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A truthful double auction for two-sided heterogeneous mobile crowdsensing markets

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ABSTRACT

Incentive mechanisms are critical for the success of mobile crowdsensing (MCS). Existing mechanisms mainly focus on scenarios where all sensing tasks are belong to a monopolistic campaign, while ignoring the situation where multiple campaigns coexist and compete for potential sensing capacities. In this paper, we study mechanisms in a two-sided heterogeneous MCS market with multiple requesters and users, where each requester publishes a sensing campaign consisting of various tasks whereas each user can undertake multiple tasks from one or more campaigns. The mechanism design in such a market is very challenging as the demands and supplies are extremely diverse. To fairly and effectively allocate resources and facilitate trades, we propose a novel truthful double auction mechanism named TDMC. By introducing a carefully designed virtual padding requester, a two-stage allocation approach and corresponding pricing schemes for both requesters and users are developed in TDMC. Through theoretical analysis, we prove that TDMC has the properties of truthfulness, individual rationality, budget balance, computational tractability, and asymptotic efficiency as the workload supply compared with demand becomes more and more sufficient. To make TDMC more adaptable, we further introduce two more flexible bid profiles for both requesters and users, and two adjustment methods to control the sensing quality. Extensive simulations demonstrate the effectiveness of TDMC.

1. Introduction

Mobile Crowdsensing (MCS) [1] has become a promising paradigm to solve large-scale and complex data collection problems by leveraging pervasive sensor-equipped mobile devices of the crowd (e.g., smartphones, Tablet PCs, wearable devices). In a MCS platform, a big data collection problem is usually divided into small tasks, thus mobile device users can contribute their relatively small sensing capacities to accomplish the problem in a *crowdsourcing* way. So far, a number of crowd sensing applications have been developed for a variety of purposes, such as traffic information collecting [2], environment monitoring [3], crowdsourced commercial activities [4], and so on.

One critical issue in practical MCS applications is how to stimulate users to participate in the sensing campaigns, as executing sensing tasks will undoubtedly consume physical resources of devices, time, and even human intelligence. Similar to the employment relationship in a labor market, appropriate incentives are needed to compensate users in order to recruit enough sensing workforce.

However, current incentive mechanisms are mainly based on a *monopoly campaign scenario*, which means they simply assume all sensing tasks are belong to a globally unique campaign, and all participating users are working for the same campaign. This may be reasonable for some specific-purpose applications, but things become different in an *integrated MCS platform*. In such a platform, many kinds of MCS applications are available, and different requesters can publish multiple sensing campaigns in a unified platform concurrently. Some platforms such as *Medusa* [5] and *gPS* [6] have been designed in this way. Integrated MCS brings significant benefits, including total overhead reduction and more efficient management. What is more, it also relieves the users from switching between various MCS platforms and provides them more sensing choices.

In this paper, we consider the case where multiple campaign requesters demand for sensing workforce and multiple users supply their sensing capacities. Besides, both requesters and users are self-interested and want to maximize their own benefits *strategically*. This actually builds up a further developed *two-sided market*, which is fundamentally different from the traditional monopoly campaign scenario. As multiple requesters with different interests may *compete* for potential sensing capacities, it is unsuitable to regard all

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campaigns as a whole and apply a single incentive mechanism in a monopolistic way. Letting each campaign apply an independent incentive mechanism is also inconvenient, since users have to contemplate different strategies among various campaigns to maximize their utilities. Indeed, none of existing incentive mechanisms [7–19] can work well in the multiple-campaign competing situations.

In order to fairly and effectively allocate resources and facilitate trades between requesters and users, we propose a Truthful Double auction mechanism for the two-sided Mobile Crowdsensing market (TDMC). However, the design is challenging as the market is intrinsically *heterogeneous*. Further to say, requesters demand for tasks with diverse requirements in aspects of locations, time and sensing methods, while users have different availabilities and preferences for different tasks based on their spatio-temporal and device states. This makes it extremely difficult to allocate tasks and achieve *efficiency*, i.e., the total valuation of all allocated resources of all requesters and users, or called the *social welfare*, is maximum. Besides, *truthfulness* is critical for an auction, which means bidders should truthfully reveal their private information for the items they bid. However, to fully stimulate the sensing capacities, users should be allowed to freely bid for multiple heterogeneous tasks as long as they can undertake. Their private information is actually multi-dimensional, which makes it harder to ensure truthfulness. What is more, it is also important for a double auction to guarantee: (i) *individual rationality*: bidders have non-negative utilities by reporting truthfully, (ii) *budget balance*: auctioneer would not suffer a deficit, and (iii) *computational tractability*: auction runs in polynomial time.

To overcome above challenges, we first categorize all tasks from different campaigns into orthogonal *sensing patterns* to characterize the heterogeneity of the market. Then we allow users to bid personalized maximum available workload and associated (unit) costs for different patterns based on their sensing capacities. Finally, we adopt a two-stage allocation approach to determine the trading results and optimize the social welfare. In stage one, by introducing a carefully designed virtual padding requester, we intentionally intensify the competition among requesters and screen out a set of more competitive requesters to be the winners. In stage two, we match these selected requesters with users who offer the cheapest workload and get the final allocation. Novel pricing schemes are also designed for both requesters and users, which ensures the truthfulness as well as budget balance. Furthermore, we also show TDMC can asymptotically approach the efficiency as the workload supply compared with demand becomes more and more sufficient. The contributions of this paper are as follows.

- To the best of our knowledge, TDMC is the first truthful auction mechanism for a two-sided heterogeneous MCS market, where multiple requesters and users have diverse demands and supplies. A joint consideration of competition among requesters and heterogeneity in the market significantly complicates the design.
- Utilizing a padding idea, TDMC develops a two-stage allocation approach and corresponding pricing schemes for requesters and users to achieve approximate efficiency while preserving truthfulness and budget balance.
- We theoretically prove that TDMC possesses the attractive properties of truthfulness, individual rationality, budget balance, computational tractability, and asymptotic efficiency as the workload supply compared with demand becomes more and more sufficient.
- We further consider several practical issues to make TDMC more adaptable, including more flexible bid profiles for both requesters and users, and two adjustment methods of *price intervention* and *workload quota* to control the sensing quality.

The rest of the paper is organized as follows. In Section 2, we review the related work. In Section 3, we introduce the model and formulate the problem. In Section 4, we elaborate the details of TDMC and provide theoretical proofs of desired properties. Then in Section 5 we consider several practical issues of TDMC. In Section 6 we show some simulation results. In Section 7, we conclude the paper.

2. Related Work

2.1. Incentive mechanisms for mobile crowdsensing

A number of incentive mechanisms [7–19] have been developed for MCS. In [8,9], the platform (also the campaign organizer) applies a stackelberg game to maximize its utility by deciding an optimal total reward. Koutsopoulos [7] proposes a reverse auction in which the platform determines users' participation levels based on their reported unit costs to minimize the total payments under certain service quality limits. An all-pay auction is introduced in [10], where the platform allocates a contribution-dependent prize and only the user who makes the highest contribution can win. After that a Tullock context model is designed in [11], which gives weak players more opportunities to win compared with all-pay auctions to attract more users to participate. These works consider that the market is homogeneous and single user has a uniform cost to all tasks. Some works [8,12–18] also deal with the heterogeneity of MCS from different aspects. In [8], each user bids for a bundle of tasks with a single private cost and the platform selects a subset of users to maximize its submodular utility function. Following this way, Zhao et al. [12] develop two online auctions by adopting a multiple-stage sampling-accepting process. The work in [13] considers the location-awareness of tasks while in [14] considers the dynamic arrivals of users and tasks. Sun and Ma [16] focus on designing long-term user participation incentives by modelling the problem as a restless multi-armed bandit process. He et al. [15] study a unified platform where multiple tasks are distributed in different locations and focuses on optimal task allocation to maximize the total reward for the platform. Cheung et al. [17] develop a finite-step task selection game for users to make their plans of undertaking location-based and time-sensitive tasks. Jin et al. [18] introduce a critical metric of information quality into the design of reverse auction mechanisms for MCS systems. However, all above works regard that tasks in MCS are belong to a unique campaign without caring whether tasks are from multiple self-interested requesters. As far as we know, there is only one work [19] that is related to our two-sided MCS market, where the platform recruits workers to participate in multiple sensing processes, but its target is to maximize total number of satisfied users without considering the processes' utilities and consequent competition among them.

2.2. Double auctions for two-sided markets

In economics, double auctions are widely used for a two-sided market with multiple buyers and sellers. Traditional VCG mechanism is truthfulness, individual rationality and efficiency, but it cannot guarantee budget balance. McAfee double auction [20] is truthful and budget balanced to trade single units of items, and [21] extends it to the multi-unit situation, but the items they study are homogeneous. When trading multiple heterogeneous items, the problem becomes more difficult. Actually, the general form is a multi-unit combinatorial auction, whose optimal allocation problem is NP-hard [22]. Only a few truthful and budget balanced mechanisms with approximate efficiency have been designed in specific cases. Babaioff and Walsh [23] and Chu and Shen [24] consider a scenario where each buyer wants a bundle of items while each seller only offers single unit of one item. Chu [25] studies the case where a buyer's demand is a bundle while a seller can offer multiple units of one item. The padding idea in our work is inspired by Chu [25], but it cannot be directly applied to our work, as we further allow each seller (user) to offer multiple heterogeneous items (maximum available workload for different sensing patterns).

3. System model and problem formulation

In this section, we first give some preliminaries and describe the system model for a two-sided heterogeneous MCS market. Then we formulate the problem and state our design targets.

3.1. System model

In a two-sided MCS market, three kinds of players exist: sensing campaign *requesters*, mobile device *users* and a third party *platform*. Each requester wants to initiate a sensing campaign consisting of a series of tasks. Each user wants to undertake available tasks regardless of which campaign they belong to. The platform acts as an auctioneer and periodically runs a *sealed-bid double auction* to allocate tasks and determine trading prices. We think that players do not collude with each other.

Considering a single round, $\mathcal{M} = \{1, 2, \ldots, M\}$ denotes the set of requesters, $\mathcal{N} = \{1, 2, \ldots, N\}$ denotes the set of users. A requester i submits a bid $B_i = (S_i, v_i)$, where S_i is a specification sheet of all tasks in his campaign, v_i is the reported valuation for his campaign representing the highest price he wants to pay.

As the market is heterogeneous, users have different availabilities and private costs for different tasks. To characterize the heterogeneity, we introduce a practical concept of *sensing pattern*. A pattern uniquely defines all necessary features of a class of similar tasks, including *area*, *period*, *sensing method*, etc. The platform categorize all tasks from campaigns of requesters into orthogonal sensing patterns, by aggregating tasks of same features into a pattern. i.e., tasks executed in the same area, same period of time and with a same sensing method are aggregated into a pattern. The rationality behind this setting is, as long as tasks in a pattern are similar enough, it can be ensured that a user has the same privacy information for these tasks, as he is usually *insensitive* to execute tasks with the same features. But he may still have different private information for tasks of different patterns. Note that in practice the granularity of patterns' features should be carefully chosen to enable the rationality of pattern categorization as well as to make a tradeoff between accuracy and simplicity, which should depend on specific scenarios.

Without loss of generality, let the set of all sensing patterns be $\mathcal{T} = \{1, 2, \ldots, T\}$. Tasks of a certain pattern may come from one or more campaigns, tasks in a certain campaign may also belong to one or more patterns. we consider that all tasks in the same pattern could be represented as several sub-tasks of uniform size, which is rational due to the similarity of tasks in the same pattern. For example, for tasks of traffic condition monitoring and parking slot monitoring in one pattern, a uniform sub-task can be taking a small fixed number of pictures. For the retail good price reporting and the commodity inventory reporting tasks in another pattern, a uniform sub-task can be updating a small fixed number of records. We can always define a proper uniform sub-task for each pattern, so that each task can be divided into several units of such sub-tasks. For convenience, we call the amount of uniform sub-tasks for any pattern as *workload*, which should be an integer number.

As a result, the bid of requester i can be rewritten as $B_i = (\boldsymbol{d}_i, v_i)$. $\boldsymbol{d}_i = (d_{i1}, d_{i2}, \ldots, d_{iT})$ is a demand vector, where d_{it} is the required workload of requester i for pattern t. If pattern t is not required by requester i, $d_{it} = 0$. To fully stimulate the sensing capacities, users should be allowed to freely undertake multiple tasks of different patterns as long as they can accomplish. So we let users bid a multi-dimensional *maximum available bid profile*, which contains maximum available workload and associated private unit costs for different patterns. Formally, user j bids $A_j = (\boldsymbol{m}_j, \boldsymbol{c}_j)$. In the supply vector $\boldsymbol{m}_j = (m_{j1}, m_{j2}, \ldots, m_{jT})$, each m_{jt} is the maximum available workload of user j for pattern t, while in associated reported cost vector $\boldsymbol{c}_j = (c_{j1}, c_{j2}, \ldots, c_{jT})$, each c_{jt} is the reported *unit* workload cost of user j for pattern t. If pattern t is unavailable for user j, $m_{jt} = 0$ and $c_{jt} = \infty$.

Notice that v_i, $\boldsymbol{m}_j$ and $\boldsymbol{c}_j$ are not necessary equal to the true valuation $\bar{v}_i$ for the campaign of requester i, the true supply vector $\bar{\boldsymbol{m}}_j$ of user j and the true cost vector $\bar{\boldsymbol{c}}_j$ of user j, considering the potential dishonest behaviors of both requesters and users. As a requester has no motivation to misreport his true demand, we think that $\boldsymbol{d}_i$ is always true.

After receiving bids from both requesters and users, the platform decides each one's outcome, including task allocation and trading prices. In the outcome (x_i, p_i) of requester i, the allocation $x_i \in \{0, 1\}$ means whether i wins or not in the auction, the payment p_i is the price requester i needs to pay to the platform. The utility of requester i is

$$U_i^r = \bar{v}_i x_i - p_i. \quad (1)$$

Here we consider the utility functions of requesters are single-minded, which means they either win and successfully recruit all their required workload or lose and get nothing. In Section 5.1.1 we will introduce a more flexible solution, which allows requesters to win campaigns partially.

The outcome of user j is $(\boldsymbol{w}_j, \boldsymbol{r}_j)$. In the allocation vector $\boldsymbol{w}_j = (w_{j1}, w_{j2}, \ldots, w_{jT})$, each w_{jt} is the workload of pattern t finally assigned to user j, while in the reward vector $\boldsymbol{r}_j = (r_{j1}, r_{j2}, \ldots, r_{jT})$, each r_{jt} is the reward paid by the platform for accomplishing w_{jt} units of workload for pattern t, $r_j = \sum_{t \in \mathcal{T}} r_{jt}$. The utility of user j is

$$U_j^u = \sum_{t \in \mathcal{T}} U_{jt}^u = \sum_{t \in \mathcal{T}} (r_{jt} - \bar{c}_{jt} w_{jt}). \quad (2)$$

We consider the utility function is linear and all the rewards and costs are simply additive, more complex situations such as non-linear functions are left for future work. More frequently used notations are listed in Table 1.

3.2. Problem formulation

Unlike requesters and users, we assume the third party platform aims to benefit the whole market rather than only itself. So we focus on designing a mechanism to maximize the *social welfare*. If all bidders bid truthfully, the social welfare optimization problem $\mathcal{P}(\mathcal{M}, \mathcal{N})$ can be formulated as follows:

$$\begin{aligned} \max \quad & \mathcal{SW}(\mathcal{M}, \mathcal{N}) = \sum_{i \in \mathcal{M}} v_i x_i - \sum_{j \in \mathcal{N}} \sum_{t \in \mathcal{T}} c_{jt} w_{jt} \\ s.t. \quad & \begin{cases} \sum_{i \in \mathcal{M}} d_{it} x_i = \sum_{j \in \mathcal{N}} w_{jt} & \forall t \in \mathcal{T}, \\ x_i \in \{0, 1\} \quad \forall i \in \mathcal{M}, \\ w_{jt} \in \{0, 1, \ldots, m_{jt}\} \quad \forall j \in \mathcal{N}, t \in \mathcal{T}, \end{cases} \end{aligned} \quad (3)$$

where all x_i and w_{jt} are integers and the allocated workload w_{jt} must not exceed the maximum available workload m_{jt}. The first condition of (3) means the demand and supply for all patterns are balanced. The optimal solution of $\mathcal{P}(\mathcal{M}, \mathcal{N})$ is defined as $(\boldsymbol{x}^*, \boldsymbol{w}^*)$.

Obviously (3) is an integer programming (IP) problem, we show it is NP-hard. Briefly speaking, if we degenerate (3) to a specific case where there are multiple requesters and only one user, $v_i = 1$ for all requesters and $m_{1t} = 1$, $c_{1t} = 0$ for all patterns of the only user 1, the problem will straightly become the *set packing problem*, which is a well-known NP-complete problem [26]. So problem (3) must be NP-hard. To make it tractable, approximate methods should be applied. What is more, several critical economic properties should also be guaranteed. In general, the design targets of TDMC include:

- *Truthfulness:* Bidders cannot benefit from bidding dishonestly. i.e., for any requester i, $U_i^r(\bar{v}_i) \geq U_i^r(v_i)$, $\forall v_i$, for any user j, $U_j^u(\bar{\boldsymbol{m}}_j, \bar{\boldsymbol{c}}_j) \geq U_j^u(\boldsymbol{m}_j, \boldsymbol{c}_j)$, $\forall \boldsymbol{m}_j, \boldsymbol{c}_j$.
- *Individual rationality:* Bidders have non-negative utilities by reporting true valuations, i.e., $U_i^r(\bar{v}_i) \geq 0$ and $U_j^u(\bar{\boldsymbol{m}}_j, \bar{\boldsymbol{c}}_j) \geq 0$ always hold.
- *Budget balance:* For the platform, the total payment paid by all requesters is no less than the total reward paying to all users, i.e., $\sum_{i \in \mathcal{M}} p_i - \sum_{j \in \mathcal{N}} \sum_{t \in \mathcal{T}} r_{jt} \geq 0$.

Table 1
Frequently used notations.

Notation	Description
$\mathcal{M}, \mathcal{N}, \mathcal{T}$	Set of requesters, users and patterns
i, j	Requester and user
B_i, S_i	Bid and specification sheet of requester i
$\boldsymbol{d}_i$	Demand vector of requester i
d_{it}	Required workload of requester i for pattern t
$v_i, \overline{v}_i$	Reported valuation and true valuation of requester i
A_j	Bid of user j
$\boldsymbol{m}_j, \overline{\boldsymbol{m}}_j$	Supply vector and true supply vector of user j
$\boldsymbol{c}_j, \overline{\boldsymbol{c}}_j$	Reported cost vector and true cost vector of user j
m_{jt}, c_{jt}	Maximum available workload and reported unit cost of user j for pattern t
U_i^r, U_j^u	Utility of requester i and user j
x_i, p_i	Allocation and payment of requester i
$\boldsymbol{w}_j, \boldsymbol{r}_j, r_j$	Allocation vector, reward vector and total reward of user j
w_{jt}, r_{jt}	Allocated workload and reward of user j for pattern t
$\mathcal{SW}, \overline{\mathcal{SW}}$	Social welfare
$(\boldsymbol{x}^*, \boldsymbol{w}^*)$	Optimal solution of social welfare optimization problem
$(\boldsymbol{x}', \boldsymbol{w}')$	Stage-one allocation of TDMC
$(\boldsymbol{x}'', \boldsymbol{w}'')$	Stage-two allocation of TDMC
$\mathcal{V}$	Virtual padding requester (VPR)
$\mathcal{M}^s$	Set of survived requesters
$\boldsymbol{m}^v$	Demand vector of VPR
m_t^v	Required workload of VPR for pattern t
b_i^c	Critical price of requester i
$C^t[r], C^t(s)$	Discrete and continuous marginal cost function of workload for pattern t
$C_{-j}^t[r], C_{-j}^t(s)$	Discrete and continuous marginal cost function of workload for pattern t excluding user j
H_t	Total traded workload of pattern t
$\boldsymbol{\alpha}_i^L$	Discount vector of requester i
$\boldsymbol{m}_{jt}^E, \boldsymbol{c}_{jt}^E$	Tiered supply vector and tiered cost vector of user j for pattern t
$\beta_j, \gamma_j,$	Quality factor of user j

- *Computational tractability:* The outcome of TDMC can be computed in polynomial time.
- *Asymptotic efficiency:* TDMC is approaching optimal social welfare as the workload supply of users becomes more and more sufficient compared with the workload demand of requesters.

4. Mechanism details and analysis

In this section, we first elaborate the details of TDMC. Then, we prove TDMC is truthful, individual rational, budget balanced, computational tractable, and asymptotic efficient as the workload supply compared with demand becomes more and more sufficient.

4.1. Mechanism details

In order to solve the social welfare optimization problem in polynomial time, a straight thought is to turn to the linear relaxation form $\overline{\mathcal{P}}(\mathcal{M}, \mathcal{N})$, which is formulated as follows[1]:

$$\max \quad \overline{\mathcal{SW}}(\mathcal{M}, \mathcal{N}) = \sum_{i \in \mathcal{M}} v_i x_i - \sum_{j \in \mathcal{N}} \sum_{t \in \mathcal{T}} c_{jt} w_{jt}$$
$$s.t. \quad \begin{cases} \sum_{i \in \mathcal{M}} d_{it} x_i = \sum_{j \in \mathcal{N}} w_{jt} & \forall t \in \mathcal{T}. \\ 0 \le x_i \le 1 \quad \forall i \in \mathcal{M}. \\ 0 \le w_{jt} \le m_{jt} \quad \forall j \in \mathcal{N}, t \in \mathcal{T}. \end{cases} \tag{4}$$

However, simply solving (4) is not enough. We should further ensure: (1) the allocation is feasible, which means $\boldsymbol{x}$ and $\boldsymbol{w}$ must be integer solutions, (2) all targets we have mentioned above must be satisfied, especially the critical properties of truthfulness and budget balance.

Inspired by the padding idea in [25], we introduce a *virtual padding requester* (VPR), which has a special demand vector $\boldsymbol{m}^v = (m_1^v, m_2^v, \ldots, m_T^v)$ and *unlimited* budget. We let $m_t^v = \max_{j \in \mathcal{N}} \{m_{jt}\}$, $\forall t \in \mathcal{T}$. That means, the demand vector of VPR can just cover the supply vector of any user.

[1] We assume both $\mathcal{P}(\mathcal{M}, \mathcal{N})$ and $\overline{\mathcal{P}}(\mathcal{M}, \mathcal{N})$ output unique optimal solutions, ties are broken randomly if multiple solutions exist.

Through this, we design a two-stage allocation approach to determine allocation for requesters and users. In the first stage, we add VPR into the market to intensify the competition between requesters, and solve a linear programming problem involving requester set $\mathcal{M}$, user set $\mathcal{N}$ and the VPR $\mathcal{V}$. As $\mathcal{V}$ has unlimited budget, his demand must be satisfied, so the problem $\overline{\mathcal{P}}(\mathcal{M}, \mathcal{N}, \mathcal{V})$ is formulated as follows:

$$\max \quad \overline{\mathcal{SW}}(\mathcal{M}, \mathcal{N}, \mathcal{V}) = \sum_{i \in \mathcal{M}} v_i x_i - \sum_{j \in \mathcal{N}} \sum_{t \in \mathcal{T}} c_{jt} w_{jt}$$
$$s.t. \quad \begin{cases} \sum_{i \in \mathcal{M}} d_{it} x_i + m_t^v = \sum_{j \in \mathcal{N}} w_{jt} & \forall t \in \mathcal{T}. \\ 0 \le x_i \le 1 \quad \forall i \in \mathcal{M}. \\ 0 \le w_{jt} \le m_{jt} \quad \forall j \in \mathcal{N}, t \in \mathcal{T}. \end{cases} \tag{5}$$

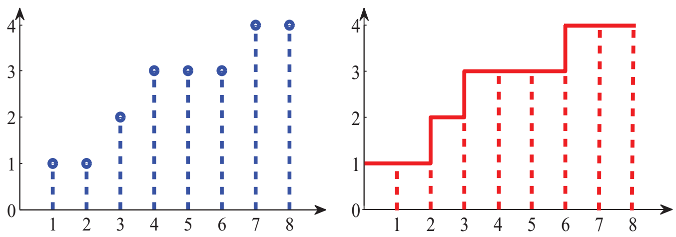
Assume the optimal solution of $\overline{\mathcal{P}}(\mathcal{M}, \mathcal{N}, \mathcal{V})$ is $(\boldsymbol{x}', \boldsymbol{w}')$. For each requester i, define the critical price $b_i^c = \inf\{v_i | x_i' = 1\}$, which means the minimum price requester i can bid while satisfying $x_i' = 1$ in the optimal solution of $\overline{\mathcal{P}}(\mathcal{M}, \mathcal{N}, \mathcal{V})$, given the bids of others unchanged. Then we screen out a survived requester set $\mathcal{M}^s = \{i | x_i' = 1\}$, representing that only more competitive requesters who bid higher than their critical prices can enter the next stage. In Section 4.2 we will see, they are also winners in the final allocation.

In the second stage, we let requesters in $\mathcal{M}^s$ trade with users in $\mathcal{N}$. To maximize the social welfare, the problem can be formulated as another linear programming problem $\overline{\mathcal{P}}(\mathcal{M}^s, \mathcal{N})$, which is formulated as follows:

$$\max \quad \overline{\mathcal{SW}}(\mathcal{M}^s, \mathcal{N}) = \sum_{i \in \mathcal{M}} v_i x_i - \sum_{j \in \mathcal{N}} \sum_{t \in \mathcal{T}} c_{jt} w_{jt}$$
$$s.t. \quad \begin{cases} \sum_{i \in \mathcal{M}^s} d_{it} x_i = \sum_{j \in \mathcal{N}} w_{jt} & \forall t \in \mathcal{T}. \\ 0 \le x_i \le 1 \quad \forall i \in \mathcal{M}^s. \\ 0 \le w_{jt} \le m_{jt} \quad \forall j \in \mathcal{N}, t \in \mathcal{T}. \end{cases} \tag{6}$$

The optimal solution of $\overline{\mathcal{P}}(\mathcal{M}^s, \mathcal{N})$ is defined as $(\boldsymbol{x}'', \boldsymbol{w}'')$. $(\boldsymbol{x}'', \boldsymbol{w}'')$ also determines the final allocation, i.e., $(\boldsymbol{x}, \boldsymbol{w}) = (\boldsymbol{x}'', \boldsymbol{w}'')$. If $i \notin \mathcal{M}^s$, set $x_i = 0$ by default.

We also design pricing schemes for both requesters and users. For requesters, we develop a critical pricing scheme. If $\boldsymbol{x}_i = \boldsymbol{x}_i'' = 1$, requester i will win and pay the critical price b_i^c to the platform, else he



(a) X axis: r; Y axis: $C^t[r]$ (b) X axis: s; Y axis: $C^t(s)$

Fig. 1. An illustration of marginal cost function.

will lose and pay nothing. The payment of requester i is defined as:

$$p_i = \begin{cases} b_i^c & x_i = 1; \\ 0 & \text{otherwise.} \end{cases} \quad (7)$$

For users, we develop a VCG-like pricing scheme. The reward of user j paid by the platform is defined as the change of all other bidders' social welfare caused by user j's participation, which is:

$$r_j = \sum_{t\in\mathcal{T}} c_{jt} w_{jt} + \overline{\mathcal{SW}}(\mathcal{M}^s, \mathcal{N}) - \overline{\mathcal{SW}}(\mathcal{M}^s, \mathcal{N}\backslash\{j\}). \quad (8)$$

Roughly speaking, by adding the VPR, TDMC aims to intentionally shrink the potential transactions and loss some efficiency in order to preserve the truthfulness and budget balance. However, a higher VPR may lead to a larger loss of efficiency. In Section 4.2 we will prove, by setting $m_t^v = \max_{j\in\mathcal{N}}\{m_{jt}\}$, $\forall t \in \mathcal{T}$ for VPR as we defined, both truthfulness and budget balance can be ensured. Note that in the MCS environment, the sensing capacity of a single user is usually much smaller compared to the sizes of campaigns, so VPR would not be very large and the loss of efficiency is limited, which makes TDMC effective enough.

Before the mechanism analysis, we should first introduce a concept of *marginal cost function* of workload for any pattern. Given user set $\mathcal{N}$, for any pattern t, we sort all units of workload offered by users based on their reported costs in an ascending order, and define the cost of rth cheapest unit of workload for pattern t as the marginal cost $C^t[r]$.[2] We also define a continuous form $C^t(s) = C^t[\lceil s \rceil]$, where $\lceil s \rceil$ is the smallest number no less than s. $C^t_{-j}[r]$ and $C^t_{-j}(s)$ are similar concepts except that the user set becomes $\mathcal{N}\backslash\{j\}$. A illustration is showed in Fig. 1, where bids of users are $(m_{1t}, c_{1t}) = (2, 1)$, $(m_{2t}, c_{2t}) = (1, 2)$, $(m_{3t}, c_{3t}) = (3, 3)$, $(m_{4t}, c_{4t}) = (2, 4)$. As an example, we have $C^t[4] = C^t(3.5) = 3$ while $C^t_{-3}[4] = C^t_{-3}(3.5) = 4$. Obviously, $C^t[r]$, $C^t_{-j}[r]$, $C^t(s)$ and $C^t_{-j}(s)$ are all monotone increasing.

Particularly, Eq. (8) can be re-expressed as:

$$r_j = \sum_{t\in\mathcal{T}} r_{jt} = \sum_{t\in\mathcal{T}} \sum_{r=1}^{w_{jt}} C^t_{-j}[H_t - r + 1], \quad (9)$$

where $H_t = \sum_{j\in\mathcal{N}} w_{jt}$ is the total traded workload of pattern t. We will prove the correctness of Eq. (9) in Section 4.2.

4.2. Mechanism analysis

First we will show, although by solving two LP problems, the allocation $(\boldsymbol{x}, \boldsymbol{w})$ is guaranteed to be an integer solution. We begin by introducing the following lemma.

Lemma 1. *For any requester $i \in \mathcal{M}^s$, $x_i'' = 1$ is in the optimal solution of $\overline{\mathcal{P}}(\mathcal{M}^s, \mathcal{N})$.*

Proof. In stage one, the allocated workload of any pattern t is $\sum_{j\in\mathcal{N}} w'_{jt} = \sum_{k\in\mathcal{M}} d_{kt}x'_k + m_t^v$. In stage two, the allocated workload of any pattern t is $\sum_{j\in\mathcal{N}} w''_{jt} = \sum_{k\in\mathcal{M}^s} d_{kt}x''_k$. Since $x'_k = 1$ if $k \in \mathcal{M}^s$ and $m_t^v \geq 0$, so $\sum_{k\in\mathcal{M}} d_{kt}x'_k + m_t^v \geq \sum_{k\in\mathcal{M}^s} d_{kt}$. Note that $C^t(s)$ is monotone increasing, so we have $C^t(\sum_{k\in\mathcal{M}} d_{kt}x'_k + m_t^v) \geq C^t(\sum_{k\in\mathcal{M}^s} d_{kt})$.

On the other hand, for any requester $i \in \mathcal{M}^s$, $x'_i = 1$, we must have $v_i \geq \sum_{t\in\mathcal{T}} C^t(\sum_{k\in\mathcal{M}} d_{kt}x'_k + m_t^v)d_{it}$. If not, due to the continuity of linear programming, we can always let $x'_i = 1$ less a small number ε to be $1 - \varepsilon$, and make $\overline{\mathcal{SW}}(\mathcal{M}, \mathcal{N}, \mathcal{V})$ increase by $\varepsilon(\sum_{t\in\mathcal{T}} C^t(\sum_{k\in\mathcal{M}} d_{kt}x'_k + m_t^v)d_{it} - v_i) > 0$. In this case, $x'_i = 1$ must not be in the optimal solution of $\overline{\mathcal{P}}(\mathcal{M}, \mathcal{N}, \mathcal{V})$, which leads to contradiction. Note that $\forall t \in \mathcal{T}$, there exists:

$$\sum_{k\in\mathcal{M}^s} d_{kt} \geq \sum_{k\in\mathcal{M}^s\backslash\{i\}} d_{kt}x''_k + d_{it} \geq \sum_{k\in\mathcal{M}^s} d_{kt}x''_k,$$

thus we have:

$$\begin{aligned} v_i &\geq \sum_{t\in\mathcal{T}} C^t\left(\sum_{k\in\mathcal{M}^s} d_{kt}\right)d_{it} \\ &\geq \sum_{t\in\mathcal{T}} C^t\left(\sum_{k\in\mathcal{M}^s\backslash\{i\}} d_{kt}x''_k + d_{it}\right)d_{it} \\ &\geq \sum_{t\in\mathcal{T}} C^t\left(\sum_{k\in\mathcal{M}^s} d_{kt}x''_k\right)d_{it}. \end{aligned}$$

In stage two, if $x''_i < 1$, we could always increase x''_i to 1 to achieve a higher social welfare, so $x''_i = 1$ must be in the optimal solution of $\overline{\mathcal{P}}(\mathcal{M}^s, \mathcal{N})$. □

Theorem 1. *The allocation of TDMC is feasible.*

Proof. According to Lemma 1, $x''_i = 1$ exists for all requesters who enter stage two. Therefore, the total traded workload of any pattern t is an integer number. To achieve an optimal allocation, the allocated workload of users should be chosen according to their reported costs from low to high. As we have assumed the rank of users' workload according to their reported costs is unique, each user will be allocated discrete units of workload. □

The next, we will prove the desired properties of TDMC.

Theorem 2. *TDMC is truthful and individual rational for requesters.*

Proof. Based on Eq. (7), for any requester i who wins, the payment to the platform is the critical price b_i^c, for any losing requester, the payment is zero. If requester i bids lower than b_i^c, i.e. $x'_i < 1$, he will not be in the survived requester set $\mathcal{M}^s$ and enter stage two. Thus he will not win. If requester i bids higher than b_i^c, he will survive in stage one, according to Lemma 1, he will also win in stage two. When his true valuation $\overline{v}_i < b_i^c$, he prefers to loss to avoid a negative utility, which can be achieved by bidding truthfully. When his true valuation $\overline{v}_i > b_i^c$, he prefers to win to obtain a positive utility, which can also be achieved by bidding truthfully. When $\overline{v}_i = b_i^c$, he is indifferent to win or not. As a conclusion, truthfulness is a dominant strategy. Thus, TDMC is truthful for requesters.

By bidding truthfully, a requester can always follow his preference and have a non-negative utility. Thus, TDMC is individual rational for requesters. □

Before proving the truthfulness and individual rationality for the users, we introduce the following lemma.

Lemma 2. *For any requester $i \in \mathcal{M}^s$, $x'''_i = 1$ is in the optimal solution of $\overline{\mathcal{P}}(\mathcal{M}^s, \mathcal{N}\backslash\{j\})$, given the optimal solution $(\boldsymbol{x}''', \boldsymbol{w}''')$ of $\overline{\mathcal{P}}(\mathcal{M}^s, \mathcal{N}\backslash\{j\})$ and any user $j \in \mathcal{N}$.*

Proof. According to Lemma 1, for any requester $i \in \mathcal{M}^s$, $x'_i = 1$, we have $v_i \geq \sum_{t\in\mathcal{T}} C^t(\sum_{k\in\mathcal{M}} d_{kt}x'_k + m_t^v)d_{it}$. As $m_t^v \geq m_{jt}$, $\forall t \in \mathcal{T}, j \in \mathcal{N}$

[2] We assume all reported costs of users are different so the rank is unique, ties are broken randomly.

by the definition of m_t^v, we have $\sum_{k\in\mathcal{M}} d_{kt}x'_k + m_t^v \geq \sum_{k\in\mathcal{M}^s} d_{kt} + m_{jt}$. Thus:

$$C^t\left(\sum_{k\in\mathcal{M}} d_{kt}x'_k + m_t^v\right) \geq C^t\left(\sum_{k\in\mathcal{M}^s} d_{kt} + m_{jt}\right).$$

On the other hand, we always have:

$$C^t\left(\sum_{k\in\mathcal{M}^s} d_{kt}x'''_k + m_{jt}\right) \geq C^t_{-j}\left(\sum_{k\in\mathcal{M}^s} d_{kt}x'''_k\right).$$

Note that $\forall t \in \mathcal{T}$, there exists:

$$\sum_{k\in\mathcal{M}^s} d_{kt} \geq \sum_{k\in\mathcal{M}^s\setminus\{i\}} d_{kt}x'''_k + d_{it} \geq \sum_{k\in\mathcal{M}^s} d_{kt}x'''_k,$$

so we have:

$$\begin{aligned} v_i &\geq \sum_{t\in\mathcal{T}} C^t\left(\sum_{k\in\mathcal{M}^s} d_{kt} + m_{jt}\right)d_{it} \\ &\geq \sum_{t\in\mathcal{T}} C^t\left(\sum_{k\in\mathcal{M}^s\setminus\{i\}} d_{kt}x'''_k + d_{it} + m_{jt}\right)d_{it} \\ &\geq \sum_{t\in\mathcal{T}} C^t\left(\sum_{k\in\mathcal{M}^s} d_{kt}x'''_k + m_{jt}\right)d_{it} \\ &\geq \sum_{t\in\mathcal{T}} C^t_{-j}\left(\sum_{k\in\mathcal{M}^s} d_{kt}x'''_k\right)d_{it}. \end{aligned}$$

In $\overline{\mathcal{P}}(\mathcal{M}^s, \mathcal{N}\setminus\{j\})$, if $x'''_i < 1$, we could always increase x'''_i to 1 to achieve a higher social welfare, so $x'''_i = 1$ must be in the optimal solution of $\overline{\mathcal{P}}(\mathcal{M}^s, \mathcal{N}\setminus\{j\})$. □

Lemma 3. *Eq. (8) is equivalent to Eq. (9).*

Proof. By Lemmas 1 and 2, all requesters in $\mathcal{M}^s$ will always win in the optimal solution of both $\overline{\mathcal{P}}(\mathcal{M}^s, \mathcal{N})$ and $\overline{\mathcal{P}}(\mathcal{M}^s, \mathcal{N}\setminus\{j\})$, which holds for any user j. Recall that H_t is the total traded workload of any pattern t, we see $H_t = \sum_{j\in\mathcal{N}} w''_{jt} = \sum_{g\in\mathcal{N}\setminus\{j\}} w'''_{gt} = \sum_{i\in\mathcal{M}^s} d_{jt}$ is fixed no matter whether user j participates in stage two. Given the optimal allocation of $\overline{\mathcal{P}}(\mathcal{M}^s, \mathcal{N}\setminus\{j\})$, let user j enter the game, to achieve an optimal allocation again, workload of user j will be allocated by replacing others' if his reported costs are lower. Further to say, for any pattern t, if $c_{jt} > C^t_{-j}[H_t]$, w_{jt} will be zero by replacing no workload of others. If $c_{jt} < C^t_{-j}[H_t - m_{jt} + 1]$, w_{jt} will be allocated as the maximum available workload of m_{jt}, by replacing m_{jt} units of highest-cost allocated workload of others. If $C^t_{-j}[H_t - h] < c_{jt} < C^t_{-j}[H_t - h + 1]$, where $h \in \{1, 2, \ldots, m_{jt} - 1\}$, w_{jt} will be allocated as h units, by replacing h units of highest-cost allocated workload of others. The change of social welfare is actually caused by the new allocated workload and its replaced workload, i.e. $\overline{\mathcal{SW}}(\mathcal{M}^s, \mathcal{N}) - \overline{\mathcal{SW}}(\mathcal{M}^s, \mathcal{N}\setminus\{j\}) = \sum_{t\in\mathcal{T}}\sum_{r=1}^{w_{jt}} C^t_{-j}[H_t - r + 1] - \sum_{t\in\mathcal{T}} c_{jt}w_{jt}$.

Based on Eq. (8) and above allocation method, we can directly express the reward r_j as the sum of costs of the workload "replaced" by user j, consisting of all patterns. The formula is followed as:

$$r_j = \sum_{t\in\mathcal{T}} r_{jt} = \sum_{t\in\mathcal{T}}\sum_{r=1}^{w_{jt}} C^t_{-j}[H_t - r + 1],$$

which is just Eq. (9). □

Theorem 3. *TDMC is truthful and individual rational for users.*

Proof. Based on Eqs. (2) and (9), the utility of user j is:

$$U^u_j = \sum_{t\in\mathcal{T}}\sum_{r=1}^{w_{jt}} (C^t_{-j}[H_t - r + 1] - \overline{c}_{jt}). \quad (10)$$

We first focus on the utility of user j for any pattern t, i.e., $U^u_{jt} = \sum_{r=1}^{w_{jt}} (C^t_{-j}[H_t - r + 1] - \overline{c}_{jt})$. If his true cost $\overline{c}_{jt} > C^t_{-j}[H_t]$, to maximize U^u_{jt}, user j will prefer not to win any units of workload for pattern t, which can be achieved by bidding truthful m_{jt} and c_{jt}. If his true cost $\overline{c}_{jt} < C^t_{-j}[H_t - \overline{m}_{jt} + 1]$, to maximize U^u_{jt}, user j will prefer to win all his available workload of pattern t, which can also be achieved by bidding truthful m_{jt} and c_{jt}. If $C^t_{-j}[H_t - h] < \overline{c}_{jt} < C^t_{-j}[H_t - h + 1]$, where $h \in \{1, 2, \ldots, \overline{m}_{jt} - 1\}$, to maximize U^u_{jt}, user j will prefer to win h units of workload for pattern j, which can also be achieved by bidding truthful m_{jt} and c_{jt}. Then we can see, by truthful reporting m_{jt} and c_{jt} for all patterns, user j can always achieve the maximum possible total utility. Truthfulness is a dominant strategy. Thus, TDMC is truthful for users.

By bidding truthfully, a user can always follow his preference and have a non-negative utility. Thus, TDMC is individual rational for users. □

Theorem 4. *TDMC is budget balanced for the platform.*

Proof. We first consider the requester side and get a lower bound for the total payment paid by all the requesters. By Lemma 1, for any requester i who wins, it must satisfy $v_i \geq \sum_{t\in\mathcal{T}} C^t(\sum_{k\in\mathcal{M}^s} d_{kt} + m_t^v)d_{it}$. By Theorem 2, if $v_i > b_i^c$, requester i will win and pay $p_i = b_i^c$, which still holds when v_i is moving toward b_i^c. In the limit case we have $p_i \geq \sum_{t\in\mathcal{T}} C^t(\sum_{k\in\mathcal{M}^s} d_{kt} + m_t^v)d_{it}$. So the total payment $\sum_{i\in\mathcal{M}} p_i$ is no less than the total payment when per unit of the traded workload for each pattern t has the fixed price $C^t(\sum_{k\in\mathcal{M}^s} d_{kt} + m_t^v)$.

Then we consider the user side and get a upper bound for the total reward paying to all the users. For any user j, according to Eq. (9), the reward of per unit of the traded workload for pattern t is no more than $C^t_{-j}[H_t] = C^t_{-j}[\sum_{k\in\mathcal{M}^s} d_{kt}]$. Besides, we have $C^t_{-j}[\sum_{k\in\mathcal{M}^s} d_{kt}] \leq C^t(\sum_{k\in\mathcal{M}^s} d_{kt} + m_t^v)$. So the total reward $\sum_{j\in\mathcal{N}}\sum_{t\in\mathcal{T}} r_{jt}$ is no more than the total reward when per unit of the traded workload for each pattern t has the fixed price $C^t(\sum_{k\in\mathcal{M}^s} d_{kt} + m_t^v)$.

Therefore, for the platform, the total payment paid by requesters is always no less than the total reward paying to the users. Thus, TDMC is budget balanced. □

Theorem 5. *TDMC is computational tractable.*

Proof. We analysis the computational complexity of TDMC by studying the allocation approach and the pricing schemes respectively. For the allocation approach, it first takes $O(NT)$ time to calculate the VPR. Then two linear programming problems are processed, which can be solved in polynomial time, we express it as $O(P)$. So the computational complexity of allocation approach is $O(NT) + O(P)$. When calculating the prices for users, we use Eq. (10) directly, which is a closed-form expression and can terminate in polynomial time. Specially, $O(Nlog(N))$ time is taken to form the marginal cost function $C^t_{-j}[r]$, then $O(T + W)$ time is taken to calculate U^u_j, where W is the upper bound of w_{jt}. So the computational complexity of pricing scheme for users is $O(NTlog(N) + NW)$. When calculating the prices for requesters, Eq. (7) is used and we just need to determine the corresponding critical prices for winners. Although the critical price expression $b_i^c = \inf\{v_i | x'_i = 1\}$ is not closed-form, we can leverage numerical methods instead. According to Theorem 4, if any requester i wins, the critical price $b_i^c \geq \sum_{t\in\mathcal{T}} C^t(\sum_{k\in\mathcal{M}} d_{kt}x'_k + m_t^v)d_{it}$. On the other hand, obviously $b_i^c \leq v_i$ by the definition of individual rationality. The interval of b_i^c is limited and we can use a binary search method to achieve a solution which is accurate enough in polynomial time. Given the required accuracy Δ, the binary search takes $O(log(\frac{I}{\Delta}))$ iterations to determine b_i^c, where I is the upper bound of the interval of b_i^c. In each iteration the allocation approach needs to be applied, so the computational complexity of the pricing scheme for requesters is $O(Mlog(\frac{I}{\Delta}))O(P)$. In conclusion, the computational

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complexity of TDMC is $O(NTlog(N) + NW) + O(Mlog(\frac{1}{\Delta}))O(P)$, TDMC is computational tractable. □

Theorem 6. *TDMC is asymptotic efficient as the workload supply compared with demand becomes more and more sufficient, given bounded cost distributions of workload for all patterns.*

Proof. We only need to prove, on condition that the workload supply of users for all patterns becomes more and more sufficient compared with the workload demand of requesters, the allocation ($\boldsymbol{x}$, $\boldsymbol{w}$) of TDMC will converge to the optimal solution ($\boldsymbol{x}^*$, $\boldsymbol{w}^*$) of social welfare optimization problem $\mathcal{P}(\mathcal{M}, \mathcal{N})$ with probability 1. Without loss of generality, we fix the demand side and investigate the impacts on efficiency by increasing the workload supply. Assume the reported cost distribution of users for any pattern t is between $[\underline{c}_t, \overline{c}_t]$. For any requester i, if $v_i < \sum_{t\in\mathcal{T}} d_{it}\underline{c}_i$, as the workload supply of pattern t increases, he will never be allocated in $\mathcal{P}(\mathcal{M}, \mathcal{N})$, neither will he be allocated in TDMC. If $v_i > \sum_{t\in\mathcal{T}} d_{it}\underline{c}_i$, as the workload supply of pattern t increases, more workload with cheaper cost appears, $C^t(\sum_{k\in\mathcal{M}} d_{kt} + m_t^v)$ will approach $\underline{c}\ _t$. This holds for all patterns, so there must exist a supply threshold that satisfies $v_i > \sum_{t\in\mathcal{T}} C^t(\sum_{k\in\mathcal{M}} d_{kt} + m_t^v)d_{it} > \sum_{t\in\mathcal{T}} d_{it}\underline{c}_i$. By Lemma 1, requester i will win in TDMC. As $v_i > \sum_{t\in\mathcal{T}} C^t(\sum_{k\in\mathcal{M}} d_{kt})d_{it}$ also holds, requester i also wins in the optimal solution of $\mathcal{P}(\mathcal{M}, \mathcal{N})$.

That is to say, when the workload supply is sufficient enough to satisfy $v_i > \sum_{t\in\mathcal{T}} C^t(\sum_{k\in\mathcal{M}} d_{kt} + m_t^v)d_{it}$, requester i will win in both TDMC and $\mathcal{P}(\mathcal{M}, \mathcal{N})$. Provided that the number of requesters is finite, the overlap percent between $\boldsymbol{x}$ and $\boldsymbol{x}^*$ will approach 100% as the workload supply increases, at the same time $\boldsymbol{w}$ also converges to $\boldsymbol{w}^*$. In this way, TDMC can asymptotically approach efficiency. Typically, if all requesters win in the auction, TDMC achieves the optimal social welfare. □

Remark. Relatively sufficient workload supply compared with demand is usually common in MCS due to the large population of the crowd. In Section 6 we will see, nearly optimal social welfare can be achieved without requiring too much workload supply.

Theorem 7. *TDMC is truthful, individual rational, budget balanced, computational tractable, and asymptotic efficient as the workload supply compared with demand becomes more amd more sufficient.*[3]

5. Practical issues

In this section, we further consider several practical issues to make TDMC adaptable in more general cases, including two more flexible bid profiles for both requesters and users, and two adjustment methods to control the sensing quality. Notably, all properties proved in Section 4.2 are still preserved. Besides, we also discuss the privacy and collusion issues briefly.

5.1. Flexible bid profiles

More flexible bid methods can better satisfy participators and promote more potential transactions. Here we provide two more flexible bid profiles for requesters and users respectively.

5.1.1. Discounted bid profiles for requesters

In previous discussions, we assumed the utility functions of requesters are single-minded, which makes requesters either win the whole campaigns or lose and get nothing. However, a requester may still want to accept a win with parts of required sensing tasks at a *discounted* price as well. Thus, we allow requesters to win a partial campaign even if $x_i < 1$. Requester i now bids a new profile ($\boldsymbol{d}_i$, v_i, $\boldsymbol{\alpha}_i^L$). $\boldsymbol{\alpha}_i^L$ is a discount vector where $1 = \alpha_i^1 > \alpha_i^2 > \cdots > \alpha_i^L > 0$, representing that requester i will accept a win with partial demand of $\alpha_i^l\boldsymbol{d}_i$ if the payment is lower than $\alpha_i^l v_i$. Assume that $\alpha_i^l\boldsymbol{d}_i$ is discrete. We also regard that requester i always prefers a higher α_i^l as long as the payment does not exceed corresponding reserved price $\alpha_i^l v_i$, which is rational when requesters are demand oriented and want to complete their campaigns as much as possible.

The mechanism still takes the two-stage allocation approach. The only difference is to generate a new survived requester set $\mathcal{M}^{s'}$ like this: after determining the stage-one allocation ($\boldsymbol{x}'$, $\boldsymbol{w}'$) as usual, for any requester i, choose the highest $\alpha_i^{l_*}$ that satisfies $\alpha_i^{l_*} \le x_i'$, and set requester i into $\mathcal{M}^{s'}$ with a bid profile ($\alpha_i^{l_*}\boldsymbol{d}_i$, $\alpha_i^{l_*}v_i$). If no such an $\alpha_i^{l_*}$ exists, requester i will loss. Typically, if $x_i' = 1$, $\alpha_i^{l_*} = 1$. We now prove that all requesters in the new survived requester set $\mathcal{M}^{s'}$ will win in stage two. Assume that there is a virtual mapping two-stage allocation approach, for any requester i in $\mathcal{M}^{s'}$, we replace his bid profile ($\boldsymbol{d}_i$, v_i, $\boldsymbol{\alpha}_i^L$) with ($\alpha_i^{l_*}\boldsymbol{d}_i$, $\alpha_i^{l_*}v_i$), it must have $x_i' = 1$ in stage one according to the definition of $\alpha_i^{l_*}$, so requester i will win in stage two by Lemma 1. Notice that the survived requester set in the mapping situation is just the same with $\mathcal{M}^{s'}$, so requester i will also win in stage two in current situation with a demand of $\alpha_i^{l_*}\boldsymbol{d}_i$, i.e., $x_i = \alpha_i^{l_*}$.

For any discount α_i^l, we redefine the critical price as $b_i^c(\alpha_i^l) = \inf\{\alpha_i^l v_i | x_i' \ge \alpha_i^l\}$, and let requester i who wins pay a payment of $b_i^c(\alpha_i^{l_*})$. Before proving the truthfulness for requesters, first we show that $\frac{b_i^c(\alpha_i^1)}{\alpha_i^1} > \frac{b_i^c(\alpha_i^2)}{\alpha_i^2} >, \ldots, > \frac{b_i^c(\alpha_i^L)}{\alpha_i^L}$. For requester i, assume that $v_i = \frac{b_i^c(\alpha_i^l)}{\alpha_i^l}$, then we have $x_i' \ge \alpha_i^l > \alpha_i^{l+1}$. It must have $\frac{b_i^c(\alpha_i^l)}{\alpha_i^l} > \frac{b_i^c(\alpha_i^{l+1})}{\alpha_i^{l+1}}$ by the definition of $b_i^c(\alpha_i^{l+1})$. This holds for all l, so we can deduce $\frac{b_i^c(\alpha_i^1)}{\alpha_i^1} > \frac{b_i^c(\alpha_i^2)}{\alpha_i^2} >, \ldots, > \frac{b_i^c(\alpha_i^L)}{\alpha_i^L}$. For requester i, if $\overline{v}_i > b_i^c(\alpha_i^1)$, he will prefer to win the whole campaign with demand of $\boldsymbol{d}_i$. If $\frac{b_i^c(\alpha_i^l)}{\alpha_i^l} > \overline{v}_i \ge \frac{b_i^c(\alpha_i^{l+1})}{\alpha_i^{l+1}}$ where $l \in \{1, 2, \ldots, L-1\}$, he will prefer to win a partial campaign with demand of $\alpha_i^{l+1}\boldsymbol{d}_i$. If $\overline{v}_i < \frac{b_i^c(\alpha_i^L)}{\alpha_i^L}$, he will prefer to loss. All these preferences can be followed by bidding the truthful valuation $\overline{v}_i$. Thus, truthfulness and individual rationality are preserved for requesters. For requester i who wins, the payment $p_i = b_i^c(\alpha_i^{l_*}) \ge \sum_{t\in\mathcal{T}} C^t(\sum_{k\in\mathcal{M}^{s'}} \alpha_k^{l_*}d_{kt} + m_t^v)d_{it}$. Similar to Theorem 4, budget balance can be guaranteed. Other properties obviously hold and we omit the proofs.

5.1.2. Tiered bid profiles for users

Based on the maximum available bid profile, we further allow users to report tiered costs for different units of workload. We take pattern t as an example. Formally, for any pattern t, user j can bid profile ($\boldsymbol{m}_{jt}^E$, $\boldsymbol{c}_{jt}^E$) instead of (m_{jt}, c_{jt}). $\boldsymbol{c}_{jt}^E$ is a tiered cost vector, where $c_{jt}^1 < c_{jt}^2 <, \ldots, < c_{jt}^E$. It means his reported unit cost for the first m_{jt}^1 units of workload is c_{jt}^1, next m_{jt}^2 units is c_{jt}^2..., the last m_{jt}^E units is c_{jt}^E, which reflects that the marginal cost of users is increasing as the workload grows.

In this case, we modify the demand vector of VPR by letting $m_t^v = max_{j\in\mathcal{N}}\{\sum_{e=1}^{E} m_{jt}^e\}$ for any pattern t. When taking the two-stage allocation approach, ($\boldsymbol{m}_{jt}^E$, $\boldsymbol{c}_{jt}^E$) can be regarded as E individual bids each with a tiered cost. We sort the offered workload of all users according to their reported tiered costs from low to high, and still define the cost of rth cheapest unit of workload for pattern t as $C^t[r]$. The outcome of user j is ($\boldsymbol{w}_{jt}^E$, $\boldsymbol{r}_{jt}^E$). As c_{jt}^e increases with tier e, in the two-state allocation approach, w_{jt}^e must be fully allocated before w_{jt}^{e+1} is allocated. The reward r_j of user j is defined the same as Eq. (8). According to

[3] In fact, we can further prove, Theorem 7 holds if and only if $m_t^v > \max_{j\in\mathcal{N}}\{m_{jt}\} - 1$, $\forall t \in \mathcal{T}$. Details are omitted here. But larger VPRs may lead to more losses of efficiency, which are not needed.

Lemma 3, r_{jt} can be calculated as:

$$r_{jt} = \sum_{e=1}^{E} r_{jt}^{e} = \sum_{e=1}^{E} \sum_{r=1}^{w_{jt}^{e}} C_{-j}^{t}[H_t - r + 1].$$

The true unit cost of user j for pattern t now becomes a function as $\overline{C}_j^t[r]$, which means his true cost for rth unit of workload for pattern t is $\overline{C}_j^t[r]$, $\overline{m}_{jt}$ is still the maximum available workload. If $\overline{C}_j^t[1] > C_{-j}^t[H_t]$, user j prefers not to win any units of workload for pattern t. If $\overline{C}_j^t[\overline{m}_{jt}] < C_{-j}^t[H_t - \overline{m}_{jt} + 1]$, user j prefers to win all available workload for pattern t. If $C_{-j}^t[H_t - h] < \overline{C}_j^t[h+1]$ and $\overline{C}_j^t[h] < C_{-j}^t[H_t - h + 1]$, where $h \in \{1, 2, \ldots, \overline{m}_{jt} - 1\}$, user j prefers to win h units of workload for pattern j. All these preferences can be followed by bidding truthful cost function $\overline{C}_j^t[r]$ and maximum available workload $\overline{m}_{jt}$. Truthfulness and individual rationality are preserved for users. Similar to Theorem 4, budget balance is guaranteed. Other properties obviously hold.

Remark. These two methods still focus on the two-stage allocation approach based on TDMC by solving two LP problems, which is the key to keep computational tractable. More general bid profiles for requesters and users are left for future work.

5.2. Sensing quality control

The quality of sensing data is also critical for the success of mobile crowdsensing. We provide two quality control methods to prompt users to offer high quality data based on TDMC.

5.2.1. Price intervention

The intuition is to manually intervene the reported costs of users to let users with low sensing qualities become less competitive in the auction and vice versa. We define a quality factor $\beta_j \in (0, 1]$ to reflect the sensing quality of user j based on his previous performances, a higher β_j means a higher sensing quality. Take any pattern t as an example, when running the auction, we replace the reported cost c_{jt} of user j with $c'_{jt} = \frac{c_{jt}}{\beta_j}$, and the corresponding outcome are calculated as $(w_{jt}(\beta_j), r'_{jt})$. We let the final allocation of user j for pattern t just be $w_{jt}(\beta_j)$, but let the corresponding final reward be $\beta_j r'_{jt}$. So the utility of user j for pattern t is $U_{jt}^u(\beta_j) = \beta_j(r'_{jt} - c'_{jt})$. Notice that maximum $r'_{jt} - c'_{jt}$ can be achieved by bidding truthful (m_{jt}, c'_{jt}) in original TDMC according to Theorem 3, so maximum $\beta_j(r'_{jt} - c'_{jt})$ can also be achieved by bidding truthful (m_{jt}, c_{jt}) here. In this way, truthfulness and individual rationality are preserved for users. Budget balance has be satisfied even if the reward is r'_{jt}, so it is also satisfied with a less reward of $\beta_j r'_{jt}$. Other properties obviously hold.

This method is similar with the reputation score proposed in [27], but here we further show that a higher quality factor β_j must lead to a higher utility $U_{jt}^u(\beta_j)$. As $r'_{jt} = \sum_{r=1}^{w_{jt}(\beta_j)} C_{-j}^t[H_t(\beta_j) - r + 1]$, $U_{jt}^u(\beta_j)$ can also be expressed as:

$$U_{jt}^u(\beta_j) = \sum_{r=1}^{w_{jt}(\beta_j)} \beta_j \left(C_{-j}^t[H_t(\beta_j) - r + 1] - \frac{\overline{c}_{jt}}{\beta_j} \right),$$

where $H_t(\beta_j)$ is total traded workload of pattern t. When β_j increases, c'_{jt} will reduce, thus $w_{jt}(\beta_j)$ would not reduce as the price is more competitive. Accordingly, $H_t(\beta_j)$ also would not reduce given other inputs unchanged. We also have $C_{-j}^t[H_t(\beta_j) - r + 1] \geq \frac{\overline{c}_{jt}}{\beta_j}$, for all $r \in \{1, 2, \ldots, w_{jt}(\beta_j)\}$, so $U_{jt}^u(\beta_j)$ must increase. In this way, users have the motivation to improve their sensing quality to achieve higher utilities.

5.2.2. Workload quota

A more direct way to control sensing quality is to restrict the maximum available workload of users with low sensing qualities. Take any pattern t as an example. We define the workload quota of user j for pattern t as $\gamma_j M_t$, where M_t is a global workload threshold for pattern t, which can be appropriately determined according to historical information of m_t^v. Another quality factor $\gamma_j \in [0, 1]$ also reflects the sensing quality of users, a higher γ_j means a higher quality. Then, the maximum available workload of user j for pattern t becomes $m_{jt}(\gamma_j) = max\{m_{jt}, \lfloor \gamma_j M_t \rfloor\}$. Truthfulness is preserved as M_t is independent with m_{jt}. Other properties obviously hold.

Similarly, the utility of user j for pattern t is:

$$U_{jt}^u(\gamma_j) = \sum_{r=1}^{w_{jt}(\gamma_j)} (C_{-j}^t[H_t(\gamma_j) - r + 1] - \overline{c}_{jt}),$$

When γ_j is lower, $w_{jt}(\gamma_j)$ and $H_t(\gamma_j)$ would not be higher, $U_{jt}^u(\gamma_j)$ would not be higher either. So users also have the motivation to improve the sensing quality for a higher utility.

Remark. These two methods can be used together to obtain a more powerful quality control ability.

5.3. Discussions about privacy and collusion

5.3.1. Privacy issues

Mobile users in the MCS market may suffer privacy threats: reporting the pattern-tagged data with location and time information may leak their home and workplace locations, whereabouts, habits, lifestyles, or other private information to the requesters and the third-party platform, which makes users reluctant to participate [28]. So we consider the solutions of user privacy preserving for TDMC. First, users should take the privacy preferences into account when determining their available bid profiles based on the sensing patterns in TDMC, by which users can either avoid choosing the task patterns implying sensitive information, such as those around their homes or workplaces, or bid higher prices to execute these tasks for the compensation of privacy disclosure. What is more, technical methods should be used to protect user privacy more actively. Many recently emerged techniques have made much progress on privacy preserving in MCS from different aspects, which can contribute to our model's solution. Further to say, if coarse-grained data is required for the MCS applications, some information obfuscation methods can be adopted to hide data's private information, including pseudonymity [29], anonymization [30], data aggregation [31], data perturbation [32], etc. Otherwise if fine-grained data is needed, a more direct solution is to use encryption methods. For example, [33] develops a cryptographic technique to encrypt the sensing data, which prevents the platform from eavesdropping and only target requesters have access to the contents. For more about privacy preserving techniques in MCS, we refer readers to [34,35]. Note that these techniques are orthogonal to the mechanism proposed in this paper and can be integrated with TDMC, we leave the details for future work.

5.3.2. Collusion issues

In above analyses, we assumed that users do not collude in the auction, but they may communicate in practice. Here we relax this assumption and discuss the impacts of user collusion on TDMC. As collusive users share individual private information, they can coordinate their bid strategies and deviate from truthfulness to achieve higher utilities, which may harm other legal players' utilities and the system's efficiency [36]. But we claim that the very characteristics existing in TDMC can significantly counteract these effects. In fact, in the MCS market, the workload supply of any single user is usually much smaller compared with that of the total crowd, which means no user has an independent power to influence the market greatly.

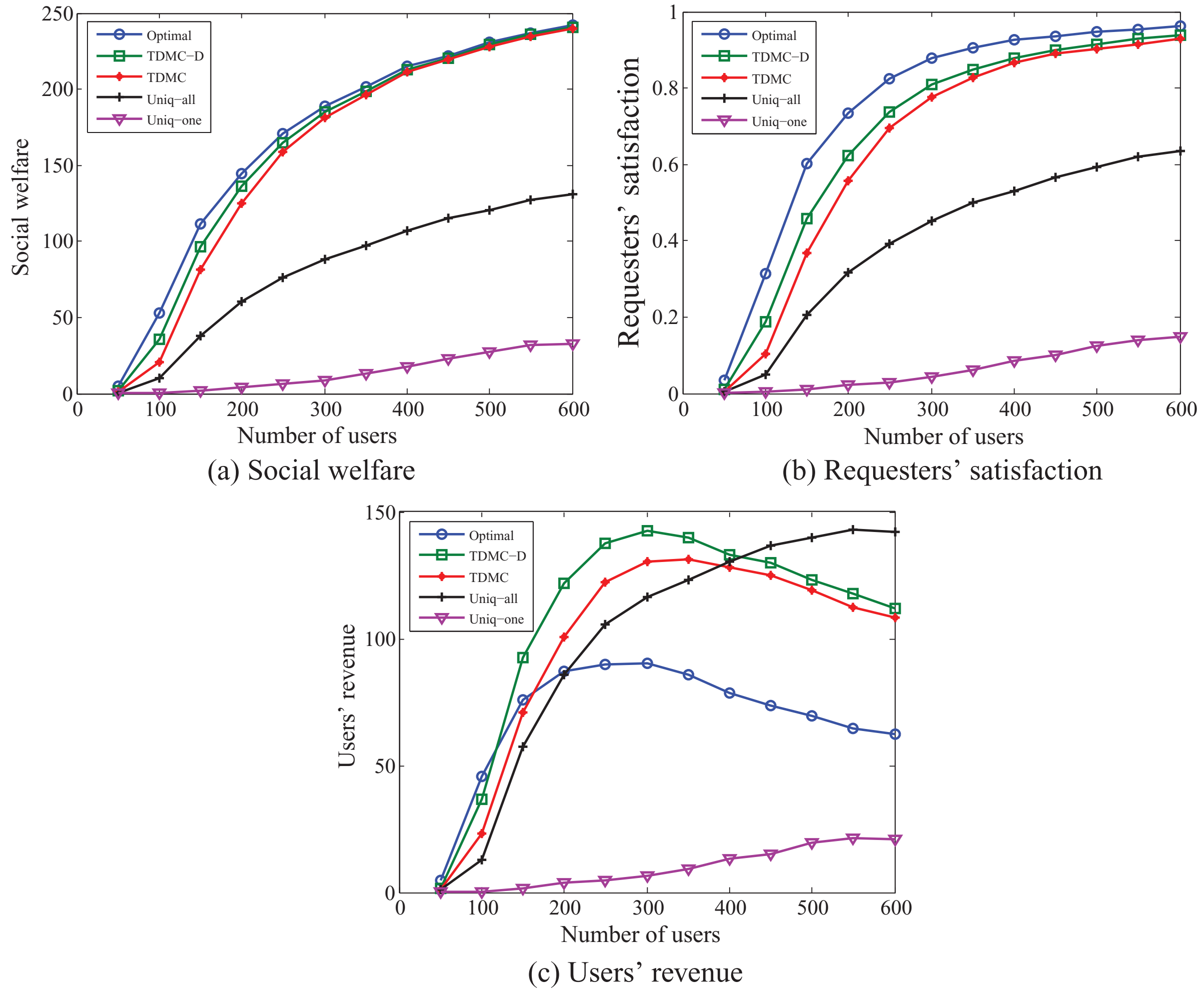


Fig. 2. Social welfare, requesters' satisfaction and users' revenue vs. the number of users N ($M = 10$).

When only small-scale collusion occurs in TDMC, the collusive users still cannot affect the workload supply and bid prices of the majority of the crowd, so the influence on the outcome of TDMC is limited. On the other hand, if large-scale collusion happens, the impacts indeed can be considerable. In an extreme case, all relevant users collude together to form a powerful cartel, and they can effectively improve their profits by intentionally raising bid prices meanwhile reducing the whole supply, which may lead to large losses of requesters' utilities and the social welfare [37]. But actually forming large-scale collusion is difficult in TDMC. As it will take high costs for users to maintain cooperation and coordinate strategies, faced with the facts of strong liquidity, loose organization and trust shortage of the crowd in the MCS market, without saying the challenges of preventing betrayals and dividing spoils. Of course, more operations such as communication restriction, severe detection and punishment can be added to further suppress collusion in TDMC, we do not elaborate here for the limit of paper's space.

6. Simulation results

In this section, we conduct extensive simulations to evaluate the performance of TDMC. All simulations are run on MATLAB. We first implement TDMC and its extended form named TDMC-D which considers the discounted bid profiles for requests. For comparison, we introduce two mechanisms denoted by Uniq-one and Uniq-all, which means they only allow each user to bid a unique cost for all tasks. In Uniq-one, users only bid for maximum available workload of a single pattern by reporting corresponding cost. In Uniq-all, users bid for maximum available workload of all available patterns, but the reported cost is the highest cost of all these patterns in order to ensure individual rationality. We also implement the optimal solution in the complete information scenario, i.e. the optimal solution $(\boldsymbol{x}^*, \boldsymbol{w}^*)$ of the social welfare optimization problem $\mathcal{P}(\mathcal{M}, \mathcal{N})$ as a benchmark, which is denoted by Optimal. Three metrics are examined: social welfare, requesters' satisfaction and users' revenue. Requesters' satisfaction is a ratio of the total valuation of winning requesters to the total valuation of all requesters, which is defined as $\sum_{i\in\mathcal{M}} v_i x_i / \sum_{i\in\mathcal{M}} v_i$. Users' revenue is the sum of rewards all users acquire. We calculate it as the total true cost of traded workload in Optimal. Then, we further consider different degrees of competition on both sides of the market in TDMC to investigate their impacts on requesters and users. Two metrics of requesters' satisfaction and users' revenue *per workload* are evaluated. The latter is a ratio of users' revenue to the total traded workload, which reflects the average price of unit workload offered in the market. Finally, we verify the effectiveness of the two quality control methods of price intervention and workload quota based on TDMC.

6.1. Simulation setup

In simulations, the default settings are as follows. The number of requesters M is 10, the number of users N is 300, the number of sensing patterns T is 20. For any requester i, the required patterns are randomly chosen among $\mathcal{T}$ with an average number of 4, and the

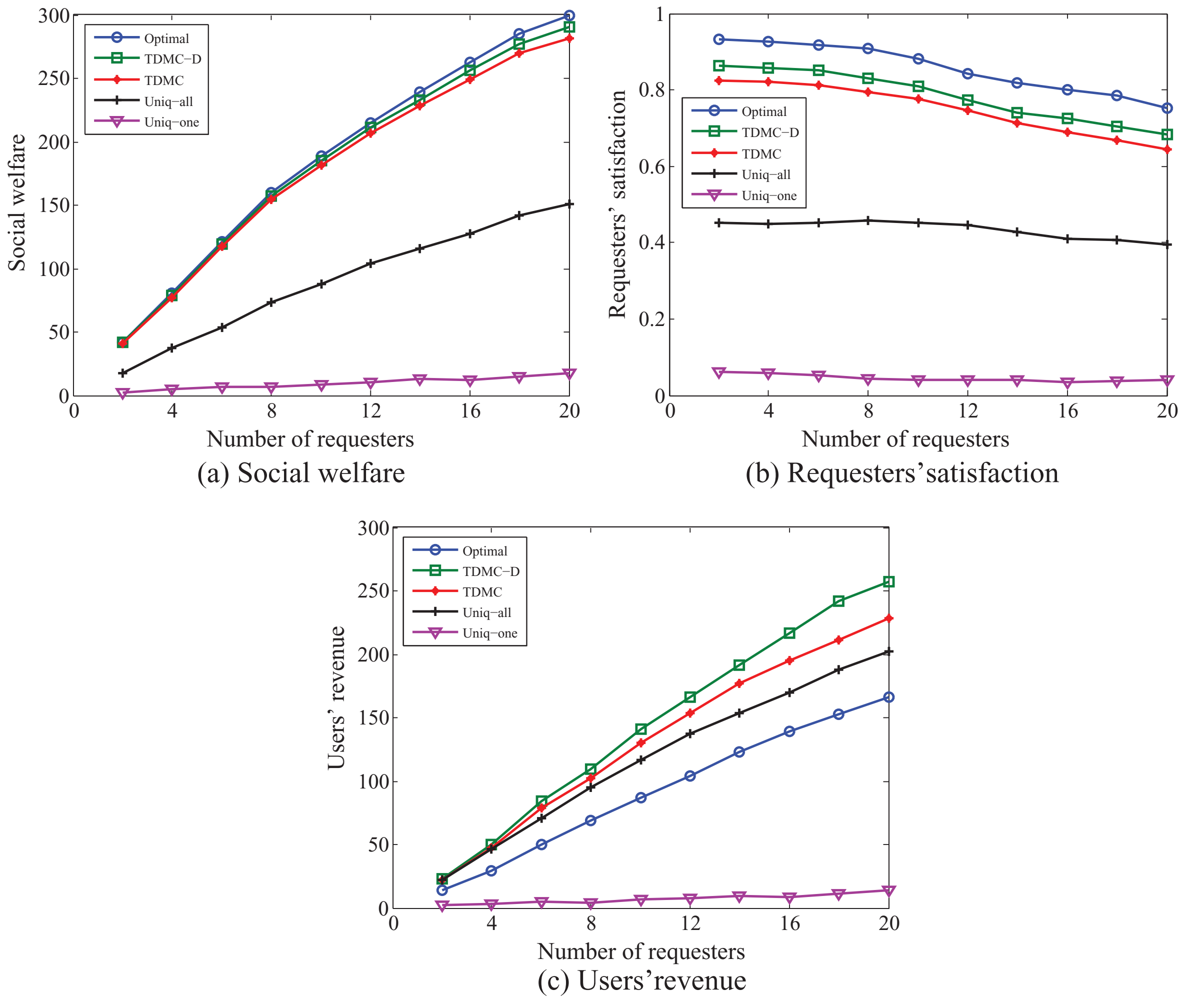


Fig. 3. Social welfare, requesters' satisfaction and users' revenue vs. the number of requesters M ($N = 300$).

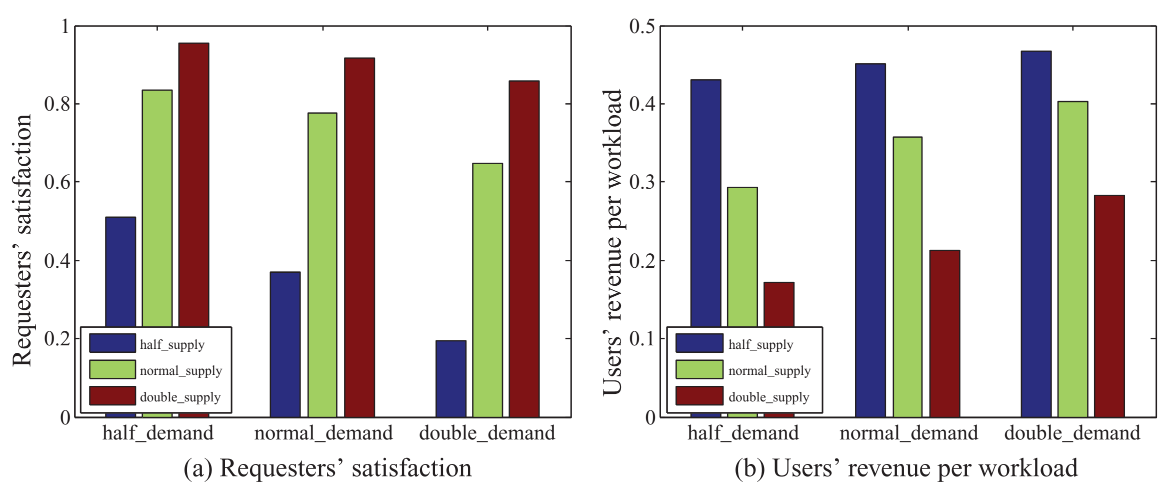
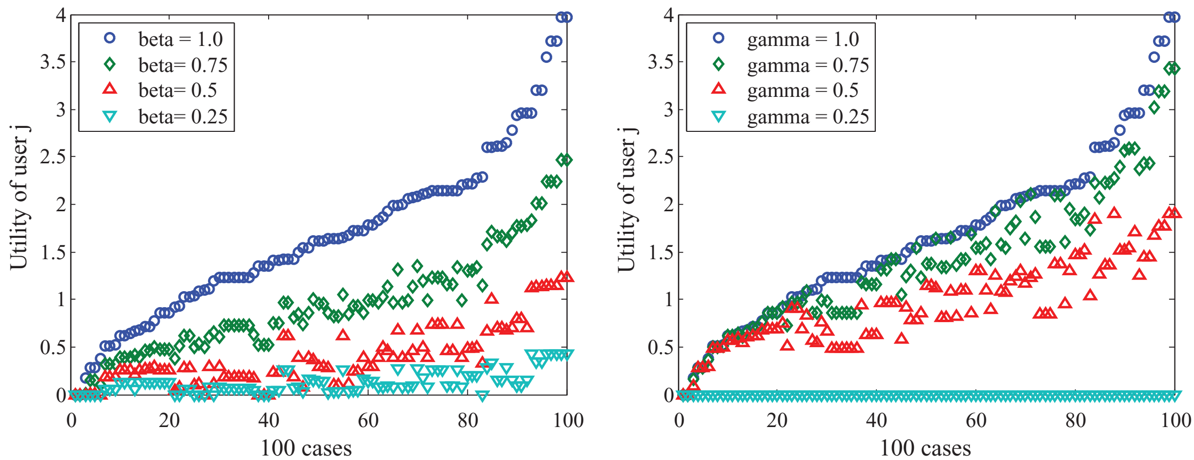


Fig. 4. Requesters' satisfaction and users' revenue per workload with various demand/supply ($M = 10$, $N = 300$).

required workload of any required pattern is equally distributed between 1 and 30. For any user j, the available patterns are randomly chosen among $\mathcal{T}$ with an average number of 3, and the maximum available workload of any available pattern is equality distributed between 1 and 3. We assume the cost c_{jt} of any user j for any pattern t is uniformly distributed in (0, 1). Accordingly, the valuation of any requester i is uniformly distributed in $(0, \sum_{t\in\mathcal{T}} d_{it})$, where $\sum_{t\in\mathcal{T}} d_{it}$ is his total required workload. In TDMC-D, we set α_i^L of any requester i as {1, 0.8}. For workload quota, we set M_t of any pattern t as 3.

We first evaluate social welfare, requesters' satisfaction and users' revenue of TDMC and TDMC-D compared with Optimal, Uniq-one and Uniq-all by varying the number of users from 50 to 600 and varying the number of requesters from 2 to 20, respectively. All results are averaged over 1000 times. Then we enable various degrees of competition on both sides of the market in TDMC to evaluate



(a) Utility of user j with various β_j (b) Utility of user j with various γ_j

Fig. 5. 100 cases of profit of user *j* with various quality factors ($M = 10, N = 300$).

requesters' satisfaction and users' revenue per workload by applying different workload demand and supply respectively. We consider the settings of half, normal and double demand (supply), which successively achieve higher degree of competition on the requester (user) side. Further to say, given $M = 10$ and $N = 300$, the normal demand (supply) is set for requesters (users) by having default bids, the half-demand (supply) is set for requesters (users) by cutting all their default average number of required patterns (available patterns) in half, and double demand (supply) is set for requesters (users) by expanding all their default average number of required patterns (available patterns) to two times. The results are also averaged by 1000 times. Finally we focus on a certain user *j* to evaluate his utility given various values of quality factor β_j and γ_j. 100 random-sampled cases with different bid profiles of requesters and users are displayed.

6.2. Performance analysis

Fig. 2 (a) and (b) shows that the social welfare and requesters' satisfaction of both TDMC-D and TDMC always outperform Uniq-all and Uniq-one, and are only a little worse than Optimal. TDMC-D is better than TDMC as more flexible bid profiles make more requesters win. Uniq-one performs the worst due to the offered workload is strongly restricted while Uniq-all does not work well as higher reported costs reduce the trading volume, both of which indicate that bidding a unique cost for all tasks is unsuitable in a heterogeneous MCS environment. As the number of users increases, social welfare increases for all mechanisms, since more workload is available and resources can be allocated more effectively. Requesters' satisfaction also increases, as more requesters win while the number of requesters is fixed. Specially, the social welfare of TDMC-D and TDMC closes to Optimal as *N* increases, and almost equals to Optimal when *N* exceeds 400, which verifies our theoretical analysis that TDMC can asymptotically approach efficiency as the workload supply compared with demand becomes more and more sufficient. As shown in Fig. 2(c), the users' revenue first increases as the traded workload increases, then reduces because users with lower reported costs attend and are allocated. Besides, higher reported costs drive up the revenue of Uniq-all. Thus, TDMC-D and TDMC first acquire higher revenue and then are catched up by Uniq-all. The Optimal is lower as the rewards are the true costs of workload.

From Fig. 3(a) and (b), again we can see, TDMC-D and TDMC always outperform Uniq-all and Uniq-one by social welfare and users' satisfaction, while only having a small gap compared with Optimal. The reason is the same as we elaborated above. As the number of requesters increases, the social welfare increases since more transactions are completed in the market. The requesters' satisfaction reduces since more requesters make the competition more intense and only more competitive requesters can win. At the same time, the social welfare of TDMC-D and TDMC slightly deviates from Optimal as the workload supply of users becomes relatively tighter. In Fig. 3(c), the users' revenue increases along with the number of requesters, since the total traded workload increases. Although the reported costs of workload are higher, the revenue of Uniq-all and Uniq-one is still less than the revenue of TDMC-D and TDMC, as the trading volume of the formers is lower.

Fig. 4 (a) shows that requesters' satisfaction decreases with the expansion of workload demand, while increases with the expansion of workload supply, which indicates that requesters are harder to win when competition becomes more intense on their own side, but are easier to win benefiting from a more intense competition on the user side. The results in Fig. 4(b) show that users' revenue per workload increases as the workload demand increases, while decreases as the workload supply increases, which indicates that the workload offered by users is averagely priced higher when the degree of competition is higher for requesters, but is averagely priced lower when the degree of competition is higher for users. Thus we can find that in TDMC competition on one side is unfavorable for players on this side whereas is favorable for players on the other side, which is rational for a two-sided market.

Fig. 5 (a) and (b) depicts the impact of various quality factor β_j and γ_j on the utility of an arbitrary user *j*. To show the results more clearly, we rearrange the 100 random-sampled cases according to user *j*'s utility in an ascending way. We can find out that in all cases a higher β_j or γ_j must lead to a higher utility, which confirms that both price intervention and workload quota can prompt users to offer higher quality sensing data, i.e., the two quality control methods are effective.

7. Conclusion

In this paper, we propose a truthful double auction TDMC for two-sided heterogeneous mobile crowdsensing markets. TDMC develops a two-stage allocation approach and corresponding pricing schemes for both requesters and users. We prove that TDMC is truthful, individual rational, budget balanced, computational tractable, and asymptotic efficient as the workload supply compared with demand becomes more and more sufficient. Several practical issues are

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also considered to make TDMC more adaptable. Extensive simulations demonstrate the effectiveness of TDMC.

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References

[1] R.K. Ganti, F. Ye, H. Lei, Mobile crowdsensing: current state and future challenges, IEEE Commun. Mag. 49 (11) (2011) 32–39. http://dx.doi.org/10.1109/MCOM.2011.6069707.
[2] A. Thiagarajan, L. Ravindranath, K. LaCurts, S. Madden, H. Balakrishnan, S. Toledo, J. Eriksson, Vtrack: accurate, energy-aware road traffic delay estimation using mobile phones, in: Proceedings of the 7th ACM Conference on Embedded Networked Sensor Systems (SenSys), 2009, pp. 85–98. http://dx.doi.org/10.1145/1644038.1644048.
[3] P. Dutta, P.M. Aoki, N. Kumar, A. Mainwaring, C. Myers, W. Willett, A. Woodruff, Common sense: participatory urban sensing using a network of handheld air quality monitors, in: Proceedings of the 7th ACM Conference on Embedded Networked Sensor Systems (SenSys), 2009, pp. 349–350. http://dx.doi.org/10.1145/1644038.1644095.
[4] Y.F. Dong, S. Kanhere, C.T. Chou, N. Bulusu, Automatic collection of fuel prices from a network of mobile cameras, in: Proceedings of the 4th IEEE International Conference on Distributed Computing in Sensor Systems (DCOSS), 2008, pp. 140–156.
[5] M. Ra, B. Liu, T.L. Portay, R. Govindan, Medusa: a programming framework for crowd-sensing applications, in: Proceedings of the 10th ACM International Conference on Mobile Systems, Applications, and Services (MobiSys), 2012, pp. 337–350. http://dx.doi.org/10.1145/2307636.2307668.
[6] F.-J. Wu, T. Luo, A generic participatory sensing framework for multi-modal datasets, in: Proceedings of the 9th IEEE International Conference on Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP), 2014, pp. 1–6. http://dx.doi.org/10.1109/ISSNIP.2014.6827702.
[7] I. Koutsopoulos, Optimal incentive-driven design of participatory sensing systems, in: Proceedings of the 32th IEEE International Conference on Computer Communications (INFOCOM), 2013, pp. 1402–1410. http://dx.doi.org/10.1109/INFCOM.2013.6566934.
[8] D. Yang, G. Xue, X. Fang, J. Tang, Crowdsourcing to smartphones: incentive mechanism design for mobile phone sensing, in: Proceedings of the 18th ACM Annual International Conference on Mobile Computing and Networking (MobiCom), 2012, pp. 173–184. http://dx.doi.org/10.1145/2348543.2348567.
[9] L. Duan, T. Kubo, K. Sugiyama, J. Huang, T. Hasegawa, J. Walrand, Incentive mechanisms for smartphone collaboration in data acquisition and distributed computing, in: Proceedings of the 31th IEEE International Conference on Computer Communications (INFOCOM), 2012, pp. 1701–1709. http://dx.doi.org/10.1109/INFCOM.2012.6195541.
[10] T. Luo, H.-P. Tan, L. Xia, Profit-maximizing incentive for participatory sensing, in: Proceedings of the 33th IEEE International Conference on Computer Communications (INFOCOM), 2014, pp. 127–135. http://dx.doi.org/10.1109/INFOCOM.2014.6847932.
[11] T. Luo, S.S. Kanhere, H.-P. Tan, F. Wu, H. Wu, Crowdsourcing with tullock contests: a new perspective, in: Proceedings of the 34th IEEE International Conference on Computer Communications (INFOCOM), 2015, pp. 2515–2523.
[12] D. Zhao, X. Li, H. Ma, How to crowdsource tasks truthfully without sacrificing utility: online incentive mechanisms with budget constraint, in: Proceedings of the 33th IEEE International Conference on Computer Communications (INFOCOM), 2014, pp. 1213–1221. http://dx.doi.org/10.1109/INFOCOM.2014.6848053.
[13] Z. Feng, Y. Zhu, Q. Zhang, L.M. Ni, A.V. Vasilakos, Trac: truthful auction for location-aware collaborative sensing in mobile crowdsourcing, in: Proceedings of the 33th IEEE International Conference on Computer Communications (INFOCOM), 2014, pp. 1231–1239. http://dx.doi.org/10.1109/INFOCOM.2014.6848055.
[14] Z. Feng, Y. Zhu, Q. Zhang, H. Zhu, J. Yu, J. Cao, L.M. Ni, Towards truthful mechanisms for mobile crowdsourcing with dynamic smartphones, in: Proceedings of the 34th IEEE International Conference on Distributed Computing Systems (ICDCS), 2014, pp. 11–20. http://dx.doi.org/10.1109/ICDCS.2014.10.
[15] S. He, D.-H. Shin, J. Zhang, J. Chen, Toward optimal allocation of location dependent tasks in crowdsensing, in: Proceedings of the 33th IEEE International Conference on Computer Communications (INFOCOM), 2014, pp. 745–753. http://dx.doi.org/10.1109/INFOCOM.2014.6848001.
[16] J. Sun, H. Ma, Heterogeneous-belief based incentive schemes for crowd sensing in mobile social networks, J. Netw. Comput. Appl. 42 (2014) 189–196. http://dx.doi.org/10.1016/j.jnca.2014.03.004.
[17] M.H. Cheung, R. Southwell, F. Hou, J. Huang, Distributed time-sensitive task selection in mobile crowdsensing, in: Proceedings of the 16th ACM International Symposium on Mobile Ad Hoc Networking and Computing (MobiHoc), 2015, pp. 157–166. http://dx.doi.org/10.1145/2746285.2746293.
[18] H. Jin, L. Su, D. Chen, K. Nahrstedt, J. Xu, Quality of information aware incentive mechanisms for mobile crowd sensing systems, in: Proceedings of the 16th ACM International Symposium on Mobile Ad Hoc Networking and Computing (MobiHoc), 2015, pp. 167–176. http://dx.doi.org/10.1145/2746285.2746310.
[19] Y. Sun, Y. Zhu, Z. Feng, J. Yu, Sensing processes participation game of smartphones in participatory sensing systems, in: Proceedings of the 11th IEEE International Conference on Sensing, Communication, and Networking (SECON), 2014, pp. 239–247. http://dx.doi.org/10.1109/SAHCN.2014.6990359.
[20] R. McAfee, A dominant strategy double auction, J. Econ. Theory 56 (2) (1992) 434–450.
[21] P. Huang, A. Scheller-Wolf, K. Sycara, Design of a multi-unit double auction e-market, Comput. Intell. 18 (4) (2002) 596–617. http://dx.doi.org/10.1111/1467-8640.t01-1-00206.
[22] N. Nisan, T. Roughgarden, E. Tardos, V.V. Vazirani, Algorithmic game theory, Cambridge University Press, 2007.
[23] M. Babaioff, W.E. Walsh, Incentive-compatible, budget-balanced, yet highly efficient auctions for supply chain formation, in: Proceedings of the 4th ACM Conference on Electronic Commerce (EC), 2003, pp. 64–75. http://dx.doi.org/10.1145/779928.779937.
[24] L. Chu, Z. Shen, Truthful double auction mechanisms, Oper. Res. 56 (1) (2008) 102–120.
[25] L. Chu, Truthful bundle/multiunit double auctions, Manag. Sci. 55 (7) (2009) 1184–1198.
[26] R.M. Karp, Reducibility among combinatorial problems, in: Proceedings of a Symposium on the Complexity of Computer Computations, 1972, pp. 85–103.
[27] W. Dong, S. Rallapalli, L. Qiu, K.K. Ramakrishnan, Y. zhang, Double auctions for dynamic spectrum allocation, in: Proceedings of the 33th IEEE International Conference on Computer Communications (INFOCOM), 2014, pp. 709–717. http://dx.doi.org/10.1109/INFOCOM.2014.6847997.
[28] K. Shilton, Four billion little brothers?: Privacy, mobile phones, and ubiquitous data collection, Commun. ACM 52 (11) (2009) 48–53. http://dx.doi.org/10.1145/1592761.1592778.
[29] D. Christin, C. Rosskopf, M. Hollick, L.A. Martucci, S.S. Kanhere, Incognisense: an anonymity-preserving reputation framework for participatory sensing applications, in: Proceedings of the 10th IEEE International Conference on Pervasive Computing and Communications (PerCom), 2012, pp. 135–143. http://dx.doi.org/10.1109/PerCom.2012.6199860.
[30] K.L. Huang, S.S. Kanhere, W. Hu, Preserving privacy in participatory sensing systems, Comput. Commun. 33 (11) (2010) 1266–1280. http://dx.doi.org/10.1016/j.comcom.2009.08.012.
[31] Q. Li, G. Cao, Efficient and privacy-preserving data aggregation in mobile sensing, in: Proceedings of the 20th IEEE International Conference on Network Protocols (ICNP), 2012, pp. 1–10. http://dx.doi.org/10.1109/ICNP.2012.6459985.
[32] F. Zhang, L. He, W. He, X. Liu, Data perturbation with state-dependent noise for participatory sensing, in: Proceedings of the 31th IEEE International Conference on Computer Communications (INFOCOM), 2012, pp. 2246–2254. http://dx.doi.org/10.1109/INFCOM.2012.6195610.
[33] E.D. Cristofaro, C. Soriente, Participatory privacy: enabling privacy in participatory sensing, Network 27 (1) (2013) 32–36. http://dx.doi.org/10.1109/MNET.2013.6423189.
[34] D. Christin, A. Reinhardt, S.S. Kanhere, M. Hollick, A survey on privacy in mobile participatory sensing applications, J. Syst. Softw. 84 (11) (2011) 1928–1946. http://dx.doi.org/10.1016/j.jss.2011.06.073.
[35] D. Christin, Privacy in mobile participatory sensing: current trends and future challenges, J. Syst. Softw. (2015). http://dx.doi.org/10.1016/j.jss.2015.03.067.
[36] M.S. Robinson, Collusion and the choice of auction, RAND J. Econ. 16 (1) (1985) 141–145.
[37] P. Milgrom, Putting Auction Theory to Work, Cambridge University Press, 2004.