This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2018.2868180, IEEE Access

Date of publication xxxx 00, 0000, date of current version xxxx 00, 0000.

Digital Object Identifier 10.1109/ACCESS.2017.Doi Number

Time-Sensitive and Sybil-Proof Incentive Mechanisms for Mobile Crowdsensing via Social Network

LINGYUN JIANG, XIAOFU NIU, JIA XU, Member, IEEE, YUCHAN WANG, YONGQI WU, LIJIE XU

Jiangsu Key Laboratory of Big Data Security and Intelligent Processing, Nanjing University of Posts and Telecommunications, Nanjing, Jiangsu 210023 China

Corresponding author: JIA XU (e-mail: xujia@njupt.edu.cn).

This work has been supported in part by the NSFC (No. 61472193, 61872193, 61502251).

ABSTRACT Mobile Crowdsensing (MCS) has become a popular and promising paradigm in various sensing applications in urban scenarios. In recent years, some social network based MCS systems, which utilizing the social relationship to recruit participants or perform sensing tasks, have been proposed. However, none of them have taken into consideration both the time-sensitive and Sybil-proofness, which are two key problems for the MCS systems in the social network context. We present two social network based MCS system models, and formulize the Sybil attack models for each model. We design two incentive mechanisms based on reverse auction, *TSSP-M* and *TSSP-S*, for each of two system models. Through both rigorous theoretical analyses and extensive simulations, we demonstrate that *TSSP-M* satisfies the desirable properties of computational efficiency, individual rationality, truthfulness, time-sensitive, Sybil-proofness, and optimization; *TSSP-S* achieves individual rationality, truthfulness, time-sensitive, and Sybil-proofness.

INDEX TERMS mobile crowdsensing; incentive mechanism design; time-sensitive; sybil-proof; social network

I. INTRODUCTION

Mobile crowdsensing (MCS) is a new paradigm that utilizes individuals or communities to collect sensory data together to form knowledge fragments [1]. It provides an attractive sensing mode due to the prominent advantages, such as wide spatio-temporal coverage, low cost, good scalability, and pervasive application scenario. Furthermore, it is especially suitable for sensing tasks that are with high complexity, huge workload, and difficult for machines.

MCS has shown its great potential in a variety of application domains, such as healthcare, mobile social network, environmental monitoring and transportation. Recently, researchers have developed many MCS based applications and systems in urban scenarios, such as Sound Map [2] for creating noise map, Smart patrolling [3] for road detection, WiFi HeatMap [2] for WiFi discovery, BatMapper [4] and SpeeNavi [5] for indoor localization and navigation, crowd-participated system for predicting the bus arrival time [7], and SmartProbe [6] for network capacity prediction.

Although there are many MCS applications and systems, most of them are based on voluntary. In fact, incentive mechanisms [10, 26, 27] are crucial to MCS while smartphone users consume battery, memory, computing ability and data traffic [30] of device to sense, store and transmit the data. Moreover, there are potential privacy threats to smartphone users while sharing their sensed data with location tags, interests or identities. Therefore, the incentive mechanism, which computes payment for users to compensate their resource consumption and potential privacy breach, is a necessary component of MCS systems. Most importantly, incentive mechanisms also help to achieve good service quality since sensing services are truly dependent on quality of users and quality of sensed data.

However, most of the incentive mechanisms [19, 23, 28] assume that there are enough participants in the mobile crowdsourcing systems. In reality, however, many tasks cannot be completed in time due to the insufficient participation, especially in the large-scale city sensing scenarios. According to the data of the fourth quarter in 2016 from *Analysys* [29], only 6.02% and 3.83% of all registered users can provide the real-time sensing data for the traffic condition in *Tencent map* and *Tianyi navigation*, respectively.

To address the insufficient participation problem, some incentive mechanisms, which recruit social users from online social network, have been proposed. For example, Xu *et al.* consider the compatibility of users in the online community for multiple cooperative tasks [8]. Xiao *et al.* focus on the makespan sensitive task assignment problem for the MCS in the social networks [9]. However, none of them take the Sybil attack and time-sensitive into consideration.

This paper designs the truthful incentive mechanisms for the MCS systems in the social network context, and aim to solve the following two key issues:

- How to stimulate social users to diffuse sensing tasks in the social network quickly?

Despite the MCS is not a real-time sensing mode , the timeliness is very important in many applications. For example, the applications such as the crowd-participated system for the arrival time prediction of buses [7] and the Haze Watch [10] for pollution monitoring require the timely collection of sensory data and then predict events in the near future based on the sensory data. However, users in the social networks have different interest and online time, the speed of task diffusion is difficult to guarantee. Moreover, due to the lack of network topology of social users, it is unpractical to select the users with high centrality [31] as the diffusers.

- How to prevent social users from conducting the Sybil attack?

Most MCS systems require users to register with real names, which increase the difficulty of conducting Sybil attack. However, social users are not inherent registered users of the MCS systems, and it is difficult to verify the real identities. Moreover, it is convenient for malicious social users to conduct the Sybil attack because too much personal information and sensitive information are publicly released in the social networks. Therefore, the MCS systems in the social network context are more vulnerable to the Sybil attack. Based on the analysis of [12], most of auction-based incentive mechanisms of MCS are vulnerable to Sybil attack.

In this paper, we focus on designing time-sensitive and Sybil-proof incentive mechanisms for MCS. We model the interaction of task requesters and social users as a reverse auction process. The requester publicizes tasks in the social cycle. After receiving the task information, the social neighbors can also diffuse the tasks in their social cycle (act as the recruiters) or submit bids to the requester. The above diffusion process continues in the social network until a certain moment. Then the requester selects the winners from all the bids received and notifies the winners. Different from most of MCS incentive mechanisms, the recruiters who successfully recruit the winners will be rewarded to encourage social users to diffuse the tasks in their social circles. The whole process is illustrated by Fig.1.

The problem of designing time-sensitive and Sybil-proof incentive mechanisms for MCS in social network context is very challenging. First, due to the selfishness and rationality of social users, we need to design the truthful incentive mechanisms to prevent the strategic behaviors of social users by submitting dishonest bid price or to executable task set in order to maximize their utilities. Second, the incentive mechanisms need to stimulate the social users not only to perform the sensing tasks, but also to diffuse the sensing tasks in their social cycles. Moreover, it is difficult to guarantee the efficiency of task diffusion due to the diverse interests and online time of social users. Therefore, the incentive mechanisms should satisfy the time-sensitive, i.e., incenting the social users to diffuse sensing tasks as soon as possible. Finally, the social users may launch Sybil attacks. Different from the traditional MCS system, the social users who successfully recruit other users will obtain additional rewards. Therefore, the social users have the motivation to forge the recruited users to improve their own rewards.

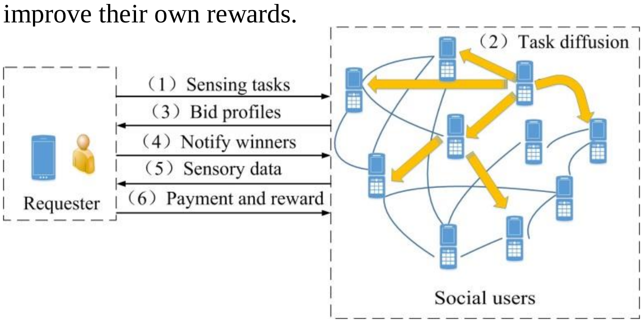

FIGURE 1. Mobile crowdsensing process through social network

The major contributions of this paper are summarized as follows:

1) A novel MCS system is proposed to increase the potential participants by diffusing the sensing tasks in the social network.
2) We present two system models, multi-bid model and single-bid model for the novel MCS system and formulize the Sybil attack models for each model.
3) We design two incentive mechanisms based on reverse auctions, *Time-Sensitive and Sybil-Proof Incentive Mechanism in Multi-Bid Model* (*TSSP-M*) and *Time-Sensitive and Sybil-Proof Incentive Mechanism in Single-Bid Model* (*TSSP-S*) for each of two system models. We show that *TSSP-M* satisfies the desirable properties of computational efficiency, individual rationality, truthfulness, time-sensitive, Sybil-proofness and social optimization, and that *TSSP-S* achieves individual rationality, truthfulness, time-sensitive, Sybil-proofness.

The rest of the paper is organized as follows. We review the state-of-art research in Section II. Section III formulates two system models and lists some desirable properties. Section IV and Section V present the detailed design and analysis of our incentive mechanisms for the multi-bid model and single-bid model, respectively. Performance evaluation is shown in section VI. We conclude this paper in Section VII.

II. RELATED WORK

A. INCENTIVE MECHANISMS IN ONLINE SOCIAL NETWORK CONTEXT

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2018.2868180, IEEE Access

There have been many studies about incentive mechanism design for MCS through online social network. Nguyen *et al.* propose the notions of *node observability* and *coverage utility score*, and design a new context-aware approximation algorithm to find vertex cover that is tailored for crowd-sensing tasks in opportunistic mobile social networks [13]. Xu *et al.* consider the compatibility of social users for multiple cooperative crowdsensing tasks and define three compatibility models through real-life relationships from social networks [7]. Chen *et al.* consider network effects as a contributing factor to intrinsic rewards, and study its influence on the design of extrinsic rewards. Rather than assuming a fixed participant population, they show that the number of participating users evolves to a steady equilibrium. They design progressively more sophisticated extrinsic reward mechanisms and propose new and optimal strategies for a crowdsourcer to obtain a higher utility [14]. Xu *et al*. present the two-tiered social crowdsourcing architecture to solve the insufficient participation problem using the social network in online scenario. An online incentive mechanism, *MTSC,* which consists of two steps: *Agent Selection* and *Online Reverse Auction*, is proposed for this mobile crowdsourcing system [33]. However, none of the above takes the Sybil attack in to consideration.

B. TIME-SENSITIVE INCENTIVE MECHANISMS

Wang *et al.* focus on the time-sensitive and location-dependent random arrival MCS system, and propose a two-level heterogeneous pricing mechanism to balance the participation degree of task participants [15]. In addition, the authors proved that the problem of task selection of random participants is an NP-hard problem, and further proposed several effective greedy task selection algorithms to help each participant to maximize the benefits when selecting tasks. Man *et al.* also focus on solving distributed time-sensitive and location-dependent task selection problem [16]. The users' initial position, movement cost, movement speed, and reputation levels are different. The authors developed the interaction between users as a non-cooperative task selection game (TSG) and proposed an asynchronous and distributed task selection (ADTS) algorithm for each user to compute her task selection and movement plan. Zhan *et al.* propose a time-sensitive incentive mechanism (TSIA) for data collection of opportunistic MCS [17], where each sensor data has an additional time-sensitive value and it is gradually fades. Zhang *et al.* use the data structure called motivational tree to motivate participants to participate in sensing tasks [18]. The contribution model they considered is time-sensitive, which is different from the linear summation model in previous MCS scenarios. However, the above studies assume that there are enough participants to perform the crowdsourcing tasks, and are vulnerable to the Sybil attack.

C. SYBIL-PROOF INCENTIVE MECHANISMS

In most recent years, the Sybil attack problem in MCS has been studied. Zhang *et al.* propose a Sybil-proof incentive tree mechanism under the submodular crowdsourcing model [18], which is more realistic compared to the linear summation model adopted by previous works. Lin *et al.* propose *SPIM-S* and *SPIM-M,* and provide a sufficient condition for a mechanism to be Sybil-proof [12]. Different from above mechanisms, we focus on designing time-sensitive and Sybil-proof incentive mechanisms for MCS in the social network context.

III. SYSTEM MODEL AND DESIRABLE PROPERTIES

In this section, we present two system models based on the bid modes of social users: multi-bid model and single-bid model. In the multi-bid model, each social user submits an independent bidding price for each task in its task set; while in the single-bid model, each social user submits a unique bidding function for its task set. The multi-bid model is suitable for scenarios, where each sensing task is independent; while the single-bid model is suitable for the correlative sensing tasks, and the cost of performing these tasks is related to the correlation between them. For example, in MCS, the cost of performing sensing tasks in close locations is usually lower than that far away from each other due to the existence of mobile cost. We list the frequently used notations in Table Ⅰ.

TABLE I
FREQUENTLY USED NOTATIONS

Notation	Description
U, i, n	set of social users; user i ; number of social users
$\mathcal{T}, t_j, \Gamma_i$	set of tasks; task j ; set of tasks that i claims to perform
TL	deadline of the process of task diffusion
$\mathbf{B}, B_i$	bid profile of social users; bid of each social user $i \in U$
β_i^e	a triple that social user i bid for task set e
t_i^e, b_i^e, c_i^e	task, bid price, and real cost of social user i for task t_i^e
l_i, d_i	recruiter of social user i ; task set size of social user i
β_S, S	set of winning triples; winners set
$\mathbf{p}, p_i, p_i^e$	payment profile; total payment to winner i ; payment to winner i for task t_i^e
$\mathbf{R}, R_i$	reward for all social users; reward for social user i
u_i, u_0, SW	utility of social user i ; utility of requester; social welfare
v_i^e	value to requester when social user i perform task t_i^e
r_{l_i}	reward for l_i to recruit i
i_h	fictitious identity that social user i forges
c_{i_h}	cost of performing the assigned task of i_h
c'_{i_h}	disguised cost if social user i forges fictitious identity i_h
B_{i_h}, b_{i_h}	bids and bid price submitted by the fictitious identities i_h
$p_{i_h}, r_{l_{i_h}}$	payment and reward for fictitious identity i_h
$\tilde{\Gamma}_i$	claimed task set of social user i
$\tilde{u}_i$	utility of social user i when i launches sybil attack
$\tilde{p}_i$	payment to social user i when i launches sybil attack
$M, V(M)$	task subset; value of the task subset
$\mathbf{D}, D_i$	assignment profile; tasks assigned to social user i
$\tilde{D}_i$	tasks assigned to fictitious identity i when i launches sybil attack
$r(M)$	reward function

A. MULTI-BID MODEL

We consider a mobile crowdsensing system consisting of a task requester and a set of social users. The requester first publicizes a set of *m* sensing tasks to his social neighbors through social network. All the sensing tasks need to be completed before the deadline *TL* due to the timeliness requirement of the requester. Each task $t_j \in \mathcal{T}$ has a value for the requester. The social neighbors of the requester may submit bids to the requester or diffuse the sensing tasks to their social cycle to recruit other social users from the social network. Each social user can recruit other social users through task diffusion until the deadline *TL*. Task diffusion is a process to send the messages to notify the social neighbors of the sensing tasks. There are many studies on influence maximization in the social networks [32]. We consider that there is a set $U=\{1,2,...,n\}$ of social users, who receive the task information and are interested in performing sensing tasks after the task diffusion. They can participate in MCS through the reverse auction before time *TL*.

The bid for each social user $i \in U$ is defined as $B_i=\{\beta_i^1,\beta_i^2,...,\beta_i^{d_i}\}$, where $\beta_i^e=(l_i,t_i^e,b_i^e), e\in\{1,2,...,d_i\}$, is a triple. l_i represents the recruiter who recruits the social user *i*. Specifically, $l_i=0$ if the social user *i* is the social neighbor of the requester. Each bid can declare only one recruiter. $t_i^e \in \mathcal{T}, e\in\{1,2,...,d_i\}$ is the task that social user *i* wants to perform, let $\Gamma_i=\{t_i^e \mid e=1,2,...,d_i\}$ be the set of tasks that *i* claims to perform. b_i^e is bidding price of social user *i* for performing task t_i^e. The real task set Γ_i and the real cost c_i^e are the private information and known only to social user *i*. Let $\mathbf{B}=(B_1,B_2,...,B_n)$ be the bid profile of all social users.

Let β_S be the set of winning triples. A social user *i* is called a winner and added into the winner set *S* if it has at least one winning triples, i.e., $\beta_i^e \in \beta_S, i\in U, e\in\{1,2,...,d_i\}$. For any $\beta_i^e \in \beta_S$, the payment for winner *i* is p_i^e, and the total payment is $p_i=\sum_{\beta_i^e\in\beta_S, e\in\{1,2,...d_i\}} p_i^e$. Let $\mathbf{p}=(p_1,p_2,...,p_n)$ be the payment profile for each social user $i\in U$. To stimulate the social users to diffuse the tasks, any winner *i*'s recruiter l_i can obtain a reward r_{l_i}, which is determined by the requester. In order to encourage the social users to diffuse the tasks as soon as possible, the value of r_{l_i} decreases with the bidding time of the winner *i*. In practice, the cost of diffusing task to the social neighbors is usually very low, thus the value of the reward is small. Let the total reward for any social user *i* be R_i, and the reward for all social users is $\mathbf{R}=(R_1,R_2,...,R_n)$. The incentive mechanism outputs the winners set S, the winning triple set β_S, the payment profile $\mathbf{p}$, and the reward profile $\mathbf{R}$.

The utility of any social user *i* is defined as:

$$u_i=\sum_{e\in\{1,2,...,d_i\},\beta_i^e\bigcap\beta_S\neq\varnothing}(p_i^e-c_i^e)+R_i \tag{1}$$

where $p_i^e-c_i^e$ represents the utility that social user *i* can achieve when he completes task t_i^e.

Since we consider the social users are selfish and rational, each social user can behave strategically by submitting a dishonest bidding price or task set to maximize its utility.

We define the utility of the requester as:

$$u_o=\sum_{e\in\{1,2,...,d_i\},\beta_i^e\in\beta_S}(v_i^e-p_i^e-r_{l_i}) \tag{2}$$

where v_i^e is the value to the requester when social user *i* perform task t_i^e.

The social welfare is defined as:

$$SW=u_0+\sum_{i\in U}u_i \tag{3}$$

The objective of the incentive mechanism is maximizing the social welfare such that each of sensing tasks in $\mathcal{T}$ can be completed. Since $\sum_{i\in U}\sum_{e\in\{1,2,...,d_i\}}r_i=\sum_{i\in U}R_i$, we have $SW=\sum_{\beta_i^h\in\beta_S}v_i^e-\sum_{\beta_i^h\in\beta_S}c_i^e$. Obviously, there is $\sum_{\beta_i^e\in\beta_S}v_i^e=\sum_{j\in\mathcal{T}}v_j$, where $\sum_{j\in\mathrm{T}}v_j$ is a fixed constant if all sensing tasks can be completed. Therefore, maximizing social welfare can be achieved by minimizing the social costs $\sum_{\beta_i^e\in\beta_S}c_i^e$. The problem can be formulated as follows:

$$\begin{aligned}&\min\sum_{\beta_i^e\in\beta_S}c_i^e\\&\text{s.t.}\,\mathcal{T}\subseteq\bigcup_{\beta_i^e\in\beta_S}t_i^e\end{aligned} \tag{4}$$

Remark: Although the real cost $c_i^e, \forall e\in\{1,2,...,d_i\}$ is only known by user *i*, we will prove that claiming a different cost b_i^e cannot help increase the utility of *i* in our designed mechanisms. Thus, we still use the notation c_i^e in the mechanisms designed below.

To prevent the monopoly, we assume that all tasks still can be completed if any social user does not participate in the auction. This assumption is reasonable for MCS systems as made in [19, 20, 21]. If any task can only be completed by a specific social user, the requester can simply prolong the deadline *TL* or remove it from $\mathcal{T}$.

Sybil Attack Model: The social users may increase their own utility by forging fictitious identities. If any social user forges at least one fictitious identity, we say that a Sybil attack is conducted.

We consider that there is a disguised cost c'_{i_h} if any social user *i* forges any fictitious identity i_h, who is selected as the winner in the auction, i.e., $i_h\in S$. The disguised cost refers to the extra cost of using fictitious identity to sense and upload the data. For example, the social user, who conducts the Sybil attack, has to upload the sensing data separately with different identities in order to pretend as multiple users, leading extra energy consumption and data traffic. Therefore, the disguised cost will be generated only when i_h is a winner. Let $r_{l_{i_h}}$ be the reward to

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2018.2868180, IEEE Access

social user i for recruiting i_h. We assume $c'_{i_h} \geq r_{l_{i_h}} > 0$ since the value of the reward is small.

Note that the fictitious identity cannot obtain the extra reward since they have the same social neighbors as the social user i in practice.

Without losing the generality, consider that any social user i conducts a Sybil attack and forges k fictitious identities $i_1, i_2, ..., i_k$ to participate in the auction. According to whether the social user i participates in the auction, there are two cases for the Sybil attack:

Case 1: The social users i does not participate in the auction. The social user i submits bids only using the fictitious identities. The utility of the social users i in this case is:

$$\tilde{u}_i = R_i + \sum_{h=1}^{k} (p_{i_h} - c_{i_h} + r_{l_{i_h}} - c'_{i_h}) \tag{5}$$

where c_{i_h} is the total cost of performing the assigned task of fictitious identity i_h. Specifically, $p_{i_h} = c_{i_h} = c'_{i_h} = 0$ if $i_h \notin S$.

Case 2: The social user i participates in the auction. The social user i submits the bids using both fictitious identities and the real identity of i. The utility of the social users i in this case is:

$$\tilde{u}_i = \tilde{p}_i - c_i + R_i + \sum_{h=1}^{k} (p_{i_h} - c_{i_h} + r_{l_{i_h}} - c'_{i_h}) \tag{6}$$

where c_i is the total cost of the social user i to perform the assigned task, and $\tilde{p}_i$ is the payment of the real identity i. Same as case 1, $p_{i_h} = c_{i_h} = 0$ if $i_h \notin S$.

B. SINGLE-BID MODEL

Different from the multi-bid model, each social user can submit a unique bidding function for its task set in the single-bid model. Suppose that each social user i is with a task set $\Gamma_i \subseteq \mathcal{T}$ based on its interests and abilities. Each social user $i \in U$ submits a bid $B_i = \{l_i, \tilde{\Gamma}_i, b_i(.)\}$, where l_i is the recruiter of social user i, $\tilde{\Gamma}_i$ is the claimed task set, $b_i(.)$ is the bidding function of social user i. Assume that the real cost function is $c_i(.)$, which is related to the tasks assigned to the socal user i, and satisfies the following properties:

1) $c_i(\phi) = 0$

2) $c_i(\{t_j\}) = \infty, \forall t_j \in \mathcal{T} \setminus \Gamma_i$

3) $c_i(M_1) \leq c_i(M_2), \forall M_1 \subseteq \mathcal{T}, M_2 \subseteq \mathcal{T}, M_1 \subseteq M_2$

These assumptions are realistic. The first property means that the cost is zero if the user doesn't perform any sensing task. The second one shows that the cost would be infinite if the user cannot perform the task he reports. This means that the user, who cannot perform the reported tasks, would be the loser since we minimize the social cost in our incentive mechanisms. The last one means the cost is monotonous with the task set.

The real task set Γ_i and the real cost $c_i(.)$ are the private information and known only to social user i.

Assume that all social users are multi-minded, which means they are willing to perform any subset of the task set hey submit. The requester calculates the assignment profile $\mathbf{D} = (D_1, D_2, ..., D_n)$ according to all bids of the social users, where $D_i, i \in U, D_i \subseteq \tilde{\Gamma}_i$ is a subset of tasks assigned to i.

The reward for any recruiter for recruiting any social user is a function about the assigned task subset of the social user and the social user's bidding time. Considering any social user is assigned a task subset M, the reward of the corresponding recruiter is $r(M)$. The reward function is determined by the requester, and satisfies the following properties:

1) $r(M) = 0, M = \varnothing$;

2) $r(M) = 0,$ if the recruiter is the requester;

3) For any fixed M, $r(M)$ is a decreasing function about the bidding time of the recruited social user.

The first property means that the reward of the recruiter would be zero if the winner doesn't perform any sensing task. The second property means that the requester cannot get the reward since he is the crowdsourcer. The last property can guarantee the time sensibility of the proposed incentive mechanism.

The incentive mechanism $\mathcal{M}(\mathcal{T}, \mathbf{B})$ outputs the winners set S, the assignment profile $\mathbf{D}$, the payment profile $\mathbf{P}$, and the reward profile $\mathbf{R}$.

For any task subset $M \subseteq \mathcal{T}$, let $V(M)$ be the value of the task subset for the requester:

$$V(M) = \sum\nolimits_{t_j \in M} v_j, M \subseteq \mathcal{T} \tag{7}$$

The utility of any social user $i \in U$ is:

$$u_i = \begin{cases} p_i - c_i(D_i) + R_i, & if\ D_i \subseteq \Gamma_i \\ R_i, & \text{otherwise} \end{cases} \tag{8}$$

where $R_i = \sum_{l_k = i, D_k \subseteq \mathcal{T}} r(D_k)$ is the total reward to social user i.

Note that $p_i = 0$ if . In this case, $c_i(D_i) = 0$ according to the first property of the cost function, thus the utility of social user i equal to R_i.

Since we consider the social users are selfish and rational, each social user can behave strategically by submitting a dishonest bidding price or task set to maximize its utility. Moreover, the social users may conduct the Sybil attacks to maximize their utility.

Sybil attack model: We consider that there is a disguised cost function $c'(M)$ when using any fictitious identity to perform any assigned task subset M. We assume $c'(M) \geq r(M) \geq 0$ since the value of the reward is small.

Without losing the generality, consider that any social user i conducts a Sybil attack and forges k fictitious identities $i_1, i_2, ..., i_k$ to participate in the auction. The bids submitted by the fictitious identities are: $B_{i_1} = \{i, \tilde{\Gamma}_{i_1}, b_{i_1}(.)\}$, $B_{i_2} = \{i, \tilde{\Gamma}_{i_2}, b_{i_2}(.)\}, ...,$ $B_{i_k} = \{i, \tilde{\Gamma}_{i_k}, b_{i_k}(.)\}$. According to whether the social user i participates in the auction, there are two cases for the Sybil attack:

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2018.2868180, IEEE Access

Case 1: The social user i does not participate in auctions. The social user i submits bids only using the fictitious identities. The utility of the social users i in this case is:

$$\tilde{u}_i = \begin{cases} \sum_{h=1}^{k}\left(p_{i_h} + r(D_{i_h}) - c'(D_{i_h})\right) - c_i\left(\bigcup_{h=1}^{k} D_{i_h}\right) \\ + \sum_{l_y=i, D_y \in D \setminus \left\{\bigcup_{h=1}^{k} D_{i_h}\right\}} r(D_y), & if \ \bigcup_{h=1}^{k} D_{i_h} \subseteq \Gamma_i \\ \sum_{l_y=i, D_y \in D \setminus \left\{\bigcup_{h=1}^{k} D_{i_h}\right\}} r(D_y), & otherwise \end{cases} \tag{9}$$

Case 2: The social user i participates in the auction. The social user i submits the bids using both fictitious identities and the real identity of i. The utility of the social users i in this case is:

$$\tilde{u}_i = \begin{cases} \tilde{p}_i - c_i(\tilde{D}_i \cup (\bigcup_{h=1}^{k} D_{i_h})) + \sum_{h=1}^{k}\left(p_{i_h} + r(D_{i_h}) - c'(\tilde{\Gamma}_{i_h})\right) \\ + \sum_{l_y=i, D_y \in D \setminus \left\{\bigcup_{h=1}^{k} D_{i_h}\right\}} r(D_y), & if \ \tilde{D}_i \cup (\bigcup_{h=1}^{k} D_{i_h}) \subseteq \Gamma_i \\ \sum_{l_y=i, D_y \in D \setminus \left\{\bigcup_{h=1}^{k} D_{i_h}\right\}} r(D_y), & otherwise \end{cases} \tag{10}$$

C. DESIRABLE PROPERTIES

Our objective is to design a reverse auction-based incentive mechanism that satisfies the following properties:

- **Computational Efficiency:** An incentive mechanism is computationally efficient if the outcome can be computed in polynomial time.
- **Individual Rationality:** The reward of any social user is determined by external factors, and the social user cannot obtain the reward in some extreme cases. Thus, we say that the mechanism is individually rational if $u_i - R_i \geq 0$, $i \in U$.
- **Time-Sensitivity:** An incentive mechanism is time-sensitive if it can stimulate the social users to diffuse the sensing tasks as soon as possible, i.e., the earlier the time for any social user to diffuse the sensing tasks, the more utility he will obtain.
- **Truthfulness:** For the multi-bid model, an incentive mechanism is truthful if any social user i cannot improve his utility by submitting false task sets $\tilde{\Gamma}_i \neq \Gamma_i$ or false bidding price $b_i^h \neq c_i^h$, $h \in \{1, 2, ..., k_i\}$, no matter what other social users submit; For the single-bid model, an incentive mechanism is truthful if any social user cannot improve his utility by submitting false task sets $\tilde{\Gamma}_i \neq \Gamma_i$ or false bidding function $b_i(.) \neq c_i(.)$, no matter what other social users submit.
- **Sybil-Proofness:** An incentive mechanism is Sybil-proof if any social user i cannot improve his utility by conducting the Sybil attack, i.e., $u_i \geq \tilde{u}_i$.
- **Optimization:** an incentive mechanism is optimal if it can output the optimal solution for minimizing the

IV. INCENTIVE MECHANISM FOR MULTI-BID MODEL

In this section, we propose a time-sensitive and Sybil-proof incentive mechanism, called *TSSP-M*, for the multi-bid model. *TSSP-M* is a enhanced *Vickrey Auction* [22] by integrating the time-sensitive rewards to the recruiters.

A. MECHANISM DESIGN

First of all, the requester collects bids submitted by users within time [1, *TL*]. Then the incentive mechanism, which consists of *winner selection* and *payment/reward determination*, is executed.

In the *winner selection* phase, we process all tasks iteratively. In each iteration, we select the triple $\beta_{i''}^{j'}$ with the lowest cost from all triples as the winning triple. The task t_j is assigned to the social user i', and i' is added into the winning set *S*.

Algorithm 1: TSSP-M

Input: task set $\mathcal{T}$, social user set U, bid profile $\mathbf{B}$
Output: $S, \beta_S, \mathbf{R}, \mathbf{p}$
//Winner Selection
Initialization: $S \leftarrow \varnothing, \beta_S \leftarrow \varnothing, \mathbf{R} \leftarrow 0, \mathbf{p} \leftarrow 0, \mathcal{T}' \leftarrow \mathcal{T}$;
while $\mathcal{T}' \neq \varnothing$ **do**
  $\beta_{i'}^{j'} \leftarrow \arg\min_{\beta_i^j \in B_i, i \in U, t_j \in \mathcal{T}'} c_i^j$;
  $\beta_S \leftarrow \beta_S \cup \{\beta_{i'}^{j'}\}; S \leftarrow S \cup \{i'\}; \mathcal{T}' \leftarrow \mathcal{T}' \setminus \{t_{j'}\}$;
end
//Payment/Reward Determination
foreach $i \in U$
  do $p_i \leftarrow 0$;
  foreach $t_j \in \mathcal{T}$
    do $p_i^j \leftarrow 0$;
  end
end
foreach $\beta_i^j \in \beta_S$ **do**
  $p_i^j \leftarrow \min_{k \in U \setminus \{i\}} c_k^j$;
  set r_{l_i} according to a decreasing function of the bidding time of i;
end
foreach $i \in U$ **do**
  $p_i \leftarrow \sum_{\beta_i^j \in \beta_S} p_i^j$;
  $R_i \leftarrow \sum_{\beta_k^j \in \beta_S, l_k = i} r_k$;
end

In the *payment/reward determination* phase, the second price payment rule is applied to calculate the payment of the winning triples. For each $\beta_i^j, i \in S, j \in \mathcal{T}$, the corresponding payment is the second lowest bid among all social users, i.e., $p_i^j = \min_{k \in U \setminus \{i\}} b_k^j$, and the recruiter

l_i obtain the reward r_{l_i}, which decreases with the bidding time of the winner *i*.

The whole process is illustrated in Algorithm 1.

B. MECHANISM ANALYSIS

In this subsection, we analyze the properties of *TSSP-M*.

Lemma 1. *TSSP-M is computationally efficient.*

Proof: The algorithm firstly finds the lowest bid triples from all triples in the *winner selection* phase. Since there are *n* social users, and each social user can submit at most *m* triples, thus finding the triple with lowest bidding price from all triples (Lines 2-5) takes *O*(*nm*). *TSSP-M* selects a winning triple for all m tasks, thus the *winner selection* phase terminates within $O(nm^2)$. In the *payment/reward determination* phase, the time complexity is determined by the for-loop (Lines 10-13). For each winning triple, it takes *O*(*nm*) to find the triple with second lowest bidding price from all triples (Line 11). There are at most *m* winning triples, thus the time complexity of the *payment/reward determination* phase is $O(nm^2)$. Hence the time complexity of the whole auction is bounded by $O(nm^2)$. ■

Lemma 2. *TSSP-M is individually rational.*

Proof: According to formula (1), we have $u_i - R_i = \sum_{e\in\{1,2,...,d_i\},\beta_i^e\in\beta_S}(p_i^e - c_i^e)$. It suffices to prove that $p_i^e - c_i^e \geq 0$ for each $e\in\{1,2,...,d_i\},\beta_i^e\in\beta_S$. Based on line 11 of Algorithm 1, $p_i^e = \min_{k\in U\setminus\{i\}} c_k^e$, thus $p_i^e - c_i^e = \min_{k\in U\setminus\{i\}} c_k^e - \min_{k\in U} c_k^e \geq 0$. ■

Lemma 3. *TSSP-M is time-sensitive.*

Proof: Considering the utility of any social user *i*: $u_i = \sum_{e\in\{1,2,...,d_i\},\beta_i^e\in\beta_S}(p_i^e - c_i^e) + R_i$, it is obvious that the payment and the cost of performing tasks are independent of task diffusion. Hence, it suffices to prove that diffusing tasks earlier can improve the value of $R_i = \sum r_i$. Considering any winner i', the recruiter $i = l_{i'}$ will receive a reward r_i, and the value of r_i is determined by a decreasing function of the bidding time of winner i' according to line 12 of Algorithm 1. Hence, the earlier the recruiter *i* diffuses tasks, the more reward he will obtain. ■

Lemma 4. *TSSP-M is truthful.*

Proof: First, we prove that any social user *i* cannot improve its utility by submitting a false bidding price. Remember that the utility of any social user *i* is $u_i = \sum_{e\in\{1,2,...,d_i\},\beta_i^e\in\beta_S}(p_i^e - c_i^e) + R_i$ where the reward R_i has nothing to do with the bidding price. Let $u_i^e = p_i^e - c_i^e$ be i's utility for performing the task t_i^e. Thus, we just need to prove that any social user *i* cannot improve u_i^e by submitting $b_i^e \neq c_i^e$, $e\in\{1,2,...,d_i\}$. In Algorithm 1, the payment is determined by the second price payment rule of *Vickrey Auction*, which is known as a truthful auction. Therefore, any social user *i* cannot increase u_i^e by submitting $b_i^e \neq c_i^e$.

Then, we demonstrate that any social user *i* cannot improve its utility by submitting a false task set $\tilde{\Gamma}_i \neq \Gamma_i$. There are two cases:

Case 1: $\tilde{\Gamma}_i \subset \Gamma_i$. Algorithm 1 traverses every task in the task set and finds the winning triple for each task.

Based on Lemma 2, we have $p_i^e - c_i^e \geq 0$ for any $t_i^e \in \Gamma_i$. However, the social user has no chance to win the tasks in $\Gamma_i \setminus \tilde{\Gamma}_i$ if he submits the task set $\tilde{\Gamma}_i \subset \Gamma_i$. Thus, the social user *i* cannot improve its utility in this case.

Case 2: $\tilde{\Gamma}_i \setminus \Gamma_i \neq \varnothing$. For any $t_i^e \in \Gamma_i$, $\beta_i^e \in \beta_S$, The utility of social user for performing task is $u_i^e = p_i^e - c_i^e$, and nothing changes. For any $t_i^e \notin \Gamma_i$, $\beta_i^e \in \beta_S$, the social user *i* will be unable to perform the task t_i^e, and the payment for task t_i^e is zero. Thus, the social user *i* cannot improve its utility in this case. ■

Lemma 5. *TSSP-M is Sybil-proof.*

Proof: We prove this lemma for the two cases of Sybil attack model in multi-bid model, respectively:

Case 1: The social users *i* does not participate in the auction. The social user *i* submits bids only using the fictitious identities. According to formula (1) and formula (5), we have:

$$u_i - \tilde{u}_i = \sum_{e\in\{1,2,...,d_i\},\beta_i^e\in\beta_S}(p_i^e - c_i^e) + R_i - (R_i + \sum_{h=1}^{k}(p_{i_h} - c_{i_h} + r_{l_{i_h}} - c'_{i_h}))$$

Because $r_{l_{i_h}} - c'_{i_h} \leq 0$ for any $h\in\{1,2,...,k\}$, we have:

$$u_i - \tilde{u}_i \geq \sum_{e\in\{1,2,...,d_i\},\beta_i^e\in\beta_S}(p_i^e - c_i^e) - \sum_{h=1}^{k}(p_{i_h} - c_{i_h})$$

Since *TSSP-M* is truthful, all fictitious identities will submit the real task sets, i.e., $\Gamma_{i_h} \subseteq \Gamma_i, h\in\{1,2,...,k\}$. Moreover, because of the truthfulness, all fictitious identities will submit a real bidding price, that is, for the same task, the bidding price of each fictitious identity is the same as that of the original social user *i* without conducting the Sybil attack. Further, the Sybil attack has no effect on the payment since the payment is determined by the second price rule, and each task is assigned to the unique winner according to Algorithm 1. Hence, we have $\sum_{e\in\{1,2,...,d_i\},\beta_i^e\in\beta_S}(p_i^e - c_i^e) = \sum_{h=1}^{k}(p_{i_h} - c_{i_h})$, and $u_i - \tilde{u}_i \geq 0$.

Case 2: The social user *i* participates in the auction. The social user *i* submits the bids using both fictitious identities and the real identity of *i*. In this case, according to formula (1) and formula (6), we have:

$$u_i - \tilde{u}_i = \sum_{e\in\{1,2,...,d_i\},\beta_i^e\in\beta_S}(p_i^e - c_i^e) + R_i - (\tilde{p}_i - c_i + R_i + \sum_{h=1}^{k}(p_{i_h} - c_{i_h} + r_{l_{i_h}} - c'_{i_h}))$$

$$\geq \sum_{e\in\{1,2,...,d_i\},\beta_i^e\in\beta_S}(p_i^e - c_i^e) - (\tilde{p}_i - c_i) - \sum_{h=1}^{k}(p_{i_h} - c_{i_h})$$

It is not difficult to obtain:

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2018.2868180, IEEE Access

$$\sum_{e\in\{1,2,...,d_i\},\beta_i^e\in\beta_S}(p_i^e-c_i^e)=(\tilde{p}_i-c_i)+\sum_{h=1}^{k}(p_{i_h}-c_{i_h})$$

using the similar analysis in case 1. Therefore, $u_i-\tilde{u}_i\geq 0$.■

Lemma 6. *TSSP-M is optimal.*

Proof: Since *Vickrey Auction* is efficient, *TSSP-M* can output the optimal solution.

The above six lemmas together prove the following theorem. ■

Theorem 1. *TSSP-M is computationally efficient, individually rational, time-sensitive, truthful, Sybil-proof, and optimal.*

V. INCENTIVE MECHANISM FOR SINGLE-BID MODEL

In this section, we propose the *TSSP-S*, a time-sensitive and Sybil-proof incentive mechanism for the single-bid model. *TSSP-S* first calculates the payments to each social user for any subset of his task set. To guarantee the truthfulness, the payment is determined independently of its own cost function. Then, *TSSP-S* assigns each social user a task set that maximizes its utility independently of the assignments to other users. At last, *TSSP-S* calculates the total rewards to each recruiter.

A. MECHANISM DESIGN

Like *TSSP-M*, *TSSP-S* is executed at time *TL*. The requester performs winner selection, task assignment, payment calculation, and reward calculation based on the bids received.

For any subset $M\subseteq\Gamma_i$ of social user i, let $m_i=\max_{h\neq i,M'\subseteq\Gamma_h,M'\cap M\neq\phi}(V(M')-C_h(M'))$, where $h\in U\setminus\{i\}$, $V(M')$ is the value of the task subset M' to the requester, $C_h(M')$ is the cost of social user h for performing M'. If $m_i\geq 0$, then we calculate $p_{i,M}=V(M)-m_i$ as the payment for any subset $M\subseteq\Gamma_i$ of social user i, i.e.,

$$p_{i,M}=V(M)-\max_{h\neq i,M'\subseteq\Gamma_h,M'\cap M\neq\phi}(V(M')-c_h(M')) \tag{11}$$

The requester assigns $D_i\subseteq\Gamma_i$ to social user *i*, where D_i is a task subset to maximize the value of $p_{i,D_i}-c_i(D_i)$. Excluding the reward, which determined by the external factors, the assigned task subset D_i essentially maximize the utility of the social user *i* according to formula (8), i.e.,

$$D_i\leftarrow\arg\max_{M\subseteq\Gamma_i}(p_{i,M}-c_i(M)) \tag{12}$$

Then, the payment of social user *i* is $p_i=p_{i,D_i}$. Note that $D_i=\phi$, $p_i=0$ if $p_{i,D_i}-c_i(D_i)<0$.

Finally, the requester calculates the total reward, which is the summation of the reward functions of all recruited social users, for every recruiter, As defined in Section Ⅲ-*B*, the reward function is a decreasing function about the bidding time in order to satisfy the property of time sensitivity.

The whole process is illustrated in Algorithm 2.

Algorithm 2: TSSP-S

Input: task set $\mathcal{T}$, social user set *U*, bid profile $\mathbf{B}$
Output: $S,\beta_S,\mathbf{R},\mathbf{p}$
1 Initialization: $S\leftarrow\varnothing,\mathbf{R}\leftarrow 0,\mathbf{D}\leftarrow 0,\mathbf{P}\leftarrow 0$;
2 **foreach** $i\in U$ **do**
3 | **foreach** $M\subseteq\Gamma_i$ **do**
4 | | $p_{i,M}\leftarrow 0$;
5 | | $m_i\leftarrow\max_{h\neq i,M'\subseteq\Gamma_h,M'\cap M\neq\phi}(V(M')-c_h(M'))$;
6 | | **if** $m_i\geq 0$ **then**
7 | | $p_{i,M}\leftarrow V(M)-m_i$;
8 | | **end**
9 | **end**
10 **end**
11 **foreach** $i\in U$ **do**
12 | $D_i\leftarrow\arg\max_{M\subseteq\Gamma_i}(p_{i,M}-c_i(M))$;
13 | **if** $p_{i,D_i}-c_i(D_i)\geq 0$ **then**
14 | $S\leftarrow S\bigcup\{i\}$; $p_i\leftarrow p_{i,D_i}$;
15 | **else**
16 | $D_i\leftarrow\varnothing$; $p_i\leftarrow 0$;
17 | **end**
18 | $R_i\leftarrow\sum_{l_k=i,D_k\in\mathbf{D},D_k\neq 0}r(D_k)$;
19 **end**

B. MECHANISM ANALYSIS

In this subsection, we analyze the properties of *TSSP-S.*

Lemma 7. *TSSP-S is individually rational.*

Proof: According to the definition of individual rationality and formula (8), it suffices to prove that $u_i-R_i=p_i-c_i(D_i)\geq 0$ for any social user $i\in U$. Based on line 13 and line 14 of Algorithm 2, there will be $p_i=p_{i,D_i}$ if $p_{i,D_i}-c_i(D_i)\geq 0$. Thus, *TSSP-S* is individually rational. ■

Lemma 8. *TSSP-S* is time-sensitive.

Proof: Considering the utility of any social user *i* defined in formula (8), it is obvious that the payment and the cost of performing tasks are independent of task diffusion. Hence, it suffices to prove that diffusing tasks earlier can improve the value of $R_i=\sum_{l_k=i,D_k\subseteq\mathcal{T}}r(D_k)$. Considering any winner *k*, the recruiter $i=l_k$ will receive a reward $r(D_k)$, and the value of $r(D_k)$ is determined by a decreasing function of the bidding time of winner *k*. Hence, the earlier the recruiter *i* diffuses the tasks, the more reward he will obtain. ■

Lemma 9. *TSSP-S is truthful.*

Proof: First, we prove that any social user *i* cannot improve its utility by submitting a false cost function $b_i(.)\neq c_i(.)$. The false cost function $b_i(.)$ can only affect the result of formula (12). We use $\tilde{D}_i,D_i$ denote the subsets of assigned tasks when the social user *i* submits the false cost function and the real cost function, respectively. According to formula (11), there will be $p_{i,\tilde{D}_i} = p_{i,D_i}$ if $\tilde{D}_i = D_i$. Therefore, the utility does not change. If $\tilde{D}_i \neq D_i$, according to social user *i*'s real cost function, there must be $p_{i,\tilde{D}_i} - c_i(\tilde{D}_i) + R_i \le p_{i,D_i} - c_i(D_i) + R_i$, because $\tilde{D}_i$ and D_i are both subsets of Γ_i, and D_i is the task subset that maximizes the utility of social user *i*. Thus, submitting false cost function cannot help to improve the utility of social user *i*.

Then, we prove that any social user *i* cannot improve its utility by submitting the false task set. Firstly, according to formula (11), it can be known that the payment for any task subset $M \subseteq \Gamma_i$ to social user *i* is independent of *i*'s cost function. Assume that user *i* submits a false task set $\tilde{\Gamma}_i$, and there two cases:

Case 1: $\tilde{\Gamma}_i \subset \Gamma_i$. Let $\tilde{D}_i$ be the assigned task set to social user i. Based on formula (12), $D_i \subseteq \Gamma_i$ is the task subset, which can maximize the utility of social user i. Therefore, we have $p_{i,\tilde{D}_i} - c_i(\tilde{D}_i) + R_i \le p_{i,D_i} - c_i(D_i) + R_i$. This means the social user i cannot improve his utility by submitting a false task set $\tilde{\Gamma}_i \subset \Gamma_i$.

Case 2: $\tilde{\Gamma}_i \setminus \Gamma_i \neq \varnothing$. If $\tilde{D}_i \subseteq \Gamma_i$, the social user *i* cannot improve its utility according to the analysis of case 1; if $\tilde{D}_i \setminus \Gamma_i \neq \varnothing$, the social user *i* cannot complete the task in $D_i \setminus \Gamma_i$, and the utility of social user *i* is R_i According to formula (8). Therefore, we have $R_i \le p_{i,D_i} - c_i(D_i) + R_i$ since $p_{i,D_i} - c_i(D_i)$ according to line 13 of Algorithm 2. This means the social user i cannot improve his utility by submitting a false task set $\tilde{\Gamma}_i \setminus \Gamma_i \neq \varnothing$.

In conclusion, *TSSP-S* is truthful. ■

Lemma 10. *TSSP-S is Sybil-proof.*

Proof: We prove this lemma for the two cases of Sybil attack model in single-bid model, respectively:

Case 1: The social user *i* does not participate in auctions. The social user *i* submits bids only using the fictitious identities. Consider that the bids submitted by the fictitious identities are $B_{i_1} = \{i, \tilde{\Gamma}_{i_1}, b_{i_1}(.)\}, B_{i_2} = \{i, \tilde{\Gamma}_{i_2}, b_{i_2}(.)\}, ..., B_{i_k} = \{i, \tilde{\Gamma}_{i_k}, b_{i_k}(.)\}$. Since *TSSP-S* is truthful, we have

$$\tilde{\Gamma}_{i_1} \subset \Gamma_i, \tilde{\Gamma}_{i_2} \subset \Gamma_i, ..., \tilde{\Gamma}_{i_k} \subset \Gamma_i .$$

Let D_i be the assigned task subset of social user *i* when he does not conduct the Sybil attack. We consider the case $D_i = \bigcup_{h=1}^{k} D_{i_h}$, which obtains the maximum value of $\tilde{u}_i$. We have

$$\{M \mid j \neq i, M \subseteq \Gamma_j, M \cap D_i \neq 0\}$$
$$= \bigcup_{h=1}^{k} \{M_h \mid j \neq i_h, M_h \subseteq \Gamma_j, M_h \cap D_{i_h} \neq 0\}$$

Let $n_i \leftarrow \max_{h \neq i, M' \subseteq \Gamma_h, M' \cap D_i \neq \phi} (V(M') - c_h(M'))$, $n_{i_h} \leftarrow \max_{j \neq i, M_h \subseteq \Gamma_j, M_h \cap D_{i_h} \neq \phi} (V(M_h) - c_j(M_h))$, $h \in \{1, 2, ..., k\}$.

Thus, we have $n_i = \max\{n_{i_1}, n_{i_2}, ..., n_{i_k}\}$, $n_i \le \sum_{h=1}^{k} n_{i_h}$.

Next, we prove $D_{i_h} \cap D_{i_{h'}} = \varnothing$ for any $h \neq h'$, $h \in \{1, 2, ..., k\}, h' \in \{1, 2, ..., k\}$ by contradiction. Assume $D_{i_h} \cap D_{i_{h'}} \neq \varnothing$, since $D_{i_{h'}} \in \{M_h \mid j \neq i_h, M_h \subseteq \Gamma_j, M_h \cap D_{i_h} \neq 0\}$, we can obtain $V(D_{i_{h'}}) - c_i(D_{i_{h'}}) \le n_{i_h}$, and $p_{i_h, D_{i_h}} = V(D_{i_h}) - n_{i_h} \le V(D_{i_h}) - (V(D_{i_{h'}}) - c_i(D_{i_{h'}}))$. Similarly, we have $p_{i_{h'}, D_{i_{h'}}} \le V(D_{i_{h'}}) - (V(D_{i_h}) - c_i(D_{i_h}))$. For the fictitious identities i_h and $i_{h'}$, we have

$$\begin{aligned}(u_{i_h} - R_{i_h}) + (u_{i_{h'}} - R_{i_{h'}}) &= p_{i_h, D_{i_h}} - c_i(D_{i_h}) + p_{i_{h'}, D_{i_{h'}}} - c_i(D_{i_{h'}}) \\ &\le V(D_{i_h}) - (V(D_{i_{h'}}) - c_i(D_{i_{h'}})) - c_i(D_{i_h}) + V(D_{i_{h'}}) \\ &\quad - (V(D_{i_h}) - c_i(D_{i_h})) - c_i(D_{i_{h'}}) = 0\end{aligned}$$

Since *TSSP-S* is individual rational, there must be $D_{i_h} = D_{i_{h'}} = \varnothing$, which contradicts the assumption. Therefore, $D_{i_h} \cap D_{i_{h'}} = \varnothing$.

This means that the assigned task subsets of the fictitious identities are disjoint. According to formula (7), there is $V(D_i) = V(\bigcup_{h=1}^{k} D_{i_h}) = \sum_{h=1}^{k} V(D_{i_h})$. According to formula (11), the payment to social user *i* is:

$$\begin{aligned} p_i &= p_{i,D_i} = V(D_i) - n_i \\ &\ge V(D_i) - \sum_{h=1}^{k} n_{i_h} = \sum_{h=1}^{k} V(D_{i_h}) - \sum_{h=1}^{k} n_{i_h} = \sum_{h=1}^{k} (V(D_{i_h}) - n_{i_h}) \\ &= \sum_{h=1}^{k} p_{i_h, D_{i_h}} = \sum_{h=1}^{k} p_{i_h} \end{aligned}$$

The utility difference for social user *i* without and with Sybil attacks is:

$$u_i - \tilde{u}_i$$
$$= p_i - c_i(D_i) + R_i - \left(\begin{array}{l} \sum_{h=1}^{k} \left(p_{i_h} + r(D_{i_h}) - c'(D_{i_h}) \right) - c_i(\bigcup_{h=1}^{k} D_{i_h}) \\ + \sum_{l_y = i, D_y \in D \setminus \left\{ \bigcup_{h=1}^{k} D_{i_h} \right\}} r(D_y) \end{array} \right)$$

$$\ge c_i(\bigcup_{h=1}^{k} D_{i_h}) - c_i(D_i) + \sum_{h=1}^{k} \left(c'(D_{i_h}) - r(D_{i_h}) \right) + R_i - \sum_{l_y = i, D_y \in D \setminus \left\{ \bigcup_{h=1}^{k} D_{i_h} \right\}} r(D_y)$$

Note that $D_i = \bigcup_{h=1}^{k} D_{i_h}$, and $c'(D_{i_h}) \ge r(D_{i_h}) n_i \le \sum_{h=1}^{k} n_{i_h} + \tilde{n}_i$ for $\forall i_h \in \{i_1, i_2, ..., i_k\}$. Furthermore, the social circle of fictitious identities is the same as the social user *i*. Thus we have $R_i = \sum_{l_y=i, D_y \in D \setminus \left\{ \bigcup_{h=1}^{k} D_{i_h} \right\}} r(D_y)$. We have the conclusion of $u_i - \tilde{u}_i \geq 0$, and *TSSP-S* can prevent the Sybil attack.

Case 2: The social user *i* participates in the auction. The social user *i* submits the bids using both fictitious identities and the real identity of *i*. Assume the task subsets assigned for *i* and *k* identities are $\tilde{D}_i, D_{i_1}, D_{i_2}, ..., D_{i_k}$. Based on a similar analysis of case 1, it can be known that $D_i = \tilde{D}_i \cup (\bigcup_{h=1}^{k} D_{i_h})$, and

$$\left\{ M \mid j \neq i, M \subseteq \Gamma_j, M \cap D_i \neq 0 \right\} = \left\{ \begin{matrix} \tilde{M} \mid j \neq i, \tilde{M} \subseteq \Gamma_j, \\ \tilde{M} \cap \tilde{D}_i \neq 0 \end{matrix} \right\}$$

$$\cup (\bigcup_{h=1}^{k} \left\{ M_h \mid j \neq i_h, M_h \subseteq \Gamma_j, M_h \cap D_{i_h} \neq 0 \right\})$$

Let $n_i \leftarrow \max_{h \neq i, M' \subseteq \Gamma_h, M' \cap D_i \neq \phi} (V(M') - c_h(M'))$, $\tilde{n}_i \leftarrow \max_{h \neq i, \tilde{M} \subseteq \Gamma_h, \tilde{M} \cap \tilde{D}_i \neq \phi} (V(\tilde{M}) - c_h(\tilde{M}))$, $n_{i_h} \leftarrow \max_{j \neq i, M_h \subseteq \Gamma_j, M_h \cap D_{i_h} \neq \phi} (V(M_h) - c_j(M_h))$, $h \in \{1, 2, ..., k\}$ We have $n_i = \max \left\{ \tilde{n}_i, n_{i_1}, n_{i_2}, ..., n_{i_k} \right\}$,.

All assigned task subsets of both the fictitious identities and the real identity *i* are disjoint based on the similar analysis of case 1. According to formula (7), there is $V(D_i) = V((\bigcup_{h=1}^{k} D_{i_h}) \cup \tilde{D}_i) = \sum_{h=1}^{k} V(D_{i_h}) + V(\tilde{D}_i)$. According to formula (11), the payment to social user *i* is:

$$\begin{aligned} p_i = p_{i,D_i} &= V(D_i) - n_i \geq V(D_i) - (\sum_{h=1}^{k} n_{i_h} + \tilde{n}_i) \\ &= \sum_{h=1}^{k} V(D_{i_h}) + V(\tilde{D}_i) - (\sum_{h=1}^{k} n_{i_h} + \tilde{n}_i) \\ &= \sum_{h=1}^{k} (V(D_{i_h}) - n_{i_h}) + (V(\tilde{D}_i) - \tilde{n}_i) \\ &= (\sum_{h=1}^{k} p_{i_h, D_{i_h}}) + \tilde{p}_{i, \tilde{D}_i} = \sum_{h=1}^{k} p_{i_h} + \tilde{p}_i \end{aligned}$$

The utility difference for social user *i* without and with Sybil attacks is:

$$u_i - \tilde{u}_i = p_i - c_i(D_i) + R_i - \left(\begin{matrix} \tilde{p}_i - c_i(\tilde{D}_i \cup (\bigcup_{h=1}^{k} D_{i_h})) + \\ \sum_{h=1}^{k} \left(p_{i_h} + r(D_{i_h}) - c'(\tilde{\Gamma}_{i_h}) \right) \\ + \sum_{l_y=i, D_y \in D \setminus \left\{ \bigcup_{h=1}^{k} D_{i_h} \right\}} r(D_y) \end{matrix} \right)$$

$$\geq c_i(\tilde{D}_i \cup (\bigcup_{h=1}^{k} D_{i_h})) - c_i(D_i) + \sum_{h=1}^{k} \left(c'(D_{i_h}) - r(D_{i_h}) \right) + R_i - \sum_{l_y=i, D_y \in D \setminus \left\{ \bigcup_{h=1}^{k} D_{i_h} \right\}} r(D_y)$$

Since $D_i = \tilde{D}_i \cup (\bigcup_{h=1}^{k} D_{i_h})$, $c'(D_{i_h}) \geq r(D_{i_h})$ for $\forall i_h \in \{i_1, i_2, ..., i_k\}$, and $R_i = \sum_{l_y=i, D_y \in D \setminus \left\{ \bigcup_{h=1}^{k} D_{i_h} \right\}} r(D_y)$.We can conclude that $u_i - \tilde{u}_i \geq 0$, and *TSSP-S* is Sybil-proof in this case. ■

The above four lemmas together prove the following theorem.

Theorem 2. *TSSP-S is individually rational, time-sensitive, truthful, and Sybil-proof.*

Remark: the time complexity of *TSSP-S* is $O(n \cdot 2^{\max|\Gamma_i|}), i \in U$, where $|\Gamma_i|$ is the size of task set submitted by the social user *i*, since *TSSP-S* will calculate the payments to each social user for every subset of his task set. In practice, $|\Gamma_i| \ll m$, and we will show the running time of *TSSP-S* is still reasonable in section 6.

VI. PERFORMANCE EVALUATION

In this section, we compare the performances of *TSSP-M* and *TSSP-S* with two algorithms: *MSensing* [23] and *MMT* [19]. We measure the performance in terms of running time, social cost, diffusion efficiency, and truthfulness. Moreover, we implement two other benchmark algorithms: *TI-M* (*Time Insensitive Incentive Mechanism for the Multi-Bid Model*) and *TI-S* (*Time Insensitive Incentive Mechanism for the Single-Bid Model*), where the reward function is a constant, to show the property of time-sensitivity of *TSSP-M* and *TSSP-S*, respectively. All the simulations were run on an Ubuntu 17.10 machine with Intel Xeon CPU E5-2420 and 16 GB memory. Each measurement is averaged over 100 instances.

A. SIMULATION SETUP

The simulations are based on the Facebook Dataset [24], which includes 4039 nodes and 88234 edges. We assume that each round of diffusion (broadcast to social cycle) will consume one-unit time. Let *m*=50, *TL*=4 as the default setting. However, we will vary the value of *m* and *TL* to explore the impacts on the performance metrics. Both the number of triples in *TSSP-M* and the size of task set submitted in *TSSP-S* of each social user is uniformly distributed in [1,4]. The cost of each social user is selected randomly from the auction dataset [25], which contains 5017 bid prices for Palm Pilot M515 PDA from eBay users in Dec. 2012. Specifically, we set $c_i(.) = \bar{A} * |D_i|$ for any social user *i* in *TSSP-S*, where $\bar{A}$ is the average bidding price in the auction dataset. Further, we consider there are 500 users in *MSensing* and *MMT*.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2018.2868180, IEEE Access

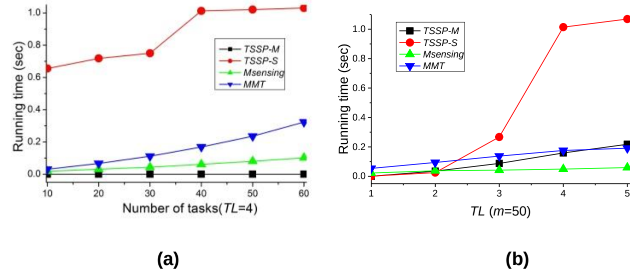

FIGURE 2. **Running time: (a) Impact of *m*. (b) Impact of *TL*.**

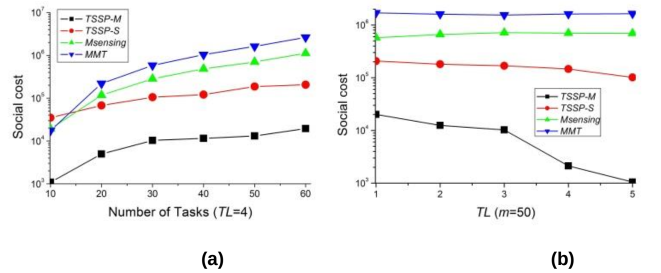

FIGURE 3. **Social cost: (a) Impact of *m*. (b) Impact of *TL*.**

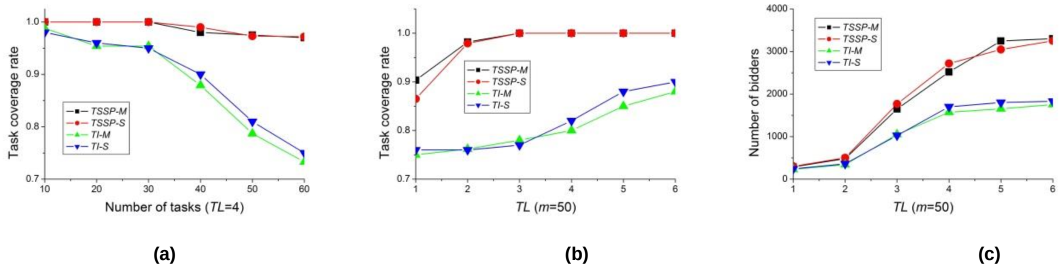

FIGURE 4. **Diffusion efficiency: (a) Impact of *m* on task coverage rate (b) Impact of *TL* on task coverage rate (c) Impact of *TL* on number of bidders**

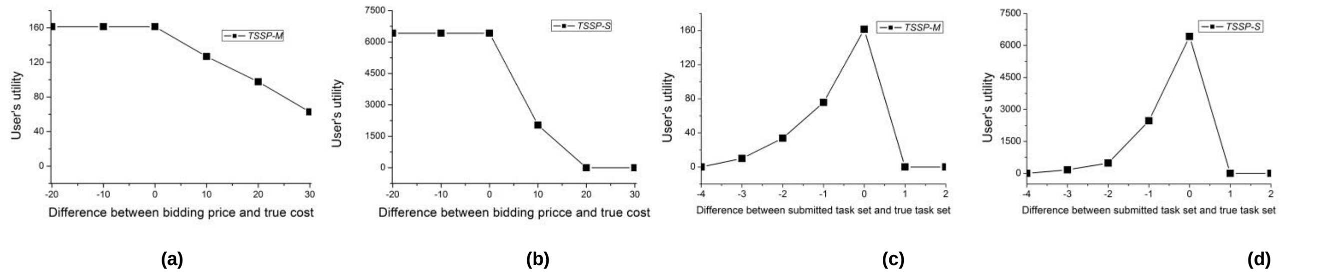

FIGURE 5. **Utility of social user (ID=500): (a) Impact of bidding price in *TSSP-M*. (b) Impact of bidding price in *TSSP-S*. (c) Impact of submitted task set in *TSSP-M*. (d) Impact of submitted task set in *TSSP-S*.**

We set the reward of any recruiter l_i in *TSSP-M* as $r_{l_i}^j = \frac{\chi}{\log T_i + 1}$, where $T_i \in [1,\ TL]$ is the bidding time of social user *i*, $\chi \in (0,1)$ is a system parameter, $\log T_i + 1$ indicates the time-sensitive diminishing to the recruiter l_i. The disguised cost in *TSSP-M* is χ. For *TSSP-S*, the reward function for recruiting any social user *i* is $r(D_i) = \frac{\chi | D_i |}{\log T_i + 1}$, and the disguised cost for using any fictitious identity $i_h \in \{i_1, i_2, ..., i_k\}$ to perform any assigned task subset D_{i_h} is $\chi | D_{i_h} |$.

The rational social users would diffuse the sensing tasks as soon as possible in order to improve the reward in time sensitive incentive mechanisms. Thus, we set the probability of task diffusion for any social user at time *q* is $\frac{1}{2q}$ in both *TSSP-M* and *TSSP-S*. While *TI-M* and *TI-S* are time insensitive incentive mechanisms, and we set the probability of task diffusion for any social user at any round is $\frac{1}{TL}$ in both *TI-M* and *TI-S*, which is independent of the diffusion time.

B. EVALUATION OF RUNNING TIME

We first investigate the impacts of *m* and *TL* on the running time. From Fig.2(a), we can see that the running time of *TSSP-M*, *TSSP-S*, *MSensing* and *MMT* increase with the increase of *m*, which conforms to the expected running time properties of four mechanisms. The running time of *TSSP-S* is much more than those of other mechanisms since *TSSP-S* calculates the payment to each social user for every subset of his bidding task set. However, the running time of *TSSP-S* is within 1.02 second when *TL*=4 (more than 2500 bidders) with 50 tasks. We extend the deadline from 1 to 5, and we can see from Fig.2(b) that the running time of both *TSSP-M* and *TSSP-S* increase since the auction includes more bidders with extended deadline, while there is no distinct change for *MSensing* and *MMT* since the two mechanisms don't diffuse the tasks, and the number of bidders is independent of *TL*.

C. EVALUATION OF SOCIAL COST

Fig.3 shows the impacts of *m* and *TL* on the social cost. The social cost of all four mechanisms increase drastically with increasing number of tasks. The reason is, with more tasks, the requester need to select more winners to perform the tasks, which incurs a higher social cost. Note that *TSSP-M* show great superiority in terms of social cost since it can output the optimal social cost. When the deadline is extended, the social cost of both *TSSP-M* and *TSSP-S* decrease since there are more bidders, and the mechanisms can find a set of winners with lower cost. However, the social cost of both *MMT* and *Msensing* don't change with different deadline since the number of bidders is independent of *TL*.

D. EVALUATION OF DIFFUSION EFFICIENCY

To investigate the diffusion efficiency of our incentive mechanisms, we define task coverage rate α as the ratio of the number of submitted tasks to the number of all publicized tasks, i.e., $\alpha = \frac{|\bigcup_{i\in U} \Gamma_i|}{m}$. Fig.4(a) plots the impact of *m* on the task coverage rate. We observe that both *TSSP-M* and *TSSP-S* always obtain high task coverage rate (more than 97% with 60 tasks). However, the task coverage rate of *TI-M* and *TI-S* decrease drastically with the increasing number of tasks. This is because *TSSP-M* and *TSSP-S* can recruit more users than *TI-M* and *TI-S* with the same deadline since both *TSSP-M* and *TSSP-S* are time-sensitive, and the diffusion probability is a decreasing function with time. From Fig.4(b), we can see that the task coverage rate of *TSSP-M* and *TSSP-S* reach 1 when *TL*=3. This means our incentive mechanisms can cover the tasks quickly. In contrast, the task coverage rate increases slightly both in *TI-M* and *TI-S* since the diffusion probability is same for different deadline in *TI-M* and *TI-S*. We use the number of bidders under different time to measure the time-sensitivity of the incentive mechanisms further. Fig.4(c) shows that *TSSP-M* and *TSSP-S* can recruit more users than *TI-M* and *TI-S* under the same deadline. When *TL*=6, our time-sensitive mechanisms can recruit 82% more social users than those of time-insensitive mechanisms on average.

E. EVALUATION OF TRUTHFULNESS

We randomly picked a social user (ID=500) and allowed him to bid the price that is different from his true cost. As shown in Fig.5, the social user's utility in *TSSP-S* is much more than that in *TSSP-M*. This is because *TSSP-S* calculates any subset of his task set and assigns him a task set that maximizes its utility. Moreover, we can see from Fig.5 that the social user can obtain the maximum utility when the bidding price is equal to the true cost. This means that the social user cannot increase its utility by bidding a dishonest price. Further, we test the truthfulness of submitted task set. We add the other tasks randomly to the true task set or remove the tasks in the true task set. The difference between submitted task set and true task set is defined as $|\tilde{\Gamma}_i| - |\Gamma_i|$. We can see from Fig.5 that the social user can obtain the maximum utility when $\tilde{\Gamma}_i = \Gamma_i$ in both *TSSP-M* and *TSSP-S*, which means that the social user cannot increase its utility by submitting a dishonest task set.

VII. CONCLUSION

In this paper, we have presented two MCS system models to increase the potential participants by diffusing the sensing tasks in the social network and formulize the Sybil attack models for each model. We designed two incentive mechanisms based on reverse auctions, *TSSP-M* and *TSSP-S*, for each of two system models. Through both rigorous theoretical analyses and extensive simulations, we have demonstrated that *TSSP-M* satisfies the desirable properties of computational efficiency, individual rationality, truthfulness, time-sensitive, Sybil-proofness, and social optimization; *TSSP-S* achieves individual rationality, truthfulness, time-sensitive, and Sybil-proofness. In the future, we would like to explore the lightweight Sybil-proof incentive mechanisms for the large-scale mobile crowdsensing using the local edge servers of pervasive networks nearby mobile users [34].

REFERENCES

[1] R. K. Ganti, F. Ye and H. Lei, "Mobile crowdsensing: current state and future challenges," *IEEE Commun. Mag.*, vol. 49, no. 11, pp. 32-39, Nov. 2011.
[2] G. Bajaj and P. Singh, "Mew: A Plug-n-Play Framework for Task Allocation in Mobile Crowdsensing," in *Proc. CrowdSenSys*, 2017, pp. 19-24.
[3] G. Singh, D. Bansal, S. Sofat and N. Aggarwal, "Smart patrolling: An efficient road surface monitoring using smartphone sensors and crowdsourcing," *Pervasive and Mobile Computing*, vol. 40, pp. 71-88, 2017.
[4] B. Zhou, M. Elbadry, R. Gao, and F. Ye, "BatMapper: Acoustic Sensing Based Indoor Floor Plan Construction Using Smartphones," in *Proc. MobiSys*, 2017, pp. 42-55.
[5] L. Wang, X. Su, X. Zhang, W. Liu, and B. Li "Spee-Navi: An Indoor Navigation System via Speech Crowdsourcing," in *Proc. HumanSys*, 2017, pp. 43-48.
[6] E. Gregori, A. Improta, L. Lenzini, V. Luconi, N. Redini and A. Vecchio, "Smartphone-based crowdsourcing for estimating the bottleneck capacity in wireless networks," *Journal of Network and Computer Applications*, vol. 64, no. 12, pp. 62-75, 2016.
[7] P. Zhou, Y. Zheng and M. Li, "How Long to Wait? Predicting Bus Arrival Time With Mobile Phone Based Participatory Sensing," in *IEEE Trans. Mobile Comput.*, vol. 13, no. 6, pp. 1228-1241, Jun. 2014.
[8] J. Xu, Z. Rao, L. Xu, D. Yang and T. Li, "Mobile Crowd Sensing via Online Communities: Incentive Mechanisms for Multiple Cooperative Tasks," in *Proc. MASS*, 2017, pp. 171-179.
[9] M. Xiao, J. Wu, L. Huang, R. Cheng and Y. Wang, "Online Task Assignment for Crowdsensing in Predictable Mobile Social Networks," *IEEE Transactions on Mobile Computing*, vol. 16, no. 8, pp. 2306-2320, Aug. 2017.
[10] R. Liu, J. Cao, K. Zhang, W. Gao, L. Yang, J. Liang and R. Yu, "Understanding Mobile Users' Privacy Expectations: A Recommendation-based Method through Crowdsourcing," *IEEE Transactions on Services Computing*, pp. 1-1, Dec. 2016.
[11] "Haze Watch Project," January, 2011. [Online]. Available: http://www.hazewatch.unsw.edu.au/.
[12] J. Lin, M. Li, D. Yang, G. Xue and J. Tang, "Sybil-proof incentive mechanisms for crowdsensing," in *Proc. INFOCOM*, 2017, pp. 1-9.
[13] P. Nguyen, and K. Nahrstedt. "Crowdsensing in Opportunistic Mobile Social Networks: A Context-aware and Human-centric Approach," *arXiv*, pp. 1704.08598, Apr.2017.
[14] Y. Chen, B. Li, and Q. Zhang, "Incentivizing crowdsourcing systems with network effects," in *Proc. INFOCOM*, 2016, pp. 1-9.
[15] Z. Wang, R. Tan, J. Hu, J. Zhao, Q. Wang, F. Xia and X. Niu, "Heterogeneous incentive mechanism for time-sensitive and location-dependent crowdsensing networks with random arrivals," *Computer networks*, vol. 131, pp. 96-109, 2018.

[16] M. H. Cheung, R. Southwell, F. Hou, and J. W. Huang, "Distributed Time-Sensitive Task Selection in Mobile Crowdsensing," in *Proc. MobiHoc*, 2015, pp. 157-166.
[17] Y. Zhan, Y. Xia, Y. Liu, F. Li and Y. Wang, "Incentive-Aware Time-Sensitive Data Collection in Mobile Opportunistic Crowdsensing," *IEEE Trans. Veh. Technol.*, vol. 66, no. 9, pp. 7849-7861, Sep. 2017.
[18] X. Zhang, G. Xue, D. Yang and R. Yu, "A Sybil-Proof and Time-Sensitive Incentive Tree Mechanism for Crowdsourcing," in *Proc. GLOBECOM*, 2015, pp. 1-6.
[19] J. Xu, J. Xiang and D. Yang, "Incentive Mechanisms for Time Window Dependent Tasks in Mobile Crowdsensing," *IEEE Transactions on Wireless Communications*, vol. 14, no. 11, pp. 6353-6364, Nov. 2015.
[20] J. Xu, J. Fu, D. J. Yang, L. Xu, L. Wang. and T. Li, "FIMI: A Constant Frugal Incentive Mechanism for Time Window Coverage in Mobile Crowdsensing," *Journal of Computer Science and Technology*, vol. 32, no. 5, pp. 919-935, 2017.
[21] J. Xu, J. Xiang, Y. Li, "Incentivize maximum continuous time interval coverage under budget constraint in mobile crowd sensing," *Wireless Networks*, vol. 23, no.5, pp. 1549-1562, Jul.2017.
[22] W. Vickrey, "Counterspeculation, Auctions, and Competitive Sealed Tenders," *J. FINANC.*, vol.16, no. 1, pp. 8–37, 1961.
[23] D. Yang, G. Xue, X. Fang, and J. Tang, "Crowdsourcing to smartphones: incentive mechanism design for mobile phone sensing," in *Proc. Mobicom*, 2012, pp. 173-184.
[24] J. McAuley and J. Leskovec, "Learning to Discover Social Circles in Ego Networks," in *Proc. NIPS*, 2012, pp. 539-547.
[25] "Modeling Online Auctions," July, 2010. [Online]. Available: http://www.modelingonlineauctions.com/datasets
[26] J. Xu, H. Li, Y. Li, D. Yang and T. Li, "Incentivizing the Biased Requesters: Truthful Task Assignment Mechanisms in Crowdsourcing," in *Proc. SECON*, 2017, pp. 1-9.
[27] H. Wang, S. Guo, J. Cao, M. Guo, "MELODY: A Long-term Dynamic Quality-aware Incentive Mechanism for Crowdsourcing," in *Proc. ICDCS*, 2017, pp. 933-943.
[28] Z. Feng, Y. Zhu, Q. Zhang, L. M. Ni and A. V. Vasilakos, "TRAC: Truthful auction for location-aware collaborative sensing in mobile crowdsourcing," in *Proc. INFOCOM*, 2014, pp. 1231-1239.
[29] "Analysys," February, 2017. [Online]. Available: https://www.analysys.cn/analysis/trade/detail/1000513/
[30] H. Zhou, H. Wang, X. Li, and V. Leung, "A Survey on Mobile Data Offloading Technologies," *IEEE Access*, vol. 6, no. 1, pp. 5101-5111, Jan. 2018.
[31] H. Zhou, M. Ruan, C. Zhu, V. Leung, S. Xu and C. Huang, "A Time-ordered Aggregation Model-based Centrality Metric for Mobile Social Networks," *IEEE Access*, vol. 6, no. 1, pp. 25588-25599, 2018.
[32] D. Kempe, J. Kleinberg, and V. Tardos, "Maximizing the spread of influence through a social network," in *Proc. KDD*, 2003, pp.137–146.
[33] J. Xu, C. Guan, H. Wu, D. Yang, L. Xu and T. Li, "Online incentive mechanism for mobile crowdsourcing based on two-tiered social Crowdsourcing Architecture," in *Proc. IEEE SECON*. Hongkong, June, 2018.
[34] Y. Liu, C. Xu, Y. Zhan, et al. "Incentive mechanism for computation offloading using edge computing: a Stackelberg game approach," *Computer Networks*, vol. 129, pp.399-409, 2017.