Thanos: Incentive Mechanism with Quality Awareness for Mobile Crowd Sensing

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Abstract—Recent years have witnessed the emergence of mobile crowd sensing (MCS) systems, which leverage the public crowd equipped with various mobile devices for large scale sensing tasks. In this paper, we study a critical problem in MCS systems, namely, incentivizing worker participation. Different from existing work, we propose an incentive framework for MCS systems, named Thanos, that incorporates a crucial metric, called workers' *quality of information (QoI)*. Due to various factors (e.g., sensor quality and environment noise), the quality of the sensory data contributed by individual workers varies significantly. Obtaining high quality data with little expense is always the ideal of MCS platforms. Technically, our design of Thanos is based on reverse combinatorial auctions. We investigate both the single- and multi-minded combinatorial auction models. For the former, we design a truthful, individual rational, and computationally efficient mechanism that ensures a close-to-optimal social welfare. For the latter, we design an iterative descending mechanism that satisfies individual rationality and computational efficiency, and approximately maximizes the social welfare with a guaranteed approximation ratio. Through extensive simulations, we validate our theoretical analysis on the various desirable properties guaranteed by Thanos.

Index Terms—Incentive mechanism, quality of information, mobile crowd sensing

1 Introduction

The ubiquity of human-carried mobile devices (e.g., smartphones, smartwatches) with a plethora of on-board and portable sensors (e.g., accelerometer, compass, camera) has given rise to the emergence of various people-centric *mobile crowd sensing (MCS)* systems [1], [2], [3], [4]. In a typical MCS system, a cloud-based platform aggregates and analyzes the sensory data provided by a crowd of participants, namely (crowd) workers, instead of professionals and dedicatedly deployed sensors. The mobile devices of participating workers collect and may process in certain level the data before submitting them to the platform.

Such MCS systems hold a wide spectrum of applications that cover almost every corner of our everyday life, including healthcare, ambient environment monitoring, smart transportation, indoor localization, and many others. For example, MedWatcher [1] is a US FDA advocated MCS system for post-market medical device surveillance. Participating workers upload photos of their medical devices to a cloud-based platform using the MedWatcher mobile application, which help identify visible problems with the devices. The platform aggregates and analyzes the worker-provided information, sends reports to the FDA and alerts medical device users about device problems. Such a crowdsourcing paradigm enables easier detection of device safety issues and faster propagation of alerts to medical device users compared to traditional reporting methods such as mail or telephone. Moreover, air quality monitoring [2] is another area where MCS systems obtain their recent popularity. In such systems, crowdsourced air quality data are aggregated from a large number of workers using air quality sensors ported to their smartphones, which help estimate the city or district level air quality.

Participating in such crowd sensing tasks is usually a costly procedure for individual workers. On one hand, it consumes workers' resources, such as computing power, battery and so forth. On the other hand, many sensing tasks require the submission of some types of workers' sensitive private information, which causes privacy leakage. For example, by uploading the photos of their medical devices, workers reveal the types of their illnesses. By submitting air quality estimation samples, workers usually reveal information about their locations. Therefore, without satisfactory rewards that compensate participating costs, workers will be reluctant to participate in the sensing tasks.

Aware of the paramount importance of stimulating worker participation, the research community has recently developed a series of game-theoretic incentive mechanisms for MCS systems [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37].

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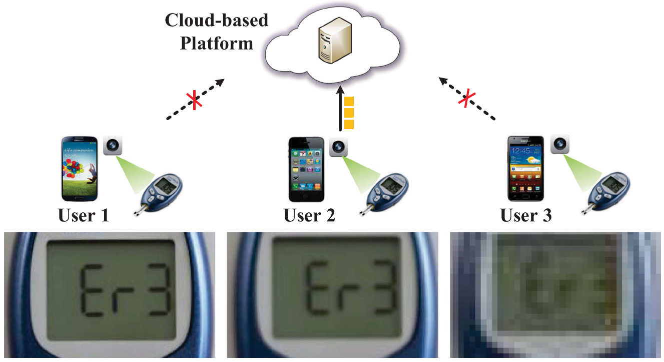


Fig. 1. A MedWatcher MCS system example (three workers try to upload the photos of the error message "`Er3`" on the screens of their blood glucose meters to the MedWatcher platform. The prices that the three workers ask for cost compensation are 100$, 10$, and 1$, respectively.).

However, most of the existing mechanisms fail to incorporate one important aspect, that is workers' *quality of information (QoI)*, into their designs. The meaning of QoI varies for different applications. For example, in the aforementioned MedWatcher system [1] QoI refers to the quality (e.g., resolution, contrast, sharpness) of uploaded photos. Higher quality ones will help the platform better identify visible device problems. In air quality monitoring MCS systems [2], QoI means a worker's estimation accuracy of air quality. The QoI of every worker could be affected by various factors, including poor sensor quality, environment noise, lack of sensor calibration, and so forth.

To compensate the cost of each worker's participation, existing incentive mechanisms have used workers' bidding prices as an important metric to allocate sensing tasks. However, as shown in the example in Fig. 1, QoI is also a major factor that should be considered together with bidding prices. Although worker 1 has the highest quality photo, her high price prohibits the platform from requesting her data. Furthermore, despite worker 3's low price, the platform will not be interested in her data either, because her low quality photo could hardly contribute to identifying the error message "`Er3`". By jointly considering price and QoI, the platform will select worker 2 with medium price and acceptable photo quality as the data provider.

Therefore, in this paper, we propose a *QoI aware incentive framework* for MCS systems, named Thanos.[1] Considering workers' *strategic* behaviors and the combinatorial nature of the tasks that every worker executes, we design Thanos based on *reverse combinatorial auctions*, where the platform acts as the auctioneer that purchases the data from participating workers. Not only do we study the *single-minded* scenario where every worker is willing to execute one subset of tasks, but also we investigate the *multi-minded* case in which any worker might be interested in executing multiple subsets of tasks. Similar to the traditional VCG mechanisms [38], [39], Thanos also aims to maximize the social welfare. Mechanism design for combinatorial auctions is typically challenging in that usually we aim to design a computationally efficient mechanism with close-to-optimal social welfare in the presence of an NP-hard winner determination problem, which meanwhile satisfies *truthfulness* and *individual rationality*. Addressing all these challenges, our paper has the following contributions.

- Different from most of the previous work, we design a *QoI aware incentive framework* for MCS systems.
- We use reverse combinatorial auction to design a truthful, individual rational and computationally efficient incentive mechanism that approximately maximizes the social welfare with a guaranteed approximation ratio for the single-minded case.
- For the multi-minded case, we design an iterative descending mechanism that achieves close-to-optimal social welfare with a guaranteed approximation ratio while satisfying individual rationality and computational efficiency.

In the rest of this paper, we first discuss the past literature that are related to this work in Section 2, and introduce the preliminaries in Section 3. Then, we provide the design and analysis of Thanos for the single- and multi-minded scenarios in Sections 4 and 5, respectively. In Section 6, we summarize our theoretical results about the proposed mechanisms, and in Section 7, we conduct extensive simulations to validate the desirable properties of Thanos. Finally in Section 8, we conclude this paper.

2 Related Work

Aware of the significance of attracting worker participation, the research community has, thus far, developed a series of incentive mechanisms [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37] for MCS systems. Among them, game-theoretic incentive mechanisms [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], which utilize either auction [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], or other game-theoretic models [5], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], have gained increasing popularity, as they are capable of dealing with workers' strategic behaviors.

Authors in [5], [6] design reverse auction-based incentive mechanisms. However, workers' strategic behaviors about bidding task sets are not incorporated into these models. Similar to the platform-centric model in [5], Duan et al. [23] propose a Stackelberg game-based incentive mechanism, which deals with the asymmetric information between workers and the platform. Various other unique aspects, such as location awareness [7], [26], network effects [28], privacy preservation [13], [14], sybil-proofness [22], as well as contest design [27], have been integrated into prior incentive mechanisms. Furthermore, other lines of past literature investigate MCS systems with multiple task requesters [8], [18], [19], [24], [25], or with online arrivals of workers and tasks [9], [10], [16], [17], [31], [32].

A common feature of the aforementioned mechanisms is that they do not consider workers' QoI in their mechanism designs. This is the major difference with our mechanisms proposed in this paper.

Although workers' QoI is taken into consideration in several existing mechanisms [11], [12], [20], [21], [29], [30], [34], [35], [37], our paper is different from them in various ways. Some of these work [11], [12], [29], [34] assume either workers have identical QoI [34], or their sensing cost distributions are known *a priori* [11], [12], [29]. However, we do not leverage such assumptions in this paper. The QoI aware mechanisms in [35], [37] do not utilize game-theoretic frameworks, and thus it cannot handle users' strategic

1. The name Thanos comes from incenTive mecHanism with quAlity awareNess for mObile crowd Sensing.

behaviors as our mechanisms. Furthermore, there exist other quality-driven mechanisms with objectives, including allocating fine-grained sensing tasks [20], providing long-term incentives [21], dealing with malicious and colluding workers [30], that are different from ours.

3 Preliminaries

In this section, we present an overview of MCS systems, our auction model and design objectives.

3.1 System Overview

The MCS system model considered in this paper consists of a platform residing in the cloud and a set of N workers, denoted as $\mathcal{N} = \{1, \ldots, N\}$. The workers execute a set of M sensing tasks, denoted as $\mathcal{T} = \{\tau_1, \ldots, \tau_M\}$ and send their sensory data to the platform. The workflow of the system is described as follows.

1) First, the platform announces the set of sensing tasks, $\mathcal{T}$, to workers.
2) Then, the platform and workers enter the auctioning stage in which the platform acts as the auctioneer that purchases the sensory data collected by individual workers. Every worker $i \in \mathcal{N}$ submits her bid, which is a tuple (Γ_i, b_i) consisting of the set of tasks $\Gamma_i \subseteq \mathcal{T}$ she wants to execute and her bidding price b_i for executing these tasks.
3) Based on workers' bids, the platform determines the set of winners, denoted as $\mathcal{S} \subseteq \mathcal{N}$ and the payment to all workers, denoted as $\overrightarrow{p} = \{p_1, \ldots, p_N\}$. Specifically, a loser does not execute any task and receives zero payment.
4) After the platform receives winners' sensory data, it gives the payment to the corresponding winners.

One major difference between this paper and most of the previous work is that we integrate the quality of information corresponding to every worker, denoted as $\overrightarrow{q} = \{q_1, \ldots, q_N\}$, into our incentive mechanisms. In the following Section 3.2, we describe in detail the QoI model adopted in this paper.

3.2 QoI Model

Generally speaking, QoI indicates the quality of workers' sensory data. The definition of QoI varies for different applications. For example, in the MedWatcher system [1], QoI refers to the quality (e.g., resolution, contrast, sharpness) of uploaded photos. Photos with higher quality will help the platform better identify visible problems with medical devices. In air quality monitoring MCS systems [2], QoI refers to a worker's estimation accuracy of air quality. In practice, workers' QoIs are usually affected by various factors, including sensing effort level, sensor quality, background noise, viewing angles, distance to the observed event or object, and many others.

We assume that the platform maintains a historical record of workers' QoI profile $\overrightarrow{q}$ used as inputs for winner and payment determination. There are many methods for the platform to calculate workers' QoIs. Intuitively, in the cases where the platform has adequate amount of ground truth data, QoIs can be obtained by directly calculating the deviation of workers' data from the ground truths. However, even without ground truths, QoIs can still be effectively inferred from workers' data by utilizing algorithms such as those proposed in [40], [41]. Alternatively in many applications, QoIs can be inferred from other factors (e.g., the price of a worker's sensors, her experience and reputation of executing specific sensing tasks) using methods proposed in previous studies such as [42]. Note that the mechanisms proposed in this paper are compatible with any QoI quantification method, and work in scenarios with either continuous and discrete QoIs. The problem of which method the platform adopts to calculate workers' QoIs is application dependent and out of the scope of this paper. Typically, workers might know some of the factors that affect their QoIs. However, workers usually do not know exactly how QoIs are calculated by the platform. Hence, they do not know the exact values of their QoIs.

3.3 Auction Model

In this paper, we consider *strategic* and *selfish* workers that aim to maximize their own utilities. The fact that workers bid on subsets of tasks motivates us to use *reverse combinatorial auction* to model the problem. In the rest of the paper, we use *bundle* to refer to any subset of tasks of $\mathcal{T}$. Different from traditional *forward combinatorial auction* [43], [44], we formally define the concept of reverse combinatorial auction for our problem setting in Definition 1.

Definition 1 (RC Auction). *In a reverse combinatorial auction (RC auction), each worker $i \in \mathcal{N}$ is interested in a set of $K_i \geq 1$ bundles, denoted as $\mathcal{T}_i = \{\Gamma_i^1, \ldots, \Gamma_i^{K_i}\}$. For any bundle $\Gamma \subseteq \mathcal{T}$, the worker has a cost function defined as*

$$C_i(\Gamma) = \begin{cases} c_i, & if\ \exists \Gamma_i^j \in \mathcal{T}_i\ s.t.\ \Gamma \subseteq \Gamma_i^j \\ +\infty, & otherwise \end{cases}. \tag{1}$$

Both $\mathcal{T}_i$ and the cost function $C_i(\cdot)$ are worker i's private information. If $K_i = 1$ for every worker, then the auction is defined as a single-minded reverse combinatorial auction (SRC auction). And it is defined as a multi-minded reverse combinatorial auction (MRC auction), if $K_i > 1$ for at least one worker.

In an SRC auction, $\mathcal{T}_i$ contains only worker i's *maximum executable task set* $\overline{\Gamma}_i$. That is, $\overline{\Gamma}_i$ consists of all the sensing tasks that worker i is able to execute. Since she is not capable to carry out tasks beyond $\overline{\Gamma}_i$, her cost for any bundle $\Gamma \not\subseteq \overline{\Gamma}_i$ can be equivalently viewed as $+\infty$. Similarly in an MRC auction, the union of all the bundles in $\mathcal{T}_i$ is $\overline{\Gamma}_i$. That is, $\bigcup_{j=1}^{K_i} \Gamma_i^j = \overline{\Gamma}_i$. If worker i is a winner of the RC auction, she will be paid p_i for executing the corresponding set of sensing tasks. In contrast, she will not be allocated any sensing task and will receive zero payment if she is a loser. We present the definitions of the utility of a worker and the profit of the platform formally in Definitions 2 and 3.

Definition 2 (A Worker's Utility). *The utility of any worker $i \in \mathcal{N}$ is*

$$u_i = \begin{cases} p_i - c_i, & if\ i \in \mathcal{S} \\ 0, & otherwise. \end{cases} \tag{2}$$

Definition 3 (Platform's Profit). *The profit of the platform given workers' QoI profile $\overrightarrow{q}$ is*

$$u_0 = V_{\overrightarrow{q}}(\mathcal{S}) - \sum_{i \in \mathcal{S}} p_i, \tag{3}$$

where the value function $V_{\overrightarrow{q}}(\cdot): 2^{\mathcal{N}} \rightarrow \mathbb{R}^+$ *maps the winner set* $\mathcal{S}$ *to the value that the winners bring to the platform. Furthermore,* $V_{\overrightarrow{q}}(\cdot)$ *is monotonic in* $\overrightarrow{q}$*. That is, for any* $\overrightarrow{q} = \{q_1, \ldots, q_N\}$ *and* $\overrightarrow{q}' = \{q_1', \ldots, q_N'\}$ *such that* $q_i \geq q_i'$ *holds* $\forall i \in \mathcal{N}$*, we have* $V_{\overrightarrow{q}}(\mathcal{S}) \geq V_{\overrightarrow{q}'}(\mathcal{S})$*.*

Similar to the traditional VCG mechanism design [38], [39], we aim to design mechanisms that maximize the social welfare, which is formally defined in Definition 4.

Definition 4 (Social Welfare). *The social welfare of the whole MCS system is*

$$u_{social} = u_0 + \sum_{i \in \mathcal{N}} u_i = V_{\overrightarrow{q}}(\mathcal{S}) - \sum_{i \in \mathcal{S}} c_i. \quad (4)$$

3.4 Design Objective

In this paper, we aim to design *dominant-strategy mechanisms* in which for every worker there exists a dominant strategy [45] defined in Definition 5.

Definition 5 (Dominant Strategy). *A strategy* st_i *is the dominant strategy for worker* i *if and only if for any other strategy* st_i' *and any strategy profile of the other workers, denoted as* st_{-i}*, the property* $u_i(\mathrm{st}_i, \mathrm{st}_{-i}) \geq u_i(\mathrm{st}_i', \mathrm{st}_{-i})$ *holds.*

In our SRC auction, each worker submits to the platform a bid (Γ_i, b_i) consisting of her declared interested bundle Γ_i and the bidding price b_i. Since workers are strategic, it is possible that she declares a bid that deviates from the true value $(\overline{\Gamma}_i, c_i)$. However, one of our goals for the SRC auction is to design a *truthful* mechanism defined in Definition 6.

Definition 6 (Truthfulness). *An SRC auction is truthful if and only if it is the dominant strategy for every worker* $i \in \mathcal{N}$ *to bid her true value* $(\overline{\Gamma}_i, c_i)$*.*

Noticed from Definition 6 that we aim to ensure the truthfulness of both the cost c_i and bundle $\overline{\Gamma}_i$. Besides truthfulness, another design objective for the SRC auction is to ensure that every worker receives non-negative utility from participating. Such property is critical in incentive mechanisms because it ensures that workers will not be disincentivized to participate for receiving negative utilities. This property is formally defined as *individual rationality* in Definition 7.

Definition 7 (Individual Rationality). *A mechanism is individual rational (IR) if and only if* $u_i \geq 0$ *is satisfied for every worker* $i \in \mathcal{N}$*.*

As mentioned in Section 3.3, our mechanism aims to maximize the social welfare. However, as will be proved in Section 4, the problem of maximizing the social welfare in the SRC auction is NP-hard. Hence, we aim to design a *polynomial-time* mechanism that gives us approximately optimal social welfare with a *guaranteed approximation ratio*.

In the domain of multi-minded combinatorial auction, requiring truthfulness limits the family of mechanisms that can be used, as pointed out in [44]. Hence, in our MRC auction, we aim to design a dominant-strategy mechanism that can still yield a *guaranteed approximation ratio* to the optimal social welfare without ensuring truthfulness. In fact, as mentioned in [44], the requirement of truthfulness is only to obtain close-to-optimal social welfare with strategic worker behaviors, but not the real essence. Therefore, as long as the approximation ratio is guaranteed when workers play their dominant strategies, it is justifiable for us to relax the truthfulness requirement. Additionally, we also require our mechanism to be *individual rational* and have a *polynomial* computational complexity.

TABLE 1
Summary of Design Objectives

Model	Dominant Strategy	Truthful	IR	Approx. Ratio	Complexity
SRC	√	√	√	Guaranteed	Polynomial
MRC	√	×	√	Guaranteed	Polynomial

Authors in [44] address the issue of mechanism design for multi-minded forward combinatorial auctions. Their mechanisms cannot ensure that workers have dominant strategies and cannot be applied to reverse combinatorial auctions. However, in contrast, we are able to design a dominant-strategy incentive mechanism for the MRC auction in this paper. We summarize our design objectives for both the SRC and MRC auctions in Table 1.

4 SRC Auction

In this section, we introduce the mathematical formulation, the proposed mechanism, as well as the corresponding analysis for the SRC auction.

4.1 Mathematical Formulation

In our SRC auction, each worker's bid (Γ_i, b_i) consists of her declared interested bundle Γ_i and the bidding price b_i. Although our model is valid for any general value function $V_{\overrightarrow{q}}(\cdot)$ that satisfies Definition 3, to simplify our analysis we assume that $V_{\overrightarrow{q}}(\cdot)$ is the sum of the value, v_i, contributed by every winner $i \in \mathcal{S}$. Furthermore, we assume that v_i is proportional to the total QoI provided by this worker. Given workers' bidding bundle profile $\overrightarrow{\Gamma} = \{\Gamma_1, \ldots, \Gamma_N\}$ and the winner set $\mathcal{S}$, the platform's value function $V_{\overrightarrow{q}}(\cdot)$ can be represented by

$$V_{\overrightarrow{q}}(\mathcal{S}) = \sum_{i \in \mathcal{S}} v_i = \sum_{i \in \mathcal{S}} \alpha q_i |\Gamma_i|, \quad (5)$$

where α is a coefficient that converts QoI to monetary reward.

In this paper, we consider *QoI coverage* in the SRC auction. Intuitively, for the task that none of the workers capable to execute it has adequately high QoI, collective efforts of multiple workers are necessary to ensure high sensing quality. We use $Q_{\tau_j, \overrightarrow{q}}(\mathcal{S})$ to denote the total QoI that all winners have on task $\tau_j \in \mathcal{T}$. Furthermore, we approximate $Q_{\tau_j, \overrightarrow{q}}(\mathcal{S})$ as the sum of the QoI of the winners that execute this task. Therefore, QoI coverage is equivalent to guaranteeing that every task is executed by workers with sufficient amount of QoI in total. Note that such additive assumption of QoI has been justified by results and analyses provided in previous work (i.e., Corollary 1 in [13], and Corollary 1 in [8]). Based on this assumption, $Q_{\tau_j, \overrightarrow{q}}(\mathcal{S})$ can be represented by the following

$$Q_{\tau_j, \overrightarrow{q}}(\mathcal{S}) = \sum_{i: \tau_j \in \Gamma_i, i \in \mathcal{S}} q_i. \quad (6)$$

Since we aim to maximize the social welfare given in Definition 4, the winner determination and pricing can be decoupled into two separate problems. We formulate the SRC auction winner determination (SRC-WD) problem as the following integer linear program.

SRC-WD Problem:

$$\max \sum_{i\in\mathcal{N}} (\alpha q_i|\Gamma_i| - b_i)x_i \tag{7}$$

$$\text{s.t.} \sum_{i:\tau_j\in\Gamma_i, i\in\mathcal{N}} q_i x_i \geq Q_j, \qquad \forall \tau_j \in \mathcal{T} \tag{8}$$

$$x_i \in \{0,1\}, \qquad \forall i \in \mathcal{N} \tag{9}$$

Constants. The SRC-WD problem takes as input constants α, workers' bid profile $\{(\Gamma_1, b_1), \ldots, (\Gamma_N, b_N)\}$, workers' QoI profile $\overrightarrow{q}$ and tasks' QoI requirement profile $\overrightarrow{Q} = \{Q_1, \ldots, Q_M\}$.

Variables. In the SRC-WD problem, we have a set of binary variables $\{x_1, \ldots, x_N\}$ for every worker $i \in \mathcal{N}$. If worker i is included in the winner set $\mathcal{S}$, then $x_i = 1$. Otherwise, $x_i = 0$.

Objective Function. Since the platform does not know the true values of workers' interested bundles and the corresponding costs, $\{(\overline{\Gamma}_1, c_1), \ldots, (\overline{\Gamma}_N, c_N)\}$, the objective function that it directly tries to maximize is the social welfare based on workers' bid profile $\{(\Gamma_1, b_1), \ldots, (\Gamma_N, b_N)\}$. We use $\overrightarrow{w} = \{w_1, \ldots, w_N\}$, in which $w_i = \alpha q_i|\Gamma_i| - b_i$, to denote the marginal social welfare profile of all workers based on workers' bids. Then, we have the objective function $\sum_{i\in\mathcal{S}} w_i = \sum_{i\in\mathcal{S}}(\alpha q_i|\Gamma_i| - b_i) = \sum_{i\in\mathcal{N}}(\alpha q_i|\Gamma_i| - b_i)x_i$. Later in Section 4.3, we will show that in our mechanism every worker in fact bids truthfully. Hence, the objective function is equivalent to the actual social welfare.

Constraints. Constraint Equation (8) represents the QoI coverage for every task $\tau_j \in \mathcal{T}$, which ensures that the total QoI of all the winners for this task, calculated as $Q_{\tau_j, \overrightarrow{q}}(\mathcal{S}) = \sum_{i:\tau_j\in\Gamma_i, i\in\mathcal{S}} q_i = \sum_{i:\tau_j\in\Gamma_i, i\in\mathcal{N}} q_i x_i$, is no less than the QoI requirement Q_j.

Next, we prove the NP-hardness of the SRC-WD problem in Theorem 1.

Theorem 1. *The SRC-WD problem is NP-hard.*

Proof. In this proof, we demonstrate that the NP-complete minimum weight set cover (MWSC) problem is polynomial-time reducible to the SRC-WD problem. The reduction starts with an instance of the MWSC problem consisting of a universe of elements $\mathcal{U} = \{\tau_1, \ldots, \tau_M\}$ and a set of N sets $\mathcal{O} = \{\Gamma_1, \ldots, \Gamma_N\}$ whose union equals $\mathcal{U}$. Every set $\Gamma_i \in \mathcal{O}$ is associated with a non-negative weight w_i. The MWSC problem is to find the subset of $\mathcal{O}$ with the minimum total weight whose union contains all the elements in $\mathcal{U}$.

Based on the instance of the MWSC problem, we construct an instance of the SRC-WD problem. First, we transform Γ_i into Γ'_i such that for every element in Γ_i there exist $l_i \in \mathbb{Z}^+$ copies of the same element in Γ'_i. We require that every element $\tau_j \in \mathcal{U}$ is covered for at least $L_j \in \mathbb{Z}^+$ times. After the reduction, we obtain an instance of the SRC-WD problem in which workers' QoI profile is $\overrightarrow{q} = \{l_1, \ldots, l_N\}$, workers' bidding bundle profile is $\overrightarrow{\Gamma} = \{\Gamma_1, \ldots, \Gamma_N\}$, workers' marginal social welfare profile is $\overrightarrow{w} = \{-w_1, \ldots, -w_N\}$ and tasks' QoI requirement profile is $\overrightarrow{Q} = \{L_1, \ldots, L_M\}$. Noticed that the SRC-WD problem represents a richer family of problems in which any worker i's QoI, q_i, and any task j's QoI requirement, Q_j, could take any value in $\mathbb{R}^+$. Furthermore, the marginal social welfare can take any value in $\mathbb{R}$. Hence, every instance of the MWSC problem is polynomial-time reducible to an instance of the SRC-WD problem. The SRC-WD problem is NP-hard. □

4.2 Mechanism Design

Because of the NP-hardness of the SRC-WD problem, it is impossible to compute the set of winners that maximize the social welfare in polynomial time unless P = NP. As a result, we cannot use the off-the-shelf VCG mechanism [38], [39] since the truthfulness of VCG mechanism requires that the social welfare is exactly maximized. Therefore, as mentioned in Section 3.4, we aim to design a mechanism that approximately maximizes the social welfare while guaranteeing truthfulness.

Myerson's characterizations of truthfulness for single-parameter auctions [46] are not directly applicable in our scenario, because our SRC auction is a double-parameter auction that considers both bundle and cost truthfulness. Moreover, different from the characterizations of truthfulness for single-minded forward combinatorial auctions proposed in [43], we describe and prove the necessary and sufficient conditions for a truthful SRC auction in the following Lemma 1.

Lemma 1. *An SRC auction is truthful if and only if the following two properties hold:*

- *Monotonicity. Any worker i who wins by bidding (Γ_i, b_i) still wins by bidding any $b'_i < b_i$ and any $\Gamma'_i \supset \Gamma_i$ given that other workers' bids are fixed.*
- *Critical payment. Any winner i with bid (Γ_i, b_i) is paid the supremum of all bidding prices b'_i such that bidding (Γ_i, b'_i) still wins, which is defined as worker i's critical payment.*

Proof. It is easily verifiable that a truthful bidder will never receive negative utility. If worker i's any untruthful bid (Γ_i, b_i) is losing or $\Gamma_i \not\subseteq \overline{\Gamma}_i$, her utility from bidding (Γ_i, b_i) will be non-positive. Therefore, we only need to consider the case in which (Γ_i, b_i) is winning and $\Gamma_i \subseteq \overline{\Gamma}_i$.

- Because of the property of monotonicity, $(\overline{\Gamma}_i, b_i)$ is also a winning bid. Suppose the payment for bid (Γ_i, b_i) is p and that for bid $(\overline{\Gamma}_i, b_i)$ is $\overline{p}$. Every bid $(\overline{\Gamma}_i, b'_i)$ with $b'_i > \overline{p}$ is losing because $\overline{p}$ is the worker i's critical payment given bundle $\overline{\Gamma}_i$. From monotonicity, bidding (Γ_i, b'_i) is also losing. Therefore, the critical payment for (Γ_i, b_i) is at most that for $(\overline{\Gamma}_i, b_i)$, which means $p \leq \overline{p}$. Hence, the worker will not increase her utility by bidding (Γ_i, b_i) instead of $(\overline{\Gamma}_i, b_i)$.
- Then, we consider the case in which bidding truthfully $(\overline{\Gamma}_i, c_i)$ wins. This bid earns the same payment $\overline{p}$ as $(\overline{\Gamma}_i, b_i)$. Then her utilities from these two bids will be the same. If bidding $(\overline{\Gamma}_i, c_i)$ loses, then we have $c_i > \overline{p} \geq b_i$. Hence, bidding $(\overline{\Gamma}_i, b_i)$ will receive negative utility. Therefore, $(\overline{\Gamma}_i, b_i)$ will also not increase her utility compared to $(\overline{\Gamma}_i, c_i)$.

Thus, we conclude that an SRC auction is truthful if and only if the monotonicity and critical payment properties hold. □

We utilize the rationale provided in Lemma 1 to design a *quality of information aware SRC (QoI-SRC) auction* for Thanos in the single-minded scenario. Specifically, we present the winner determination and pricing mechanisms of the QoI-SRC auction respectively in Algorithm 1 and 2.

Algorithm 1. QoI-SRC Auction Winner Determination

Input: $\mathcal{T}$, $\mathcal{N}$, $\overrightarrow{w}$, $\overrightarrow{q}$, $\overrightarrow{Q}$, $\overrightarrow{\Gamma}$;
Output: $\mathcal{S}$;
// Initialization
1 $\mathcal{N}^- \leftarrow \emptyset, \mathcal{S} \leftarrow \emptyset$;
// Select workers with non-negative marginal social welfare
2 **foreach** i s.t. $w_i \geq 0$ **do**
3 $\quad \mathcal{S} \leftarrow \mathcal{S} \cup \{i\}$;
4 $\mathcal{N}^- \leftarrow \mathcal{N} \setminus \mathcal{S}$;
// Calculate residual QoI requirement
5 **foreach** j s.t. $\tau_j \in \mathcal{T}$ **do**
6 $\quad Q'_j \leftarrow Q_j - \min\{Q_j, \sum_{i:\tau_j \in \Gamma_i, i \in \mathcal{S}} q_i\}$;
// Main loop
7 **while** $\sum_{j:\tau_j \in \mathcal{T}} Q'_j \neq 0$ **do**
$\quad$// Find the worker with the minimum marginal social welfare effectiveness
8 $\quad l = \arg\min_{i \in \mathcal{N}^-} \frac{|w_i|}{\sum_{j:\tau_j \in \Gamma_i} \min\{Q'_j, q_i\}}$;
9 $\quad \mathcal{S} \leftarrow \mathcal{S} \cup \{l\}$;
10 $\quad \mathcal{N}^- \leftarrow \mathcal{N}^- \setminus \{l\}$;
$\quad$// Update residual requirement
11 $\quad$ **foreach** j s.t. $\tau_j \in \mathcal{T}$ **do**
12 $\quad\quad Q'_j \leftarrow Q'_j - \min\{Q'_j, q_l\}$;
13 **return** $\mathcal{S}$;

The platform calculates workers' marginal social welfare profile $\overrightarrow{w}$ using workers' bids $\{(\Gamma_1, b_1), \ldots, (\Gamma_N, b_N)\}$ and utilizes $\overrightarrow{w}$ as input to the winner determination algorithm shown in Algorithm 1. First, the platform includes all workers with non-negative marginal social welfare into the winner set $\mathcal{S}$ (lines 2-3). By removing the current winners from $\mathcal{N}$, the platform gets the set of workers $\mathcal{N}^-$ with negative marginal social welfare (line 4). Then, the platform calculates tasks' residual QoI requirement profile $\overrightarrow{Q}'$ by subtracting from $\overrightarrow{Q}$ the QoI provided by the currently selected winners (lines 5-6). The main loop (lines 7-12) is executed until every task's QoI requirement is satisfied. In the main loop, winner selection is based on *marginal social welfare effectiveness (MSWE)*, defined as the ratio between the absolute value of worker i's marginal social welfare $|w_i|$ and her effective QoI contribution $\sum_{j:\tau_j \in \Gamma_i} \min\{Q'_j, q_i\}$. In every iteration, the worker with the minimum MSWE among the remaining workers in $\mathcal{N}^-$ is included into $\mathcal{S}$ (lines 8-9). After that, the platform updates $\mathcal{N}^-$ and tasks' residual QoI requirement profile $\overrightarrow{Q}'$ (lines 10-12).

Algorithm 2 describes the corresponding pricing mechanism. It takes the winner set $\mathcal{S}$ as input and outputs the payment profile $\overrightarrow{p}$. First, $\overrightarrow{p}$ is initialized as a zero vector (line 1). Then, the platform includes all workers with non-negative marginal social welfare into $\mathcal{N}^+$ (lines 2-3). The main loop (lines 4-12) calculates the platform's payment to every winner. For every winner $i \in \mathcal{S}$, the winner determination mechanism in Algorithm 1 is executed with all workers except worker i until the QoI requirement of every task in Γ_i has been fully satisfied (line 5). We reach the point such that it is impossible for worker i to be selected as a winner in future iterations of Algorithm 1. Then, the platform gets the current winner set $\mathcal{S}'$ (line 6) and calculates p_i differently in the following two cases.

- *Case 1* (lines 7-8). Any winner i belonging to case 1 has $w_i \geq 0$. Hence, this worker's critical payment is the bidding price b'_i that satisfies $w'_i = \alpha q_i|\Gamma_i| - b'_i = 0$. That is, $p_i = \alpha q_i |\Gamma_i|$.
- *Case 2* (lines 10-11). For any winner i belonging to case 2, we go through every worker $k \in \mathcal{S}' \setminus \mathcal{N}^+$. We calculate worker i's maximum bidding price b'_i to be able to substitute worker k as the winner. That is, b'_i satisfies

$$\frac{b'_i - \alpha q_i|\Gamma_i|}{\sum_{j:\tau_j \in \Gamma_i} \min\{Q'_j, q_i\}} = \frac{|w_k|}{\sum_{j:\tau_j \in \Gamma_k} \min\{Q'_j, q_k\}}. \tag{10}$$

This means

$$b'_i = \alpha q_i |\Gamma_i| - w_k \frac{\sum_{j:\tau_j \in \Gamma_i} \min\{Q'_j, q_i\}}{\sum_{j:\tau_j \in \Gamma_k} \min\{Q'_j, q_k\}}. \tag{11}$$

Finally, the maximum value among all b'_i's is used as the payment to worker i.

Algorithm 2. QoI-SRC Auction Pricing

Input: $\mathcal{S}$, α, $\overrightarrow{q}$, $\overrightarrow{w}$, $\overrightarrow{\Gamma}$;
Output: $\overrightarrow{p}$;
// Initialization
1 $\mathcal{N}^+ \leftarrow \emptyset$, $\overrightarrow{p} \leftarrow \{0, \ldots, 0\}$;
// Find non-negative marginal welfare workers
2 **foreach** i s.t. $w_i \geq 0$ **do**
3 $\quad \mathcal{N}^+ \leftarrow \mathcal{N}^+ \cup \{i\}$;
// Main loop
4 **foreach** $i \in \mathcal{S}$ **do**
5 $\quad$ run Algorithm 1 on $\mathcal{N} \setminus \{i\}$ until $\sum_{j:\tau_j \in \Gamma_i} Q'_j = 0$;
6 $\quad \mathcal{S}' \leftarrow$ the winner set when step 5 stops;
$\quad$// Calculate payment
7 $\quad$ **if** $|\mathcal{S}'| < |\mathcal{N}^+|$ **then**
8 $\quad\quad p_i \leftarrow \alpha q_i |\Gamma_i|$;
9 $\quad$ **else**
10 $\quad\quad$ **foreach** $k \in \mathcal{S}' \setminus \mathcal{N}^+$ **do**
11 $\quad\quad\quad \overrightarrow{Q}' \leftarrow$ tasks' residual QoI requirement profile when winner k is selected;
12 $\quad\quad\quad p_i \leftarrow \max\Big\{p_i, \alpha q_i|\Gamma_i| - w_k \frac{\sum_{j:\tau_j \in \Gamma_i} \min\{Q'_j, q_i\}}{\sum_{j:\tau_j \in \Gamma_k} \min\{Q'_j, q_k\}}\Big\}$;
13 **return** $\overrightarrow{p}$;

4.3 Analysis

First, we analyze the truthfulness and individual rationality of the QoI-SRC auction in Theorems 2 and 3.

Theorem 2. *The QoI-SRC auction is truthful.*

Proof. Suppose worker i wins by bidding (Γ_i, b_i). We consider worker i's any other bid (Γ'_i, b'_i) such that $b'_i < b_i$ or $\Gamma'_i \supset \Gamma_i$.

- *Case 1* ($w_i \geq 0$). The marginal social welfare for bidding (Γ'_i, b'_i) is $w'_i = \alpha q_i|\Gamma'_i| - b'_i > \alpha q_i|\Gamma_i| - b_i \geq 0$.
- *Case 2* ($w_i < 0$). Bidding (Γ'_i, b'_i) will make $w'_i \geq 0$ or decrease the value of worker i's MSWE.

Hence, worker i is still a winner by bidding (Γ'_i, b'_i) and the QoI-SRC auction winner determination algorithm satisfies both bidding bundle and price monotonicity. Furthermore, it is easily verifiable that the pricing mechanism in Algorithm 2 uses the supremum of bidding prices b'_i such that bidding (Γ_i, b'_i) still wins. Hence, from Lemma 1 we conclude that the QoI-SRC auction is truthful. □

Theorem 3. *The QoI-SRC auction is individual rational.*

Proof. From Theorem 2, we have proved that workers bid truthfully in our QoI-SRC auction. Hence, any worker i bids its true cost c_i. Since every winner i is paid the supremum of bidding prices given the bundle Γ_i, we have $p_i \geq c_i$ for every winner. Apparently, losers have zero utilities in our QoI-SRC auction. Therefore, the utility for every worker i satisfies $u_i \geq 0$ and the QoI-SRC auction is individual rational. □

Then, we analyze the algorithmic properties of the QoI-SRC auction including its computational complexity and approximation ratio to the optimal social welfare in Theorems 4 and 5.

Theorem 4. *The computational complexity of the QoI-SRC auction is $O(N^2M)$.*

Proof. The computational complexity of Algorithm 1 is dominated by the main loop, which terminates after N iterations in the worst case. In every iteration, the algorithm goes through every task $\tau_j \in \mathcal{T}$. Hence, the computational complexity of Algorithm 1 is $O(NM)$. Similarly, we have that the computational complexity of Algorithm 2 is $O(N^2M)$. Therefore, we conclude that computational complexity of the QoI-SRC auction is $O(N^2M)$. □

Then, we provide our analysis about the approximation ratio of the QoI-SRC auction using the method similar to the one proposed by Rajagopalan et al. [47]. In our following analysis, we use $\mathcal{N}^-$ to denote all workers $i \in \mathcal{N}$ with negative w_i and $\overrightarrow{Q}^- = \{Q_1^-, \ldots, Q_M^-\}$ to denote tasks' residual QoI requirement profile after Algorithm 1 includes all workers with $w_i \geq 0$ into the winner set. Then, we normalize the w_i for every worker $i \in \mathcal{N}^-$, such that the normalized marginal social welfare

$$w'_i = \frac{w_i}{\max_{n\in\mathcal{N}^-} w_n} > 0.$$

Thus, with only a multiplicative factor change to the objective function, we formulate the linear program relaxation of the residual SRC-WD problem defined on worker set $\mathcal{N}^-$ as the normalized primal linear program **P**. The dual program is formulated in program **D**.

$$\mathbf{P}: \min \sum_{i\in\mathcal{N}^-} w'_i x_i \tag{12}$$

$$\text{s.t.} \sum_{i:\tau_j\in\Gamma_i, i\in\mathcal{N}^-} q_i x_i \geq Q_j^-, \qquad \forall \tau_j \in \mathcal{T} \tag{13}$$

$$0 \leq x_i \leq 1, \qquad \forall i \in \mathcal{N}^- \tag{14}$$

$$\mathbf{D}: \max \sum_{j:\tau_j\in\mathcal{T}} Q_j^- y_j - \sum_{i\in\mathcal{N}^-} z_i \tag{15}$$

$$\text{s.t.} \sum_{j:\tau_j\in\Gamma_i} q_i y_j - z_i \leq w'_i, \qquad \forall i \in \mathcal{N}^- \tag{16}$$

$$y_j \geq 0, \qquad \forall \tau_j \in \mathcal{T} \tag{17}$$

$$z_i \geq 0, \qquad \forall i \in \mathcal{N}^- \tag{18}$$

It is easily verifiable that the $|\max_{i\in\mathcal{N}^-} w_i|$ multiplicative factor difference between the objective functions of **P** and the SRC-WD problem does not affect the approximation ratio of Algorithm 1. Next, we introduce several notations and concepts utilized in our following analysis.

We define any task $\tau_j \in \mathcal{T}$ as *alive* at any particular iteration of the main loop in Algorithm 1 if its QoI requirement is not fully satisfied. Furthermore, we define that task τ_j is *covered* by Γ_i if $\tau_j \in \Gamma_i$ and τ_j is alive when worker i is selected. The coverage relationship is represented as $\tau_j \preceq \Gamma_i$. Then, we define the minimum measure of QoI as Δq, the *unit QoI*. Suppose when worker i is about to be selected, the residual QoI requirement profile is $\overrightarrow{Q}' = \{Q'_1, \ldots, Q'_M\}$ and Γ_i is the i_jth set that covers τ_j, the corresponding normalized MSWE in terms of unit QoI can be represented

$$W(\tau_j, i_j) = \frac{w'_i \Delta q}{\sum_{j:\tau_j\in\Gamma_i} \min\{Q'_j, q_i\}}. \tag{19}$$

We assume that τ_j is covered by k_j sets and we have $W(\tau_j, 1) \leq \cdots \leq W(\tau_j, k_j)$ from Equation (19). Then, we define the following constants

$$\theta = \max_{i,j} q_i|\Gamma_i|w'_j,$$

as well as,

$$m = \frac{1}{\Delta q}\sum_{j:\tau_j\in\mathcal{T}} Q_j^-,$$

which are used in the presentation of Lemma 2.

Lemma 2. *The following assignments of y_j and z_i for $\forall \tau_j \in \mathcal{T}$ and $\forall i \in \mathcal{N}^-$ are feasible to **D**.*

$$y_j = \frac{W(\tau_j, k_j)}{2\theta H_m \Delta q}, \ \forall \tau_j \in \mathcal{T},$$

$$z_i = \begin{cases} \frac{\sum_{j:\tau_j\preceq\Gamma_i}\left(\min\{Q'_j, q_i\}\left(W(\tau_j,k_j) - W(\tau_j,i_j)\right)\right)}{2\theta H_m \Delta q}, & i \in \mathcal{S} \\ 0, \ i \notin \mathcal{S} \end{cases}$$

Proof. Suppose for any worker $i \in \mathcal{N}^-$, there are t_i tasks in bundle Γ_i. We reorder these tasks in the order in which they are fully covered.

If worker i is not selected as a winner in $\mathcal{S}$, then we have $z_i = 0$. Suppose when the last unit QoI of τ_j is about to be covered, the residual QoI requirement profile is $\overrightarrow{Q}'' = \{Q''_1, \ldots, Q''_M\}$, then the total residual QoI of alive tasks contained by Γ_i is represented as $\sum_{h=j}^{t_i} \min\{Q''_h, q_i\}$. We have

$$W(\tau_j, k_j) \leq \frac{w'_i \Delta q}{\sum_{h=j}^{t_i} \min\{Q''_h, q_i\}}.$$

Therefore, we have

$$\begin{aligned}\sum_{j=1}^{t_i} q_i y_j - z_i &\le \sum_{j=1}^{t_i} \frac{w_i' q_i}{2\theta H_m \sum_{h=j}^{t_i} \min\{Q_h'', q_i\}} - 0\\ &\le \frac{w_i'}{H_m}\left(1+\frac{1}{2}+\cdots+\frac{1}{m}\right)\\ &\le w_i'.\end{aligned}$$

If worker $i \in \mathcal{S}$, then we assume that when worker i is selected as a winner, t_i' tasks in Γ_i have already been fully covered. We have

$$\begin{aligned}&\sum_{j=1}^{t_i} q_i y_j - z_i\\ =&\frac{\sum_{j=1}^{t_i} q_i W(\tau_j, k_j)}{2\theta H_m \Delta q} - \\ &\frac{\sum_{j=t_i'+1}^{t_i} \min\{Q_j', q_i\}\big(W(\tau_j,k_j) - W(\tau_j, i_j)\big)}{2\theta H_m \Delta q}\\ =&\frac{\sum_{j=1}^{t_i'} q_i W(\tau_j, k_j)}{2\theta H_m \Delta q} + \frac{\sum_{j=t_i'+1}^{t_i} \min\{Q_j', q_i\} W(\tau_j, i_j)}{2\theta H_m \Delta q}\\ &+\frac{\sum_{j=t_i'+1}^{t_i}\big(q_i - \min\{Q_j', q_i\}\big) W(\tau_j, k_j)}{2\theta H_m \Delta q}\\ \le&\frac{\sum_{j=1}^{t_i'} \frac{q_i w_i'}{\sum_{h=j}^{t_i}\min\{Q_h', q_i\}}}{2\theta H_m} + \frac{w_i'}{2\theta H_m} + \frac{\theta}{2\theta H_m}\\ \le& w_i'.\end{aligned}$$

Therefore, we arrive at the conclusion that the assignments of y_j and z_i in Lemma 2 are feasible to $\mathbf{D}$. □

Then in Theorem 5, we present our result regarding the approximation ratio of Algorithm 1.

Theorem 5. *Algorithm 1 is a $2\theta H_m$-approximation algorithm for the residual SRC-WD problem defined on worker set $\mathcal{N}^-$.*

Proof. By substituting the dual assignments given in Lemma 2 into the objective function (15), we have

$$\begin{aligned}&\sum_{j:\tau_j \in \mathcal{T}} Q_j^- y_j - \sum_{i \in \mathcal{N}^-} z_i\\ =&\frac{\sum_{i\in\mathcal{N}^-\cap\mathcal{S}} \sum_{j:\tau_j \preceq \Gamma_i} \Big(\min\{Q_j', q_i\}\big(W(\tau_j, i_j) - W(\tau_j, k_j)\big)\Big)}{2\theta H_m \Delta q}\\ &+\frac{\sum_{j:\tau_j\in\mathcal{T}} Q_j^- W(\tau_j, k_j)}{2\theta H_m \Delta q}\\ =&\frac{\sum_{i\in\mathcal{N}^-\cap\mathcal{S}} \sum_{j:\tau_j\preceq\Gamma_i} \min\{Q_j', q_i\} \frac{w_i'\Delta q}{\sum_{j:\tau_j\in\Gamma_i}\min\{Q_j', q_i\}}}{2\theta H_m \Delta q}\\ =&\frac{\sum_{i\in\mathcal{N}^-\cap\mathcal{S}} w_i'}{2\theta H_m}.\end{aligned}$$

Because $\mathbf{D}$ is the dual program of $\mathbf{P}$, we have

$$\frac{\sum_{i\in\mathcal{N}^-\cap\mathcal{S}} w_i'}{2\theta H_m} \le \mathrm{OPT}_{\mathbf{D}} \le \mathrm{OPT}_{\mathbf{P}} \le \mathrm{OPT}_{\mathrm{SRC-WD}}.$$

Therefore, Algorithm 1 is a $2\theta H_m$-approximation algorithm for the residual SRC-WD problem defined on worker set $\mathcal{N}^-$. □

Note that there is a $\max_{i\in\mathcal{N}^-}|\Gamma_i|$ factor in the parameter θ, which could be large theoretically, and in worst case equals to the number of tasks M. However, practically, as any worker i typically has a limited capability and interest in terms of the number of sensing tasks she can and wants to execute, the value $\max_{i\in\mathcal{N}^-}|\Gamma_i|$ will be far less than M, which prevents θ from growing excessively large, in practice, as M increases. Furthermore, it is clear that $m = O(M)$, and $H_m = O(\log m)$, and thus we have that $H_m = O(\log M)$. Therefore, although the factor H_m is not a constant, it is still much smaller than M in order sense. Thus far, the $2\theta H_m$ approximation ratio proved in Theorem 5 is the best one we have found, and we leave the proof of the tightness of this ratio, or the derivation of a better one in our future work.

5 MRC Auction

In this section, we present the mathematical formulation, mechanism design and the analysis for the MRC auction.

5.1 Mathematical Formulation

In the MRC auction, we also use the form of the platform's value function $V_{\overrightarrow{q}}(\cdot)$ given in Equation (5). If the platform is given workers' cost function profile, denote as $\overrightarrow{C} = \{C_1(\cdot), \ldots, C_N(\cdot)\}$, the MRC auction winner determination (MRC-WD) problem can be formulated as follows.

MRC-WD Problem:

$$\max \sum_{i\in\mathcal{N}} \big(\alpha q_i |\Gamma_i| - C_i(\Gamma_i)\big) x_i \tag{20}$$

$$\text{s.t. } \Gamma_i \subseteq \Gamma_i^j,\ \exists \Gamma_i^j \in \mathcal{T}_i, \qquad \forall i \in \mathcal{N} \tag{21}$$

$$x_i \in \{0,1\}, \qquad \forall i \in \mathcal{N}. \tag{22}$$

The MRC-WD problem takes the parameter α, workers' QoI profile $\overrightarrow{q}$ and workers' cost function profile $\overrightarrow{C}$ as input. It has a set of binary variables $\{x_1, \ldots, x_n\}$ indicating whether worker i is selected in the winner set $\mathcal{S}$. That is, if $i \in \mathcal{S}$, then $x_i = 1$. Otherwise, $x_i = 0$.

Furthermore, for every worker i, we have a variable Γ_i indicating the set of sensing tasks that the platform allocates to this worker. Constraint Equation (21) ensures that Γ_i is the subset of at least one bundle $\Gamma_i^j \in \mathcal{T}_i$. Therefore, the MRC-WD problem aims to find the set of winners $\mathcal{S}$ and the corresponding task allocation profile denoted as $\overrightarrow{\Gamma} = \{\Gamma_1, \ldots, \Gamma_N\}$ that maximize the social welfare represented by the objective function. We use $\Gamma_{\max}^i$ to denote the bundle with the maximum cardinality in $\mathcal{T}_i$ and $w_{\max}^i = \alpha q_i |\Gamma_{\max}^i| - c_i$ to denote worker i's marginal social welfare for $\Gamma_{\max}^i$. The maximum social welfare is achieved by selecting all workers with positive $w_{\max}^i$ as winners and allocating to every winner i the set of tasks $\Gamma_{\max}^i$.

However, the challenge is that cost function profile $\overrightarrow{C}$ is not known by the platform and we still aim to design a mechanism that approximately maximizes the social welfare with a guaranteed approximation ratio. Then, we present the design of our mechanism in Section 5.2 that achieves this objective while ensuring individual rationality and polynomial computational complexity.

5.2 Mechanism Design

Requiring truthfulness in multi-minded combinatorial auctions limits the family of mechanisms that can be used, as mentioned in [44]. As long as the mechanism can achieve close-to-optimal social welfare with a guaranteed approximation ratio, it is justifiable for us to relax the truthfulness requirement, as pointed out in [44]. In Algorithm 3 we describe our design of the iterative descending dominant-strategy *quality of information aware MRC (QoI-MRC)* auction for Thanos in the multi-minded scenario, which is different from the mechanisms designed for multi-minded forward combinatorial auctions proposed in [44].

Algorithm 3. QoI-MRC Auction

Input: $\mathcal{N}$, $b_{\max}$, ϵ, α, β, $\overrightarrow{q}$;
Output: $\mathcal{S}$, $\overrightarrow{p}$, $\overrightarrow{\Gamma}$;
// Winner determination
// Initialize winner and loser sets
1 $\mathcal{S} \leftarrow \emptyset,\ \mathcal{L} \leftarrow \emptyset$;
// Initialize bidding bundles and prices
2 $\overrightarrow{\Gamma} \leftarrow \{\emptyset, \ldots, \emptyset\}$, $\overrightarrow{\Gamma}' \leftarrow \overrightarrow{\Gamma}$, $\overrightarrow{b} \leftarrow \{b_{\max}, \ldots, b_{\max}\}$;
// Main loop
3 **while** $\mathcal{S} \cup \mathcal{L} \neq \mathcal{N}$ **do**
4   **foreach** $i \in \mathcal{N} \setminus (\mathcal{S} \cup \mathcal{L})$ **do**
5   **if** $\alpha q_i|\Gamma_i| - b_i \geq \epsilon$ **then**
6       $\mathcal{S} \leftarrow \mathcal{S} \cup \{i\}$;
      // Give worker i the option to enlarge her bidding bundle
7   **else**
8   allow worker i to enlarge Γ_i to any Γ'_i s.t. $\Gamma'_i \supseteq \Gamma_i$;
      // Update bidding bundle
9   **if** $\Gamma_i \neq \Gamma'_i$ **then**
10         $\Gamma_i \leftarrow \Gamma'_i$;
11   **if** $\alpha q_i|\Gamma_i| - b_i \geq \epsilon$ **then**
12         $\mathcal{S} \leftarrow \mathcal{S} \cup \{i\}$;
13   **foreach** $i \in \mathcal{N} \setminus (\mathcal{S} \cup \mathcal{L})$ **do**
    // Give worker i two options
14   option 1: $b_i \leftarrow \frac{b_i}{\beta}$;
15   option 2: $b_i \leftarrow 0$;
16   **if** $b_i = 0$ **then**
17       $\mathcal{L} \leftarrow \mathcal{L} \cup \{i\}$;
18 $\overrightarrow{\Gamma} \leftarrow \{\Gamma_i \in \overrightarrow{\Gamma} | i \in \mathcal{S}\}$;
// Pricing
19 $\overrightarrow{p} \leftarrow \overrightarrow{b}$;
20 **return** $\mathcal{S}$, $\overrightarrow{p}$, $\overrightarrow{\Gamma}$;

The QoI-MRC auction described in Algorithm 3 consists of a winner determination phase (lines 1-18) and a pricing phase (line 19). Every winner $i \in \mathcal{S}$ will be allocated her bidding bundle Γ_i and be paid her bidding price b_i of the final iteration of the winner determination phase. We assume that the platform has the information about the upper bound and lower bound of workers' costs denoted as $c_{\max}$ and $c_{\min}$ respectively. The platform initializes every worker i's bidding bundle and bidding price as $\Gamma_i = \emptyset$ and $b_{\max} \geq c_{\max}$ (line 2). Moreover, the input parameters $\beta > 1$ and $\epsilon \in (0, c_{\min}]$.

The main loop (lines 3-17) is executed until every worker is either a winner or a loser. In every iteration of the main loop, every worker i such that $\alpha q_i|\Gamma_i| - b_i \geq \epsilon$ is included in the winner set $\mathcal{S}$ (lines 5-6). For any worker i that is neither a winner nor a loser in the current iteration, the Algorithm gives her an option to choose whether she will enlarge her current bidding bundle Γ_i to any bundle Γ'_i that contains Γ_i (line 5). If after the bundle enlarging $\alpha q_i|\Gamma'_i| - b_i \geq \epsilon$ holds, this worker is included in the winner set (lines 11-12). Otherwise, she is given the following two options to choose from.

- *Option 1* (line 14). By choosing option 1, worker i divides her bidding price b_i by β. As long as she is fully rational, she will choose option 1 rather than option 2 to drop out of the auction, if $\frac{b_i}{\beta} > c_i$ hold. By doing so, she keeps herself in the auction and makes it still possible for her to win in one of the future iterations to receive positive utility.
- *Option 2* (line 15). By choosing option 2, the worker i drops out of the auction. If $\frac{b_i}{\beta} \leq c_i$, any rational user i will choose option 2 because it is impossible for her to obtain positive utility even though she remains in the auction in this case.

Finally, every winner i is allocated her bidding bundle Γ_i (line 18) and be paid her bidding price b_i (line 19) of the final iteration of the winner determination phase.

5.3 Analysis

Although the QoI-MRC auction cannot guarantee truthfulness because workers' bidding prices when Algorithm 3 terminates will possibly not be equal to workers' true costs, we show in the following Theorem 6 that every worker still has a dominant strategy.

Theorem 6. *Every worker $i \in \mathcal{N}$ has the following dominant strategy in the QoI-MRC auction.*

- *Worker i enlarges bundle Γ_i to $\Gamma^i_{\max}$ in the first iteration.*
- *When worker i is given the options to divide her bidding price b_i by β or drop out of the auction, she will always choose the former as long as $\frac{b_i}{\beta} > c_i$ and the latter if $\frac{b_i}{\beta} \leq c_i$.*

Proof. Obviously, any rational worker i will choose to divide her current bidding price b_i by β as long as $\frac{b_i}{\beta} > c_i$ when she is given the two options. By doing so, it is still possible for her to win the auction and be paid $p_i > c_i$. If $\frac{b_i}{\beta} \leq c_i$, then even if she wins the auction the payment p_i will not be larger than c_i. Hence, she will drop out in this case.

Then, we study whether any worker i will enlarge her bundle to some $\Gamma'_i \neq \Gamma^i_{\max}$ in the first iteration.

- *Case 1* ($\alpha q_i|\Gamma^i_{\max}| - b_{\max} > \alpha q_i|\Gamma'_i| - b_{\max} \geq \epsilon$). Both $\Gamma^i_{\max}$ and Γ'_i will make the worker win the auction in the first iteration and be paid $b_{\max}$. We have $u(\Gamma^i_{\max}) = u(\Gamma'_i)$.
- *Case 2* ($\alpha q_i|\Gamma^i_{\max}| - b_{\max} \geq \epsilon > \alpha q_i|\Gamma'_i| - b_{\max}$). The worker will win and be paid $b_{\max}$ by enlarging to $\Gamma^i_{\max}$ in the first iteration and we have $u(\Gamma^i_{\max}) = b_{\max} - c_i$. If she proposes Γ'_i instead of $\Gamma^i_{\max}$, she will be asked to decrease her bid or drop out in the first iteration. Eventually, she could lose or win with being paid $b'_i < b_{\max}$. Her utility could either be $u(\Gamma'_i) = 0$ or $u(\Gamma'_i) = b'_i - c_i$. We have $u(\Gamma^i_{\max}) > u(\Gamma'_i)$.
- *Case 3* ($\epsilon > \alpha q_i|\Gamma^i_{\max}| - b_{\max} > \alpha q_i|\Gamma'_i| - b_{\max}$). Both $\Gamma^i_{\max}$ and Γ'_i will make the worker face the choices of decreasing her bid or dropping out in the first iteration. If eventually she wins in both

cases, then the number of iterations before she wins if she proposes $\Gamma^i_{\max}$ will be smaller than or equal to that of Γ'_i. The payments p_i and p'_i for the two cases satisfy $p_i \geq p'_i$ and we have $u(\Gamma^i_{\max}) \geq u(\Gamma'_i)$. If she loses in both cases, then $u(\Gamma^i_{\max}) = u(\Gamma'_i) = 0$. The last scenario is that she wins by proposing $\Gamma^i_{\max}$ and loses by proposing Γ'_i in the first iteration. Then, we have $u(\Gamma^i_{\max}) > 0 = u(\Gamma'_i)$.

We have $u(\Gamma^i_{\max}) \geq u(\Gamma'_i)$ with at least one scenario with strict inequality. Hence, worker i enlarges bundle Γ_i to $\Gamma^i_{\max}$ in the first iteration. We arrive at the conclusion about any user's dominant strategy stated in Theorem 6. □

Theorem 7. *The QoI-MRC auction is individual rational.*

Proof. When a worker is given the choices to decrease her bid or drops out of the auction, any worker i will drop out if $\frac{b_i}{\beta} \leq c_i$. She becomes a loser and obtains $u_i = 0$. The worker only chooses to divide b_i by β if $\frac{b_i}{\beta} > c_i$, which ensures that her payment $p_i > c_i$ if she wins. In this case, we have $u_i > 0$. Therefore, $u_i \geq 0$ and the QoI-MRC auction is individual rational. □

Then, we analyze the algorithmic properties of the QoI-MRC auction computational complexity and approximation ratio in Theorems 8 and 9.

Theorem 8. *The computational complexity of the QoI-MRC auction is $O(N)$.*

Proof. It is easily verifiable that the main loop of Algorithm 3 terminates after $O\big(\log_\beta \frac{b_{\max}}{c_{\min}}\big)$ number of iterations. The computational complexity inside the main loop is $O(N)$. Therefore, the computational complexity of the QoI-MRC auction is $O(N)$. □

In Theorem 9, we present our results about the approximation ratio of the QoI-MRC auction to the optimal social welfare. Next, we let $a_i = \frac{\alpha q_i |\Gamma^i_{\max}|}{c_i}$, and use a_i as each worker i's type that uniquely characterizes the worker. Furthermore, we let $F(\cdot)$ denote the CDF of workers' types, use $\overline{a}$ to denote the upper bound of the support of $F(\cdot)$, and let $\gamma = \frac{b_{\max}}{\epsilon}$.

Theorem 9. *The QoI-MRC auction has a*

$$1 - \frac{1}{1 + \frac{\big(F(\overline{a}) - F(\beta+1)\big)\beta^2}{\big(F(\beta+1) - F(1)\big)\big(\beta^2 + (\beta-1)\gamma\big)}}$$

approximation ratio to the optimal social welfare.

Proof. By Theorem 6, every worker $i \in \mathcal{N}$ enlarges her bundle to $\Gamma^i_{\max}$ in the first iteration. Furthermore, the winner set $\mathcal{S}$ output by Algorithm 3 consists of the set of winners $\mathcal{S}_1 = \{i \in \mathcal{N} | \alpha q_i |\Gamma^i_{\max}| - b_{\max} \geq \epsilon\}$ that win in the first iteration, as well as the winners $\mathcal{S}_2$ that win in subsequent iterations, i.e., $\mathcal{S}_2$ contains every worker i such that the following Condition,

$$\begin{cases} \alpha q_i |\Gamma^i_{\max}| - b_{\max} < \epsilon, & (23)\\ \alpha q_i |\Gamma^i_{\max}| - \frac{b_{\max}}{\beta^{r_i - 1}} < \epsilon, & (24)\\ \alpha q_i |\Gamma^i_{\max}| - \frac{b_{\max}}{\beta^{r_i}} \geq \epsilon, & (25)\\ \frac{b_{\max}}{\beta^{r_i}} > c_i, & (26) \end{cases}$$

for some integer $r_i > 1$, are satisfied. Clearly, iteration r_i is the first iteration that makes $\alpha q_i |\Gamma^i_{\max}| - \frac{b_{\max}}{\beta^{r_i}} \geq \epsilon$.

Let $\mathcal{S}_{\text{OPT}}$ be the winner set of the optimal solution of the MRC-WD problem, which clearly satisfies that $\mathcal{S}_{\text{OPT}} = \{i \in \mathcal{N} | \alpha q_i |\Gamma^i_{\max}| - c_i > 0\}$. Recall that in Algorithm 3, we set the parameter $b_{\max} \geq c_{\max}$. For any worker $i \in \mathcal{S}_1$, we have that $\alpha q_i |\Gamma^i_{\max}| - c_i \geq \alpha\ q_i |\Gamma^i_{\max}| - c_{\max} \geq \alpha q_i |\Gamma^i_{\max}| - b_{\max} \geq \epsilon > 0$, and thus $\mathcal{S}_1 \subseteq \mathcal{S}_{\text{OPT}}$. By Condition Equations (25) and (26), we have that

$$\alpha q_i |\Gamma^i_{\max}| - c_i \geq \alpha q_i |\Gamma^i_{\max}| - \frac{b_{\max}}{\beta^{r_i}} \geq \epsilon > 0,$$

and thus $\mathcal{S}_2 \subseteq \mathcal{S}_{\text{OPT}}$ also holds. Therefore, the winner set $\mathcal{S} = \mathcal{S}_1 \cup \mathcal{S}_2$ given by the QoI-MRC auction is a subset of the optimal winner set $\mathcal{S}_{\text{OPT}}$. We let $\mathcal{S}_3 = \mathcal{S}_{\text{OPT}} \setminus \mathcal{S}$, and we have that $\mathcal{S}_3$ contains every worker i such that the following Condition,

$$\begin{cases} \alpha q_i |\Gamma^i_{\max}| - c_i > 0, & (27)\\ \alpha q_i |\Gamma^i_{\max}| - b_{\max} < \epsilon, & (28)\\ \alpha q_i |\Gamma^i_{\max}| - \frac{b_{\max}}{\beta^{r_i}} < \epsilon, & (29)\\ \frac{b_{\max}}{\beta^{r_i}} > c_i, & (30)\\ \frac{b_{\max}}{\beta^{r_i+1}} \leq c_i, & (31) \end{cases}$$

for some integer $r_i \geq 1$, are satisfied. Clearly, r_i is the iteration in which the worker i drops out, and $\mathcal{S}_3$ denotes the set of workers in the loser set $\mathcal{L}$ with $\alpha q_i |\Gamma^i_{\max}| - c_i > 0$.

We use APP to denote the social welfare yielded by the QoI-MRC auction, and OPT to denote the optimal social welfare. Based on our definition of $\mathcal{S}_1$, $\mathcal{S}_2$, and $\mathcal{S}_3$, we have that

$$\begin{aligned} \frac{\text{APP}}{\text{OPT}} &= \frac{\sum_{i\in\mathcal{S}}(\alpha q_i |\Gamma^i_{\max}| - c_i)}{\sum_{i\in\mathcal{S}_{\text{OPT}}}(\alpha q_i |\Gamma^i_{\max}| - c_i)} \\ &= \frac{\sum_{i\in\mathcal{S}}(\alpha q_i |\Gamma^i_{\max}| - c_i)}{\sum_{i\in\mathcal{S}\cup\mathcal{S}_3}(\alpha q_i |\Gamma^i_{\max}| - c_i)} \\ &= 1 - \frac{1}{1 + \frac{\sum_{i\in\mathcal{S}}(\alpha q_i |\Gamma^i_{\max}| - c_i)}{\sum_{i\in\mathcal{S}_3}(\alpha q_i |\Gamma^i_{\max}| - c_i)}}. \end{aligned} \tag{32}$$

As aforementioned, we have that

$$\alpha q_i |\Gamma^i_{\max}| - c_i \geq \epsilon, \forall i \in \mathcal{S}. \tag{33}$$

Furthermore, for each worker $i \in \mathcal{S}_3$, we have that

$$\begin{aligned} \alpha q_i |\Gamma^i_{\max}| - c_i &\leq \alpha q_i |\Gamma^i_{\max}| - \frac{b_{\max}}{\beta^{r_i+1}} \\ &= \alpha q_i |\Gamma^i_{\max}| - \frac{b_{\max}}{\beta^{r_i}} + \frac{(\beta-1)b_{\max}}{\beta^{r_i+1}} \\ &< \epsilon + \frac{(\beta-1)b_{\max}}{\beta^{r_i+1}} \\ &\leq \epsilon\left(1 + \frac{(\beta-1)\gamma}{\beta^2}\right). \end{aligned} \tag{34}$$

Thus, by substituting Inequality (33) and (34) into Equation (32), we have that

$$\frac{\text{APP}}{\text{OPT}} \geq 1 - \frac{1}{1 + \frac{|\mathcal{S}|\beta^2}{|\mathcal{S}_3|\big(\beta^2 + (\beta-1)\gamma\big)}}. \tag{35}$$

Next, we derive a lower bound of $\frac{|\mathcal{S}|}{|\mathcal{S}_3|}$ represented by the CDF $F(\cdot)$ of workers' types. For all worker $i \in \mathcal{S}_3$, by Condition (27), we have that $a_i > 1$, and by Condition (29) and (31), we have that

$$\alpha q_i |\Gamma^i_{\max}| \leq \frac{b_{\max}}{\beta^{r_i}} + \epsilon \, < \, (\beta+1)c_i,$$

and thus $a_i \, < \, \beta + 1$. Therefore, we have that

$$\begin{aligned} \frac{|\mathcal{S}|}{|\mathcal{S}_3|} &= \frac{|\mathcal{S}_{\text{OPT}}| - |\mathcal{S}_3|}{|\mathcal{S}_3|} \\ &\geq \frac{\big(F(\overline{a}) - F(1)\big) - \big(F(\beta+1) - F(1)\big)}{F(\beta+1) - F(1)} \\ &= \frac{F(\overline{a}) - F(\beta+1)}{F(\beta+1) - F(1)}. \end{aligned} \tag{36}$$

Next, we substitute Inequality (36) into Inequality (35), and we have that

$$\frac{\text{APP}}{\text{OPT}} \leq 1 - \frac{1}{1 + \frac{\left(F(\overline{a}) - F(\beta+1)\right)\beta^2}{\left(F(\beta+1)-F(1)\right)\left(\beta^2 + (\beta-1)\gamma\right)}}.$$

Hereby, we finish the proof of this theorem. □

The approximation ratio given in Theorem 9 generalizes to cases where workers' types follow any arbitrary distribution. Next, we present in Corollary 1 the approximation ratio when workers' types are distributed uniformly.

Corollary 1. *If workers types follow a uniform distribution, then the QoI-MRC auction has a*

$$1 - \frac{1}{1 + \frac{(\overline{a} - \beta - 1)\beta}{\beta^2 + (\beta-1)\gamma}}$$

approximation ratio to the optimal social welfare.

Proof. When workers types are distributed uniformly, we have that

$$\frac{F(\overline{a}) - F(\beta+1)}{F(\beta+1) - F(1)} = \frac{\overline{a} - \beta - 1}{\beta}. \tag{37}$$

By substituting Equation (37) into the ratio given in Theorem 9, we get the approximation ratio in this Corollary. □

Note that when workers types follow some other kind of distribution, the approximation ratio could be calculated accordingly by plugging in the corresponding CDF.

6 Summary of Proposed Mechanisms

Thus far, we have finished the description of the design and analysis of Thanos for both the single-mined (Section 4) and multi-mined (Section 5) scenarios. For the single-minded scenario, we propose the QoI-SRC auction (Algorithms 1 and 2), which is proved to be truthful (Theorem 2), individual rational (Theorem 3), and computationally efficient (Theorem 4), and guarantees a close-to-optimal social welfare (Theorem 5). For the multi-mined scenario, we propose the iterative descending QoI-MRC auction (Algorithm 3). We prove that the proposed QoI-MRC auction is a dominant strategy mechanism (Theorem 6), which satisfies individual rationality (Theorem 7) and computational efficiency (Theorem 8), and approximately maximizes the social welfare with a guaranteed approximation ratio (Theorem 9 and Corollary 1).

TABLE 2
Simulation Settings for SRC Auction

Setting	α	c_i	q_i	Q_j	$\lvert\overline{\Gamma}_i\rvert$	N	M
I	0.1	$[2,4]$	$[1,2]$	$[10,13]$	$[20,30]$	$[200,500]$	100
II	0.1	$[4,8]$	$[2,4]$	$[10,13]$	$[20,30]$	300	$[300,600]$
III	0.25	$[1,10]$	$[1,2]$	$[10,13]$	$[20,30]$	$[1000,1250]$	1000
IV	0.25	$[1,10]$	$[2,4]$	$[10,13]$	$[20,30]$	1200	$[1000,1250]$

7 Performance Evaluation

In this section, we introduce the baseline methods used in our simulation, as well as the simulation settings and results.

7.1 Baseline Methods

The first baseline approach is a modified version of the traditional VCG auction [38], [39]. We integrate the concept of QoI and the QoI coverage constraint defined in Section 4 into the VCG winner determination (VCG-WD) problem. We call the modified VCG auction *quality of information aware VCG (QoI-VCG)* auction, in which the VCG-WD problem is solved optimally and the VCG pricing mechanism [38], [39] is utilized to derive winners' payments.

Another baseline method is the marginal social welfare greedy (MSW-Greedy) auction. Its winner determination algorithm first includes every worker i with $w_i \geq 0$ into the winner set. Then, it selects the worker with the largest marginal social welfare among the remaining workers in every iteration until tasks' QoI requirements are fully satisfied. The pricing mechanism is similar to Algorithm 4.2 which essentially pays every winner her supremum bidding price to win given her current bidding bundle. It is easily verifiable that the MSW-Greedy auction is truthful and individual rational.

7.2 Simulation Settings

For our simulation of the SRC auction, we consider setting I-IV described in Table 2. In setting I, we fix the number of tasks as $M = 100$ and vary the number of workers from 200 to 500. In setting II, we fix the number of workers as $N = 300$ and vary the number of tasks from 300 to 600. The parameter $\alpha = 0.1$ in both settings and the values of c_i, q_i, $|\overline{\Gamma}_i|$ for any worker $i \in \mathcal{N}$ and Q_j for any task $\tau_j \in \mathcal{T}$ are generated uniformly at random from the ranges given in Table 2. Workers i's maximum executable task set $\overline{\Gamma}_i$ consists of $|\overline{\Gamma}_i|$ tasks selected uniformly at random from $\mathcal{T}$. Furthermore, we also consider setting III and IV that take instances with larger sizes as inputs. Note that the optimal solution to the VCG-WD problem of the QoI-VCG mechanism is calculated using the GUROBI optimization solver [48].

For our simulation of the MRC auction, we consider the two settings described in Table 3. In setting V, we fix the number of tasks as $M = 100$ and vary the number of workers from 200 to 500. In setting VI, we fix the number of workers as $N = 300$ and vary the number of tasks from 200 to 400. The parameters $\alpha = 0.2$ and $b_{\max} = 0.2$ in both settings and the values of c_i, q_i, $|\overline{\Gamma}_i|$ for any worker $i \in \mathcal{N}$ are generated uniformly at random from the ranges given in Table 3. Worker i's maximum executable task set $\overline{\Gamma}_i$ consists of $|\overline{\Gamma}_i|$ tasks selected uniformly at random from $\mathcal{T}$. Worker i's interested bundle set consists of randomly selected subsets of $\overline{\Gamma}_i$ whose union is $\overline{\Gamma}_i$. Note that in Tables 2 and 3, we only consider settings with continuous QoIs. The experimental

TABLE 3
Simulation Settings for MRC Auction

Setting	α	$b_{\max}$	c_i	q_i	$\lvert\overline{\Gamma}_i\rvert$	N	M
V	0.2	100	$[4,6]$	$[1,2]$	$[20,30]$	$[200,500]$	100
VI	0.2	100	$[6,10]$	$[2,4]$	$[20,30]$	300	$[200,400]$

TABLE 4
Execution Time (s) for Setting I

N	200	220	240	260	280	300	320	340
QoI-VCG	10.19	16.06	11.22	11.71	58.64	63.14	79.37	10.51
QoI-SRC	0.019	0.014	0.015	0.015	0.020	0.022	0.018	0.019
N	360	380	400	420	440	460	480	500
QoI-VCG	43.52	93.44	94.25	273.6	52.54	72.26	860.9	2043
QoI-SRC	0.019	0.021	0.021	0.019	0.023	0.021	0.021	0.024

results under settings with discrete QoIs show similar trends as in Setting I-VI, and are omitted because of space limit.

7.3 Simulation Results

In Fig. 2, we compare the social welfare generated by the QoI-VCG auction, the QoI-SRC auction and the MSW-Greedy auction. The social welfare of the QoI-VCG auction equals to the optimal solution of the SRC-WD problem. From Fig. 2, we arrive at the conclusion that the social welfare of the QoI-SRC auction is close to optimal and far better than that of the baseline MSW-Greedy auction. The MSW-Greedy auction performs the worst among the three methods, because it selects new winners based on each workers' initial marginal social welfare effectiveness, instead of the updated values in each iteration as in the QoI-SRC auction.

In Tables 4 and 5, we show the comparison of the execution time of the QoI-VCG and QoI-SRC auctions. It is obvious from these two tables that the QoI-SRC auction executes in significantly less time than the QoI-VCG auction. With the increasing of the number of users and tasks, the

TABLE 5
Execution Time (s) for Setting II

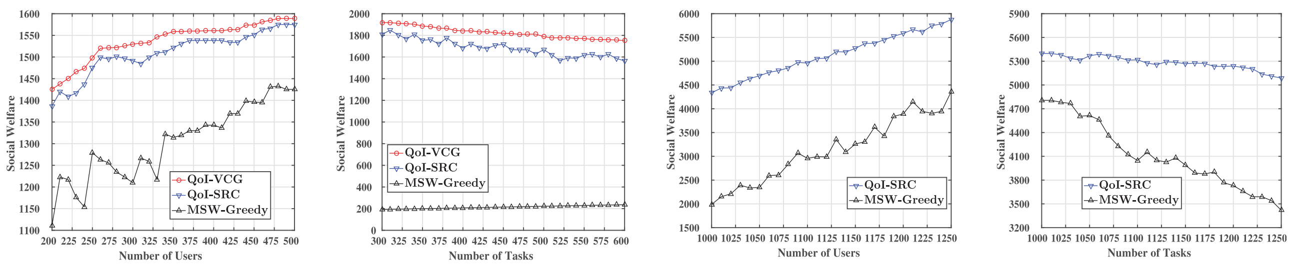
M	300	320	340	360	380	400	420	440
QoI-VCG	18.70	1.337	2.715	15.47	21.42	43.38	88.57	224.3
QoI-SRC	0.066	0.076	0.075	0.076	0.073	0.090	0.075	0.077
M	460	480	500	520	540	560	580	600
QoI-VCG	67.85	50.68	183.5	229.3	474.8	751.1	1206	1269
QoI-SRC	0.079	0.117	0.099	0.130	0.111	0.122	0.123	0.147

execution time of the QoI-VCG auction gradually becomes so long that makes it infeasible to be utilized in practice. In contrast, the QoI-SRC auction keeps low execution time regardless of the growth of the worker and task numbers. The QoI-SRC auction is much more computationally efficient than the QoI-VCG auction.

In Fig. 2, we show our simulation results about the social welfare for setting III and IV with larger-size problem instances where the QoI-VCG auction is not able to terminate in reasonable time. We can observe that the proposed QoI-SRC auction still gives us a total payment far less than that of the MSW-Greedy auction.

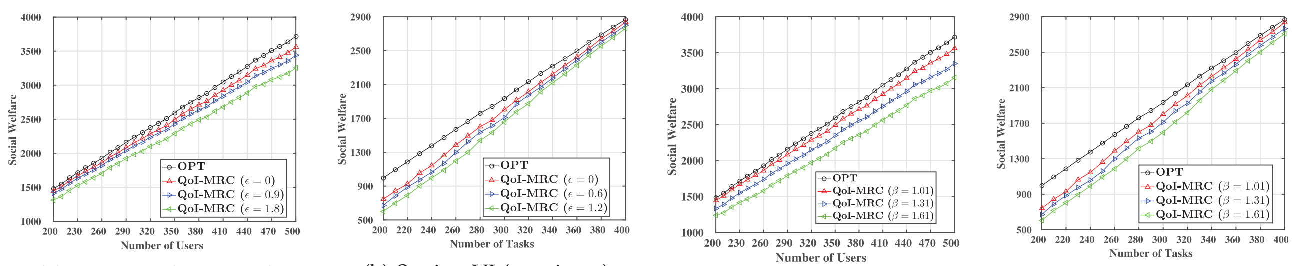
In Fig. 3, we compare the social welfare generated by the QoI-MRC auction with the optimal social welfare in both setting V and VI. We fix the parameter $\beta = 1.01$ and vary the choices of ϵ. From the two figures, we observe that the QoI-MRC auction obtains close-to-optimal social welfare and it becomes closer to the optimal social welfare when ϵ approaches 0. In Fig. 3, we fix the parameter $\epsilon = 0.01$ and vary the choices of β. From these two figures, we also observe that the QoI-MRC auction obtains close-to-optimal social welfare and as β approaches 1, it becomes closer to the optimal social welfare.

In Fig. 4, we plot the empirical CDFs of winners' utilities for both the QoI-SRC and QoI-MRC auction under different values for the number of tasks M and number of workers N. From these two figures, we can observe that every winner has non-negative utility, which shows that the QoI-SRC and QoI-MRC auction are individual rational.



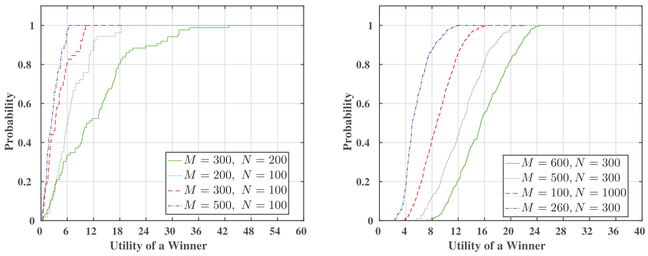
(a) Setting I (b) Setting II (c) Setting V (d) Setting VI

Fig. 2. Social Welfare for setting I-IV.



(a) Setting V (varying ϵ) (b) Setting VI (varying ϵ) (c) Setting V (varying β) (d) Setting VI (varying β)

Fig. 3. Social Welfare for setting V-VI.



(a) QoI-SRC auction (b) QoI-MRC auction

Fig. 4. Empirical CDF of winners' utilities.

8 Conclusion

In this paper, we design Thanos, a quality aware incentive framework for MCS systems based on RC auctions. For the single-minded scenario, we design a truthful, individual rational, and computationally efficient mechanism that approximately maximizes the social welfare with a guaranteed approximation ratio. For the multi-minded scenario, we design an iterative descending mechanism that achieves close-to-optimal social welfare with a guaranteed approximation ratio while satisfying individual rationality and computational efficiency. Furthermore, our theoretical analysis is validated through extensive simulations.

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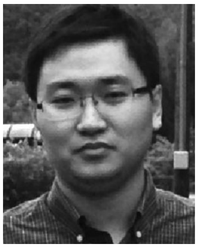

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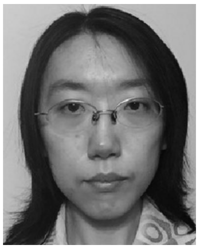

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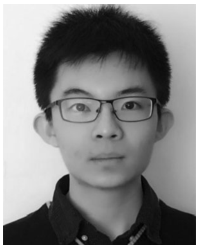

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