BiCrowd: Online Bi-Objective Incentive Mechanism for Mobile Crowd Sensing

Yifan Zhang, Xinglin Zhang, and Feng Li

***Abstract*—With the rapid development of wireless networks and mobile devices, mobile crowd sensing (MCS) has enabled many smart city applications, which are key components in the Internet of Things. In an MCS system, the sufficient participation of mobile workers plays a significant role in the quality of sensing services. Therefore, researchers have studied various incentive mechanisms to motivate mobile workers in the literature. The existing works mostly focus on optimizing one objective function when selecting workers. However, some sensing tasks are associated with more than one objective inherently. This motivates us to investigate bi-objective incentive mechanisms in this work. Specifically, we consider the scenario where the MCS system selects workers by optimizing the completion reliability and spatial diversity of sensing tasks. We first formulate the incentive model with two optimization goals, and then design two online incentive mechanisms based on the reverse auction. We prove that the proposed mechanisms possess desirable properties, including computational efficiency, individual rationality, budget feasibility, truthfulness, and constant competitiveness. The experimental results indicate that the proposed incentive mechanisms can effectively optimize the two objectives simultaneously.**

***Index Terms*—Mobile crowd sensing, online incentive mechanism, bi-objective optimization, worker selection.**

I. Introduction

Mobile crowd sensing (MCS) has become a promising sensing paradigm that can harness the potential of numerous mobile workers to perform location-based tasks thanks to the development of wireless networks and mobile devices [1]. Examples of these tasks include urban traffic information mapping [2], visual summarization of objects [3], object tracking [4], and environment monitoring [5]. With the recent advances of embedded sensors in mobile devices and IoT technologies, MCS is expected to provide more novel spatial-temporal sensing applications for smart cities and facilitate our lives. However, many challenges remain to be addressed before MCS systems can be fully deployed and embraced.

One of the key challenges for MCS systems is the incentive mechanism design because sufficient participation lays the foundation of high-quality sensing services. As workers consume various resources, such as battery power and data transmission cost, and endure the risk of privacy leakage when participating in completing sensing tasks, it is essential to provide them with sufficient rewards through an effective incentive mechanism. Therefore, a large number of incentive mechanisms have been investigated in the literature. These works mostly evaluate the potential of a worker by designing a system objective function and then propose an incentive mechanism to satisfy expected properties.

However, in some MCS scenarios, the sensing tasks possess more than one optimization goal in nature considering the assignment results. For example, for the task of taking photos of a landmark, the task requester is interested in not only collecting the correct photos of the landmark but also obtaining a full view of the landmark from diverse directions. Therefore, in this work, we consider modeling a new incentive framework termed *BiCrowd* for such sensing applications with two optimization goals: (i) Maximizing the reliability of completing sensing tasks. We would like to encourage workers to be responsible for their historical behavior in performing tasks. Specifically, we design a rating and reliability mechanism, in which the requester can rate each worker based on the submitted result. Each rating score the worker gets is recorded and used to calculate the worker's reliability, which affects his probability of being selected in the future. Based on this reliability scheme, we can model the completion reliability of each task, pursuing that the task can be completed successfully. (ii) Maximizing the spatial diversity of selected workers. For MCS tasks such as taking photos of a landmark, the spatial property of the worker has a great influence on the comprehensiveness of the collected photos. Intuitively, workers scattered around the task can report data with different perspectives. Therefore, we also model the spatial diversities of selected workers so that the sensed data can capture the diverse features of the task.

In addition to the optimization model with two objectives, BiCrowd considers the online arrival of workers and is designed based on the online reverse auction, which has been shown to be effective in designing incentive mechanisms with a single objective function [6], [7]. The challenge here is that, as there are two optimization goals in BiCrowd, the mechanism needs to optimize them simultaneously when evaluating the candidate workers and at the same time ensure the desirable properties of an effective incentive mechanism, including *computational efficiency, individual rationality, budget feasibility, truthfulness, and constant competitiveness*.

To accommodate these issues, we propose two online incentive mechanisms termed EpIM and EaIM. EpIM assumes that workers have moderate behaviors and they would like to maximize their expected utility, while EaIM assumes that workers are ambitious and they would try to maximize their possible utility. The main idea behind these two online mechanisms is that, at each time step, we flip a coin with a given probability $\lambda \in [0, 1]$ to select the function of completion reliability as

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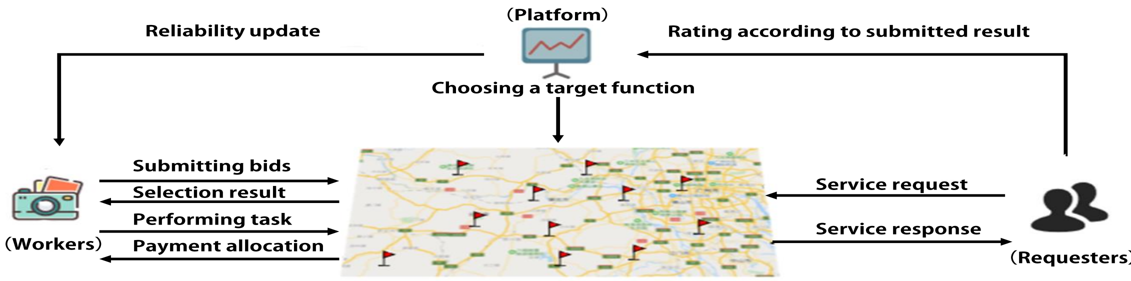


Fig. 1. The interaction flow of BiCrowd.

the evaluation function for the workers; At the same time, naturally, we have the probability $(1-\lambda)$ to select the function of spatial diversity to evaluate the workers at the current time step. After determining the evaluation function, we select the worker for one task only when the budget has not been exhausted and his marginal density is larger than or equal to a certain density threshold. We calculate this density threshold in a way that retains the expected performance properties of the mechanism.

To summarize, the main contributions of this paper are as follows:

- We propose an online bi-objective incentive framework named BiCrowd, which aims to address the incentive issues for MCS systems with two optimization goals and online arriving workers. To the best of our knowledge, this is the first work that considers bi-objective optimization in designing incentive mechanisms for MCS.
- We design two online incentive mechanisms under BiCrowd by considering two kinds of worker behaviors in submitting bidding prices, and we theoretically prove that the proposed incentive mechanisms possess many desirable properties, including computational efficiency, individual rationality, budget feasibility, truthfulness, and constant competitiveness.
- Extensive experimental results based on both synthetic and real-world datasets show that the proposed incentive mechanisms achieve more competitive and balanced results with respect to the two optimization functions simultaneously.

The remainder of this paper is organized as follows: Section II presents the related work. In Section III, we describe the system model of BiCrowd, and formulate the bi-objective optimization problem. We then present the two online mechanisms, EpIM and EaIM, in Section IV and Section V, respectively. In Section VI, we present the experiments. Finally, we conclude this work in Section VII.

II. Related Work

Researchers have devoted a lot of efforts to developing various incentive mechanisms for MCS systems [6], [7]. Considering incentive mechanisms based on reverse auction, Zhao *et al.* [8] design auctions under the scene that workers are dynamically arriving. Zhang *et al.* [9] design a truthful incentive mechanism based on auctions against false-name attacks with some countermeasures. Aiming at the problem of minimizing the social cost in mobile crowdsourcing, Li *et al.* [10] propose a combined random auction mechanism. Cui *et al.* [11] propose a truthful combinatorial auction mechanism to tackle the problem of task allocation in crowdsourcing and maximize the requester's profit. Zhu *et al.* [12] design an incentive mechanism combining reverse auction and Vickvey auction to enhance the fairness of the bidding process. Xu *et al.* [13] balance the utility property and the truthful bidding property by designing a hybrid mechanism. Zhang *et al.* [14] consider the heterogeneous sensing costs in different regions of interest and propose corresponding incentive mechanisms. Liu *et al.* [15] propose an incentive mechanism consisting of two stages based on the reverse auction model for mobile crowd sensing. Ji *et al.* [16] use the reverse auction model to design a mechanism for mobile crowdsensing, reducing the system maintenance cost maximally. These works are related to this paper in that they mostly adopt auction models. However, they only apply for the specific scenario with a single optimization goal. In this work, we accommodate the situation where the system is associated with multiple objective functions for optimization.

The rating and reputation protocols are incorporated when designing incentive mechanisms recently. Xie and Lui [17] propose an incentive and rating mechanism for crowdsourcing systems to incentivize workers to provide high-quality contributions. Wu *et al.* [18] propose a worker selection scheme, where the workers are evaluated according to the task completion status. Hong *et al.* [19] reward workers according to the quality of their sensing data and then propose incentive mechanisms containing a "rating system" and a "task bundling scheme". Xie *et al.* [20] propose an incentive mechanism that encourages the requester to rate the quality of submitted sensing data and then rewards workers based on this rating. These works mostly focus on the rating system. Another direction is to design reputation protocols. Zhang and Schaar [21] design incentive protocols based on reputation mechanisms in crowdsourcing. Lu *et al.* [22] design a novel rating protocol combining the reputation mechanism and the pricing mechanism for applications of crowdsensing. In this work, we incorporate both rating and reliability protocols to evaluate the quality of task completion and resist workers with poor performance.

There are also some research works studying multi-objective optimization in MCS. Cheng *et al.* [23] consider the worker's direction and speed of movement and then propose effective mechanisms to assign spatial tasks to workers, maximizing both the completion reliability and the spatial/temporal diversity of tasks. Zhang *et al.* [24] propose a task assignment model with hybrid sensing tasks and design a heuristic algorithm to maximize both task completion and sensing coverage. Wang *et al.* [25] formally define the heterogeneous spatial crowdsourcing task allocation problem, which has two optimization goals: maximizing the task coverage and minimizing the incentive cost. Zhang *et al.* [26] accommodate two optimization objectives in vehicle-based crowdsensing and propose a greedy heuristic algorithm and a genetic algorithm to efficiently solve the problem. The aforementioned works only focus on task assignment. In this work, we focus on designing incentive mechanisms with desirable properties, and at the same time, the tasks are assigned to the most suitable workers.

III. System Model and Problem Formulation

In this section, we first illustrate the basic system model of BiCrowd and demonstrate the rating and reliability mechanism for evaluating workers. Then, we formulate the online bi-objective optimization problem considering the completion reliability and spatial diversity of sensing tasks. Finally, we introduce the desirable properties of an incentive mechanism.

A. System Model

BiCrowd consists of a platform, task requesters and mobile workers. The platform resides in the cloud, and it collects and organizes sensing tasks from requesters. Specifically, the platform publicizes an MCS campaign which aims to recruit workers to complete a set of sensing tasks $\mathcal{T} = \{t_1, t_2, ..., t_m\}$ before a given deadline D under the budget B. A task $t_j \in \mathcal{T}$ is associated with a specific location and two optimization goals, i.e., the task completion reliability and spatial diversity. The task completion reliability represents the probability that at least one high-quality result will be submitted to the requester. The spatial diversity indicates whether the results come from diverse spatial perspectives. We assume that a group of mobile workers $\mathcal{W} = \{1, 2, ..., n\}$ interested in performing sensing tasks arrive in a random order, where n is unknown. Each worker i has an initial location l_i and a cost c_i for performing a sensing task.

We model the interactions between the platform and workers as an online reverse auction. The workers act as the sellers to send bidding prices to the platform for completing one sensing task, and the platform acts as the buyer to select the valuable workers to complete sensing tasks. Fig. 1 sketches the online reverse auction between the platform and workers. Note that in the auction process, we have also incorporated a feedback component between the platform and requesters in order to pursue a high long-term system utility.

In the auction process, the platform first publicizes an MCS campaign containing the information of sensing tasks. Each worker $i \in \mathcal{W}$ arriving online submits a bidding price b_i to the platform for performing a sensing task $t_j \in \mathcal{T}$. The platform needs to make an irrevocable decision upon receiving worker i's bid based on the evaluation with respect to the system optimization goals. If worker i is selected and assigned to a task, the platform needs to determine the payment p_i for worker i. Worker i performs the assigned task and submits the result, which will be rated by the requester. The platform then updates the reliability of worker i based on the rating from the requester.

We assume that workers are game-theoretic and tend to manipulate their bidding prices so as to maximize their received payments. When interacting with the platform, the true cost c_i of worker i is only known to himself, and the utility of worker i is thus defined as:

$$u_i = \begin{cases} p_i - c_i, & i \in \mathcal{S}, \\ 0, & \text{otherwise}, \end{cases}$$

where $\mathcal{S}$ is the set of workers who are selected.

B. Rating and Reliability Mechanism

In order to achieve a good quality of service of BiCrowd in the long term, we design a rating and reliability mechanism, in which the requester is encouraged to evaluate the worker's performance honestly and the worker is incentivized to make efforts to complete tasks.

1) Rating from the requester: We establish a three-tier rating mechanism that allows the requester to express his satisfaction degree (i.e., bad, normal, or good) to the worker who finishes the assigned task. The three-tier degrees are mapped to numerical values (i.e., bad: 0, normal: 1, good: 2) for simplicity. Intuitively, when a worker gets a score of 0, it means that the requester considers that the result submitted by this worker is of low quality. On the contrary, a score of 2 indicates a high-quality result. Note that in the interaction flow of BiCrowd, the requester needs to transfer the total reward for a task to the platform before the task is allocated, and the reward cannot be revoked. In addition, we assume that the worker-selection process and the rating-process are independent. In other words, requesters have no information about workers and they only rate the received anonymous results. Under these settings, the requester cannot decrease his payment or increase his utility by submitting false ratings.

2) Reliability update for the worker: After a worker completes a task and gets a rating, the platform updates the worker's reliability by the following formula:

$$\mu_i = \frac{\sum_{k=1}^{n_i} r_k/2}{n_i}, \tag{1}$$

where n_i is the total number of tasks completed by worker i and it is also the number of ratings worker i has received, $r_k \in \{0, 1, 2\}$ is one of the historical ratings that worker i gets. A larger r_k indicates a higher quality value. Note that

r_k is upper bounded by 2, hence dividing each rating r_k by 2 normalizes the value of μ_i to the range $[0,1]$. In this way, the computed μ_i in Eqn. (1) can be used as a probability that reflects worker i's reliability. A reliability value closer to 1 indicates that the worker has a higher probability to generate a high-quality sensing result.

C. Platform Utility

In BiCrowd, the platform aims to optimize two objectives, i.e., the completion reliability and spatial diversity of sensing tasks. We formally define these two objectives in the following.

1) Completion reliability: The completion reliability of a task is based on the worker's reliability defined above. Note that not all workers are trustable, but their reliability can reflect the probability of the worker completing a task with high quality. Some workers may always take wrong photos or unclear photos and their reliability values will be low. In such cases, the goal of BiCrowd is to pursue that the sensing tasks can be accomplished by the workers with high reliability.

Definition 1: (Completion Reliability) Given a sensing task t_j and its assigned set of workers $\mathcal{S}_j$, the completion reliability of t_j is given by:

$$CR_{t_j}(\mathcal{S}_j) = 1 - \prod_{\forall i \in \mathcal{S}_j} (1-\mu_i),$$

where μ_i is the reliability of worker i defined in Eqn. (1).

μ_i denotes the probability that worker i can submit a high-quality sensing result and it is computed by the platform. Hence, the second half of the equation, $\prod_{\forall i \in \mathcal{S}_j}(1-\mu_i)$, is the probability that all of the workers in set $\mathcal{S}_j$ will submit fake or low-quality sensing results. Namely, $CR_{t_j}(\mathcal{S}_j)$ reflects the probability that task t_j will obtain at least a high-quality response. For tasks such as taking photos, if there is no clear and correct photo, the requester cannot make a correct judgment about the current situation. High completion reliability heralds that the task will be done well with high probability.

2) Spatial diversity: For tasks like taking photos of a landmark for virtual tour or 3D model reconstruction, photos from the same direction are redundant and of low value. The requester needs photos from diverse spatial directions in order to catch the overall picture of the target of interest. Thus, we define the spatial diversity of tasks to evaluate the adequacy of the selected workers.

Definition 2: (Spatial Diversity) Given a sensing task t_j and its assigned set of workers $\mathcal{S}_j$, we draw $n = |\mathcal{S}_j|$ rays from l_j to the directions of these assigned workers. As shown in Fig. 2, with the n rays, we can obtain n angles by imaging a virtual ray rotating around l_j from any given ray clockwise for 2π. Each time the virtual ray overlaps with a neighboring ray, an angle is determined. We denote the n angles as $a_1, a_2, ..., a_n$, then $\sum_{i=1}^{n} a_i = 2\pi$. The spatial diversity of the sensing task t_j is given by:

$$SD_{t_j}(\mathcal{S}_j) = -\sum_{i=1}^{n} \frac{a_i}{2\pi} \log \frac{a_i}{2\pi},$$

where $\log$ denotes the logarithm of base 2.

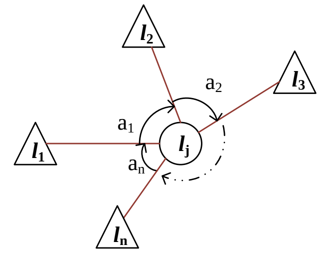


Fig. 2. Approach to space segmentation.

Note that, given the set of assigned workers for a sensing task, the set of constructed angles in Definition 2 is invariant to the labeling of workers. Similar to the definition of entropy, $SD_{t_j}(\mathcal{S}_j)$ represents the diversity of the spatial distribution of the set of selected workers, as demonstrated by the following lemma.

Lemma 3.1: A larger value of $SD_{t_j}(\mathcal{S}_j)$ indicates that the selected workers in $\mathcal{S}_j$ are more diversely distributed around task t_j.

Proof: Let us consider maximizing the value of $SD_{t_j}(\mathcal{S}_j)$, which is equivalent to the following constrained optimization problem:

$$\max \sum_{i=1}^{n} -\frac{a_i}{2\pi} \log \frac{a_i}{2\pi}, \text{ s.t. } \sum_{i=1}^{n} a_i = 2\pi; a_i \geq 0, \forall i.$$

Let $\mathcal{I}(x_i) = x_i \log x_i$ and $x_i = a_i/2\pi$. We simplify the above optimization problem as

$$\min \sum_{i=1}^{n} \mathcal{I}(x_i), \text{ s.t. } \sum_{i=1}^{n} x_i = 1; x_i \geq 0, \forall i,$$

where $\mathcal{I}(x_i)$ is convex as we have $\mathcal{I}''(x_i) = \frac{1}{x_i \ln 2} > 0$. The sum of convex functions $\sum_{i=1}^{n} \mathcal{I}(x_i)$ is also a convex function. Namely, this problem is a convex optimization problem. To prove the lemma, it is now equivalent to show that the minimum value of this convex optimization problem is obtained at the point $x_1 = x_2 = ... = x_n = 1/n$.

We use the Lagrange multiplier method to solve the problem. The Lagrange function is

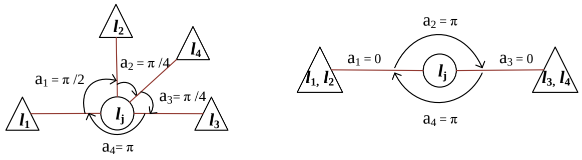
$$L(x,\lambda) = \sum_{i=1}^{n} x_i \log x_i + \lambda(\sum_{i=1}^{n} x_i - 1)).$$

We take partial derivatives for each x_i and get

$$\frac{\partial L(x,\lambda)}{\partial x_i} = \log x_i + \frac{1}{\ln 2} + \lambda = 0.$$

Then we have $x_i = 2^{-\lambda - 1/\ln 2}$. As $\sum_{i=1}^{n} x_i = 1$, we have $n*2^{-\lambda-1/\ln 2} = 1$ and thus $x_i = 1/n, i = 1,2,...,n$. Since the local minimum of the convex function is the global minimum, when $x_1 = x_2 = ... = x_n = 1/n$, $\sum_{i=1}^{n} \mathcal{I}(x_i)$ achieves the minimum value, $\log \frac{1}{n}$. In other words, when $a_1 = a_2 = ... = a_n = 2\pi/n$, $SD_{t_j}(\mathcal{S}_j)$ achieves the maximum value, which completes our proof. ■

Example 1: We give an intuitive example here to show that SD_{t_j} can capture the diversity of locations for a given task t_j.



(a) (b)

Fig. 3. A calculation example of spatial diversity.

Consider Fig. 3(a) where there is one task t_j. Assume there are four workers in the selected set $\mathcal{S}_j$ and $a_1 = \pi/2, a_2 = a_3 = \pi/4, a_4 = \pi$. Then

$$SD_{t_j}(\mathcal{S}_j) = -\frac{1}{4}\log\frac{1}{4} - 2*\frac{1}{8}\log\frac{1}{8} - \frac{1}{2}\log\frac{1}{2} = 1.75.$$

If we consider Fig. 3(b), where two workers are in one spot with respect to the task location and the other two workers are in a diametrically opposite spot, we can obtain $a_1 = \angle l_1 l_j l_2 = 0, a_2 = \angle l_2 l_j l_3 = \pi, a_3 = \angle l_3 l_j l_4 = 0, a_4 = \angle l_4 l_j l_1 = \pi$. Then the spatial diversity is

$$SD_{t_j}(\mathcal{S}_j) = -2*0\log 0 - 2*\frac{1}{2}\log\frac{1}{2} = 1.$$

It can be seen that a higher value of the spatial diversity SD_{t_j} is obtained when workers are more diversely distributed around the task.

3) Bi-objective optimization: Based on the aforementioned definitions, we use $V^1(\mathcal{S}) = \frac{1}{m}\sum_{j=1}^{m} CR_{t_j}(\mathcal{S}_j)$ to denote the average completion reliability of all tasks, and $V^2(\mathcal{S}) = \sum_{j=1}^{m} SD_{t_j}(\mathcal{S}_j)$ to denote the total spatial diversity of all tasks, given the selected worker set $\mathcal{S}$. Then, the goal of the platform is to maximize $V^1(\mathcal{S})$ and $V^2(\mathcal{S})$ given the deadline D and the budget B.

We prove that $V^1(\cdot)$ and $V^2(\cdot)$ are monotone submodular functions, which are important for designing the incentive mechanisms and proving the desirable properties.

Lemma 3.2: The two objective functions $V^1(\cdot)$ and $V^2(\cdot)$ are monotone submodular functions.

Proof: Please refer to Appendix A. ■

D. Desirable Properties

In this work, our purpose is to design online incentive mechanisms based on reverse auction to optimize the aforementioned objectives. The designed mechanisms are expected to satisfy as many of the following properties as possible.

- **Computational Efficiency:** An incentive mechanism is computationally efficient if it gets the result in polynomial time.
- **Individual Rationality:** A mechanism is individually rational if the utility of each worker for performing tasks is nonnegative.
- **Budget Feasibility:** If the sum of all the payments for workers does not exceed the budget of the platform, we call the mechanism budget feasible, i.e.,$\sum_{i\in\mathcal{S}} p_i \leq B$.
- **Truthfulness:** A mechanism is truthful if reporting the true cost is the dominant strategy for every worker, no matter what other workers bid.

TABLE I
NOTATIONS

Symbol	Description
$\mathcal{W}, n, i$	set of workers, number of workers, and one worker
$\mathcal{T}, m, t_j$	set of tasks, number of tasks, and one task
B, B'	budget, each time slot's total budget
B'_1, B'_2	each time slot's total budget for each objective function
D, D', d	deadline, each time slot's end time and each time step
b_i, c_i, p_i	bid, cost, payment of worker i
μ_i, r_i, l_i	reliability, rating, location of worker i
$u_i, \mathbb{E}[u_i]$	utility, expected utility of worker i
$\mathcal{S}, \mathcal{S}', \mathcal{S}_j$	set selected workers, sample set of workers, set of task t_j's selected workers
$\mathcal{S}^1, \mathcal{S}^2$	set of selected workers of two optimization goals
$V^1(\mathcal{S})$	average completion reliability over $\mathcal{S}$
$V^2(\mathcal{S})$	total spatial diversity over $\mathcal{S}$
$V_i^1(\mathcal{S})$	maximal marginal value of worker i over $\mathcal{S}$ w.r.t. $V^1(\cdot)$
$V_i^2(\mathcal{S})$	maximal marginal value of worker i over $\mathcal{S}$ w.r.t. $V^2(\cdot)$
λ	probability of choosing $V^1(\cdot)$ as the optimization goal
ρ_1^*, ρ_2^*	density threshold for two optimization goals
σ_1, σ_2	parameters used for computing the density threshold
κ	parameter assumed on workers' value

- **Competitiveness:** Given an objective function f, a mechanism is said to be α-competitive if it selects a worker set $\mathcal{S}$ such that $\alpha f(\mathcal{S}) \geq f(\mathcal{S}^*)$, where $\mathcal{S}^*$ is the optimal solution: the solution obtainable in the offline scenario where the platform has full knowledge about workers' bidding information.

IV. Expected Bi-objective Truthful Incentive Mechanism

In existing incentive mechanisms for MCS, the common strategy to select workers with one objective function is to greedily select the worker who can bring the largest increment of the objective function value. However, in BiCrowd, there are two objectives for optimization. If we directly try to select workers regarding the two objectives, it becomes difficult to compare the workers because they can generate nondominant function value increments. Therefore, we adopt a coin-flipping strategy to select one objective function for worker evaluation at each time step of the reverse auction. More specifically, we flip a coin with a given probability $\lambda \in [0,1]$ to select $V^1(\cdot)$ as the evaluation function for the workers; At the same time, we have the probability $(1-\lambda)$ to select $V^2(\cdot)$ as the evaluation function.

Under this selection strategy, reasonable workers may try to maximize their expected utility values when submitting their bids. Specifically, based on the definition of the worker's utility, the expected utility of worker i can be defined as:

$$\mathbb{E}[u_i] = \lambda u_i^1 + (1-\lambda)u_i^2,$$

where u_i^1 and u_i^2 are the utility values of worker i when he is evaluated by $V^1(\cdot)$ and $V^2(\cdot)$, respectively.

To accommodate this kind of strategic behaviors, we design the **exp**ected bi-objective truthful **i**ncentive **m**echanism (EpIM) in the following.

A. Mechanism design

In an online reverse auction, to make informative decisions on selecting workers, the platform usually adopts a sampling-accepting strategy. Specifically, the platform observes a portion

Algorithm 1 EpIM

Input: Budget constraint B, deadline D.

Output: Set of selected workers $\mathcal{S}$ and each worker's payment.

1: $(d, D', B', \mathcal{S}', \mathcal{S}) \leftarrow (1, \frac{D}{2^{\lfloor \log_2 D \rfloor}}, \frac{B}{2^{\lfloor \log_2 D \rfloor}}, \emptyset, \emptyset)$;
2: $(\rho_1^*, \rho_2^*, \omega, \beta, \mathcal{S}^1, \mathcal{S}^2) \leftarrow (\alpha_1, \alpha_2, 0, 0, \emptyset, \emptyset)$;
3: **while** $d \le D$ **do**
4: Let $0 \le X \le 1$ be a uniformly random value;
5: **if** $X \le \lambda$ **then**
6: $\omega \leftarrow 1; \beta \leftarrow \lambda$;
7: **else**
8: $\omega \leftarrow 2; \beta \leftarrow 1 - \lambda$;
9: **end if**
10: **while** *there is a worker i arriving at time step d* **do**
11: $j \leftarrow \arg\max_{t_k \in \mathcal{T}} (V^\omega(\mathcal{S}_k \cup i) - V^\omega(\mathcal{S}_k))$;
12: **if** $b_i \le V_i^\omega(\mathcal{S})/\rho_\omega^* \le \beta B' - \sum_{k \in \mathcal{S}^\omega} p_k$ **then**
13: $p_i \leftarrow V_i^\omega(\mathcal{S})/\rho_\omega^*$;
14: $\mathcal{S}_j \leftarrow \mathcal{S}_j \cup i; \mathcal{S}^\omega \leftarrow \mathcal{S}^\omega \cup i$;
15: **else** $p_i \leftarrow 0$;
16: **end if**
17: $\mathcal{S}' \leftarrow \mathcal{S}' \cup i$;
18: **end while**
19: **if** $d = \lfloor D' \rfloor$ **then**
20: $\rho_1^* \leftarrow$ **getDensityThreshold**$(B', \mathcal{S}', 1)$;
21: $\rho_2^* \leftarrow$ **getDensityThreshold**$(B', \mathcal{S}', 2)$;
22: $D' \leftarrow 2D'$; $B' \leftarrow 2B'$;
23: **end if**
24: $d \leftarrow d + 1$;
25: **end while**

of the online arriving workers (sampling stage) and then make informed decisions on the workers arriving later based on the observation (accepting stage). Here we also apply this strategy to design EpIM. The time interval is organized into multiple stages: $\{1, 2, ..., \lfloor \log_2 D \rfloor, \lfloor \log_2 D \rfloor + 1\}$. Each stage s ends at time $D' = \lfloor 2^{s-1} D / 2^{\lfloor \log_2 D \rfloor} \rfloor$ and the budget for s is $B' = \lfloor 2^{s-1} B / 2^{\lfloor \log_2 D \rfloor} \rfloor$. Note that, as we allocate budget for each stage, the workers arriving at each stage have chances to be selected and paid by the platform under EpIM.

Algorithm 1 demonstrates the main procedure of EpIM. At each time step d, we generate a random number X for selecting the objective function at the current time step (Line 4). If $X \le \lambda$, we set $\omega = 1$, which means that we select the objective function $V^1(\cdot)$ for worker evaluation; Otherwise, we select $V^2(\cdot)$ as the objective function and we set $\omega = 2$. At the same time, we divide the budget at each time step into two parts for each objective function according to the value of λ (Lines 5-9).

At each time step, we scan arriving workers one by one. We find the task that maximizes the marginal value for worker i and calculate worker i's maximal marginal value $V_i^\omega(\mathcal{S})$ (the while-loop in Lines 10-18). According to the definitions of $V^1(\cdot)$ and $V^2(\cdot)$, the maximal marginal value $V_i^1(\mathcal{S}) = \max_{t_j \in \mathcal{T}} \frac{V^1(\mathcal{S}_j \cup i) - V^1(\mathcal{S}_j)}{m}$ and $V_i^2(\mathcal{S}) = \max_{t_j \in \mathcal{T}} V^2(\mathcal{S}_j \cup i) - V^2(\mathcal{S}_j)$. If worker i's maximal marginal density $V_i^\omega(\mathcal{S})/b_i$ is larger than or equal to the current density threshold ρ_ω^* and

Algorithm 2 getDensityThreshold

Input: Stage budget B', sample set $\mathcal{S}'$, selected objective function V^ω.

Output: ρ/σ_ω.

$\mathcal{F} = \{\mathcal{F}_1, \mathcal{F}_2, ..., \mathcal{F}_m\} \leftarrow \{\emptyset, \emptyset, ..., \emptyset\}$;
$i \leftarrow \arg\max_{k \in \mathcal{S}'} (V_k^\omega(\mathcal{F})/b_k)$;
$j \leftarrow \arg\max_{t_k \in \mathcal{T}} (V^\omega(\mathcal{F}_k \cup i) - V^\omega(\mathcal{F}_k))$;
while $b_i \le \frac{V_i^\omega(\mathcal{F}) B'}{V^\omega(\mathcal{F} \cup i)}$ **do**
$\mathcal{F}_j \leftarrow \mathcal{F}_j \cup i$;
$i \leftarrow \arg\max_{k \in \mathcal{S}'} (V_k^\omega(\mathcal{F})/b_k)$;
$j \leftarrow \arg\max_{t_k \in \mathcal{T}} (V^\omega(\mathcal{F}_k \cup i) - V^\omega(\mathcal{F}_k))$;
end while
$\rho \leftarrow V^\omega(\mathcal{F})/B'$;

the budget of this stage $\beta B'$ has not been exhausted, we select him and give him a payment $p_i = V_i^\omega(\mathcal{S})/\rho_\omega^*$. If we choose the objective function $V^1(\cdot)$, we add the selected worker to $\mathcal{S}^1$, otherwise we add him to $\mathcal{S}^2$. Note that, at the beginning of EpIM, we initially set two small density thresholds $\alpha_1 = 0.5$ and $\alpha_2 = 0.5$, which are used for making decisions at the first stage. After observing and evaluating online arriving workers, we add all of them to the sample set $\mathcal{S}'$, which is used to calculate the more informative density threshold for the following stages.

When a stage ends, namely $d = \lfloor D' \rfloor$, we update the density threshold. As illustrated in Algorithm 2, we utilize a *proportional share allocation* rule to calculate the density threshold according to the sample set $\mathcal{S}'$ and the allocated stage budget B'. The computation process adopts a greedy strategy: the workers in $\mathcal{S}'$ are sorted based on their marginal densities. We select the workers from the beginning of the sorted worker sequence, and stop the selection process until we find worker i and his subsequent worker i', such that $b_i \le \frac{V_i^\omega(\mathcal{F}) B'}{V^\omega(\mathcal{F} \cup i)}$ and $b_{i'} > \frac{V_{i'}^\omega(\mathcal{F}) B'}{V^\omega(\mathcal{F} \cup i')}$. Note that the result of $\mathcal{F} \cup i$ is equivalent to $\{\mathcal{F}_1, ..., \mathcal{F}_j \cup i, ..., \mathcal{F}_m\}$, since $\mathcal{F}_j$ is a part of $\mathcal{F}$ and j represents the task that maximizes the marginal value of worker i. Finally, the density threshold is set to be $\frac{V^\omega(\mathcal{F})}{\sigma_\omega B'}$, where $\sigma_\omega > 1$. The value of σ_ω will influence the competitive ratio of our algorithm and we will fix it later to achieve a constant competitive ratio.

B. Mechanism Analysis

We show that EpIM satisfies computational efficiency, individual rationality, budget feasibility, truthfulness, and constant competitiveness in this section.

Lemma 4.1: EpIM is computationally efficient.

Proof: At each time step d, the *while* loop (Lines 10-18) and the function $getDensityThreshold$ are the two parts with the highest computation complexity. At first, we analyze the computational complexity of the *while* loop. For $j \leftarrow \arg\max_{t_k \in \mathcal{T}} (V^\omega(\mathcal{S}_k \cup i) - V^\omega(\mathcal{S}_k))$, finding the task that maximizes the marginal value for worker i needs to match the worker to each task and select the maximal value. Thus this process is bounded by $O(m)$. As the number of workers arriving at the time step d must be less than the total number of workers n, the process of worker selection and payment allocation has a computation complexity bounded by $O(mn)$. Next, we analyze the complexity of computing the density threshold (Algorithm 2). Finding worker i with the highest marginal threshold takes $O(m|\mathcal{S}'|)$ and obviously $|\mathcal{S}'| \leq n$, thus this part is bounded by $O(mn)$. Besides, there is no more than $\mathcal{S}'$ winners, thus the computation complexity in the *while* loop (Lines 4-8) is bounded by $O(mn^2)$. In conclusion, EpIM satisfies computational efficiency. ∎

Lemma 4.2: EpIM is individually rational.

Proof: From Line 13 in Algorithm 1, we can see that if worker i is selected, $p_i \geq b_i$; otherwise $p_i = 0$. Thus the utility of worker i is always nonnegative. ∎

Lemma 4.3: EpIM is budget-feasible.

Proof: At each stage, we have a budget B'. From Line 12 in Algorithm 1, for the objective function $V^1(\cdot)$, we select a worker only when $\lambda B'$ has not been exhausted, and for $V^2(\cdot)$, our cost cannot exceed $(1-\lambda)B'$. Thus, each stage is budget feasible and the total payment will not exceed B. ∎

Note that for a truthful mechanism, a worker cannot improve his utility by submitting a bidding price deviating from his true cost, no matter what bids the other workers submit. In our bi-objective optimization problem, we have assumed that workers try to maximize their expected utility when submitting their bids. Thus we define the expected truthfulness considering the bi-objective optimization model accordingly. Specifically, if worker i reporting any $b_i \neq c_i$ cannot improve his expected utility, we call the mechanism is expectedly truthful.

Lemma 4.4: EpIM is expectedly truthful.

Proof: Consider worker i arriving at some stage, which has the density thresholds ρ_1^* and ρ_2^*. Without loss of generality, we set $\lambda = 0.5$. If there is no budget left when worker i arrives, his bidding price does not have an influence on the allocation result and thus cannot improve his utility. If there are some budget for recruitment, we consider three cases regarding the worker's cost.

Case (a): $c_i \leq V_i^1(\mathcal{S})/\rho_1^*$ and $c_i \leq V_i^2(\mathcal{S})/\rho_2^*$. If the worker reports $b_i = c_i$, his expected utility is $\mathbb{E}[u_i] = 0.5(V_i^1(\mathcal{S})/\rho_1^* - c_i) + 0.5(V_i^2(\mathcal{S})/\rho_2^* - c_i)$. If he reports any cost between c_i and $\min\{V_i^1(\mathcal{S})/\rho_1^*, V_i^2(\mathcal{S})/\rho_2^*\}$ or reports any cost below c_i, his expected utility will not change because the payment determination of EpIM does not depend on the worker's bid. Declaring a cost above $\min\{V_i^1(\mathcal{S})/\rho_1^*, V_i^2(\mathcal{S})/\rho_2^*\}$, he will lose the possibility of being selected by the corresponding objective function and his expected utility is at most $0.5(max\{V_i^1(\mathcal{S})/\rho_1^*, V_i^2(\mathcal{S})/\rho_2^*\} - c_i) < 0.5(V_i^1(\mathcal{S})/\rho_1^* + V_i^2(\mathcal{S})/\rho_2^*) - c_i$. Thus, there is no strategy better than reporting $b_i = c_i$.

Case (b): $V_i^1(\mathcal{S})/\rho_1^* \leq c_i \leq V_i^2(\mathcal{S})/\rho_2^*$ or $V_i^2(\mathcal{S})/\rho_2^* \leq c_i \leq V_i^1(\mathcal{S})/\rho_1^*$. We only discuss the first case as the proof is the same for the second case. Reporting any cost in $[V_i^1(\mathcal{S})/\rho_1^*, V_i^2(\mathcal{S})/\rho_2^*]$ will not make a difference considering the worker's expected utility $\mathbb{E}[u_i] = 0(V_i^1(\mathcal{S})/\rho_1^* - c_i) + 0.5(V_i^2(\mathcal{S})/\rho_2^* - c_i)$. If the worker reports $b_i < V_i^1(\mathcal{S})/\rho_1^*$, he can be selected by $V^1(\mathcal{S})$ and his expected utility $\mathbb{E}[u_i] = 0.5(V_i^1(\mathcal{S})/\rho_1^* - c_i) + 0.5(V_i^2(\mathcal{S})/\rho_2^* - c_i)$, where the component $V_i^1(\mathcal{S})/\rho_1^* - c_i < 0$. It can be seen that the value of $\mathbb{E}[u_i]$ decreases. On the other hand, if the worker reports $b_i > V_i^2(\mathcal{S})/\rho_2^*$, he will not be selected and his expected utility will be zero. Thus, in this case, reporting $b_i = c_i$ is a dominating strategy.

Case (c): $c_i > \max\{V_i^1(\mathcal{S})\rho_1^*, V_i^2(\mathcal{S})\rho_2^*\}$. In this case, since $V_i^1(\mathcal{S})\rho_1^* - c < 0$ and $V_i^2(\mathcal{S})\rho_2^* - c < 0$, the worker's expected utility will always be negative and there is no chance to improve the utility.

Combining cases (a), (b) and (c), we complete our proof. ∎

Algorithm 3 Proportional Share Mechanism (offline) [27]

Input: Budget constraint B, worker set $\mathcal{W}$, task set $\mathcal{T}$

Output: Set of selected workers $\mathcal{S}$ and each worker's payment.

*/*winner selection phase*/*
$\mathcal{S} = \{\mathcal{S}_1, \mathcal{S}_2, ..., \mathcal{S}_m\} \leftarrow \{\emptyset, \emptyset, ..., \emptyset\}$;
$i \leftarrow \arg\max_{k \in \mathcal{W}}(V_k^1(\mathcal{S})/b_k)$;
$j \leftarrow \arg\max_{t_k \in \mathcal{T}}(V^1(\mathcal{S}_k \cup i) - V^1(\mathcal{S}_k))$;
while $b_i \leq \frac{V_i^1(\mathcal{S})B}{V^1(\mathcal{S} \cup i)}$ **do**
  $\mathcal{S}_j \leftarrow \mathcal{S}_j \cup i$;
  $i \leftarrow \arg\max_{k \in \mathcal{W} \setminus \mathcal{S}}(V_k^1(\mathcal{S})/b_k)$;
  $j \leftarrow \arg\max_{t_k \in \mathcal{T}}(V^1(\mathcal{S}_k \cup i) - V^1(\mathcal{S}_k))$;
end while
*/*payment determination phase*/*
for $i \in \mathcal{W}$ **do**
  $p_i \leftarrow 0$;
end for
for $i \in \mathcal{S}$ **do**
  $\mathcal{W}' \leftarrow \mathcal{W} \setminus \{i\}$;
  $\mathcal{Q} = \{\mathcal{Q}_1, \mathcal{Q}_2, ..., \mathcal{Q}_m\} \leftarrow \{\emptyset, \emptyset, ..., \emptyset\}$;
  $i_j \leftarrow \arg\max_{j \in \mathcal{W}'}(V_j^1(\mathcal{Q})/b_j)$;
  $i_k \leftarrow \arg\max_{t_k \in \mathcal{T}}(V^1(\mathcal{S}_k \cup i) - V^1(\mathcal{S}_k))$;
  while $b_i \leq \frac{V_{i_j}^1(\mathcal{Q}_{j-1})B}{V^1(\mathcal{Q})}$ **do**
    $\mathcal{Q}_{i_k} \leftarrow \mathcal{Q}_{i_k} \cup i_j$;
    $p_i \leftarrow \max\{p_i, \min\{b_{i(j)}, \eta_{i(j)}\}\}$;
    $i_j \leftarrow \arg\max_{j \in \mathcal{W}' \setminus \mathcal{Q}}(V_j^1(\mathcal{Q})/b_j)$;
    $i_k \leftarrow \arg\max_{t_k \in \mathcal{T}}(V^1(\mathcal{S}_k \cup i) - V^1(\mathcal{S}_k))$;
  end while
end for

Before proving the competitiveness of EpIM, we first introduce an offline mechanism [27] sketched in Algorithm 3. This mechanism includes the winner selection and payment determination phases. The winner selection phase works as Algorithm 2, and the payment determination phase adopts the critical value strategy to ensure the truthfulness of the mechanism. As this offline mechanism has been proved to be $O(1)$-competitive, if we can prove that compared with this mechanism, EpIM is $O(1)$-competitive, then EpIM has a constant competitive ratio compared to the optimal solution.

Now we first consider the objective function $V^1(\cdot)$, which is also used as the objective function of Algorithm 3 here. Assume $\mathcal{Q}$ is the set of selected workers calculated by Algorithm 3 and $\rho_1 = V^1(\mathcal{Q})/B$ is the density of $\mathcal{Q}$. We use $\mathcal{Q}$'s subsets $\mathcal{Q}_1$ and $\mathcal{Q}_2$ denote the selected workers that appear in the first and second half before the deadline, respectively. When the $\lfloor \log_2 D \rfloor$-th stage is over, the workers who arrive before time $\lfloor D/2 \rfloor$ are all in the sample set S'. Define $\mathcal{Q}_1'$

as the set of selected workers calculated by Algorithm 2 according to the stage budget $B/2$ and the sample set S'. The density of $\mathcal{Q}_1'$ is $\rho_1' = 2V^1(\mathcal{Q}_1')/B$. The last stage's density threshold will be $\rho_1^* = \rho_1'/\sigma_1$. Define $\mathcal{Q}_2'$ as the set of selected workers calculated by Algorithm 1 at the last stage. Besides, we assume that each worker's marginal value is at most $V^1(\mathcal{Q})/\kappa$, in which κ is a parameter that will be determined later.

We assume that all workers arrive in a random order and their reliability values, spatial locations and arrival times are i.i.d.. Namely, the workers have the same probability to be selected in the set $\mathcal{Q}$. Hence, we can get $\mathbb{E}[|\mathcal{Q}_1|] = \mathbb{E}[|\mathcal{Q}_2|] = |\mathcal{Q}|/2$. By the submodularity of $V^1(\cdot)$, we have $\mathbb{E}[V^1(\mathcal{Q}_1)] = \mathbb{E}[V^1(\mathcal{Q}_2)] \geq \mathbb{E}[V^1(\mathcal{Q})]/2$. Because $\mathcal{Q}_1'$ is the set of selected workers calculated optimally by Algorithm 2 with a stage budget $B/2$, we then have $\mathbb{E}[V^1(\mathcal{Q}_1')] \geq \mathbb{E}[V^1(\mathcal{Q}_1)] \geq V^1(\mathcal{Q})/2$ and $\mathbb{E}[\rho_1'] = 2\mathbb{E}[V^1(\mathcal{Q}_1')]/B \geq V^1(\mathcal{Q})/B \geq \rho$. Now, if we can prove that the ratio of $\mathbb{E}[V^1(\mathcal{Q}_1')]$ and $\mathbb{E}[V^1(\mathcal{Q}_2')]$ is a constant, then EpIM is $O(1)$-competitive compared to the offline mechanism.

Lemma 4.5: Under the i.i.d. model, if κ is sufficiently large, the ratio of $\mathbb{E}[V^1(\mathcal{Q}_2')]$ to $\mathbb{E}[V^1(\mathcal{Q}_1')]$ is at least a constant. Specifically, this ratio approaches $\frac{\lambda}{2(1+\lambda)}$ as $\kappa \to \infty$ and $\sigma_1 \to 2(1+\lambda)$.

To keep the fluency of the content, the proof of lemma 4.5 is given in Appendix B. Similarly, we can prove the following lemma considering the objective function $V^2(\cdot)$.

Lemma 4.6: Under the i.i.d. model, for a sufficiently large κ, the ratio of $\mathbb{E}[V^2(\mathcal{Q}_2')]$ to $\mathbb{E}[V^2(\mathcal{Q}_1')]$ is at least a constant. Specifically, this ratio approaches $\frac{1-\lambda}{2(2-\lambda)}$ as $\kappa \to \infty$ and $\sigma_2 \to 2(2-\lambda)$.

Based on the above analysis and Lemma 4.5 and Lemma 4.6, we have completed proving that EpIM is constantly competitive with respect to both objective functions.

Theorem 4.1: EpIM satisfies computational efficiency, individual rationality, budget feasibility, expected truthfulness, and constant competitiveness.

V. Exact Bi-Objective Truthful Incentive Mechanism

In this section, we study the scenario where workers have ambitious bidding behaviors. As the MCS platform has two objectives and the importance of the marginal value of a worker for each objective is usually different, the aggressive worker may try to manipulate his bidding price to pursue a higher payment, assuming that he can be selected by the objective which gives him a higher evaluation value. We use the following example to discuss this issue if EpIM is applied:

Example 2: Consider that the platform has density thresholds $\rho_1^* = 0.75$ *and* $\rho_2^* = 0.5$ *at the current stage. Given the arriving worker i, we assume that* $V_i^1(\mathcal{S}) = V_i^2(\mathcal{S}) = 1$ *and* $b_i = c_i = 1$. *By the time the platform evaluates the worker, if* $X \leq \lambda$, *we select* $V^1(\cdot)$ *for worker evaluation. Because* $V_i^1(\mathcal{S})/\rho_1^* = 1.333 > b_i$, *he will be selected and his payment will be* 1.333 *and the utility will be* $u_i = 0.333$. *If* $b_i > 1.333$, *he will be refused. In this case, the platform remains truthful. However, the platform now also has the probability of choosing* $V^2(\cdot)$ *for worker evaluation, in this case, the worker will also be selected and given a payment 2 and the utility will be improved to 1. Thus,* $p_i = 1.333$ *is not a critical value, and reporting* $1.333 < b_i < 2$ *will improve the worker's utility with the probability* $(1-\lambda)$.

Algorithm 4 EaIM

Input: Budget constraint B, deadline D.
Output: Set of selected workers $\mathcal{S}$ and each worker's payment.

$(d, D', B', \mathcal{S}', \mathcal{S}) \leftarrow (1, \frac{D}{2^{\lfloor \log_2 D \rfloor}}, \frac{B}{2^{\lfloor \log_2 D \rfloor}}, \emptyset, \emptyset)$;
$(\rho_1^*, \rho_2^*, \omega) \leftarrow (\alpha, \alpha, 0)$;
while $d \leq D$ **do**
  Let $0 \leq X \leq 1$ be a uniformly random value;
  if $X \leq \lambda$ **then**
    $\omega \leftarrow 1$;
  else
    $\omega \leftarrow 2$;
  end if
  while *there is a worker i arriving at time step* d **do**
    $j \leftarrow \arg\max_{t_k \in \mathcal{T}} (V^\omega(\mathcal{S}_k \cup i) - V^\omega(\mathcal{S}_k))$;
    if $b_i \leq \max\{\frac{V_i^1(\mathcal{S})}{\rho_1^*}, \frac{V_i^2(\mathcal{S})}{\rho_2^*}\} \leq B' - \sum_{k \in \mathcal{S}} p_k$ **then**
      $p_i \leftarrow \max\{\frac{V_i^1(\mathcal{S})}{\rho_1^*}, \frac{V_i^2(\mathcal{S})}{\rho_2^*}\}$;
      $\mathcal{S}_j \leftarrow \mathcal{S}_j \cup i$;
    else $p_i \leftarrow 0$;
    end if
    $\mathcal{S}' \leftarrow \mathcal{S}' \cup i$;
  end while
  if $d = \lfloor D' \rfloor$ **then**
    $\rho_1^* \leftarrow$ **getDensityThreshold**$(B', \mathcal{S}', 1)$;
    $\rho_2^* \leftarrow$ **getDensityThreshold**$(B', \mathcal{S}', 2)$;
    $D' \leftarrow 2D'$; $B' \leftarrow 2B'$;
  end if
  $d \leftarrow d + 1$;
end while

To accommodate this issue, we design the **exa**ct bi-objective truthful **i**ncentive **m**echanism (EaIM) here to guarantee the exact truthfulness with respect to the bi-objective platform. In other words, the mechanism ensures that the worker does not have any chance to improve his payment by submitting a bidding price deviating from his true cost.

A. Mechanism Design

In order to hold the desirable properties, we continue using the algorithm framework of EpIM. Meanwhile, in order to guarantee the property of exact truthfulness, we need to modify EpIM based on the following principle: the payment for each selected worker should be a critical value no matter which objective function is adopted to evaluate the worker.

EaIM is described in Algorithm 4. At the beginning of the mechanism, we take a random number X and set the value of ω similar to Algorithm 1. If $X \leq \lambda$, we select the objective function $V^1(\cdot)$ for worker evaluation and set $\omega = 1$, otherwise we select the objective function $V^2(\cdot)$ and set $\omega = 2$. Then, we scan arriving workers one by one. If the worker's marginal density on any of the objective functions ($V^1(\cdot)$ or $V^2(\cdot)$)

is greater than or equal to the threshold, he will be selected and given a payment $p_i = \max\{\frac{V_i^1(\mathcal{S})}{\rho_1^*}, \frac{V_i^2(\mathcal{S})}{\rho_2^*}\}$, which is the largest payment he can get. At the same time, we add the selected worker into the corresponding set $\mathcal{S}_j$. At the end of EaIM, we calculate the density threshold using the same procedure in Algorithm 1.

Now we consider *Example 2* again by running EaIM. If worker i reports $b_i = c_i = 1$, regardless of whether he is selected by $V^1(\cdot)$ or $V^2(\cdot)$, he will receive a payment $p_i = 2$ and the utility is $u_i = 2 - 1 = 1$. If the worker reports a bid larger than 2, he will not be selected by either objective function. If the worker reports $b_i = 1.5$, his utility is also $u_i = 2 - 1 = 1$ since $1.5 < \max\{1.333, 2\}$. The worker cannot improve his utility by reporting a fake cost.

B. Mechanism Analysis

In this section, we prove that EaIM satisfies computational efficiency, individual rationality, budget feasibility, and exact truthfulness.

Lemma 5.1: EaIM is computationally efficient.

Proof: In Line 12 of EaIM, for all the workers arriving at time step d, we need to calculate $\max\{\frac{V_i^1(\mathcal{S})}{\rho_1^*}, \frac{V_i^2(\mathcal{S})}{\rho_2^*}\}$, which is bounded by $O(mn)$. The other parts in EaIM is consistent with EpIM, and thus EaIM is also bounded by $O(mn^2)$. ■

Lemma 5.2: EaIM is individually rational.

Proof: From Line 13 in Algorithm 4, it can be seen that if worker i is selected, he will get a payment $p_i = \max\{\frac{V_i^1(\mathcal{S})}{\rho_1^*}, \frac{V_i^2(\mathcal{S})}{\rho_2^*}\}$, otherwise $p_i = 0$. The utility of worker i is

$$u_i = \begin{cases} \max\{\frac{V_i^1(\mathcal{S})}{\rho_1^*}, \frac{V_i^2(\mathcal{S})}{\rho_2^*}\} - c_i, & i \in \mathcal{S}, \\ 0, & \text{otherwise.} \end{cases}$$

As $\max\{\frac{V_i^1(\mathcal{S})}{\rho_1^*}, \frac{V_i^2(\mathcal{S})}{\rho_2^*}\} \geq b_i$, in this case, we have $u_i \geq 0$. Therefore, the proposed mechanism is individually rational. ■

Lemma 5.3: EaIM is budget feasible.

Proof: Although the process of allocating payments has changed compared to EpIM, selecting a worker is always under the condition $B' - \sum_{k\in\mathcal{S}} p_k$, which means that we cannot exceed the stage budget. Thus, the whole process is budget feasible. ■

Lemma 5.4: EaIM is exact truthful.

Proof: Consider worker i with bid b_i and true cost c_i. We show that at time step d, reporting the true cost is a dominant strategy for worker i by discussing the following cases.

Case (a): If the budget has been exhausted when the worker arrives, no matter how much he bids, the platform will not choose him, so he has no way to improve his earnings. In other cases, we assume $c_i \leq B' - \sum_{k\in\mathcal{S}} p_k$.

Case (b): Consider $c_i \leq \max\{\frac{V_i^1(\mathcal{S})}{\rho_1^*}, \frac{V_i^2(\mathcal{S})}{\rho_2^*}\}$. Worker i will be chosen no matter which objective function is used and his payment is always $\max\{\frac{V_i^1(\mathcal{S})}{\rho_1^*}, \frac{V_i^2(\mathcal{S})}{\rho_2^*}\}$. His utility will be $u_i = \max\{\frac{V_i^1(\mathcal{S})}{\rho_1^*}, \frac{V_i^2(\mathcal{S})}{\rho_2^*}\} - c_i$. Reporting any bid $b_i \leq \max\{\frac{V_i^1(\mathcal{S})}{\rho_1^*}, \frac{V_i^2(\mathcal{S})}{\rho_2^*}\}$ will not make a difference to his utility. Besides, any bid $b_i \geq \max\{\frac{V_i^1(\mathcal{S})}{\rho_1^*}, \frac{V_i^2(\mathcal{S})}{\rho_2^*}\}$ will let him lose the auction and the utility will drop to 0.

Case (c): Consider $c_i > \max\{\frac{V_i^1(\mathcal{S})}{\rho_1^*}, \frac{V_i^2(\mathcal{S})}{\rho_2^*}\}$. In this case a truthful bidder has $b_i > \max\{\frac{V_i^1(\mathcal{S})}{\rho_1^*}, \frac{V_i^2(\mathcal{S})}{\rho_2^*}\}$, and the worker will not be selected. The worker can report a lower bid such that he will be selected and get a payment. If he reports a bid $b_i \leq \max\{\frac{V_i^1(\mathcal{S})}{\rho_1^*}, \frac{V_i^2(\mathcal{S})}{\rho_2^*}\}$. His utility at time step d is $u_i = \max\{\frac{V_i^1(\mathcal{S})}{\rho_1^*}, \frac{V_i^2(\mathcal{S})}{\rho_2^*}\} - c_i$. Because $c_i > \max\{\frac{V_i^1(\mathcal{S})}{\rho_1^*}, \frac{V_i^2(\mathcal{S})}{\rho_2^*}\}$, his utility becomes negative.

In summary, reporting a fake cost cannot improve the worker's utility. ■

Theorem 5.1: EaIM satisfies computational efficiency, individual rationality, budget feasibility, and exact truthfulness.

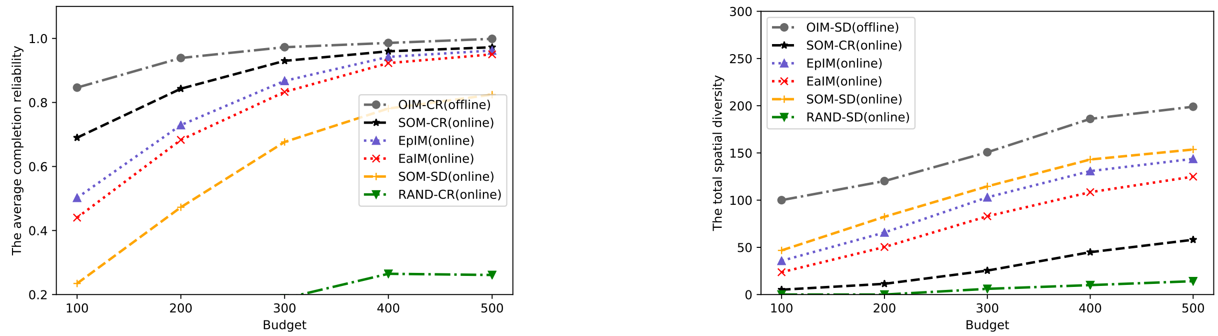
VI. EXPERIMENT

In this section, we evaluate the performance of EpIM and EaIM with three benchmarks concerning the two optimization goals. The first benchmark is the single objective online mechanism (SOM) proposed in [8]. The second benchmark is the offline incentive mechanism (OIM) introduced in Algorithm 3, which has full knowledge of workers' bidding information and thus is used as an upper bound for the online incentive mechanisms. The last benchmark is the random selection mechanism (RAND). RAND simply selects workers based on a fixed density threshold and is used as a lower bound. We implement the above mechanisms by using $V^1(\cdot)$ and $V^2(\cdot)$ as the objective functions, respectively, generating six implementations: SOM-CR, SOM-SD, OIM-CR, OIM-SD, RAND-CR, and RAND-SD.

A. Experimental Setup

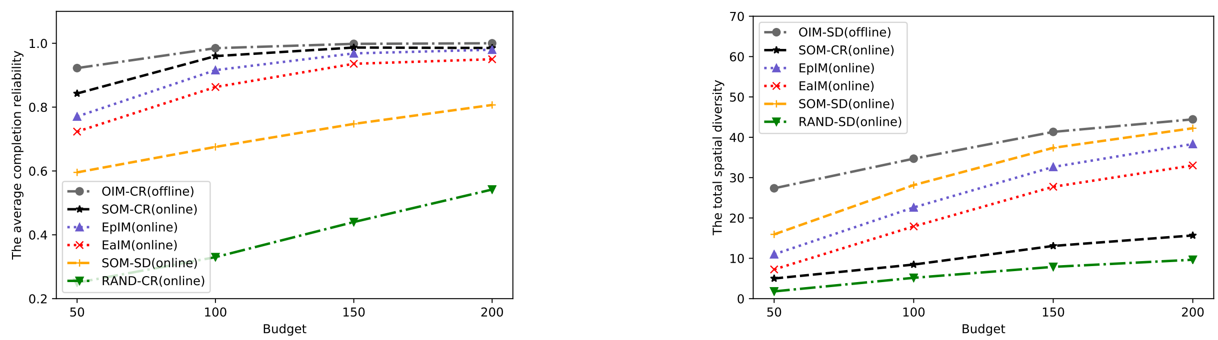
We conduct experiments with both synthetic and real datasets. For the synthetic data, we generate locations of workers and tasks in a 2D space $[0, 5000]^2$. We generate 100 tasks (m=100) in total, setting the deadline $D = 1000s$ and varying the budget B from 0 to 500. The worker's arrival time satisfies the uniform distribution and we vary the number of workers from 200 to 800 with an increment of 200. Each worker is placed at a random location when he arrives. Each worker's cost is uniformly distributed between $[1, 10]$. As we have proved earlier, when $\sigma_1 \to 2(1+\lambda)$, $\sigma_2 \to 2(2-\lambda)$ and κ is sufficiently large, EpIM is $O(1)$-competitive. Note that κ increases with the number of arriving workers, thus we set an initial $\sigma_1 = \sigma_2 = 1$, and then change them to $2(1+\lambda)$ and $2(2-\lambda)$ respectively once the number of arrived workers becomes larger than a specified threshold. In our simulation, we set this threshold to 100 for the objective function $V^1(\cdot)$ and 300 for the objective function $V^2(\cdot)$. For the random mechanism, the density threshold is chosen randomly from $[0, 1]$. When the worker arrives, we will randomly match a task for him and calculate the marginal value of the worker based on the result of the match.

We also use the real-world dataset T-Drive [23] in the experiment. T-Drive contains the GPS trajectories of 10,357 taxis during the period from Feb. 2 to Feb. 8, 2008, within Beijing, China. We randomly select 1000 trajectories in the experiment. By clustering the position coordinates of these trajectories into 25 categories, we obtain 25 center points of clusters. The



(a) (b)

Fig. 4. Impact of budget on the synthetic dataset (n=2000). (a) Average completion reliability. (b) Total spatial diversity.



(a) (b)

Fig. 5. Impact of budget on the real dataset (n=800). (a) Average completion reliability. (b) Total spatial diversity.

position coordinates of these center points are used to initialize the positions of tasks. Then, we vary the number of trajectories used in the experiment from 50 to 150 and extract the position of a worker from each trajectory. Besides, we vary the budget from 50 to 200 with an increment of 50 to study the impact of the budget. We also set $\sigma_1 = \sigma_2 = 1$ initially, and then change them to $2(1+\lambda)$ and $2(2-\lambda)$ when the numbers of arrived workers reach the threshold values of 25 and 75 for the objective functions $V^1(\cdot)$ and $V^2(\cdot)$, respectively. For the other parameters, we follow the same settings as the synthetic dataset.

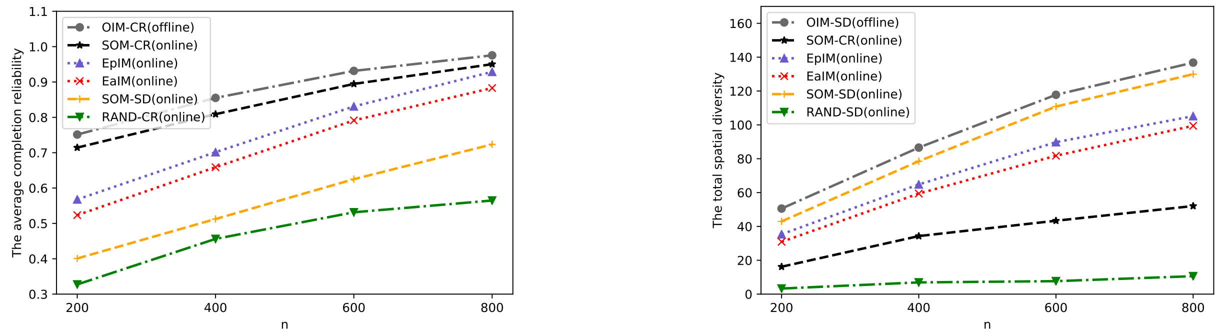
B. Experimental result

1) Impact of the budget B: Fig. 4 and Fig. 5 show the performance comparison regarding the average completion reliability and the total spatial diversity for all compared mechanisms in the synthetic and real datasets, respectively.

From Fig. 4 and Fig. 5 we can observe that the platform obtains higher values of both objective functions when the budget increases. OIMs operate in the offline scenario, where the information of all workers is known a priori. Therefore, OIMs always outperform the other algorithms regarding the corresponding objective function. For EpIM and EaIM, in the synthetic dataset, when the budget is 100, the gap between our mechanisms and the upper bound mechanisms OIMs is the largest. Even so, the biggest competitive ratio is just 2.487 in Fig. 4(a) and 4.228 in Fig. 4(b). In the real dataset, when the budget is 50, the biggest competitive ratio is 1.275 in Fig. 5(a) and 5.294 in Fig. 5(b). As the budget grows, the competitive ratio gets smaller. When $B = 500$, the competitive ratio is 1.042 in Fig. 4(a) and 1.593 in Fig. 4(b). When $B = 200$, the competitive ratio is 1.053 in Fig. 5(a) and 1.749 in Fig. 5(b).

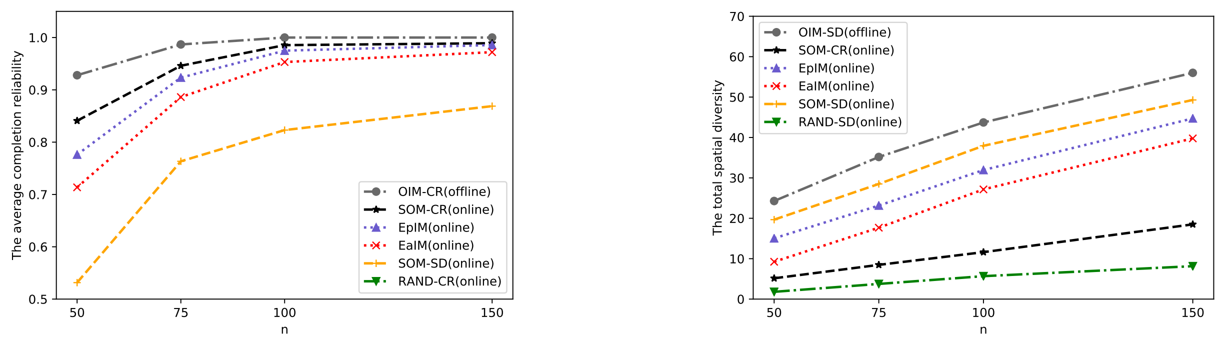
Among the compared online algorithms, it can be seen that the proposed mechanisms (EpIM and EaIM) and the single objective mechanisms (SOM-CR and SOM-SD) perform better than RANDs. As SOM-CR and SOM-SD only optimize one objective, their curves of the two objective functions exhibit a large deviation. Considering the average completion reliability, SOM-CR achieves high performance because it is designed to optimize the completion reliability. The proposed EpIM and EaIM perform closely to SOM-CR when the budget is sufficient as depicted in Fig. 4(a). As comparison, SOM-SD performs poorly compared to EpIM, EaIM, and SOM-CR. On the other hand, when considering the spatial diversity, SOM-SD performs well since it is designed to optimize this value. Again, the proposed EpIM and EaIM have comparable performance with SOM-SD. SOM-CR, as comparison, performs only slightly better than RAND-SD as shown in Fig. 4(b). In summary, the proposed EpIM and EaIM have a competitive performance on both objective functions simultaneously, while SOM-CR and SOM-SD can only perform well on one objective, which shows the superiority of the proposed mechanisms for the bi-objective sensing scenarios.

2) Impact of the number of workers n: Fig. 6 and Fig. 7 show the performance comparison when we vary the number of workers n. We can observe that when the number of workers increases, the platform gets a higher value of the two



(a) (b)

Fig. 6. Impact of n on the synthetic dataset (B=1000). (a) Average completion reliability. (b) Total spatial diversity.



(a) (b)

Fig. 7. Impact of n on the real dataset (B=1500). (a) Average completion reliability. (b) Total spatial diversity.

objective functions. The gap between EpIM, EaIM and the offline mechanisms OIMs is the largest when the value of n is small. In Fig. 6(a) and Fig. 6(b), the biggest competitive ratios are 1.435 and 1.635 when $n = 200$, respectively. In Fig. 7(a) and Fig. 7(b), the biggest competitive ratios are 1.745 and 2.945 when $n = 50$, respectively. As the number of workers grows, the performance of our proposed mechanisms gets closer to the offline algorithms. In Fig. 6(a) and Fig. 6(b), the competitive ratios reduce to 1.105 and 1.375 when $n = 800$, respectively. When $n = 150$, the competitive ratios reduce to 1.0827 and 1.408 in Fig. 7(a) and Fig. 7(b), respectively.

Among the compared online algorithms, it can be seen that the performance of RANDs is the worst. When the optimization goal is $V^1(\cdot)$, SOM-CR achieves a slightly better performance than the proposed mechanisms (EpIM and EaIM) while SOM-SD performs poorly. On the other hand, when the optimization goal is $V^2(\cdot)$, SOM-SD performs well while SOM-CR performs only slightly better than RAND-SD. Again, the results show the superiority of the proposed mechanisms considering the bi-objective sensing tasks.

3) Truthfulness: Fig. 8 shows the truthfulness of EpIM and EaIM. We randomly select two workers (ID = 50 and ID = 117) and allow them to submit bids that are not equal to their actual costs. As can be seen, in Fig. 8(a), worker 50 achieves his maximal utility if he bids truthfully ($b_{50} = c_{50} = 4$). In Fig. 8(b), worker 117 achieves his maximal utility if he bids truthfully ($b_{117} = c_{117} = 8$). Fig. 8(c)-(d) show the truthfulness of EaIM. Similarly, we select two workers (ID = 128 and ID = 104) randomly and allow them to submit fake bids. It can be seen that these two workers also achieve the maximal utility when they bid truthfully ($b_{128} = c_{128} = 8$ and $b_{104} = c_{104} = 2$).

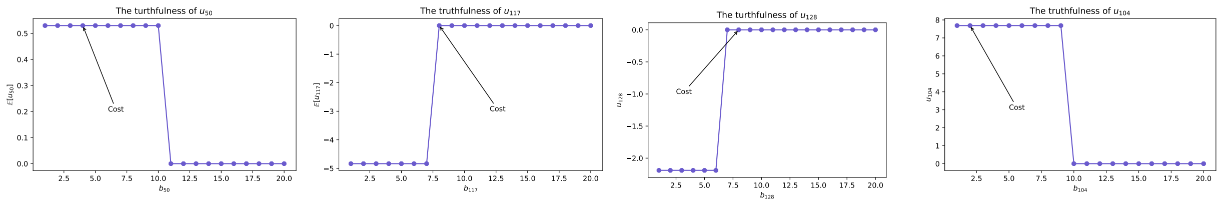
VII. Conclusion

In this paper, we have designed two online incentive mechanisms for MCS systems with two optimization goals. First, we proposed the BiCrowd framework where the objectives of completion reliability and spatial diversity are formulated. Then we designed two effective incentive mechanisms based on the online reverse auction. We have shown that the proposed mechanisms satisfy many desirable properties, including computational efficiency, budget feasibility, individual rationality, truthfulness, and good competitiveness. We have evaluated the performance of the proposed mechanisms based on both synthetic and real-world datasets. The experimental results have shown the superiority of the proposed mechanisms considering the two objectives simultaneously.

Appendix

A. proof of lemma 3.2

We transform $V^1(\cdot)$ to a representation based on pairwise elements. Consider a worker-task pair (i, j), which represents that worker i is assigned to task t_j. The ground set $\mathcal{E}$ is the set of all possible pairs, i.e., $\mathcal{E} = \{(i, j)|i \in [n], j \in [m]\}$, where $[n]$ and $[m]$ are the worker set of size n and the task set of size m, respectively. Since each selected worker $i \in \mathcal{S}$



(a) (b) (c) (d)

Fig. 8. Truthfulness. (a)-(b) Truthfulness of EpIM. (c)-(d) Truthfulness of EaIM.

in our problem is assigned to a task t_j, $V^1(\cdot)$ is equivalent to the following function:

$$f(\mathcal{A}) = \frac{1}{m} \sum_{j \in \mathcal{A}_m} (1 - \prod_{i \in \mathcal{A}_n^j} (1 - \mu_i)), \tag{2}$$

where $\mathcal{A} \subseteq \mathcal{E}$, $\mathcal{A}_n = \{i|(i,j) \in \mathcal{A}\}$, $\mathcal{A}_m = \{j|(i,j) \in \mathcal{A}\}$, and $\mathcal{A}_n^j$ represents the set of workers assigned to task t_j. In this formulation, $\mathcal{A}_n$, $\mathcal{A}_m$, and $\mathcal{A}_n^j$ are mapped to $\mathcal{S}$, $\mathcal{T}$, and $\mathcal{S}_j$ in our problem. As $f(\mathcal{A})$ has been proved to be monotone submodular in [28], $V^1(\mathcal{S})$ is also monotone submodular.

As $SD_{t_j}(\cdot)$ has been proved to be monotone submodular [24] and each worker can be assigned to only one task, the summation of $SD_{t_j}(\cdot)$ for all worker-task pairs preserves the monotone submodularity [29], i.e. $V^2(\cdot)$ is monotone submodular.

B. *proof of lemma 4.5*

To prove this lemma, we consider two cases with regard to the total payment paid for the selected workers at the last stage.

Case (a): At the last stage, the total payment given to the workers selected by $V^1(\cdot)$ is at least αB ($\alpha \in (0, \lambda/2]$), namely $\sum_{i=1}^{|\mathcal{Q}_2'|} b_i \geq \alpha B$. In this case, because each selected worker has a marginal density not less than ρ_1^*, we have $V_i^1(\mathcal{Q}'_{2,(i-1)}) \geq b_i \rho_1^*$, where $\mathcal{Q}'_{2,(i-1)}$ denotes the workers who had been selected to $\mathcal{Q}_2'$ before worker i. Note that the sum of the marginal values of all workers in $\mathcal{Q}_2'$ is the value of $\mathcal{Q}_2'$. Thus, we sum up the marginal values of all workers in $\mathcal{Q}_2'$ and get

$$\sum_{i=1}^{|\mathcal{Q}_2'|} V_i^1(\mathcal{Q}'_{2,(i-1)}) = V^1(\mathcal{Q}_2') \geq \rho_1^* \sum_{i=1}^{|\mathcal{Q}_2'|} b_i \geq \rho_1^* \alpha B.$$

For $\rho_1^* = \rho_1'/\sigma_1$ and $\rho_1' = 2V^1(\mathcal{Q}_1')/B$, we have

$$V^1(\mathcal{Q}_2') \geq \frac{2\alpha V^1(\mathcal{Q}_1')}{\sigma_1}.$$

Case (b): At the last stage, the total payment given to the workers selected by $V^1(\cdot)$ is less than αB ($\alpha \in (0, \lambda/2]$).

There are three reasons causing that the workers from $\mathcal{Q}_2$ are not selected in $\mathcal{Q}_2'$. The first reason is that some portion of budget is exhausted by the objective function $V^2(\cdot)$. This portion of budget is less than $\frac{B(1-\lambda)}{2}$, then the total loss due to the missed budget is at most

$$\rho_1^* \frac{B(1-\lambda)}{2} = \frac{V^1(\mathcal{Q}_1')(1-\lambda)}{\sigma_1}.$$

The second case is that, some workers from $\mathcal{Q}_2$ have marginal densities less than ρ_1^*, hence they will not be selected to $\mathcal{Q}_2'$. The worst case is that these workers are all in $\mathcal{Q}_2$, and even if this happens, the maximum expected total payment for these workers will not exceed $\frac{B\lambda}{2}$. Thus the expected total loss caused by these missed workers is less than

$$\frac{\rho_1^* B\lambda}{2} = \frac{V^1(\mathcal{Q}_1')\lambda}{\sigma_1}.$$

The last case is that for some workers with a marginal density larger than or equal to ρ_1^*, we have no budget to hire him, which means that such a worker's payment is larger than $(\lambda/2 - \alpha)B$ and $\frac{V_i^1(\mathcal{Q}'_{2,(i-1)})}{(\lambda/2-\alpha)B} \geq \rho_1^*$. Otherwise the payment will not exceed the stage budget $B\lambda/2$ even if we select that worker. Thus, for such a worker i in $\mathcal{Q}_2$, we have:

$$V_i^1(\mathcal{Q}'_{2,(i-1)}) \geq \rho_1^* (\frac{\lambda}{2} - \alpha) B.$$

As $\rho_1^* = \rho_1'/\sigma_1$ and $\mathbb{E}[\rho_1'] \geq \rho_1$, we have

$$V_i^1(\mathcal{Q}'_{2,(i-1)}) \geq \frac{(\lambda - 2\alpha)\rho_1 B}{2\sigma_1}.$$

Because the stage budget for $V^1(\cdot)$ is at most $B\lambda/2$, there cannot be more than $\lfloor \frac{\sigma_1 \lambda}{\lambda - 2\alpha} \rfloor$ such workers in $\mathcal{Q}_2$. We have assumed that the marginal value of each worker is at most $V^1(\mathcal{Q})/\kappa$, thus the total loss here is less than

$$\lfloor \frac{\sigma_1 \lambda}{\lambda - 2\alpha} \rfloor \frac{V^1(\mathcal{Q})}{\kappa}.$$

Combining the above three losses, we get the gap between $\mathbb{E}[V^1(\mathcal{Q}_2')]$ and $\mathbb{E}[V^1(\mathcal{Q}_2)]$, which satisfies the following relationship:

$$\mathbb{E}[V^1(\mathcal{Q}_2)] - \mathbb{E}[V^1(\mathcal{Q}_2')] \leq \frac{V^1(\mathcal{Q}_1')(1-\lambda)}{\sigma_1} + \frac{V^1(\mathcal{Q}_1')\lambda}{\sigma_1} + \lfloor \frac{\sigma_1 \lambda}{\lambda - 2\alpha} \rfloor \frac{V^1(\mathcal{Q})}{\kappa},$$

$$\mathbb{E}[V^1(\mathcal{Q}_2')] \geq \mathbb{E}[V^1(\mathcal{Q}_2)] - \frac{V^1(\mathcal{Q}_1')(1-\lambda)}{\sigma_1} - \frac{V^1(\mathcal{Q}_1')\lambda}{\sigma_1} - \frac{V^1(\mathcal{Q})}{\kappa} \lfloor \frac{\sigma_1 \lambda}{\lambda - 2\alpha} \rfloor.$$

Since $\mathbb{E}[V^1(\mathcal{Q}_2)] \geq \mathbb{E}[V^1(\mathcal{Q})]/2$ and $\mathbb{E}[V^1(\mathcal{Q})] \geq \mathbb{E}[V^1(\mathcal{Q}_1')]$, we have

$$\mathbb{E}[V^1(\mathcal{Q}_2')] \geq \frac{\mathbb{E}[V^1(\mathcal{Q}_1')]}{2} - \frac{\mathbb{E}[V^1(\mathcal{Q}_1')](1-\lambda)}{\sigma_1} - \frac{\mathbb{E}[V^1(\mathcal{Q}_1')]\lambda}{\sigma_1} - \frac{\mathbb{E}[V^1(\mathcal{Q}_1')]}{\kappa} \lfloor \frac{\sigma_1 \lambda}{\lambda - 2\alpha} \rfloor.$$

The ratio for $\mathbb{E}[V^1(\mathcal{Q}_2')]$ to $\mathbb{E}[V^1(\mathcal{Q}_1')]$ is

$$\frac{1}{2}-\frac{1}{\sigma_1}-\frac{1}{\kappa}\lfloor\frac{\sigma_1\lambda}{\lambda-2\alpha}\rfloor(\alpha\in(0,\lambda/2]).$$

Considering both cases (a) and (b), our objective is to maximize $\frac{1}{2}-\frac{1}{\sigma_1}-\frac{1}{\kappa}\lfloor\frac{\sigma_1\lambda}{\lambda-2\alpha}\rfloor$ or $\frac{2\alpha}{\sigma_1}$ subject to

$$\frac{1}{2}-\frac{1}{\sigma_1}-\frac{1}{\kappa}\lfloor\frac{\sigma_1\lambda}{\lambda-2\alpha}\rfloor=\frac{2\alpha}{\sigma_1}.$$

We can see that $\lfloor\frac{\sigma_1\lambda}{\lambda-2\alpha}\rfloor$ is an integer larger than zero. Thus, a sufficiently large κ is preferred. For $\frac{2\alpha}{\sigma_1}$, when $\alpha=\lambda/2$, it gets the maximum value. However, $\frac{1}{2}-\frac{1}{\sigma_1}-\frac{1}{\kappa}\lfloor\frac{\sigma_1\lambda}{\lambda-2\alpha}\rfloor$ is undefined when $\alpha=\lambda/2$. Thus, we calculate the limit of both sides of the equation when $\kappa\to\infty$ and $\alpha\to\lambda/2$ and have:

$$\lim_{\substack{\kappa\to\infty\\ \alpha\to\lambda/2}}\frac{1}{2}-\frac{1}{\sigma_1}-\frac{1}{\kappa}\lfloor\frac{\sigma_1\lambda}{\lambda-2\alpha}\rfloor=\frac{1}{2}-\frac{1}{\sigma_1},$$

$$\lim_{\substack{\kappa\to\infty\\ \alpha\to\lambda/2}}\frac{2\alpha}{\sigma_1}=\frac{\lambda}{\sigma_1}.$$

Combining these two equations, we have $\sigma_1=2(1+\lambda)$. Specifically, the ratio approaches $\frac{\lambda}{2(1+\lambda)}$ as $\kappa\to\infty$ and $\alpha\to\lambda/2$.

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