization problem can be denoted as $CO(S, f)$, that is,

$$\text{minimize } f(x), \text{ subject to } x \in S.$$

We extend the above convex optimization problem into an n-player noncooperative game $g = (S, f)$, where $S = S_1 \times \cdots \times S_n$ and $f = (f_1(x), f_2(x), \ldots, f_n(x))$, $x = (x_i, x_{-i})$, x_{-i} denotes the vector of all players' variables other than player i. Since the purpose of a game is to find the Nash equilibrium, we have a set of n coupled convex optimization problems $CO(S_i, f_i)$, where f_i is a convex function of x_i, $1 \le i \le n$. The aim of player i, given x_{-i}, is to

$$\text{minimize } f_i(x_i, x_{-i}), \text{ subject to } x_i \in S_i.$$

Furthermore, according to the theorem mentioned in Reference [17], we know that for all $1 \le i \le n$, if S_i is a compact convex set, $f_i(x_i, x_{-i})$ is a continuous function on S, and $f_i(x_i, x_{-i})$ is a convex function on S_i, then there is a Nash equilibrium for the game $g = (S, f)$.

According to the information of the convex optimization problem, for the sake of the discussion, we set function $w_{j,i} = -u_{j,i}$; therefore, we have

$$w_{j,i} = \begin{cases} -\left(v_i \frac{q_j/b_{j,i}}{\sum_{l \in \phi_i} \frac{q_l}{b_{l,i}}}(b_{j,i} - d_j) - \gamma_{j,i}\right), & \text{if } j \in \phi_i, \\ 0, & otherwise. \end{cases} \tag{19}$$

Therefore, we redefine Equation (8) as

$$\begin{aligned} &\text{minimize} \quad w_{j,i}\left(s_i^j, s_i^{-j}, \phi_i\right), \\ &\text{s.t.} \quad \phi_i \subseteq \Phi, \left\langle s_i^j, s_i^{-j}\right\rangle \in S_i^j. \end{aligned} \tag{20}$$

The IMSTMP game can be redefined as $G = (\Phi, S_i, g_i, w_i)$, where $w_i = (w_{1,i}, \ldots, w_{j,i}, \ldots, w_{M,i})$. In addition, the purpose of the game $G = (\Phi, S_i, g_i, w_i)$ is to find the Nash equilibrium, which can be denoted as (ϕ_i^*, s_i^*), where

$$\begin{aligned} s_i^* &\in \arg\min_{s_i^j \in S_i^j} w_{j,i}\left(s_i^j, s_i^{-j}, \phi_i\right), \quad s_i^* \in S_i, \\ \phi_i^* &\in \arg\max_{\phi_i \in \Phi_i} g_i\left(s_i^j, s_i^{-j}, \phi_i\right), \quad \phi_i^* \in \Phi. \end{aligned} \tag{21}$$

Now, let us discuss a special case of the IMSTMP game. Suppose that the crowdsourcer's optimal strategy is given as $\phi_i = m$. In other words, these m selected users are the optimal participators in the system. Then, these selected users will bid against each other, and the purpose of each user is to maximize its utility. Therefore, the selected users can be considered as players in a game, and the game is represented by $G' = (S_i, w_i)$. The purpose of $G' = (S_i, w_i)$ is to find an equilibrium point, which is denoted as

$$s_i^* \in \arg\min_{s_i^j \in S_i^j} w_{j,i}\left(s_i^j, s_i^{-j}\right), \quad s_i^* \in S_i. \tag{22}$$

Theorem 1. *Suppose that the optimal strategy of the crowdsourcer is given as $\phi_i = m$. The game $G' = (S_i, w_i)$ has a Nash equilibrium.*

Proof. First, we prove the strategy set S_i^j of user φ_j $(1 \le j \le m)$ is a convex set. For user φ_j, his/her ability q_j is a constant, and the strategy s_i^j depends on the bidding price $b_{j,i}$; therefore, S_i^j can be regarded as a one-dimensional variable space about $b_{j,i}$. Moreover, since the optimal strategy of the crowdsourcer is given as $\phi_i = m$, that is, $j \in \phi_i$, $b_{j,i}$ must satisfy $b_{j,i} \in (b_{min}, b_{max}]$, and so S_i^j is compact. For any $x, y \in S_i^j$, we have $\rho x + (1-\rho)y \in S_i^j$, $\rho \in [0,1]$, and so S_i^j is a convex set.

Second, we prove that $w_{j,i}$ is a convex function. Since S_i^j can be regarded as a one-dimensional variable space about $b_{j,i}$, when $b_{j,i} \in (b_{min}, b_{max}]$, we can determine that $w_{j,i}$ is a continuous function on S_i^j. Therefore, we can determine that the function of $w_{j,i}$ is

$$\begin{aligned} w_{j,i} &= -\left(v_i \frac{q_j/b_{j,i}}{\sum_{l\in\phi_i} \frac{q_l}{b_{l,i}}}(b_{j,i} - d_j) - \gamma_{j,i}\right) \\ &= -v_i \frac{b_{j,i} - d_j}{1 + \frac{b_{j,i}}{q_j}\sum_{l\in\phi_i\backslash j}\frac{q_l}{b_{l,i}}} + \gamma_{j,i}. \end{aligned}$$

Then, we have

$$\begin{aligned} \frac{\partial w_{j,i}}{\partial b_{j,i}} &= -v_i \times \frac{\left(1 + \frac{b_{j,i}}{q_j}\sum_{l\in\phi_i\backslash j}\frac{q_l}{b_{l,i}}\right) - \frac{b_{j,i}-d_j}{q_j} \times \sum_{l\in\phi_i\backslash j}\frac{q_l}{b_{l,i}}}{\left(1 + \frac{b_{j,i}}{q_j}\sum_{l\in\phi_i\backslash j}\frac{q_l}{b_{l,i}}\right)^2} \\ &= -v_i q_j \times \frac{q_j + d_j \sum_{l\in\phi_i\backslash j} q_l/b_{l,i}}{\left(q_j + b_{j,i}\sum_{l\in\phi_i\backslash j} q_l/b_{l,i}\right)^2} < 0, \end{aligned}$$

and

$$\frac{\partial^2 w_{j,i}}{\partial b_{j,i}^2} = 2 v_i q_j \times \frac{q_j + d_j \sum_{l\in\phi_i\backslash j} q_l/b_{l,i}}{\left(q_j + b_{j,i}\sum_{l\in\phi_i\backslash j} q_l/b_{l,i}\right)^3} \times \sum_{l\in\phi_i\backslash j}\frac{q_l}{b_{l,i}} > 0.$$

Therefore, we obtain that $w_{j,i}$ is a convex function on S_i^j. According to $\frac{\partial w_{j,i}}{\partial b_{j,i}} < 0$, and the purpose of user φ_j is to minimize $w_{j,i}$, we can get that the optimal bidding price $b_{j,i}^*$ is the maximum value in its feasible interval, that is, $b^*_{j,i} = b_{max}$. Thus, we can get the optimal bidding strategy $s_i^{j*} = (b^*_{j,i}, q_j)$. Therefore, we prove that the game $G' = (S_i, w_i)$ has a Nash equilibrium. □

Theorem 2. *In $G' = (S_i, w_i)$, the bidding price sequence of user φ_j is monotonic and bounded.*

Proof. According to Theorem 1, in each round, user φ_j's bidding price is $b_{j,i} = b^*_{j,i} = b_{max}$. We initialize $b^{(0)}_{j,i} = \frac{p_i}{v_i}$ $(1 \le j \le m)$. Therefore, in the first round, we can get $b^{(1)}_{j,i} \le b^{(0)}_{j,i}$. Then, in the kth round, we assume that $b^{(k)}_{j,i} \le b^{(k-1)}_{j,i}$ $(1 \le j \le m)$. As mentioned in Theorem 1, we have

$$b^*_{j,i} = b_{max} = \frac{\sum_{l \in \phi_i \setminus j} q_l}{\sum_{l \in \phi_i \setminus j} \frac{q_l}{b_{l,i}}}.$$

We can observe that, for user φ_j, the optimal bidding price $b^*_{j,i}$ increases with $b_{l,i}$, where $l \in \phi_i \setminus j$. Therefore, in the $(k+1)th$ round, we can obtain that the bidding price is $b^{(k+1)}_{j,i} = b^{*(k+1)}_{j,i} \le b^{*(k)}_{j,i} = b^{(k)}_{j,i}$. Therefore, we get that $b_{j,i}$ is monotonic in $G' = (S_i, w_i)$.

Based on Inequality (16) and Inequality (17), each user's bidding price must satisfy $b_{j,i} \in (b_{min}, b_{max}]$, and so we get that $b^*_{j,i}$ is bounded. The proof of the theorem has been completed. □

Based on Theorem 1 and Theorem 2, for the IMSTMP game, we have the following theorem:

Theorem 3. *The IMSTMP game $G = (\Phi, S_i, g_i, w_i)$ has a Nash equilibrium (ϕ^*_i, s^*_i).*

Proof. We assume that there are M users who are initially interested in participating in the crowdsensing system. In other words, the strategy of the crowdsourcer is initialized as $\phi_i = M$. According to Theorem 1, if $\phi^*_i = M$, then there is a Nash equilibrium $s^*_i = (s_i^{1*}, \ldots, s_i^{j*}, \ldots, s_i^{M*})$ for the game $G' = (S_i, w_i)$. In addition, we can get that $G = (\Phi, S_i, g_i, w_i)$ has a Nash equilibrium (ϕ^*_i, s^*_i).

However, if user φ_j's bidding price does not satisfy $b_{min} < b_{j,i} \le b_{max}$, then the crowdsourcer will update the selection strategy $\phi_i = \phi_i \setminus j$. Thus, user φ_j will not be selected to participate in the next round of bidding. Therefore, we can determine that the strategy sequence of the crowdsourcer is monotonic and bounded. Through multiple rounds of bidding, until ϕ_i does not change, according to Theorem 1, there is a Nash equilibrium s^*_i for the game $G' = (S_i, w_i)$. Then, $G = (\Phi, S_i, g_i, w_i)$ can reach a Nash equilibrium (ϕ^*_i, s^*_i).

In addition, based on Theorem 2, the bidding price sequence of each user is monotonic and bounded in $G' = (S_i, w_i)$. Therefore, we can observe that the solution of $G = (\Phi, S_i, g_i, w_i)$ converges to an equilibrium. □

The detailed steps of the solution for the IMSTMP game are described in Algorithm 1.

In Algorithm 1, ϕ^*_i and s^*_i are the respective strategies of the crowdsourcer and users, where ϕ_i and s_i are used to save the previous strategies of the crowdsourcer and users, respectively (line 1). In each iteration, the system first compares the loop conditions of $\phi_i \ne \phi^*_i$ and $s_i \ne s^*_i$ (line 2), which means that the loop conditions are met, and the system equilibrium is not reached. Then, the system will update ϕ_i and s_i (line 3); otherwise, go to line 20. In each round of bidding, the users in ϕ^*_i will set their bidding strategies in turn (lines 4–14). Specifically, for user φ_j, he/she will obtain a filtered strategy set s'_i by calling a function, $filter$, which will be detailed in Algorithm 2 (lines 4–5). Based on s'_i, user φ_j calculates q^*_j by calling Inequality (10) at first (line 6). If $q_j \le q^*_j$, it means that user φ_j cannot profit in the system. Therefore, he/she will set the bidding price as $b^*_{j,i} = 0$ (lines 7–8); otherwise, user φ_j will calculate the range of his/her bidding price by calling Inequality (16) and Inequality (17) and get the optimal bidding price $b^*_{j,i} = b_{j,i,max}$ (lines 9–13). After each user has conducted his/her bidding strategy, the crowdsourcer will update the selection

ALGORITHM 1: IMSTMP

Require: A set of users φ, task i and reward R
Ensure: A equilibrium (ϕ_i^*, s_i^*)
1: Initialize ϕ_i, ϕ_i^*, s_i, s_i^*
2: **while** ($\phi_i \neq \phi_i^*$ and $s_i \neq s_i^*$) **do**
3: $\quad\phi_i \leftarrow \phi_i^*$, $s_i \leftarrow s_i^*$
4: $\quad$**for** (each user j in ϕ_i^*) **do**
5: $\quad\quad s_i' \leftarrow filter(s_i^*, \phi_i^*)$
6: $\quad\quad$Calculate q_j^* using Inequality (10) based on s_i'
7: $\quad\quad$**if** ($q_j \leq q_j^*$) **then**
8: $\quad\quad\quad b_{j,i}^* \leftarrow 0$
9: $\quad\quad$**else**
10: $\quad\quad\quad$Calculate $b_{j,i,min}$ using Inequality (16) based on s_i'
11: $\quad\quad\quad$Calculate $b_{j,i,max}$ using Inequality (17) based on s_i'
12: $\quad\quad\quad b_{j,i}^* \leftarrow b_{j,i,max}$
13: $\quad\quad$**end if**
14: $\quad\quad$Update s_i^* based on $b_{j,i}^*$
15: $\quad$**end for**
16: $\quad$**if** ($b_{j,i,max} \leq b_{j,i,min}$ or $b_{j,i}^* = 0, j \in \phi_i^*$) **then**
17: $\quad\quad b_{j,i}^* \leftarrow 0$
18: $\quad\quad$Update $\phi_i^* \leftarrow \phi_i^* \setminus j$
19: $\quad$**end if**
20: **end while**
21: **return** (ϕ_i^*, s_i^*)

strategy ϕ_i^* (lines 16–19). Finally, the iteration loop will stop if the strategies of the crowdsourcer and users are not changed, and the algorithm will return ϕ_i^* and s_i^* as the optimal results (line 21).

ALGORITHM 2: $filter$

Require: A set of users φ, task i, reward R, s_i^*, and ϕ_i^*
Ensure: s_i''
Initialize $s_i' \leftarrow 0$, $s_i'' \leftarrow s_i^*$, and $\phi_i'' \leftarrow \phi_i^*$
for (each user $j \in \phi_i''$) **do**
$\quad$**if** ($b_{j,i}'' > p_i/v_i$) **then**
$\quad\quad b_{j,i}'' \leftarrow p_i/v_i$
$\quad$**end if**
end for
Update s_i'' based on $b_{j,i}''$
return s_i''

Since the reward to motivate users to complete task i is given, we introduce a function named $filter$ in Algorithm 2, which is used by each user to correct the bids over p_i/v_i.

4.1.3 *The Performance of IMSTMP.* We have designed an incentive mechanism for the STMP model in Section 4.1.2. Now, let us discuss the IMSTMP incentive mechanism using the four desirable properties introduced in Section 3.3 as the performance metrics.

- **Rationality:** In the IMSTMP incentive mechanism, users will not participate in the crowdsensing system unless they make enough profits to compensate for their resource consumption. In addition, for the participants in the crowdsensing system, the crowdsourcer will pay them based on their bidding prices. Therefore, the IMSTMP incentive mechanism is individually rational.
- **Profitability:** We guarantee $g_i > 0$ from two aspects. One aspect is that according to Inequality (12), the bidding price $b_{j,i}$ should be less than p_i/v_i; and for the case of $b_{j,i} > p_i/v_i$, the crowdsourcer views it as $b_{j,i} = p_i/v_i$. Moreover, p_i is part of the crowdsourcer's utility g_i. The other aspect is that according to Inequality (14), the bidding strategy of user φ_j should satisfy $g_i(s_i^j, s_i^{-j}) > g_i(s_i^{-j})$. Above all, we can guarantee that the IMSTMP incentive mechanism is profitable.
- **Efficiency:** The time complexity of Algorithm 2 is $O(M)$. According to Theorem 3, we can conclude that the strategy sequence of the crowdsourcer is monotonic and bounded. In addition, based on Theorem 2, the bidding price sequence of each user is monotonic and bounded in $G' = (S_i, w_i)$. Therefore, we can see that the number of iterations of the *while* loop in Algorithm 1 is $O(b)$. In Algorithm 1, the crowdsourcer and users will conduct their strategies in each loop, so we can determine that the time complexity of Algorithm 1 in the worst case is $O(bM^2)$. Hence, the IMSTMP incentive mechanism is computationally efficient.
- **Truthfulness:** According to Theorem 1 and Theorem 3, the optimal bidding price of each user must be the maximum value in his/her available interval, i.e., $b_{j,i}^* = b_{max}$. If $b_{j,i}^* > b_{max}$, then according to Equation (17), user φ_j will not be selected. Based on Equation (5), we can observe that the utility of the crowdsourcer increases as $b_{j,i}$ decreases; therefore, if user φ_j wins by making his/her bidding price $b_{j,i}^* = b_{max}$, he/she will also be selected by the crowdsourcer by making his/her bidding price $b_{j,i}^{*'} \leq b_{j,i}^* = b_{max}$. Therefore, the IMSTMP incentive mechanism is truthful.

4.2 Incentive Mechanism for the MTMP Model

In this section, we first formulate the utility maximization problems of the MTMP model. Then, we design an incentive mechanism, namely, the IMMTMP, for the MTMP model. Finally, we analyze the performance of the incentive mechanism.

4.2.1 Problem Formulation of the MTMP Model. In the MTMP model, the crowdsourcer publishes N independent tasks with a total reward R, and M users are interested in participating in the crowdsensing system. According to Equation (6), the utility function of user φ_j is $u_j = \sum_{i=1}^{N} u_{j,i}$. In each round of bidding, user φ_j will set a bidding strategy for N tasks, which is denoted as $s^j = (s_1^j, \ldots, s_i^j, \ldots, s_N^j)$, where $s^j \in S^j$ and $S^j = S_1^j \times \cdots \times S_i^j \times \cdots \times S_N^j$. The *strategy profile* consisting of all users' strategies is $s = (s^j, s^{-j})$, where $s^{-j} = (s^1, \ldots, s^{j-1}, s^{j+1} \ldots, s^M)$, $S = S^1 \times \cdots \times S^j \times \cdots \times S^M$ and $s \in S$.

According to Equation (7), the utility function of the crowdsourcer is $g = \sum_{i=1}^{N} g_i$. After users have made their strategies, the crowdsourcer will select the users, $\phi = (\phi_1, \ldots, \phi_i, \ldots, \phi_N)$, to participate in the next round of bidding for each task, where $\phi_i \in \Phi$ and $\phi \in \Phi^N$.

We know the purposes of both the crowdsourcer and users are to maximize their utilities. Based on Equation (6) and Equation (7), the purposes of the users and the crowdsourcer can be formulated as

$$\begin{aligned} &\text{maximize} \;\; u_j(s^j, s^{-j}, \phi), \\ &\text{s.t.} \quad \phi \in \Phi^N, \langle s^j, s^{-j} \rangle \in S; \end{aligned} \tag{23}$$

and

$$\begin{aligned} &\text{maximize} \;\; g(s^j, s^{-j}, \phi), \\ &\text{s.t.} \quad \phi \in \Phi^N, \langle s^j, s^{-j} \rangle \in S. \end{aligned} \tag{24}$$

4.2.2 IMMTMP. Based on the reverse auction and IMSTMP, we design an incentive mechanism, namely, the IMMTMP, for the MTMP model. In the IMMTMP incentive mechanism, the crowdsourcer is the buyer, who recruits users to complete the sensing tasks; and the users are the sellers, who will independently set the bidding strategies for the tasks in which they are interested.

The detailed steps of the IMMTMP are described in Algorithm 3.

ALGORITHM 3: IMMTMP

Require: A set of users φ, a set of tasks τ and reward R
Ensure: s^*, ϕ^*

1: Initialize s, s^*, ϕ and ϕ^*
2: **while** ($|s - s^*| > \xi_2$) **do**
3: $\quad s \leftarrow s^*, \phi \leftarrow \phi^*$
4: $\quad$ **for** ($j = 1$ to M) **do**
5: $\quad\quad$ **for** ($i = 1$ to N) **do**
6: $\quad\quad\quad s'_i \leftarrow filter(s^*_i, \phi^*_i)$
7: $\quad\quad\quad$ Calculate q_{j,i^*} using Inequality (10) based on s'_i
8: $\quad\quad\quad$ **if** $q_j \leq q_{j,i^*}$ **then**
9: $\quad\quad\quad\quad b^*_{j,i} \leftarrow 0$
10: $\quad\quad\quad$ **else**
11: $\quad\quad\quad\quad$ Calculate $b_{j,i,min}$ using Inequality (16) based on s'_i
12: $\quad\quad\quad\quad$ Calculate $b_{j,i,max}$ using Inequality (17) based on s'_i
13: $\quad\quad\quad\quad b^*_{j,i} \leftarrow b_{j,i,max}$
14: $\quad\quad\quad$ **end if**
15: $\quad\quad$ **end for**
16: $\quad\quad$ Update s^* based on $b^*_{j,i}$
17: $\quad$ **end for**
18: $\quad$ **for** ($i = 1$ to N) **do**
19: $\quad\quad$ **if** ($b_{j,i,max} \leq b_{j,i,min}$ or $b^*_{j,i} = 0, j \in \phi^*$) **then**
20: $\quad\quad\quad b^*_{j,i} \leftarrow 0$
21: $\quad\quad\quad$ Update ϕ^* based on s^*
22: $\quad\quad$ **end if**
23: $\quad$ **end for**
24: **end while**
25: **return** s^*, ϕ^*

In Algorithm 3, ϕ^* and s^* are strategies of the crowdsourcer and users, respectively, whereas ϕ and s, respectively, are used to save their previous strategies (line 1). In each iteration, the system compares the loop conditions at first (line 2). Specifically, if the difference between s^* and s is smaller than ξ_2, then the iteration will stop and go to line 24; otherwise, the system will update ϕ and s (line 3). Based on the IMSTMP, in each round, users give their optimal bidding strategies for their interesting tasks in turn (lines 4–17). After users have given their bidding strategies, the crowdsourcer will select the users to participate in the next round for each task (lines 18–23). As in the IMSTMP, if user φ_j is not selected to participate in the next round for a task, he/she cannot continue to develop a strategy for this task. The iteration will continue until a termination condition is met (line 1). When the termination condition is met, the algorithm will return the latest ϕ^* and s^* as the optimal strategies of the crowdsourcer and users, respectively (line 25).

4.2.3 The Performance of IMMTMP. Now, let us analyze the IMMTMP incentive mechanism using the four desirable properties introduced in Section 3.3 as performance metrics.

- **IMMTMP is Rational:** Based on Inequality (10) and Inequality (11), users will not participate in a task unless the utility obtained from the task is not negative. In other words, for user φ_j $(1 \leq j \leq M)$, if $u_{j,i} \leq 0$, then he/she will set $b_{j,i} = 0$.
- **IMMTMP is Efficient:** For the IMSTMP, we can observe that the time complexity of Algorithm 1 is $O(bM^2)$. Since the IMMTMP is based on the IMSTMP, and there are N tasks in IMMTMP, we can observe that the worst time complexity of Algorithm 3 is $O(bNM^2)$.
- **IMMTMP is Profitable:** As discussed with the IMSTMP, we guarantee $g(\phi, s) > 0$ from the following aspects: First, according to Inequality (12), user φ_j's bidding price $b_{j,i}$ should be less than $\frac{p_i}{v_i}$. For the situation $b_{j,i} > \frac{p_i}{v_i}$, the crowdsourcer views it as $b_{j,i} = \frac{p_i}{v_i}$. Second, by Equation (1), we know that p_i is part of the given reward R, whereas R comes from the crowdsourcer's utility. Finally, as mentioned in Inequality (14), for user φ_j, the bidding strategy s_i^j should satisfy $g_i(s_i^j, s_i^{-j}) > g_i(s_i^{-j})$; otherwise, user φ_j will not be selected. Above all, if user φ_j wants to win, he/she should bring profits to the crowdsourcer.
- **IMMTMP is Truthful:** According to the definition, we can determine that an auction mechanism is truthful if and only if it satisfies the following points. If user φ_j $(1 \leq j \leq M)$ is selected as a participant by bidding $s_i^j = (b_{j,i}, q_j)$, it also wins by using the bidding price $b'_{j,i} \leq b_{j,i}$. In addition, user φ_j would not be selected if it bids $b'_{j,i} > b_{j,i}$. In the MTMP model, the published tasks are independent, and each user's purpose is to maximize its utility. Therefore, as discussed in Section 4.1, user φ_j's optimal bidding price for each task is the maximum value in its feasible interval. Therefore, we can observe that the IMMTMP incentive mechanism is truthful.

5 EXPERIMENTS

In this section, we evaluate the performance of our incentive mechanisms. As mentioned in Reference [46], the performance metrics include the users' average utility ($\overline{u}$), the crowdsourcer's utility (g), and the number of participants. We analyze the impact of the following factors on our incentive mechanisms: the number of users (m), user's cost per unit data (d), and task reward (R). For the IMMTMP, we also study the impact of the number of tasks (n) on its performance.

5.1 Simulation Setup

This section describes the parameter settings of the system. The amount of data required by a task (v) is randomly varied from 180 to 200. The importance of a task (c) is distributed over [1,3]. We assume that o is linearly dependent on c and q, which is defined as $o = 2 \times cq$ in this article. For the sake of discussion, each user's preprocessing ability (q) is set to a constant of 1. The cost is uniformly distributed over (0.1,d], where d is varied from 0.1 to 1.3. The consumption required for preparation (γ) is distributed over [1,3].

5.2 Evaluation of IMSTMP

To evaluate the performance of the IMSTMP, the number of users (m) is varied from 10 to 300 at an increment of 50, d is varied from 0.1 to 1.3 at an increment of 0.2, and reward R is varied from 0 to 400 at an increment of 50.

(1) Users' average utility: Figure 3 shows the impact of the number of users, m, on $\overline{u}$, and we can see that $\overline{u}$ decreases as m increases; the reason is that, with the increases of m, more users will

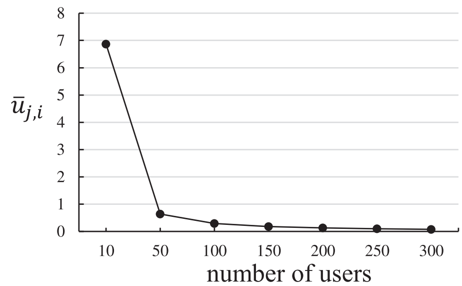
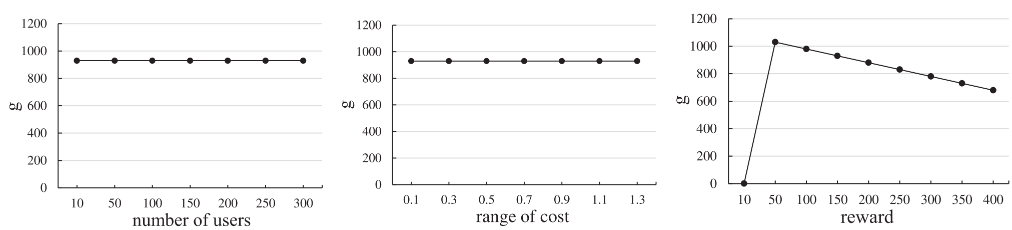


Fig. 3. Users' average utility.



(a) setting m (b) setting d (c) setting R

Fig. 4. The crowdsourcer's utility.

participate in the system, and according to Equation (3), more participants means more consumption, so $\overline{u}$ decreases as m increases. In addition, in Figure 3, the value of $\overline{u}$ declines sharply when the number of users increases from 10 to 50, and then there is a slow decline. It is because, at the beginning, when m increases from 10 to 50, the given reward R makes the tasks very attractive, so the number of participants increases sharply, but more participants means more consumption, so the value of $\overline{u}$ declines sharply; when m increases from 50 to 300, the number of participants shows a slow growth trend, so the decline of $\overline{u}$ is a slow trend.

(2) The crowdsourcer's utility: Figure 4 illustrates the impacts of m, d, and R on the crowdsourcer's utility (g). In Figure 4(a), we fix d and R, and we observe that g remains steady as m increases. The reason is that, when R is given, for the crowdsourcer, as long as the reward R can motivate users to provide sensing services, the value of the task will remain stable. In Figure 4(b), m and R are fixed. We can get that g also remains steady as d increases. Because when R is given, although the range of d is increasing, there are always some users who can be motivated to provide sensing services for the task. In Figure 4(c), we fix m and d, and we can see that g increases sharply when R increases from 10 to 50, and then g decreases with the further increase of R. The reason is that, at the beginning, R is too small to motivate users to provide sensing services, so $g = 0$; then, when R increases from 10 to 50, some users can be motivated to provide sensing services, so the task can be completed by these participants and the utility of the crowdsourcer increases sharply; however, the value of the task is limited, and R comes from it, so when R increases further, the utility of the crowdsourcer will decrease. Moreover, if R increases to $R = o \times v$, then $g = 0$.

(3) The number of participants: Figure 5 presents the impacts of m, d, and R on the number of participants. In Figure 5(a), we fix d and R, we can get that the number of participants increases with the increase of m; but more participants means more consumption, and the reward R is given, so the growth trend of participants will gradually decrease. In Figure 5(b), the number of participants decreases as d increases. Because a larger d means the costs of users become more diverse, users are more likely to fail to meet the winning conditions. In Figure 5(c), the number of participants

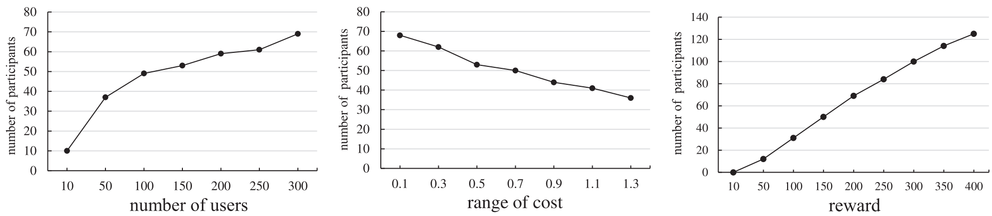


Fig. 5. The number of participants.

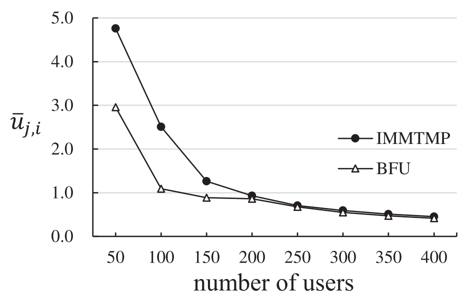


Fig. 6. Users' average utility.

increases with R, but its upper limit is m. The reason is that, when R becomes larger, users' bids will also increase, so more users can get profits from it, thus the number of participants increases with R.

5.3 Evaluation of IMMTMP

For the IMMTMP, the parameters are set as follows: the number of users (m) is varied from 50 to 400 at an increment of 50, d is varied from 0.3 to 1.3 at an increment of 0.2, the reward R is varied from 500 to 3500 at an increment of 500, the number of tasks (n) is varied from 50 to 225 at an increment of 25, and the consumption required for preparation (γ) is distributed over [0, 0.3].

In addition, the existing mechanisms [11, 13, 33, 39] were based on the situation that users directly submit the collected data to the crowdsourcer and ignored the fact that users' computing power can also be utilized to preprocess the collected raw data for the crowdsourcer. Besides, in our incentive mechanisms, users without any data preprocessing ability will not be selected as participants in the crowdsensing system. Thereby, the existing mechanisms cannot be directly used in our system, so we compare our mechanism with a baseline method, called BFU, where users only consider their own profits when making bidding strategies. Specifically, in the BFU, before users make their bidding strategies, assume that the crowdsourcer will distribute tasks equally to all users; then to obtain more profit, each user only considers his/her own profit when making bidding strategy; that is, each user randomly decides the bidding strategy according to Equation (10) and Equation (11); finally, the crowdsourcer will select users who meet the winner conditions mentioned in Section 4.1.1 as participants.

(1) Users' average utility: Figure 6 shows the impact of m on $\overline{u}$. We observe that $\overline{u}$ decreases as m increases; the reason is that, with the increases of m, more and more users will participate in the system, and according to Equation (3), more participants means more consumption, so $\overline{u}$ decreases as m increases. Besides, in Figure 6, we can find that the value of $\overline{u}$ declines sharply

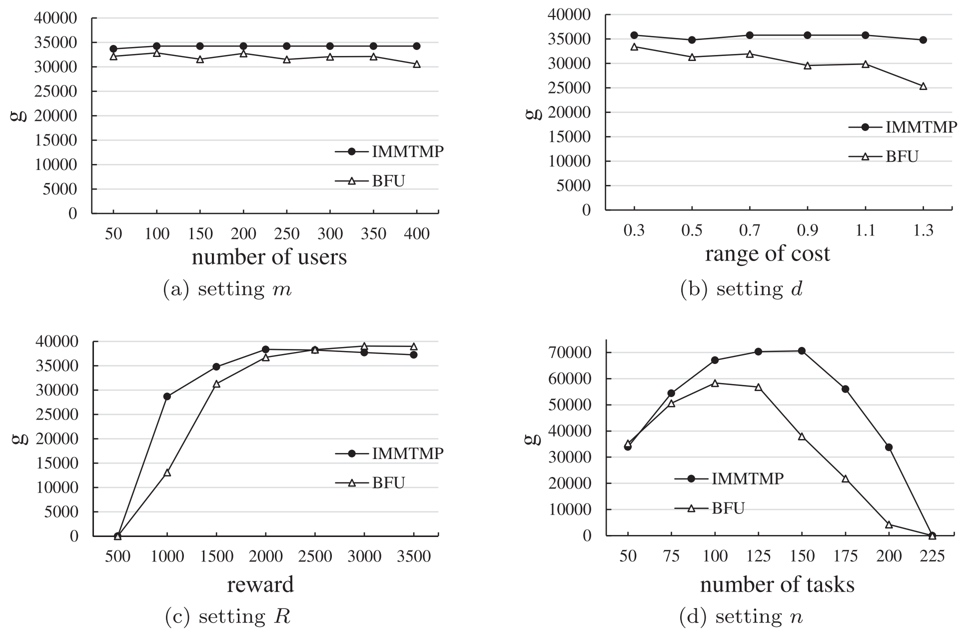
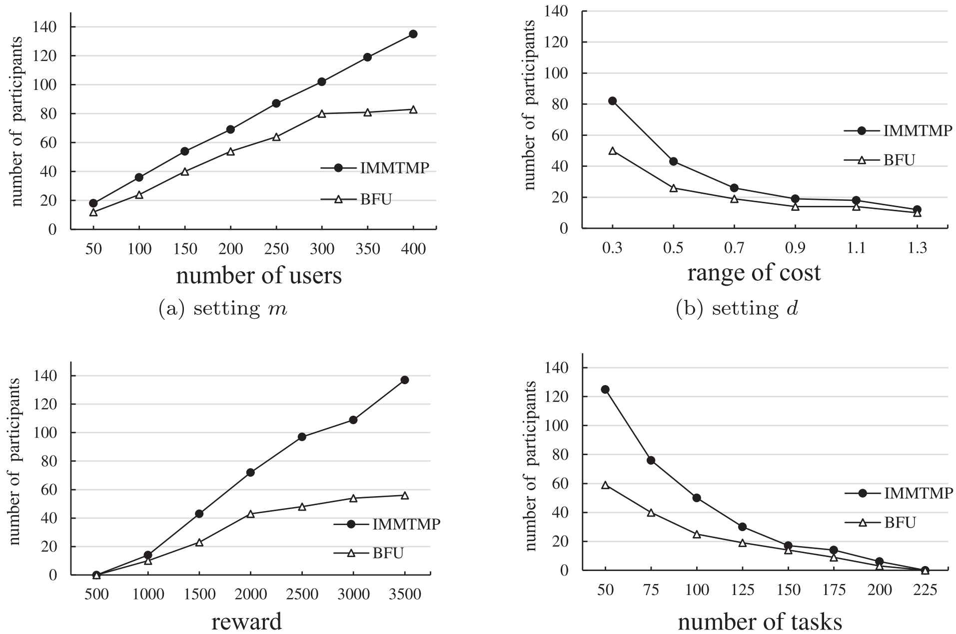


Fig. 7. The crowdsourcer's utility.

when the number of users increases from 50 to 100, and then there is a slow decline. The reason is similar to Figure 3. Moreover, the IMMTMP achieves higher $\overline{u}$ than the BFU.

(2) The crowdsourcer's utility: Figure 7 shows the impacts of m, d, R, and n on g. In Figure 7(a), we fix d, R, and n. We observe that g remains steady as m increases, because the given reward R can motivate users to complete a certain number of tasks, and the number of tasks that can be completed remains stable with the increase of m. In addition, the IMMTMP achieves higher g than the BFU. In Figure 7(b), g also remains steady as d increases; the reason is similar to Figure 4(b). In Figure 7(c), we fix m, d, and n, and we observe that, at first, g increases with the increase of R, then g decreases with the further increase of R. The reason is similar to Figure 4(c). Moreover, at the beginning, the IMMTMP achieves a higher g than the BFU when R increases from 500 to 2500, then the BFU gets a higher g than the IMMTMP when R increases from 2500 to 3500, because, first, when R increases from 500 to 2500, although the actual cost of paying participants in the IMMTMP is higher than that in the BFU, the profit brought by participants through completing tasks in the IMMTMP is much more than that in the BFU; second, when R increases to 2500, in the IMMTMP, all tasks can be completed by the participants, thereby, the crowdsourcer can get the maximum utility g before the reward R increases to 2500; third, because the reward R comes from the completed tasks, when R increases from 2500 to 3500, the actual cost of paying participants in the IMMTMP is equal to R, which is much higher than that in the BFU, and the profit brought by participants through completing tasks in the IMMTMP is less than that in the BFU, so when R increases from 2500 to 3500, the BFU gets a higher g. In Figure 7(d), we fix m, d, and R, and we observe that with the increase of n, g first increases then decreases. Because R is given and shared by all tasks, at the beginning, with the increase of n, the number of tasks that can attract users to provide sensing services will increase, so the crowdsourcer's utility g also increases. However, according to Equation (1), we can get that, with the increase of n, the reward assigned to each task will be less and less; that is, the attraction of a task decreases with the increase of n. Finally, no



(a) setting m (b) setting d (c) setting R (d) setting n

Fig. 8. The number of participants.

task can attract users to provide sensing services. Furthermore, the IMMTMP achieves higher g than the BFU.

(3) The number of participants: Figure 8 shows the impacts of m, d, R, and n on the number of participants. In Figure 8(a), we can observe that the number of participants basically increases as m increases, and the IMMTMP achieves more participants than the BFU. The reason is that, when m increases from 50 to 400, the given reward R can continuously attract users to participate in the crowdsensing system. In Figure 8(b), when d increases, the number of participants decreases, because, according to Equation (16) and Equation (17), the smaller the value of d, the less the users' consumption, the greater the possibility of users will win, so the number of participants decreases as d increases. In addition, more users can meet the winner conditions in the IMMTMP than in the BFU. In Figure 8(c), we can see that the number of participants increases with the increase of R, but the upper limit is m—the reason is similar to Figure 5(c); and the IMMTMP achieves more participants than the BFU. In Figure 8(d), we can get that the number of participants decreases as n increases, because with the increase of n, the reward assigned to each task will be less and less and, finally, no task can attract users to provide sensing services. In addition, in the IMMTMP, when making bidding strategies, users will consider both their own profits and the crowdsourcer's profit, but in the BFU, users only take into account their own interests, so the IMMTMP achieves more participants than the BFU.

6 CONCLUSION

In this article, we propose monetary-based incentive mechanisms to motivate users to preprocess the collected data for the crowdsourcer. We first study the single-task-multiple-participants model, where the crowdsourcer only publishes one task. Then, we extend the model to discuss the multiple-tasks-multiple-participants model, where multiple tasks are published.

Based on an auction mechanism and game theory, we propose an incentive mechanism (called the IMSTMP) for the STMP model and prove that the IMSTMP game has a Nash equilibrium. Based on the IMSTMP, we develop an incentive mechanism (called the IMMTMP) for the MTMP model. Both incentive mechanisms are truthful, individually rational, profitable, and computationally efficient. Furthermore, the utility maximization problems of both the crowdsourcer and users are simultaneously considered in our incentive mechanisms. Finally, we evaluate the performance of the incentive mechanisms through theoretical analysis and extensive experiments.

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REFERENCES

[1] Andrea Capponi, Claudio Fiandrino, Burak Kantarci, Luca Foschini, Dzmitry Kliazovich, and Pascal Bouvry. 2019. A survey on mobile crowdsensing systems: Challenges, solutions, and opportunities. *IEEE Commun. Surv. Tutor.* 21, 3 (2019), 2419–2465.

[2] Fei Chen, Cong Zhang, Feng Wang, and Jiangchuan Liu. 2015. Crowdsourced live streaming over the cloud. In *Proceedings of the IEEE Conference on Computer Communications (INFOCOM'15)*. IEEE, 2524–2532.

[3] Guanling Chen, Bo Yan, Minho Shin, David Kotz, and Ethan Berke. 2009. MPCS: Mobile-phone based patient compliance system for chronic illness care. In *Proceedings of the 6th Annual International Mobile and Ubiquitous Systems: Networking & Services (MobiQuitous'09)*. IEEE, 1–7.

[4] Yanjiao Chen, Baochun Li, and Zhang Qian. 2016. Incentivizing crowdsourcing systems with network effects. In *Proceedings of the IEEE International Conference on Computer Communications (INFOCOM'16)*.

[5] Driss Choujaa and Naranker Dulay. 2009. Activity recognition from mobile phone data: State of the art, prospects and open problems. *Imper. Coll. London* 5 (2009), 32.

[6] George Danezis, Stephen Lewis, and Ross J. Anderson. 2005. How much is location privacy worth? In *Proceedings of the Workshop on the Economics of Information Security (WEIS'05)*, Vol. 5. Citeseer.

[7] Boi Faltings, Jason Jingshi Li, and Radu Jurca. 2013. Incentive mechanisms for community sensing. *IEEE Trans. Comput.* 63, 1 (2013), 115–128.

[8] Arsham Farshad, Mahesh K. Marina, and Francisco Garcia. 2014. Urban Wi-Fi characterization via mobile crowdsensing. In *Proceedings of the IEEE Network Operations and Management Symposium (NOMS'14)*. IEEE, 1–9.

[9] Chunming Gao, Fanyu Kong, and Jindong Tan. 2009. Healthaware: Tackling obesity with health aware smart phone systems. In *Proceedings of the IEEE International Conference on Robotics and Biomimetics (ROBIO'09)*. IEEE, 1549–1554.

[10] Hui Gao, Chi Harold Liu, Jian Tang, Dejun Yang, and Wendong Wang. 2018. Online quality-aware incentive mechanism for mobile crowd sensing with extra bonus. *IEEE Trans. Mob. Comput.* PP, 99 (2018), 1–1.

[11] Kyungsik Han, Eric A. Graham, Dylan Vassallo, and Deborah Estrin. 2011. Enhancing motivation in a mobile participatory sensing project through gaming. In *Proceedings of the IEEE 3rd International Conference on Privacy, Security, Risk and Trust and the IEEE 3rd International Conference on Social Computing*. IEEE, 1443–1448.

[12] Junyan Hu, Kenli Li, Chubo Liu, and Keqin Li. 2018. A game-based price bidding algorithm for multi-attribute cloud resource provision. *IEEE Trans. Serv. Comput.* (2018), 1–1.

[13] Haiming Jin, Lu Su, Houping Xiao, and Klara Nahrstedt. 2016. INCEPTION: Incentivizing privacy-preserving data aggregation for mobile crowd sensing systems. In *Proceedings of the 17th ACM International Symposium on Mobile Ad Hoc Networking and Computing*. ACM, 341–350.

[14] Wenqiang Jin, Mingyan Xiao, Ming Li, and Linke Guo. 2019. If you do not care about it, sell it: Trading location privacy in mobile crowd sensing. In *Proceedings of the IEEE Conference on Computer Communications (INFOCOM'19)*. IEEE, 1045–1053.

[15] Ioannis Koukoutsidis. 2018. Estimating spatial averages of environmental parameters based on mobile crowdsensing. *ACM Trans. Sens. Netw.* 14, 1 (2018), 2.

[16] Juong-Sik Lee and Baik Hoh. 2010. Sell your experiences: A market mechanism based incentive for participatory sensing. In *Proceedings of the IEEE International Conference on Pervasive Computing and Communications (PerCom'10)*. IEEE, 60–68.

[17] Keqin Li. 2018. A game theoretic approach to computation offloading strategy optimization for non-cooperative users in mobile edge computing. *IEEE Trans. Sustain. Comput.* PP, 99 (2018), 1–1.

[18] Lin Gao, Fen Hou, and Jianwei Huang. 2016. Providing long-term participation incentive in participatory sensing. In *Proceedings of the IEEE Conference on Computer Communications (INFOCOM'16)*.

[19] Jian Lin, Dejun Yang, Ming Li, Jia Xu, and Guoliang Xue. 2017. Frameworks for privacy-preserving mobile crowdsensing incentive mechanisms. *IEEE Trans. Mob. Comput.* 17, 8 (2017), 1851–1864.
[20] Chubo Liu, Kenli Li, Zhuo Tang, and Keqin Li. 2018. Bargaining game-based scheduling for performance guarantees in cloud computing. *ACM Trans. Model. Perform. Eval. Comput. Syst.* 3, 1 (2018), 1.
[21] Chi Harold Liu, Jun Fan, Pan Hui, Jie Wu, and Kin K. Leung. 2015. Toward QoI and energy efficiency in participatory crowdsourcing. *IEEE Trans. Vehic. Technol.* 64, 10 (2015), 4684–4700.
[22] Qian Ma, Lin Gao, Ya Feng Liu, and Jianwei Huang. 2018. Incentivizing Wi-Fi network crowdsourcing: A contract theoretic approach. *IEEE/ACM Trans. Netw.* PP, 99 (2018), 1–14.
[23] Sabita Maharjan, Yan Zhang, and Stein Gjessing. 2016. Optimal incentive design for cloud-enabled multimedia crowdsourcing. *IEEE Trans. Multimedia* 18, 12 (2016), 2470–2481.
[24] Prashanth Mohan, Venkata N. Padmanabhan, and Ramachandran Ramjee. 2008. Nericell: Rich monitoring of road and traffic conditions using mobile smartphones. In *Proceedings of the 6th ACM Conference on Embedded Network Sensor Systems.* ACM, 323–336.
[25] Federico Montori, Luca Bedogni, and Luciano Bononi. 2017. A collaborative Internet of Things architecture for smart cities and environmental monitoring. *IEEE Internet Things J.* PP, 99 (2017), 1–1.
[26] Rabia Nessah and Guoqiang Tian. 2016. On the existence of Nash equilibrium in discontinuous games. *Econ. Theor.* 61, 3 (2016), 515–540.
[27] Cisco Visual Networking. 2016. *Cisco Global Cloud Index: Forecast and Methodology, 2015–2020.* White paper. *Cisco Public, San Jose.*
[28] Victor Pankratius, Frank Lind, Anthea Coster, Philip Erickson, and Joshua Semeter. 2014. Mobile crowd sensing in space weather monitoring: The Mahali project. *IEEE Commun. Mag.* 52, 8 (2014), 22–28.
[29] Dan Peng, Fan Wu, and Guihai Chen. 2015. Pay as how well you do: A quality based incentive mechanism for crowdsensing. In *Proceedings of the 16th ACM International Symposium on Mobile Ad Hoc Networking and Computing.* ACM, 177–186.
[30] Dan Peng, Fan Wu, and Guihai Chen. 2017. Data quality guided incentive mechanism design for crowdsensing. *IEEE Trans. Mob. Comput.* 17, 2 (2017), 307–319.
[31] Zhang Qi, Yutian Wen, Xiaohua Tian, Xiaoying Gan, and Xinbing Wang. 2015. Incentivize crowd labeling under budget constraint. In *Proceedings of the IEEE Conference on Computer Communications (INFOCOM'15).*
[32] Francesco Restuccia, Pierluca Ferraro, Simone Silvestri, Sajal K. Das, and Giuseppe Lo Re. 2018. IncentMe: Effective mechanism design to stimulate crowdsensing participants with uncertain mobility. *IEEE Trans. Mob. Comput.* 18, 7 (2018), 1571–1584.
[33] Francesco Restuccia, Nirnay Ghosh, Shameek Bhattacharjee, Sajal K. Das, and Tommaso Melodia. 2017. Quality of information in mobile crowdsensing: Survey and research challenges. *ACM Trans. Sens. Netw.* 13, 4 (2017), 34.
[34] John P. Rula, Vishnu Navda, Fabián E. Bustamante, Ranjita Bhagwan, and Saikat Guha. 2014. No one-size fits all: Towards a principled approach for incentives in mobile crowdsourcing. In *Proceedings of the 15th Workshop on Mobile Computing Systems and Applications.* ACM, 3.
[35] Immanuel Schweizer, Roman Bärtl, Axel Schulz, Florian Probst, and Max Mühläuser. 2011. NoiseMap-real-time participatory noise maps. In *Proceedings of the 2nd International Workshop on Sensing Applications on Mobile Phones.* Citeseer, 1–5.
[36] Vikrant Singh, Deepthi Chander, Umang Chhaparia, and Bhaskaran Raman. 2018. SafeStreet: An automated road anomaly detection and early-warning system using mobile crowdsensing. In *Proceedings of the 10th International Conference on Communication Systems & Networks (COMSNETS'18).* IEEE, 549–552.
[37] Xiaoqiang Teng, Deke Guo, Yulan Guo, Xiaolei Zhou, Zeliu Ding, and Zhong Liu. 2017. IONavi: An indoor-outdoor navigation service via mobile crowdsensing. *ACM Trans. Sens. Netw.* 13, 2 (2017), 12.
[38] Leye Wang, Dingqi Yang, Han Xiao, Tianben Wang, Daqing Zhang, and Xiaojuan Ma. 2018. Location privacy-preserving task allocation for mobile crowdsensing with differential geo-obfuscation. In *Proceedings of the International Conference.*
[39] Xiaojie Wang, Zhaolong Ning, Xiping Hu, C. H. Ngai, and Ricky Y. K. Kwok. 2018. A city-wide real-time traffic management system: Enabling crowdsensing in social Internet of vehicles. *IEEE Commun. Mag.* 56, 9 (2018), 19–25.
[40] Yufeng Wang, Xueyu Jia, Qun Jin, and Jianhua Ma. 2016. QuaCentive: A quality-aware incentive mechanism in mobile crowdsourced sensing (MCS). *J. Supercomput.* 72, 8 (2016), 2924–2941.
[41] Yanting Wang, Sheng Min, Xijun Wang, Wang Liang, and Jiandong Li. 2016. Mobile-edge computing: Partial computation offloading using dynamic voltage scaling. *IEEE Trans. Commun.* 64, 10 (2016), 1–1.
[42] Yutian Wen, Jinyu Shi, Qi Zhang, Xiaohua Tian, Zhengyong Huang, Hui Yu, Yu Cheng, and Xuemin Shen. 2015. Quality-driven auction-based incentive mechanism for mobile crowd sensing. *IEEE Trans. Vehic. Technol.* 64, 9 (2015), 4203–4214.

[43] Zheng Xiao, Zhao Tong, Kenli Li, and Keqin Li. 2017. Learning non-cooperative game for load balancing under self-interested distributed environment. *Appl. Soft Comput.* 52 (2017), 376–386.

[44] Jinliang Xu, Shangguang Wang, Ning Zhang, Fangchun Yang, and Xuemin Shen. 2018. Reward or penalty: Aligning incentives of stakeholders in crowdsourcing. *IEEE Trans. Mob. Comput.* 18, 4 (2018), 974–985.

[45] Qiang Xu and Rong Zheng. 2017. When data acquisition meets data analytics: A distributed active learning framework for optimal budgeted mobile crowdsensing. In *Proceedings of the IEEE Conference on Computer Communications (INFOCOM'17)*. IEEE, 1–9.

[46] Dejun Yang, Guoliang Xue, Fang Xi, and Tang Jian. 2015. Incentive mechanisms for crowdsensing: Crowdsourcing with smartphones. *IEEE/ACM Trans. Netw.* 99, 3 (2015), 1–13.

[47] Ruiyun Yu, Jiannong Cao, Rui Liu, Wenyu Gao, Xingwei Wang, and Junbin Liang. 2019. Participant incentive mechanism toward quality-oriented sensing: Understanding and application. *ACM Trans. Sens. Netw.* 15, 2 (2019), 21.

[48] Xinglin Zhang, Zheng Yang, Wei Sun, Yunhao Liu, Shaohua Tang, Kai Xing, and Xufei Mao. 2015. Incentives for mobile crowd sensing: A survey. *IEEE Commun. Surv. Tutor.* 18, 1 (2015), 54–67.

[49] Dong Zhao, Huadong Ma, and Liang Liu. 2016. Budget-feasible online incentive mechanisms for crowdsourcing tasks truthfully. *IEEE/ACM Trans. Netw.* 24, 2 (2016), 647–661.

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