Multi-Stage Optimization of Incentive Mechanisms for Mobile Crowd Sensing based on Top-Trading Cycles

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Abstract. For collaborative tasks requiring multiple users, in Mobile Crowd Sensing (MCS), low user interest in certain tasks usually results in insufficient user recruitment. However, the interest of the user directly affects the quality and efficiency of task completion. To address this issue, we propose a multi-stage incentive mechanism based on the Top-Trading Cycles (TTC) from economics, enabling users to participate in tasks that align with their interest through the optimization of multiple stages. Firstly, we perform an initial screening of users using a reverse auction. Then, we adopt the Top-Trading Cycles algorithm to determine the optimal task-user pairs. For tasks with insufficient collaborators, an interest-based task recommendation algorithm is proposed, which calculates user interest similarity in the social network, recommends tasks to other users, and evaluates rewards based on their contributions. The proposed incentive mechanism can theoretically guarantee computational effectiveness, truthfulness, and individual rationality in this paper. Simulation experiments show that the proposed mechanism outperforms traditional incentives in terms of user participation rates, task coverage, and average user utility.

Keywords: Mobile Crowd Sensing, Incentive Mechanisms, Top-Trading Cycles; Multi-Stage Optimization.

1 Introduction

With the rapid development of wireless networks, smartphones have become an indispensable necessity in people's lives. They integrate multiple sensors, such as magnetic sensors, gyroscopes, GPS location sensors, and fingerprint sensors [1], which enable them to perceive and analyze data from the surrounding environment and complete Mobile Crowd Sensing tasks. Currently, MCS has a wide range of applications in various fields, including environmental monitoring, disaster emergency search and rescue, and Smart Cities [2]. However, performing sensing tasks may incur significant costs for users, including data traffic, CPU computation, time consumption, battery usage, and potential privacy issues [3-4], which can lead to decreased user participation in sensing activities. Therefore, in order to encourage more users to participate in sensing activities and enhance their enthusiasm, it is necessary to design reasonable incentive mechanisms [5-6].

The existing incentive mechanisms can be broadly classified into two categories: monetary incentives and entertainment incentives. The former is the most direct and effective mean for motivation [7]. Reverse auction is the most widely adopted incentive method, although, it is an incomplete information mechanism [8]. For instance users can only submit bids based on their own costs, and the service platform make decisions on the optimal bid. Thus, users have only one chance to participate in a sensing task, which may reduce their willingness to participate. Furthermore, the user's sensing ability depends on various factors, such as the sensing device's capability and the user's interest in the task, and it is often impossible to recruit enough users to participate in collaborative tasks. Therefore, it is feasible to design incentive mechanisms by considering the interest of the users.

To address the aforementioned issues, we consider the similarity of user interest in social network scenarios [9]. Merely considering the similarity of users' interest is insufficient to solve the aforementioned issues. We introduce the concept of Top-Trading Cycles from economics [10] and propose to use the You Request My House-I Get Your Turn (YRMH-IGYT) mechanism for secondary transactions based on users' preference sequences, enabling them to acquire tasks of higher interest levels. For tasks with insufficient collaboration, we put forward a task recommendation algorithm based on interest similarity. With this multi-stage strategy, users have more opportunities to participate in tasks, ultimately resulting in a higher task coverage rate.

The primary contributions of this paper are as follows:

- We proposed two trading models and developed user selection criteria for each. Additionally, in order to address tasks with a shortage of users, we proposed a task recommendation model. This model recommends tasks to other users based on the similarity of their interest.
- We provide evidence that the proposed mechanism meets the expected characteristics of computational efficiency, veracity, and individual rationality. Furthermore, MO-TTC can output the optimal solution.

2 Related Works

Reverse auctions have been widely used in the incentive mechanisms of mobile crowdsensing, which are mainly designed to maximize social welfare with a platform-centered incentive mechanism. Under the uncertain task execution, Zheng et al. [11] designed a reverse auction model and considered the completion of tasks, minimizing the social cost of user recruitment. Gu et al. [12] proposed an information quality incentive mechanism for multimedia crowdsensing, maximizing social welfare by designing a reverse auction model. Ji et al. [13] designed an incentive mechanism based on reverse auctions, which minimizes costs and retains users who are about to exit through the lottery mechanism. Furthermore, Luo et al. [14] designed two capacity reputation systems to evaluate the online staff abilities and proposed an incentive mechanism based on reverse auctions and fine-grained capacity reputation. The reward is determined based on user bids and fine-grained capacity reputation. Jin et al. [15] introduced the Quality of Information indicator, designed an incentive mechanism based on reverse combination auctions, accomplishing the optimal social welfare while meeting individual rationality and computational efficiency. Although the incentive mechanism based on reverse auction minimizes costs and maximizes social welfare from the perspective of the platform, it ignores the characteristics of users, resulting in a decrease in data quality and user enthusiasm.

Li et al. [16] proposed an incentive mechanism for an interest tagging application program, which maximizes platform revenue through a three-stage decision process. Meanwhile, Xiong et al. [17] introduced a cosine similarity calculation protocol with privacy protection, which computes the similarity between task and user vectors and conducts a second selection of users to ensure fairness of user perception of being selected. In social networks, Xu et al. [18] considered the collaboration compatibility of users for multiple collaborative tasks and designed two incentive mechanisms based on reverse auction. Additionally, they presented a user grouping method based on neural network model and clustering algorithm to minimize social cost by introducing a neural network-based method for learning the similarity between users and clustering them accordingly. This approach helps avoid uneven task allocation and incomplete tasks that can result from varying user interest in tasks.

This paper proposes a Multi-Stage Optimization of Top-Trading Cycles (MO-TTC) incentive mechanism to address the issues of the existing incentive mechanism. We innovatively integrated the TTC into the incentive mechanism of MCS. TTC is a resource allocation algorithm that divides agents into non-overlapping sets or cycles, exchanging resources internally within each cycle, and ensuring that each agent acquires their preferred resources. The paper preliminarily screens users using a reverse auction model and performs a secondary selection of users based on their preference sequence submitted through the TTC algorithm. For tasks lacking collaboration, user interest similarities are calculated, and the tasks are assigned to users who may be intrigued by them. Finally, the reward is determined based on the degree of their contributions.

3 System Model

In this paper, all users in the MCS are considered to be part of a social network, and the platform serves as the auctioneer, and tasks are the auctioned items. Table 1 presents the primary symbols used in this paper.

The set of users is denoted as $U = \{u_1, u_2, \ldots, u_i, \ldots, u_n\}$. The corresponding user reputation values are expressed by $RP = \{rp_1, rp_2, \ldots, rp_i, \ldots, rp_n\}$. The perceptual task set is denoted as $T = \{t_1, t_2, \ldots, t_j, \ldots, t_m\}$. The task preference set of user u_i is F_{ui}. The number of users required for the task is referred to as the collaboration number and is expressed by the set $NUM = \{num_1, num_2, \ldots, num_j, \ldots, num_m\}$. n represents the number of users, while m represents the number of tasks.

The contribution of users to tasks in this paper is integrated into the incentive mechanism, with the Quality of Information (QoI) they provide used as a measure. The users' contributions are categorized into five levels in this paper and represented by the set Q = {1, 2, 3, 4, 5}.

Table 1. Notations used

Notations	Definitions
U	set of users
URW	set of winners in reverse auction
URL	set of users entering the second phase
$UTTC$	set of task-user in the second phase
UIQ	set of task owners with insufficient collaboration count
UIW	set of users finally participating in the task
T	set of tasks
TW	set of tasks with successfully bids
TL	set of tasks with failed bids
num_j	collaboration count required for task t_j
rp_i	reputation value of user u_i
$c_{i.j}$	true cost of user u_i for task t_j
$b_{i,j}$	bidding price made by user u_i for task t_j
$p_{i,j}$	reward for user u_i completing task t_j
$q_{i,j}$	contribution of user u_i to task t_j
r_j	maximum budget for task t_j in reverse auction

3.1 Design Objectives

For each task, denoted as $t_j \in T$, a limited budget is assigned to the incentive mechanism, which requires the selection of num_j users from the user set U to perform the task. If the number of collaborative users falls short, the task is recommended to other users in the social network based on their interest similarity, allowing them to decide whether to participate. To enhance the QoI of users, a credibility mechanism is implemented to update based on their contributions. The contribution values of users are linearly normalized, and defined in Equation (1).

$$rp_i = rp_i + \frac{q_{i,j} - \min(q_{tj})}{\max(q_{tj}) - \min(q_{tj})} \tag{1}$$

where $\min(q_{tj})$ represents the minimum contribution value required by the platform for task t_j, $\max(q_{tj})$ denotes the maximum contribution value needed for the same task by the platform.

The profit of user u_i is the difference between the compensation provided by the service platform and the user's self-costs, given as below:

$$e_i = p_i - c_i, u_i \in UIW \tag{2}$$

where $p_i = \sum_{j=1}^{m} p_{i.j}$ represents the total reward that user u_i receives for completing all the tasks, and $c_i = \sum_{j=1}^{m} c_{i.j}$ represents the total costs incurred by the user for participating in the tasks.

This paper aims to identify the optimal set of tasks and users from task set T using two transaction models. Additionally, we utilize information submitted by users through the reverse auction process to recruit other users to collaborate with those in the $UTTC$. For tasks that lack sufficient collaboration, an interest-based task recommendation algorithm is applied to suggest tasks to users who may be interested. Finally, user compensation and reputation values are updated based on their contribution.

3.2 Reverse Auction Model

During the first phase, the service platform releases tasks and each user, denoted as $u_i \in U$, sends a tuple $(\zeta_i, \ B_i)$ to the platform. ζ_i represents the task set that the user u_i is bidding on, and B_i represents the corresponding bid set. The platform selects the user with the lowest bid $b_{i,j}$, where $b_{i,j}$ is less than the maximum budget r_j, to be the task owner and added to the URW set. The tasks that have been successfully bid on are added to the TW set, as illustrated in Fig.1.

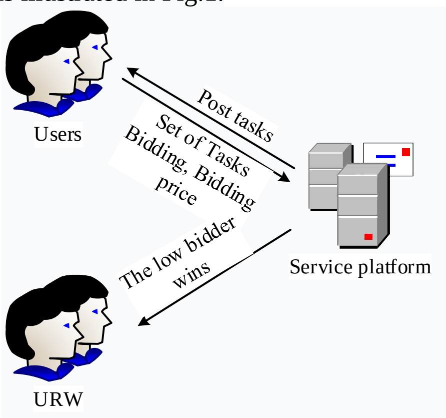


Fig. 1. Reverse auction

At this stage, the winning participant u_i in URW is tasked with undertaking task t_j in the second phase of the project. The unsuccessful bidders' tasks will also move to the second phase and are collectively represented as TL.

3.3 Secondary Trading Model based on TTC Algorithm

In the second phase, the platform sorts failed users in the reverse auction by their reputation values, denoted as rp_i. The platform then gathers a set of potential users, denoted as URL, by requesting their agreement to participate in the second phase based on their $(\zeta_i, \ B_i)$ values. Users in URL are not assigned any tasks, whereas tasks in $TL$are unclaimed. Users in URW and URL indicate their preferences for tasks to the platform, while tasks in $TW$and TLreveal their preferred users. The TTC algorithm is employed to construct the task-user set $UTTC$.

Before introducing the TTC algorithm, some concepts need to be introduced. In URW, users who are dissatisfied are labeled as unsatisfied users, while users who enter the third stage after their transactions are considered satisfied users. In TW, tasks are referred to as old tasks, while in URL, new users are added, and in TL, new tasks are added. This article utilizes graph theory to define the transactions between users and tasks in the YRMH-IGYT mechanism by constructing a TTC graph.

Definition 1(The construction rules of the graph): *In the TTC graph, the set of vertices consists of users and task sets; directed edges represent task vertices pointing to their owner users. If there is no owner for a task, the user set without a task is sorted based on credibility, and all tasks without owners are assigned to the user with the highest credibility. User vertices point to their most interesting task.*

The following steps constitute the second transaction phase based on the TTC:

Step 1: Assign old tasks to their respective owners while assigning new tasks to the user with the highest reputation. Each user is linked to the task of their maximum interest.

Step 2: In case of no cycle, the new user moves to the next task in their preference list.

Step 3: Identify any cycle and eliminate it by allocating tasks linked to each user within the cycle.

Step 4: Assign old tasks to their respective owners while assigning new tasks to the remaining new users with the highest reputation, and each user is linked to the task of their maximum interest among the remaining tasks.

Step 5: Identify any cycle that may arise in this phase and eliminate it by allocating tasks linked to each user within the cycle.

Step 6: Repeat steps 2 to 5 until all users and tasks have been assigned. The assignment process ends upon exhaustion.

3.4 Task Recommendation Model based on Interest Level

In the third phase of the project, secondary trades will match all tasks with users. The service platform will select $num_j - 1$ users with the lowest $b_{i,j}$ that is below the maximum budget r_j, based on the collaboration number of each task and users' (ζ_i, B_i). These users will be added to the UIW set. If there are not enough users that meet the requirements, the task owner will be included in the UIQ set. As the social relationships between users are private, the interest level of users for a particular task will be calculated based on their $(\zeta_i, \ B_i)$, and those users who are potentially interested in a task will be recommended. The recommendation process, which is based on interest level, mainly comprises the following steps:

Step 1: involves constructing a user-task rating matrix (UT) based on the sets of users and tasks.

Step 2: the cosine similarity formula is used to calculate the similarity of interest among users in both UIQ and $U\backslash UIQ$, resulting in the interest similarity matrix W. The cosine similarity formula is shown in Equation (3).

$$w_{uv} = \frac{|N(u) \cap N(v)|}{\sqrt{|N(u)||N(v)|}} \tag{3}$$

where $N(u)$ represents the set of tasks that user u is interested in within the set $U \backslash UIQ$, and $N(v)$ represents the set of tasks that user v is interested in within the UIQ set, and w_{uv} is the similarity of interest between user u and user v.

Step 3: Sort users based on the similarity of their interest and recommend the tasks to them.

Step 4: When the required number of collaborators for a task is met, add the users to the UIW set.

Step 5: After recruiting enough users, tasks will be carried out and compensation will be determined based on their contributions. The compensation formula is defined by Equation (4).

$$p_{i,j} = \begin{cases} b_{i,j}, & \frac{q_{i,j} num_j r_j}{\sum_i^{num_j} q_{i,j}} < b_{i,j} \\ \frac{q_{i,j} num_j r_j}{\sum_i^{num_j} q_{i,j}}, & \frac{q_{i,j} num_j r_j}{\sum_i^{num_j} q_{i,j}} \geq b_{i,j} \end{cases} \tag{4}$$

where $\frac{q_{i,j}}{\sum_i^{num_j} q_{i,j}}$ is the proportion of contribution from user u_i, and $num_j r_j$ is the total budget of task t_j.

3.5 Desirable Properties

This paper aims to design an incentive mechanism that achieves efficiency within a reasonable time frame. In a reverse auction, each user submits a tuple (ζ_i, B_i) to the platform, which includes the set of tasks they are interested in bidding for ζ_i and their bidding price B_i. Users can submit a tuple (ζ_i', C_i) that deviates from the truthful value, where C_i represents the user's cost set. It is critical for the incentive mechanism to ensure non-negative utility for each user to prevent negative utility from causing them to withdraw from the platform.

Based on the descriptions given above, this paper expects the incentive mechanism designed to satisfy the following features:

- **Computational Efficiency:** Algorithmic incentivization mechanisms can be completed in polynomial time.
- **Truthfulness:** The tuples (ζ_i, B_i) and preference order F_{ui} submitted by each user $u_i \in U$ are truthful.
- **Individual Rationality:** For every user $u_i \in UIW$, the variable $e_i \geq 0$.

4 Construction of MO-TTC

In this section, we present two algorithms: the TTC algorithm and an interest-based task recommendation algorithm. We use an example to demonstrate the process of the second phase using TTC. Finally, we demonstrate the characteristics possessed by the proposed incentive mechanism.

4.1 Secondary Trading Algorithm

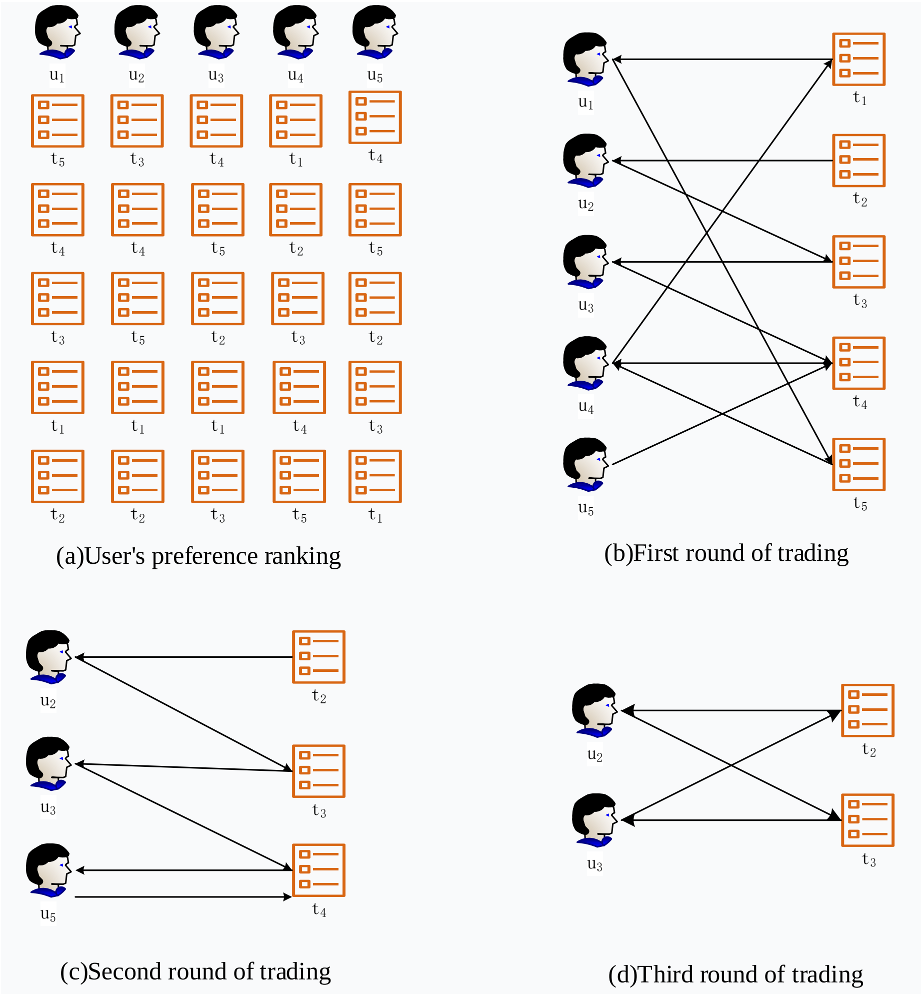


Fig. 2. Trading process

The second-hand trading process based on the TTC is exemplified in Fig.2. Users rank their preferred tasks, as indicated in Fig.2(a), where u_1, u_2, and u_3 are users in the URW set who own tasks t_1, t_2, and t_3, respectively (t_1, t_2, $t_3 \in TW$), u_4, u_5 are users in the URL set who don't own any tasks, and t_4, t_5 are tasks in TL that don't belong to any user. In Fig.2(b), users point to their favorite tasks, which in turn point to their owners; t_4, t_5 do not have owners. Assuming that u_4 has a higher reputation score than u_5, they point to the new user with the highest reputation score, u_4. Hence, TTC leads to the cycle $u_1 \rightarrow t_5 \rightarrow u_4 \rightarrow t_1 \rightarrow u_1$. As a result, users u_1 acquire tasks t_5 and u_4 acquires task t_1, which are both subsequently removed from the cycle, completing the first round of trading. Fig.2(c) displays the updated preference orders for the users and tasks. In the second round, a cycle $u_5 \rightarrow t_4 \rightarrow u_5$ is discovered, and user u_5 gets task t_4, which is then removed from the system. The third round is illustrated in Fig.2(d), where a cycle $u_2 \rightarrow t_3 \rightarrow u_3 \rightarrow t_2 \rightarrow u_2$ is found. As a result, user u_2 acquires task t_3 and user u_3 acquires task t_2, which are both subsequently removed from the cycle. The transaction comes to an end because there are no tasks or users left to trade.

After the completion of the transaction, all users involved in the subsequent exchange demonstrate a preference for the final allocated task that is equal to or greater than their initial task allocation, indicating a preference for higher interest level tasks during the exchange process.

This paper presents the TTC algorithm to implement the transaction process during the second phase. The specific procedures are outlined in Algorithm 1.

Algorithm 1. TTC algorithm

```
input: User set U = URW ∪ URL, Task set T = TW ∪ TL
Output: UTTC
Initialize users' preference sequence F_ui
Construct the TTC graph G based on Definition 1 and user preference order
while G Number of nodes > 0
    Find all cycles in G
    for each cycle ∈ cycles
        UTTC := {task-user}
        Remove node and update graph G
        Update task owner
    end for
end while
```

4.2 Interest-based Task Recommendation Algorithm

At this stage, the paper considers recommending tasks with insufficient user numbers based on similarity of user interest, to other users, to achieve sufficient user numbers.

In the first stage of the reverse auction, all users submitted bids to the platform, bidding on the task set ζ_i that they were interested in, which serves as their behavior towards tasks in the third stage. A user-task rating matrix, denoted as UT, is then constructed. For a user u_i, if a task $t_j \in \zeta_i$, the rating for this task by the user is considered 1; otherwise, it is considered 0. Similarly, user's similarity matrix W is calculated based on the UT matrix using Equation (3). Finally, the recommendation list is generated by multiplying the UT matrix and the user similarity matrix W.

Firstly, we identify the K users in the similarity matrix W who are most similar to user u_i. The set of K users, denoted as $S(u_i, K)$, are the owners of tasks in the UIQ set, where user recruitment has been insufficient. Subsequently, we extract all tasks from S that users are interested in and remove tasks which u_i has already expressed an interest in. The degree of interest that user u_i has towards task t_j is computed using Equation (5).

$$p(u_i, t_j) = \sum_{v \in S(u_i,K) \cap N(t_j)} w_{uv} \times ut_{vt_j} \tag{5}$$

where ut_{vt_j} represents the degree of liking or rating that user v gives to task t_j, and $N(t_j)$ refers to users who have interacted with task t_j.

Algorithm 2. Interest-based Task Recommendation Algorithm

input: User set U; Under-recruited user set UIQ; K users
1: Build user-task rating matrix UT
2: Calculate similarity matrix W by Equation (3)
3: **for** $u \in U \backslash v$
4:     **for** $v \in UIQ \backslash u \cap N(t)$
5:         Find the K users in the UIQ set that are most similar to user u
6:         Calculate the level of interest of u in task t using Equation (5)
7:     **end for**
8: **end for**
9: descending order sorting U base on $F(u)$
10: Select the top N users according to Equation (5) to participate in the task and add them to the UIW collection
11: Update the reputation of the users in the UIW collection by using Equation (1)
12: Determine the rewards for the users in the UIW collection by using Equation(4)

4.3 Mechanism Analysis

The following section conducts theoretical analysis to demonstrate that the incentive mechanism proposed in this article can achieve the following characteristics:

Lemma 1. *MO-TTC is computationally efficient.*

Proof. Both Algorithm 1 and Algorithm 2 satisfy the computational effectiveness. In Algorithm 1, initializing the preference sequence of users and constructing the directed graph G both traverse the user and task sets, costing $O(n^2)$ time. The worst-case scenario for finding the set of winning users UIW (lines 3-10) is when only one task-user match occurs each time, costing $O(n^2)$ time in this case. Therefore, Algorithm 1 costs $O(n^2)$ time. In Algorithm 2, building the user-task scoring matrix and calculating the similarity matrix both traverse the user set, costing $O(n)$ time. Finding the top K similar users (lines 3-8) costs $O(n^2)$ time, sorting and selecting N users (lines 9-10) costs $O(n)$ time, and updating the reputation and reward (lines 11-12) costs $O(n)$ time. Therefore, Algorithm 2 costs $O(n^2)$ time.

Lemma 2. *MO-TTC is truthful.*

Proof. Each user submits a tuple (ζ_i, B_i) to the platform, which contains the set of tasks of interest ζ_i and the bid set B_i. Users have strategic considerations in bidding and may provide a tuple (ζ_i', C_i) that deviates from the true value. Since the filtering process in all three stages considers B_i, users' participation rates will decrease when submitting false bids. Additionally, if ζ_i and the user's preference sequence F_{u_i} are false, the user cannot obtain the tasks that they truly desire because task trades will only occur based on the user's genuine preference sequence in the second stage, while the third stage constructs a user-scoring matrix based on ζ_i to search for users with high similarity.

Lemma 3. *Benchmark-S is individually rational.*

Proof. It is evident, as shown by Equation (2), that e_i is greater than or equal to zero.

5 Experimental Evaluation

5.1 Simulation Setup

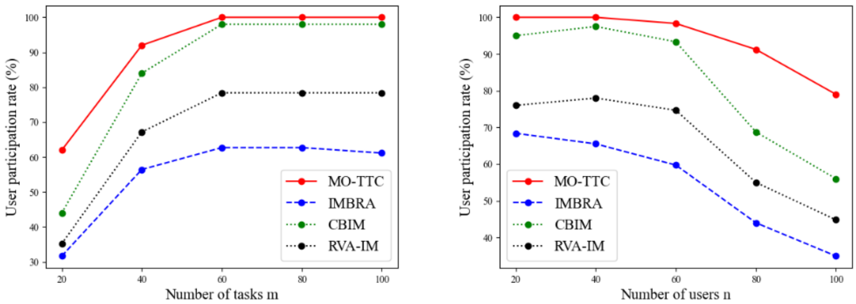
In order to evaluate the effectiveness of the MO-TTC algorithm, this paper conducts simulation on three performance indicators: user participation rate, task coverage rate, and average user utility. The simulation parameters are shown in Table 2. The simulation experiments run on Windows 11 system with hardware configuration of AMD R7-6800H CPU, RTX3060 GPU, and 16GB RAM.

The performance of MO-TTC is compared with three other incentive mechanisms, including the Incentive Mechanism Based on Reverse Auction (IMBRA), the Contribution Based Incentive Mechanism (CBIM), and the Reverse Vickrey Auction Incentive Mechanism (RVA-IM). In IMBRA, low bidders are selected to perform tasks, and if there are not enough users, the task is not executed, with user rewards being based on their bidding value. In CBIM, task performers are randomly selected, with user acceptance being random as well. If there are not enough users available, the task is not executed, and rewards are determined based on the user's contribution. In RVA-IM, the second lowest bidder becomes the task performer, and other users are selected as collaborators based on their reputation value, with rewards being determined using the Vickrey-Clark-Groves (VCG) mechanism.

Table 2. Simulation parameters

Parameter	Range
Number of users n	[20,100]
Number of tasks m	[20,100]
Maximum budget for reverse auction r_j	[20,40]
Number of task collaborators num_j	[2,4]
User bid $b_{i,j}$	[10,50]
User contribution $q_{i,j}$	[1,5]
User reputation value rp_i	[0,1]
Whether the user accepts the task	[0,1]

5.2 User Participation Rate



(a) (b)

Fig. 3. Comparison of user participation rates

Fig.3 show a comparison of user participation rates between MO-TTC, IMBRA, CBIM and RVA-IM. Fig.3(a) depicts the comparison of user participation rates at different task numbers, with 50 users. The figure shows that the proportion of participating users increases with the number of tasks. This is because, when the number of tasks is smaller than the number of users, there are relatively fewer users participating in sensing tasks, and as the number of tasks increases, so too does the number of users participating in sensing tasks. With 50 users, MO-TTC outperformed IMBRA, CBIM, and RVA-IM by an average of 36%, 6%, and 23%, respectively, in terms of user participation rate when the number of tasks varies. Fig.3(b) shows that user participation rates decrease with an increase in the number of users. When the number of tasks is constant, an increase in the number of users quickly recruits enough users to reach saturation in the tasks. With 50 tasks, MO-TTC outperformed IMBRA, CBIM and RVA-IM by an average of 39%, 12%, and 28%, respectively, in terms of user participation rate when there were varying numbers of users. For MO-TTC, a multi-stage optimization strategy was used to provide users with more opportunities to choose whether to participate in sensing tasks, thereby increasing the number of users executing sensing tasks. Therefore, user participation rates were always higher with MO-TTC than with IMBRA, CBIM and RVA-IM.

5.3 Task Coverage Rate

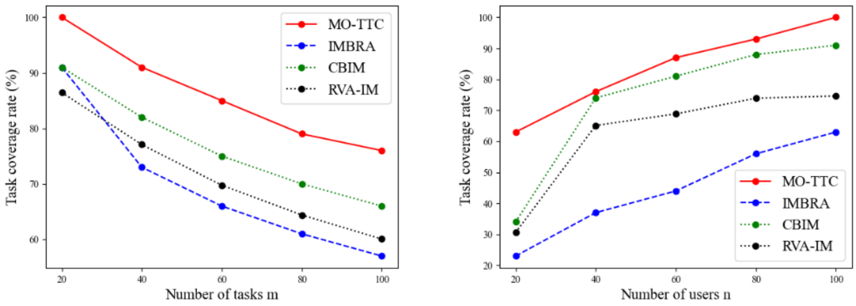
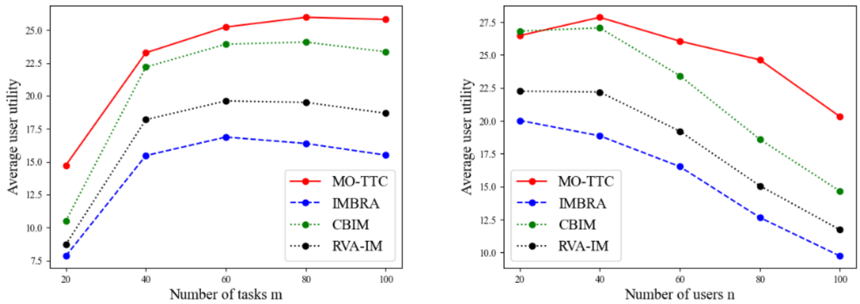


Fig. 4. Comparison of task coverage rates

Fig.4 illustrate a comparison of task coverage rates between MO-TTC, IMBRA, CBIM, and RVA-IM. Fig.4(a) represents the comparison of task coverage rates for different task numbers when the user number is 50, while Fig.4(b) shows the task coverage rate comparison for different user numbers when the task number is 50. The figures demonstrate that the task coverage rate decreases with an increase in the number of tasks due to the users' limited budget for task completion. Fig.4(a) reveals that MO-TTC outperforms IMBRA, CBIM, and RVA-IM by an average of roughly 17%, 9%, and 15%, respectively, regarding user participation rate when the user number is 50 and the task number increases. Fig.4(b) demonstrates that the task coverage rate increases with an increase in the number of users, as recruiting more users means more task coverage opportunities. When the task number is 50, MO-TTC outperforms IMBRA, CBIM, and RVA-IM by an average of roughly 39%, 10%, and 21%, respectively, concerning the user participation rate as the user number increases. Interest-based task recommendation algorithms can effectively recommend remaining tasks to users, thereby allowing MO-TTC to achieve higher task coverage rates than those of IMBRA, CBIM, and RVA-IM.

5.4 Average User Utility



(a) (b)

Fig. 5. Comparison of average user utility

Fig.5 compare the average user utility of MO-TTC, IMBRA, CBIM, and RVA-IM. Fig.5(a) presents a comparison of the average user utility concerning different task numbers at constant user quantity of 50. Fig.5(b) shows a comparison of the average user utility with different user quantities but constant task number of 50. From Fig.5(a), it is evident that the average user utility increases with task quantity due to the increased involvement of users when the number of tasks increases. When there are 50 users, MO-TTC shows an average increase of 63%, 14%, and 40% in average user utility compared to IMBRA, CBIM, and RVA-IM, respectively. In contrast, from Fig.5(b), the average user utility decreases as the number of users increases because the participation rate is reduced with an increase in tasks. When there are 50 tasks, MO-TTC results in an average increase of 67%, 17%, and 50% in average user utility compared to IMBRA, CBIM, and RVA-IM, respectively, with increasing numbers of users. IMBRA shows relatively lower average user utility as only low bidding users are chosen. CBIM randomly selects users only once, leading to decreased participation rates and lower average user utility as the number of users increases. In contrast, RVA-IM determines rewards according to the VCG mechanism, achieving maximum welfare instead of high average user utility. MO-TTC utilizes a multi-stage optimization strategy, incentivizing users based on their interest and recommending tasks requiring inadequate collaboration to other users. This approach results in consistently higher average user utility than IMBRA, CBIM, and RVA-IM.

6 Conclusion

In social networks, perceptual tasks usually require multi-user collaboration. Considering the low user interest in certain tasks, it is challenging for these tasks to recruit enough contributors. This paper proposes an incentive mechanism based on MO-TTC. The paper first uses a reverse auction model to select users and then employs the TTC algorithm to assign tasks to users with higher interest for secondary transactions. If tasks have insufficient collaborative efforts, we recommend them to other users with similar interest in the social network. Rewards are then allocated to users based on their contributions, and their reputation values are updated accordingly. We have proven that MO-TTC is computationally efficient, truthful, and individually rational. Furthermore, the simulation results show that the MO-TTC incentive mechanism proposed in this paper outperforms other approaches such as IMBRA, CBIM, and RVA-IM in terms of user participation rate, task coverage, and average user utility.

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