Budget Constraint Task Allocation for Mobile Crowd Sensing with Hybrid Participant

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Abstract. In the Mobile crowdsensing (MCS) system, the task allocation problem is a crucial problem. In this paper, we focus on the task allocation problem for hybrid participants with a budget-constrained MCS system. There are two types of participants: mobile participants and static participants. Mobile participants have low cost, large numbers, and flexibility. However, most of the sensing data they submitted are of low quality. On the other hand, static participants, such as city cameras, roadside infrastructure, have high-quality sensing data. Despite the benefit of high quality, static participants have less coverage and high cost. Given a budget, the problem is how to assign the task to the two types of participants, such that the social welfare is maximized. To solve the problem, we propose a reverse auction-based task allocation method (ORA) to select winning bids round by round. Then, a Shapley value based online algorithm (OAA) is proposed to ensure the task is finished. Moreover, we consider the different types of participants to have a different probability to finish tasks. We exploit the semi-Markov model to calculate the probability that participants finished tasks. We prove that the proposed task allocation method has truthfulness and individual rationality. We conduct extensive experiments to evaluate the performance of our system, and the evaluation results demonstrate the remarkable effect of the proposed task allocation method.

Keywords: Mobile crowdsensing · Task allocation · Reverse auction · Shapely value · Semi-Markov model

1 Introduction

Mobile crowdsensing (MCS) [1] is a new sensing paradigm that uses the powerful sensing ability of mobile devices. Mobile devices such as smartphones are

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carried by mobile users who have the potential to finish the sensing tasks. In the MCS system, the number of mobile users is huge and multiple mobile users could finish one task together. So mobile users always finish tasks at a low cost. The cost of users is critical because the platform publishes tasks always with budget constraints. The advantage of low cost means the platform could hire more users to guarantee the quality of sensing data. Because of this advantage of MCS, we can use MCS on some new systems to accomplish tasks, *e.g.*, monitoring of water distribution [2], traffic density estimation [3], and air pollution inference [4]. In this paper, we focus on the task allocation problem with the budget-constrained to maximize social welfare, which is called the maximize-social-welfare task allocation problem (MSW-PR). The MCS will be effective when the users submit high-quality sensing data. So how to allocate the sensing task to proper users is a crucial problem. Much former research studied this problem. In these studies, researchers' methods include the reverse auction [5] and semi-Markov-based prediction [6]. All of these studies assumed that there always have adequate users to participate. However, this is not valid in reality. Moreover, mobile users' performance is limited by the personal ability, weather, and stability of sensors on mobile devices, it is hard to guarantee the quality of sensing data. Accordingly, the task allocation problem is challenging when the number of mobile users is scarce and most of the mobile users have a low ability to perform tasks.

Generally, sensing tasks are location-sensitive [7]. The difficulty of the task varies with the location of the task, however, most previous studies only consider homogeneous participants. In fact, there are at least two types of participants in the MCS system, mobile participants, and static participants. Mobile participants have the advantage of low cost, flexible cover task locations. Static participants such as stationary cameras, roadside infrastructure, etc. Compared with the mobile participants, static participants have a high ability to perform the sensing task. However, the installation cost and maintenance cost is very high. Therefore, it is a non-trivial problem to reasonably allocate tasks to hybrid participants with the budget constraint.

To solve the above two challenges, we propose a reverse auction-based task allocation model with hybrid participants, including mobile participants, and static participants. The main contributions of our work are:

- We first propose a one-round auction (ORA) algorithm to select winning bids. Through this algorithm, we could determine which kinds of participants are proper for a certain sensing task. In the one round auction, we use the semi-Markov model to calculate the probability that the participant could submit high-quality sensing data.
- We propose the budget allocation strategy (BAS) based on Shapely value. We calculate the Shapely value of the different subregions. We will allocate more budget to this subregion which has a low Shapely value next sensing period to ensure the task completion rate. Based on the ORA and BAS algorithms, we propose an online auction algorithm to achieve the maximum social welfare goal.

- We prove that the proposed ORA and OAA algorithm has truthfulness and individual rationality.
- We conduct an extensive simulation. Through the real data simulation experiment, we demonstrate the remarkable effect of the proposed ORA and OAA algorithm.

2 Related Work

In recent years, many studies focus on user recruitment in MCS. Zhou *et al.* [5] proposed a highly credible incentive mechanism based on the reverse auction theory. This incentive minimizes the cost of the platform by controlling participants' bids through reverse auction and recruiting proper participants to finish tasks. In these works, researchers assume the number of users is always adequate. They ignore the situation of rare user participation. Moreover, in the real world, there is more than one kind of participant, but researchers only focus on a single kind of participant. So the existing studies cannot solve our MSW-PR problem. Many studies consider the budget constraints in MCS. Wang *et al.* [1] studied the coverage requirements and workload balancing requirements of mobile crowdsourcing and used dynamic programming to solve the problem in one-dimensional scenarios, and proposed greedy algorithms to solve the CBCR problem with submodule properties in two-dimensional scenarios. The above research concentrates on task allocation. Their studies all consider budget constraints. However, they allocate the budget equally, which can not guarantee the quality of the sensing task. In our work, we allocate the budget based on Shapely value, avoiding the equalitarianism which makes the budget allocation more reasonable.

3 System Description and Problem Definition

3.1 System Model

Our MCS system with hybrid participants includes a cloud platform, static participants, and mobile participants. In this paper, the platform divides the sensing region into subregions, denoted as $L = \{l_1, l_2, ..., l_m\}$. There are some tasks, denoted as $S = \{s_1, s_2, ..., s_k\}$. The platform can release multiple tasks in a certain sensing period t_i, where $t_i \in T$, $T = \{t_1, t_2, ..., t_n\}$ represents the set of sensing periods and t_i represents the i-th sensing period. Each sensing task is assigned with attributes, *e.g.*, the deadline D, and the subregion l which the task belongs. Participants could make multiple bids to different tasks, *e.g.*, participant i made j-th bid at sensing period t, denoted as b^t_{ij}. Mobile participants and static participants make a bid b^t_{ij} for the sensing task s^t_k they want to complete. For a certain user, the cloud platform can obtain the completion rate h_i of the participants i. Then, we use δ^t_{ijk} to represent participant i make j-th bid at sensing period t to participate in the sensing task k. Before the recruitment of participants, the completion rate of tasks can be estimated by the h_i. To improve the performance of participants, we have specified the minimum completion rate of each task $\{\mu_1, \mu_2, ..., \mu_k\}$. In the end, the cloud platform selects the proper participants $I = \{i_1, i_2, ..., i_n\}$ to complete the tasks. The final rewards p_i^t are paid by the platform to the participants.

3.2 Reverse Auction Based Participants Recruitment

The recruitment method of our reverse auction mainly includes the following five steps:

1. The cloud platform publishes k sensing tasks in a certain sensing period $t_i \in T$. Each sensing task $s_i \in S, S = \{s_1, s_2, ..., s_k\}$ needs to be completed within a time interval $[t_1, t_2]$, and the location of each task belongs to $L = \{l_1, l_2, ..., l_m\}$.
2. After participant i receives sensing task information, he will pack his bid price b_{ij}^t and the task he bid s_k^t into task-bid pair (b_{ijk}^t) and send to the platform. Then the platform receives the task-bid pairing, adding the participant's historical task-completion rate h_i into the task-bid pair, forming the task-bid-completion rate pair (b_{ijk}^t, h_i), which is also written as δ_{ijk}^t.
3. The cloud platform selects the winning bid pair through comparison of the task-bid-completion rate pair and adds the winning bid pair into the set of winners Φ.
4. After the winner gets the task, he/she starts to perform the task within the time interval of $[t_1, t_2]$, where t_1 is the beginning time. The winner must finish the task before the deadline, $t_2 = D$, and send the acquired sensing task data to the cloud platform.
5. The cloud platform receives the sensing task, pays p_i^t for the participants. The number of unsold tasks $|S^{remain}|$ on the sensing platform and the number of low-quality sensing tasks $|S^{low}|$ was calculated to calculate the task completion rate of different regions l_i.

We next define the utility u of the participant i:

$$u_i(b_{ij}^t) = \begin{cases} p_i^t - c_i^t & x_{ij} = 1 \\ 0 & x_{ij} = 0 \end{cases} \tag{1}$$

Among the participants' utility definition, the cost of a participant performing a task c_i^t is hard to reduce, so the utility mainly comes from the reward given by the platform. The reward is also the actual expenditure of the platform.

3.3 Problem Formulation

In this section, we solve the maximized social welfare task allocation problem (MSW-PR). For the MSW-PR problem, our goal is to maximize social welfare.

As thus, we could represent our system welfare to:

$$\sum_{t\in[T]}\sum_{i\in[I]}\sum_{j\in[J]} z_{ij}^t(v_i^t - p_i^t) + \sum_{t\in[T]}\sum_{i\in[I]}\sum_{j\in[J]} z_{ij}^t(p_i^t - c_i^t) \tag{2}$$

Where $z_{ij}^t = 1$ represents participant i provide high-quality sensing data to task j and $z_{ij}^t = 0$ represents participant i provide low-quality sensing data or provide nothing to task j.

Our MSW-PR problem can be formulated as:

$$\max e = \sum_{t\in[T]}\sum_{i\in[I]}\sum_{j\in[J]} z_{ij}^t(v_i^t - c_i^t) \tag{3}$$

subject to:

$$\sum_{i=1}^{l}\sum_{j=1}^{J} p_i^t x_{ij}^t \le B^t \tag{4}$$

$$x_{ij}^t \in \{0,1\} \tag{5}$$

Where constraint (4) represents the payment p_i^t should be less than or equal to the budget B^t of a certain period t. Constraint (5) shows that x_{ij}^t is 0 or 1. $x_{ij}^t = 1$ represents the bid that is accepted by the cloud platform. Otherwise, it is rejected.

When selecting participants for the platform, we compare their weighted bids b_{ij}^t with their task completion rate h_i to determine the final winner of the task: $b_{ij}^{t\,\prime} = b_{ij}^t / h_i$.

The weighted bid price avoids the appearance of low-quality sensing data. In this way, we both consider the bid price and data quality in task allocation, which ensures the sensing data quality.

4 The MSW-PR Problem

In this section, we first propose a one-round auction algorithm (ORA). Next, we propose the semi-Markov-based participant task completion rate prediction method and the Shapely value-based budget allocation strategy (BAS). At last, we propose our online-auction algorithm (OAA) to solve the MSW-PR problem.

4.1 One-Round Auction Algorithm

First, calculate the task completion probability: $P_k^{\Phi} = 1 - \prod_{\delta_{ijk}^t \in \Phi \wedge k \in \delta_{ijk}^t}(1 - h_i)$.

Where Φ represents the win-bid set, h_i denotes the task completion probability of participant i, δ_{ijk}^t represents participant i make j-th bid at sensing period t to participate in the sensing task k.

Then, we calculate the utility u of the win-bid set Φ, where μ_k is the given minimum task completion probability of task s: $U(\Phi) \triangleq \sum_{i=1}^{k} \min\{P_k^{\Phi}, \mu_k\}$.

Through the reverse auction, we continuously add bid-pairs δ^t_{ijk} to the win-bid set Φ so that we can obtain the utility equation:

$$U_{\delta^t_{ijk}}(\Phi) = \sum\nolimits_{s_i \in \delta^t_{ijk}} (\min\{P_k^{\Phi \cup \{\delta^t_{ijk}\}}, \mu_k\} - \min\{P_k^{\Phi}, \mu_k\}) \tag{6}$$

The marginal contribution utility Eq. (6) ensures that these winning bids are the optimal choice of the current round t.

Algorithm 1. One-Round Auction Algorithm (ORA)

Input: Budget B, tasks s, bid-pair set Γ, winning bid-pair set Φ, task completion threshold θ

Output: winning bid-pair set Φ

1: Begin
2: $\Phi = \varnothing$; $\forall i \in [I], j \in [J], k \in [K]$; $x^t_{ij} = 0$; $z^t_{ij} = 0$; p^t_i; $B^t = B$
3: **while** $U(\Phi) < k\mu \&\& \sum_{i=1}^{n} p^t_i < B^t$ **do**
4: $\quad \delta^t_{i^*j^*k} = \arg\min_{\delta^t_{ijk} \in \Gamma} \frac{U_{\delta^t_{ijk}}(\Phi)}{b^t_{ijk}}(h_i + \xi)$
5: $\quad$ **if** $h_i > \theta$ **then**
6: $\quad\quad z^t_{i^*j^*} = 1$
7: $\quad$ **else**
8: $\quad\quad z^t_{i^*j^*} = 0$
9: $\quad \delta^t_{i'j'k} = \arg\min_{\delta^t_{i'j'k} \in \Gamma_{-\delta^t_{i^*j^*k}}} \frac{U_{\delta^t_{i'j'k}}(\Phi)}{b^t_{i'j'k}}(h_{i'} + \xi)$
10: $\quad p^t_i = \frac{b^t_{i'j'k} U_{\delta^t_{i^*j^*k}}(\Phi') h_{i^*}}{U_{\delta^{t'}_{i'j'k}}(\Phi') h'_i}$
11: $\quad$ update $U(\Phi) = U(\Phi) + U_{\delta^t_{i^*j^*k}}(\Phi)$
12: $\quad$ update $\Phi = \Phi \cup \{\delta^t_{i^*j^*k}\}$
13: $\quad$ update $\Gamma = \Gamma \backslash (\cup_{i \in [I]} \delta^t_{i^*j^*k})$
return Φ
14: End

The one-round auction algorithm is shown in Algorithm 1. During the iteration, we judge whether the utility of the winning bid-pair satisfies the needs of the platform. If the conditions are met, we will select the bid-pair $\delta^t_{i^*j^*k}$ with the highest marginal utility (line 3). Then, we mark the bid users as being recruited (line 4), where $\xi > 0$ avoids $h_i = 0$. When $h_i > \theta$, the threshold of task completion probability, we think the participant could provide high-quality sensing data and mark $z_{ij} = 1$. Otherwise, $z_{ij} = 0$ (line 5–7). We use the second price auction to pay the reward (line 9–10). After selecting the win-bid pair, we need to add the win-bid pair to the win-bid set Φ and update the utility of the win-bid set $U(\Phi)$ (line 11–12). Finally, since we only allow the participant i to complete one task in one sensing period, we need to exclude all bid-pairs for this participant (line 13).

4.2 Probability Calculation of High-Quality Sensing Data Methods for Hybrid Participants

For static participants, since the conditions (hardware conditions and operation mode) for completing tasks are almost the same each time, the completion probability of tasks can be calculated simply by the historical statistics: $h_i = num_i^h/num_i$. Where num_i^h is the historical high-quality sensing data count submitted by static participants, and num_i is the historical win-bid count. Both counts are from historical statistics.

However, for the mobile participants, it is impossible to use their historical task completion result to make statistics, since the condition of performing tasks may be different each time.

In this case, we choose to use the semi-Markov model to predict the participants' ability to provide high-quality sensing data in the current sensing period. First, we define the kernel part of the semi-Markov model: $Z_i^{bg}(t) = P(q_i^t = g, t_{ik} \leq T | q_i^{t-1} = b)$. $Z_i^{bg}(t)$ is the probability that participant i could provide high-quality sensing data at t-round sensing period, while he provides low-quality sensing data at $(t-1)$-round. $q_i^{t-1} = b$ and $q_i^t = g$ represent whether participant i provides good or bad sensing data, respectively. $t_{ik} < T$ represents that the participant i should finish the task k and send sensing data to the cloud platform within sensing time limit T.

To calculate $Z_i^{bg}(t)$, we define the probability $W_i^{bg}(t) = P(x|q_i^t = g, q_i^{t-1} = b)$, which represents that participant i sends sensing data within time limit T, where he provides low-quality sensing data at t-round sensing period and he provides high-quality sensing data at $t-1$-round.

Next, we define the probability $P_i^{bg} = P(q_i^t = g|q_i^{t-1} = b)$, which shows that the participant i provides high-quality sensing data at t-round sensing period while he provides low-quality sensing data at $(t-1)$-round.

Therefore, we could rewrite $Z_i^{bg}(t)$ by $W_i^{bg}(t)$ and q_i^{t-1}: $Z_i^{bg}(t) = P(q_i^t = g, t_{ik} \leq T|q_i^{t-1} = b) = W_i^{bg}(T)P_i^{bg}$ Similarly, we can get the probability of h_i that the participant can provide high-quality sensing data in the t-round under other circumstances. So we can get the probability that the participant can provide high-quality sensing data in the t-round:

$$h_i = P_i^g(t) = \frac{(Z_i^{bg}(t) + Z_i^{gg}(t))}{(Z_i^{bg}(t) + Z_i^{gg}(t) + Z_i^{bb}(t) + Z_i^{gb}(t))} \tag{7}$$

4.3 Budget Allocation Method Based on Shapley Value

In the MCS system, we expect participants to provide enough high-quality sensing data in a budget constraint. However, sensing tasks are very sensitive to the location. Some tasks may be difficult and not be completed well. This will seriously affect sensing data quality. For this problem, we use the Shapley value to allocate budgets to different regions.

We first define the concept of task completion rate for the regions.

Definition 1. *We define the task completion rate F_l, which is a measure of the task completion status of subregion l, and always have $F_l \leq 1$.*

After the sensing data is submitted by participants, the cloud platform calculates the number of all low-quality sensing data $\left|S_l^{low}\right|$ and the number of sensing tasks that no one bids for or fails to auction $\left|S_l^{remain}\right|$. Then we could calculate the task completion ratio with: $F_l = (|S_l| - \left|S_l^{low}\right| - \left|S_l^{remain}\right|)/\,|S_l|$.

Where $|S_l|$ is the count of all tasks s.

We employ the Shapley value method to allocate budget:

$$\zeta_l = \sum_{L' \subseteq L \backslash \{l\}} [U(L' \cup \{l\}) - U(L')] \frac{|L'|!(|L| - |L'| - 1)}{|L|} \tag{8}$$

$$B_l = B \frac{\zeta_l}{\sum_{l \in L} \zeta_l} \tag{9}$$

Where $L' \subseteq L \backslash \{l\}$, represent the subset of region set and $U(L')$ represent the utility of subset L'. After calculating the Shapley value, we can use Eq. (9) to allocate budget. Where B_l represent the budget B of subregion l.

Algorithm 2. Budget Allocation Algorithm (BAA)

Input: Total budget B, Location set L, task completion rate F_l
Output: subregions budget B_l

1: Begin
2: $B_l = \varnothing$; $\forall t \in [T], l \in [L]$
3: **for** $l = 1, 2, ..., L$ **do**
4: use Eq. (17) to calculate the F_l for each subregion;
5: use Eq. (18) to calculate the B_l
return B_l, which is the budget of subregion l
6: End

4.4 Online Auction Algorithm

After proposed the one round auction algorithm ORA and the budget allocation strategy BAS, we now propose our online auction algorithm.

In our online auction algorithm, we calculated the Shapley value of different regions (line 3–7). It is noting that in the first period since there is no data of the previous sensing period, we cannot allocate the budget of each region according to the Shapley value, so we allocate the budget of each region equally (line 5). The winner in each region was calculated using the ORA algorithm (line 8) and the budget of subregion l is calculated by BAS (line 7).

Algorithm 3. Online Auction Algorithm (OAA)

Input: Budget of subregions B_l, Location set L, all bid-pair set $\varGamma_t$, win bid-pair $\varPhi_t$
Output: win bid-pair $\varPhi_t$

1: Begin
2: $\varPhi_t = \varnothing$; $\forall t \in [T], l \in [L], k \in [K], x_{ij}^t = 0, z_{ij}^t, p_i^t$
3: **for** $1 < t < T$ **do**
4: **if** $t = 1$ **then**
5: $B_l = \frac{B}{|L|}$
6: **else**
7: use algrithom BAS to caculate B_l
8: $\varPhi_t = ORA(B_l, \varGamma_t, \varPhi_t)$
return $\varPhi_t, \forall t \in [T]$
9: End

5 Theoretical Analysis

In this section, we will prove that ORA and OAA have truthfulness and individually rational. In our subsequent experiment in Sect. 6, we analyze ORA by comparing the mixing ratio of different mobile participants and static participants. We select the winning bid-pair of current round t, from all the current auction pairs through reverse auction, and add it into the winner set $\varPhi_t$. For the OAA algorithm, in addition to the operation of the ORA algorithm, we also introduce the Shapley value to allocate budget B more reasonably.

5.1 Truthfulness

We give some definitions. $\varPhi_t$ represents the win-bid pair set. ${\varPhi_t}'$ the win bid pair set which remove the pair bid-pair δ_{ijk}^t from $\varGamma$. According to [8], we have $\varPhi_t = {\varPhi_t}'$. Then we have the following lemma.

Lemma 1. *Algorithm ORA is bid-monotonic.*

Proof. Since our reverse auction selects the win bid-pair for each round, the number of bid pairs we select for algorithm ORA will increase when the auction proceeds. For example, if participant i is the winner of auction t, his weighted bid must be the minimum value of this round of auction. Suppose that participant i now puts forward a lower bid than his former win bid, and we will put it into algorithm ORA:

$$\frac{U_{\delta_{ijk}^t}(\varPhi)}{b_{ijk}^t}(h_i + \xi) < \frac{U_{\delta_{i'j'k}^t}(\varPhi)}{b_{i'j'k}^t}(h_{i'} + \xi) \tag{10}$$

We find that participant i still win the t round auction. So our Lemma 1 is proved.

Lemma 2. *The reward payment of algorithm ORA is critical for all winning bids.*

Proof. We assume the current win-bid pair δ^t_{ijk} *makes another bid* $b^t_{i'j'k}$. *If* $b^t_{i'j'k} \geq p^t_i$, *which means participant* i's *new bid is larger than the original bid's reward. Therefore, we have:*

$$\begin{aligned}\frac{U_{\delta^t_{i'j'k}}(\Phi_{t-1})}{b^t_{i'j'k}}(h_i+\xi) &= \frac{U_{\delta^t_{i'j'k}}({\Phi'}_{t-1})}{b^t_{i'j'k}}(h_i+\xi)\\ &\leq \frac{U_{\delta^t_{ijk}}({\Phi'}_{t-1})}{p^t_i}(h_i+\xi)\\ &< \frac{U_{\delta^t_{i^*j^*k}}(\Phi_{t-1})}{b^t_{i^*j^*k}}(h_i+\xi)\end{aligned} \tag{11}$$

We can see if participant i *has a new bid* $b^t_{i'j'k} \geq p^t_i$, *he can not win in round* t. *We assume there is a participant* i^* *who has the same task completion probability with* i' *and he makes a bid lower than* p^t_i. *Then he can win in round* t. *So the reward for all winning bids is critical, and Lemma 2 holds.*

Lemma 3. *Our Algorithm ORA and OAA is truthfulness.*

Proof. Because our algorithm ORA is bid-monotone (i.e., Lemma 1) and the reward for participant is critical value (i.e., Lemma 2) from algorithm OAA, so our algorithm ORA and OAA are both truthfulness.

5.2 Individual Rationality

Lemma 4. *Our reverse auction based participant allocation strategy is individually rational.*

Proof. We assume that the bid-pair δ^t_{ijk} *won in round* t, *and the second lowest bid in round* t *is* $\delta^t_{i^*j^*k}$. *We have:*

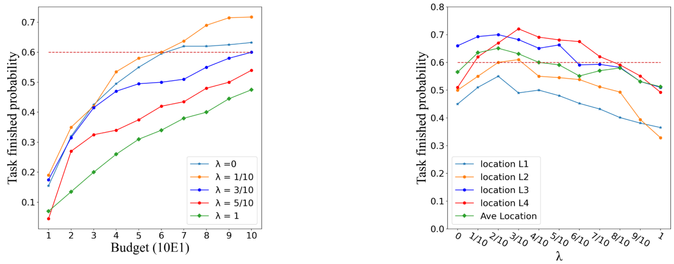
$$b^t_{ijk} < \frac{b^t_{ijk} U_{\delta^t_{i^*j^*k}}(\Phi_{t-1}) h_{i^*}}{U_{\delta^t_{ijk}}(\Phi_{t-1}) h_i} = \frac{b^t_{i^*j^*k} U_{\delta^{s_j}_{i^*j^*k}}({\Phi'}_{t-1}) h_{i^*}}{U_{\delta^t_{ijk}}({\Phi'}_{t-1}) h_i} \leq p^t_i \tag{12}$$

So if a participant i wants to win an auction, he have to make a real bid to reach $p^t_i \geq b^t_{ijk}$, which means the participant's income is non-negative.

6 Performance Evaluation

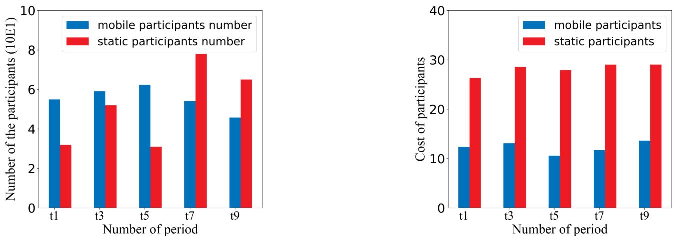
In this section, we use the simulation set and Chengdu/taxi trace set [9] to evaluate the performance of our algorithms OAA and ORA.

The bid price of mobile participants is generated between [10–15], and the bid price of static participants is defined as twice that of mobile participants [20–30]. The sensing period is always 30 mins. We use $\lambda = s/m$ to represent the ratio of mobile participants and static participants, where s and m represent the count of static participants and mobile participants, respectively.



(a) TFP vs. B (b) TFP vs. λ

Fig. 1. Task finished probability under different λ and budget



(a) I vs. t (b) c vs. t

Fig. 2. The number of the win bid participants and social cost

6.1 Evaluation of Offline Task Allocation Strategy and Online Task Allocation Strategy

To better evaluate our algorithm ORA, we introduce the task completion rate, which is the ratio of the complete task count and all task count. The following evaluation gave a minimum task completion rate ($\mu = 0.6$) and participant count ($i = 1000$). As shown in Fig. 1a, we can observe that with the increase of budget, the task completion rate has been increased when $\lambda < 3/10$, which is better than the situation of $\lambda = 0$. As shown in Fig. 1b, we can see that the task completion rate becomes bigger with λ increased. When λ is between 1/10 and 3/10, the task completion rate is better than there is no static participant. This is because the task completion probability of static participants is better than mobile participants.

Next, we evaluate the performance of the online task allocation strategy.

Win-Bid Participants: We can see the number of winners from Fig. 2a, in which the number of mobile participants is much higher than that of static participants because the bid price of mobile participants is much lower than static participants.

Average Social Cost of Participants: We can see the average social cost of participants from Fig. 2b. We can see that despite a large number of mobile participants, their social cost is much lower than that of static participants. This is also why we need to compare the social cost of mobile participants with static participants, that is, the social cost of mobile participants is much lower than that of static participants.

7 Conclusion

In this paper, we investigate the problem of task allocation strategy in mobile crowdsensing. First, we recruit participants and allocate tasks through a one-round auction algorithm (OAA). Then, according to the semi-Markov model, we propose a participant task completion probability prediction for mobile crowdsensing, where the platform could calculate the task completion probability for a certain round auction. Moreover, we propose an online auction algorithm using Shapely value. Through the use of Shapely value, we calculated the task finishing probability on different subregions and re-allocated the budget more reasonably. We conduct extensive simulations based on real traces: Chengdu/taxi. The results show that our online algorithm achieves a high task completion rate and one-round auction achieves the highest social welfare.

References

1. Wang, Z., et al.: Personalized privacy-preserving task allocation for mobile crowdsensing. IEEE Trans. Mob. Comput. **18**(6), 1330–1341 (2019)
2. Du, R., Fischione, C., Xiao, M.: Flowing with the water: on optimal monitoring of water distribution networks by mobile sensors. In: IEEE INFOCOM 2016 - The 35th Annual IEEE International Conference on Computer Communications, pp. 1–9 (2016)
3. Panichpapiboon, S., Leakkaw, P.: Traffic density estimation: a mobile sensing approach. IEEE Commun. Mag. **55**(12), 126–131 (2017)
4. Ma, R., et al.: Enhancing the data learning with physical knowledge in fine-grained air pollution inference. IEEE Access **8**, 88372–88384 (2020)
5. Zhou, R., Li, Z., Wu, C.: A truthful online mechanism for location-aware tasks in mobile crowd sensing. IEEE Trans. Mob. Comput. **17**(8), 1737–1749 (2018)
6. Wang, E., Yang, Y., Wu, J., Liu, W., Wang, X.: An efficient prediction-based user recruitment for mobile crowdsensing. IEEE Trans. Mob. Comput. **17**(1), 16–28 (2018)
7. Yang, Y., Liu, W., Wang, E., Wu, J.: A prediction-based user selection framework for heterogeneous mobile crowdsensing. IEEE Trans. Mob. Comput. **18**(11), 2460–2473 (2019)
8. Gao, G., Xiao, M., Wu, J., Huang, L., Hu, C.: Truthful incentive mechanism for nondeterministic crowdsensing with vehicles. IEEE Trans. Mob. Comput. **17**, 2982–2997 (2018)
9. Didi: Data Source: Didi Chuxing GAIA Initiative. https://outreach.didichuxing.com/app-vue/TTItrajectory?id=1001