Incentive Mechanism Design for Uncertain Tasks in Mobile Crowd Sensing Systems Utilizing Smart Contract in Blockchain

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Abstract. Mobile crowd sensing (MCS) systems recently have been regarded as a newly-emerged sensing paradigm, where the platform receives the requested tasks from requesters and outsources the collection of sensory data to participating workers. However, the centralized structure of the MCS system is vulnerable to a single point of failure, and there is a lack of trust between participants and the platform. Additionally, participating in MCS is often costly. So the paramount problem is how to solve these problems associated with centralized structures and incentivize more participation. Most existing works design the incentive mechanisms only considering static sensing tasks whose information is completely known a priori (*e.g.,* when and which task arrives). Due to the dynamic environment and severe resource constraints, the tasks are usually uncertain, *i.e.,* the information of tasks is incompletely known by the platform. Therefore, in this paper, we design an incentive mechanism, HERALD, for the uncertain tasks in MCS systems by using smart contracts. Specifically, the uncertain tasks are low sensitive to time (that is, tasks do not require real-time information) and arrive according to a probability distribution. HERALD utilizes the decentralized nature of the blockchain to eliminate the system's reliance on third parties and satisfies truthfulness, individual rationality, as well as low computational complexity and low social cost. The desirable properties of HERALD are validated through both theoretical analysis and extensive simulations.

Keywords: Incentive mechanism · Uncertain sensing tasks · Mobile crowd sensing · Smart contract

H. Gao et al. (Eds.): CollaborateCom 2022, LNICST 460, pp. 475–493, 2022.
https://doi.org/10.1007/978-3-031-24383-7_26

1 Introduction

The recent unprecedented development of mobile devices which are embedded with powerful processors and plentiful sensors (*e.g.,* GPS, microphone, camera) has impelled the rise of mobile crowd sensing, a newly emerged sensing paradigm that outsources the collection of sensory data to a crowd of workers who carry the mobile devices. Currently, numerous MCS systems have been devised and applied to a broad scope of applications [1–5], including smart transportation, traffic control, and so on.

However, in the process of data sharing, traditional MCS systems are generally proposed and implemented in a centralized manner under the control of the platform, are susceptible to a single point of failure, and need to rely on a trusted third party. Since it is not easy to solve the problems caused by a centralized structure, and it is difficult for participants to establish a trusting relationship with third parties, the establishment of such a platform is impractical. To solve this problem, we use the decentralized nature of the blockchain to eliminate the system's dependence on third parties. In fact, as a decentralized ledger, the blockchain is maintained by all participants in the network, effectively realizing the decentralization feature [6]. For more complex transactions in the blockchain, the smart contract is introduced, which was first implemented in the real world by Ethereum in 2014 [7]. The decentralized nature of blockchain prompted us to design an incentive mechanism using the smart contract.

A typical blockchain-based MCS system is shown in Fig. 1, all participants, including requesters and workers, must create their accounts and interact with the blockchain. Specifically, the requesters interact with the blockchain through the smart contract to publish their sensing tasks, and workers interact with the blockchain through the smart contract for the delivery of encrypted sensory data. Most applications of the MCS system depend on the sufficient participation of mobile workers such that the quality of service can be ensured. However, performing sensing tasks is usually costly for individual workers. For example, collecting the sensory data of requested tasks often consumes workers' battery power, storage resource, computing energy, and some additional costs for data transmission. Furthermore, it may also reveal workers' private information during collecting and exchanging data. It means a participant is not willing to provide the sensory data unless receiving a satisfying reward to compensate for the consumption. Therefore, it is necessary to design a proper incentive mechanism to attract more participation such that the corresponding applications of the MCS system can provide the sensing service with high quality.

Due to the paramount significance of incentives, many mechanisms [8–25] have been proposed in recent years to attract more participation. Thus far, some existing works considered the *offline* scenario [8,9], where the information of tasks and workers is known by the platform a priori, *e.g.,* when and which task or worker arrives. Furthermore, some works considered the *online* scenario [13], where the workers arrive dynamically in an online manner and the platform must collect the sensory data from the arrived workers without the information of future arriving workers. In particular, most of them are under the assumption

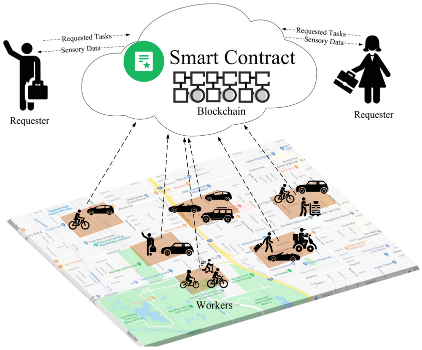


Fig. 1. A typical blockchain-based MCS system.

that the sensing tasks are static whose information is completely known by the platform a priori. However, due to the complicated practical environment, the sensing tasks are usually uncertain and their information is incompletely known by the platform *e.g.,* when and which task arrives. Therefore, it requires us to *use smart contracts to design a blockchain-based incentive mechanism in the MCS system under uncertain sensing tasks, which has nice properties* e.g., *truthfulness, individual rationality, and low social cost.*

Usually in the MCS system, for some tasks that do not require real-time performance, for example, when the requested task is to collect the number of bends on a road, the number of forks, or information about shops on both sides of the road, the platform can collect such task data in advance. It may incur heavy latency and lower efficiency if the platform collects the sensory data after the sensing tasks arrive. Therefore, the platform needs to collect the sensing tasks before the real tasks arrive such that the sensory data can be obtained once they arrive. Since the platform collects the tasks from the workers before the real tasks arrive, which causes it does not know any information about sensing tasks, *e.g.,* when and which tasks will arrive in the future. Therefore, we refer to this scenario as a *uncertain scenario.*

However, due to the uncertain nature of sensing tasks in the above practical scenario, it is difficult to design a proper incentive mechanism, which can guarantee the truthfulness and individual rationality which are two basic requirements in the design of an incentive mechanism, and meanwhile maintain the low computational complexity and low social cost. Therefore, to design a mechanism in the uncertain scenario, we assume that the tasks arrive in the future according to a probability distribution. Considering the above scenario with uncertain tasks, we propose an incentive mechanism based on blockchain and smart contracts, namely, HERALD[1], which utilizes the decentralized nature of blockchain to eliminate the system's dependence on third parties and satisfies the truthfulness and individual rationality, as well as the low computational complexity and social cost. In summary, the main contributions of this paper are as follows.

[1] The name HERALD is from incentive mecHanism for uncERtAin tasks in mobiLe crowD sensing.

– *Mechanism:* Unlike the prior works, we propose a novel blockchain-based incentive mechanism, HERALD, using the smart contract. In particular, HERALD is designed for the uncertain scenario such that the smart contract can collect the sensory data before the real tasks arrive by assuming the tasks arrive in the future according to a probability distribution.
– *Properties of HERALD:* HERALD can stimulate the participation of workers and bears many desirable properties, including truthfulness, individual rationality, low computational complexity, and low social cost. Although some incentive mechanisms [8–11] have been proposed for the traditional MCS, they are simply designed to collect massive sensory data, which can not be applied in this work. Furthermore, we prove that its competitive ratio on expected social cost is $\mathcal{O}(\ln mn)$, where m and n are the numbers of workers and tasks published in advance.
– *Evaluations:* We further conduct extensive simulations to validate the desirable properties of HERALD. The simulation results show that compared with state-of-the-art approaches, HERALD has the lower expected social cost and expected total payment.

In the rest of this paper, we first present some existing works that are related to this work in Sect. 2 and introduce the preliminaries in Sect. 3. Then, the design details and theoretic analysis of HERALD are described in Sect. 4. In Sect. 5, we conduct extensive simulations to validate the desirable properties of HERALD. Finally, the conclusion of this paper is shown in Sect. 6.

2 Related Work

Due to the paramount significance of attracting more participation, various incentive mechanisms [8–25] for MCS systems have been developed recently. Apart from truthfulness and individual rationality, which are two critical properties in the incentive mechanism, these works also aim to guarantee the benefit of workers or platforms.

The authors in [8,9] designed the mechanisms to minimize the social cost. The proposed mechanisms in [10,11] maximized the platform's profit. The mechanisms designed in [12–18] minimized the platform's payment. Additionally, the authors in [19–21] devised the mechanisms that maximize social welfare. Apart from the above optimization objectives, there are also some works focusing on some other objectives. Hu *et al.* in [22] proposed a privacy-preserving incentive mechanism in dynamic spectrum sharing crowdsensing. Bhattacharjee *et al.* in [23] stimulated the workers to act honestly by investigating their data's quantity and quality. Han *et al.* in [24] considered the privacy-preserving in budget limited crowdsensing. Gong *et al.* in [25] proposed an incentive mechanism to stimulate workers to submit high-quality data.

Almost all existing works recruit workers to collect the corresponding sensory data under the static sensing tasks whose information is completely known by the platform a priori. However, due to the complicated practical environment and

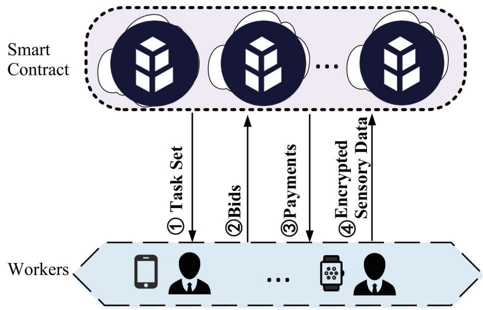


Fig. 2. Framework of HERALD where the tasks arrive according to a probability distribution. (The circled numbers represent the order of events).

severe resource constraints, the sensing tasks are usually uncertain, *i.e.*, their information is incompletely known by the platform. Therefore, different from the existing works, this paper is the first attempt to propose a novel incentive mechanism for the uncertain tasks in MCS systems by using smart contracts. Specifically, the uncertain tasks arrive according to a probability distribution and the platform does not know any information about these tasks.

3 Preliminaries

In this section, we introduce the system overview and design objectives.

3.1 System Overview

We consider a blockchain-based MCS system consisting of a smart contract and a set of participating workers which is denoted as $\mathcal{W} = \{1, 2, \ldots, m\}$. In HERALD, we assume that the smart contract has a set $\mathcal{T} = \{\tau_1, \ldots \tau_n\}$ of n sensing tasks known *a priori* and all requested tasks arriving in the future belong to $\mathcal{T}$. This assumption is rational since, in practice, the smart contract usually knows which tasks need to be completed. For example, in the service of a traffic monitor, the task set is the collection of forks on all roads in a region, with each task corresponding to the number of forks on each road. The task set in this service does not change over time and has no real-time requirements, and the data requests should be within the task set regardless of when they arrive. Similar service includes road curve monitor. The framework of HERALD is shown in Fig. 2, whose workflow is described as follows.

Incentive Mechanism for Uncertain Scenario: As shown in Fig. 2, the smart contract first publishes all sensing tasks in $\mathcal{T}$ to workers before the real requested tasks arrive (step ①). After receiving the task set $\mathcal{T}$, every worker i sends her preferred task set denoted as $\Gamma_i \subseteq \mathcal{T}$ to the smart contract, as well as a bid b_i, which is her bidding price for executing these tasks (step ②). Based on the received bids, the smart contract determines the set $\mathcal{S}$ of winners and the payment p_i to each winning worker i (step ③), and collects the winners' sensory data (step ④) such that the requested tasks are responded immediately when they arrive in the future. Note that since the smart contract collects the sensory data of tasks in $\mathcal{T}$ before the requested tasks arrive and do not know any information about the future tasks, we assume that all tasks in $\mathcal{T}$ arrive in the future following probability distribution.

Specifically, a loser does not execute any task and receives zero payment in the incentive mechanism. For notational convenience, we denote the payment profile of workers in this paper as $\overrightarrow{p} = (p_1, \ldots, p_m)$. When we denote the real cost of worker i as c_i in HERALD, her utility can be defined as

$$u_i = \begin{cases} p_i - c_i & \text{if worker } i \text{ wins} \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

Without loss of generality, in this paper, we assume that the bid b_i of each worker i is bounded by $[b_{min}, b_{max}]$, where b_{min} is normalized to 1 and b_{max} is a constant. We further assume that for each worker i with a preferred task set Γ_i, there exist some workers j with preferred task sets Γ_j such that $\Gamma_i \subseteq \cup_j \Gamma_j$.

3.2 Blockchain and Smart Contract

The incentive mechanism proposed in this paper, HERALD, which is based on the blockchain with a smart contract, removes the centralized nature of a centralized MCS system to avoid single points of failure and resolve trust issues between participants. Specifically, each participant including requesters and workers needs to create their account and interact with the blockchain. The requesters and workers interact with the blockchain through the smart contract to complete their task publish and encrypted sensory data delivery, respectively.

Each worker registers at the registration authority (RA) and gets a certificate such that they can participate in the MCS. This step is described as follows.

Registration for the In-Chain Participants: RA generates a public-secret key pair for the certification and broadcasts. Then, each arrived worker with a unique ID creates a public-secret key pair for the signature and registers with RA. Furthermore, the worker gets a certificate from RA to bind the public key and her ID by utilizing the secret key. Similarly, each arrived requester with a unique ID creates a public-secret key pair for the signature and registers with RA. The requesters get a certificate from RA to bind the public key and their ID by utilizing the secret key.

The worker submits the encrypted data to the SC. The corresponding operations of workers are as follows.

Operation of Workers: After receiving the corresponding information, the worker encrypts the sensory data with the signature and address to obtain the ciphertext utilizing the public key of the requester. Then, the encrypted data is sent to Smart Contract and can be optionally saved on a decentralized storage system such as Swarm or IPFS. The truth of data is verified by an attestation service.

3.3 Design Objectives

In this paper, we aim to ensure that HERALD bears the following advantageous properties.

Due to workers' *selfish* and *strategic* nature, it is possible that any worker i may submit a bid b_i that differs from her real cost c_i for executing all of tasks in Γ_i. Therefore, one of our goals is to design a truthful incentive mechanism defined as follows.

Definition 1 (Truthfulness). *An incentive mechanism is truthful if for any worker $i \in \mathcal{W}$, her utility is maximized when bidding her real cost c_i.*

By Definition 1, we aim to ensure that workers bid truthfully to the smart contract. Apart from truthfulness, another desirable property that we aim to achieve is individual rationality defined as follows.

Definition 2 (Individual Rationality). *An incentive mechanism is individual rationality if, for any worker $i \in \mathcal{W}$, her utility u_i satisfies $u_i \geq 0$.*

Additionally, for HERALD, since the tasks in $\mathcal{T}$ arrive according to a probability distribution, we also aim to ensure it has a low expected social cost. To achieve this goal, we investigate its competitive ratio on expected social cost defined as follows.

Definition 3 (Competitive Ratio on Expected Social Cost). *When the tasks in sensing task set $\mathcal{T}$ arrive according to a probability distribution, for any set $\mathcal{A}$ of k tasks that possibly arrive simultaneously from $\mathcal{T}$, let $\mathcal{S}(\mathcal{A})$ be the set of winners selected by the mechanism such that $\mathcal{A} \subseteq \cup_{i \in \mathcal{S}(\mathcal{A})} \Gamma_i$ and $\Gamma_i \cap \mathcal{A} \neq \emptyset$ for $\forall i \in \mathcal{S}(\mathcal{A})$, $C(\mathcal{S}(\mathcal{A})) = \sum_{i \in \mathcal{S}(\mathcal{A})} c_i$ be the corresponding social cost, and $C_{\mathcal{OPT}}(\mathcal{A})$ be the minimum social cost of requested task set $\mathcal{A}$, respectively. The competitive ratio on expected social cost is defined as $\max_k \mathbb{E}_{\mathcal{A} \subseteq \mathcal{T}}[C(\mathcal{S}(\mathcal{A}))]/\mathbb{E}_{\mathcal{A} \subseteq \mathcal{T}}\ [C_{\mathcal{OPT}}(\mathcal{A})]$, where $\mathbb{E}_{\mathcal{A} \subseteq \mathcal{T}}[\cdot]$ is the expectation over all sets of possibly k arriving tasks in the future.*

Note that some tasks in task set $\mathcal{A}$ may be identical. Therefore, when we say $\mathcal{A} \subseteq \mathcal{T}$ in the investigation of competitive ratio, it means that every task in $\mathcal{A}$ is also in $\mathcal{T}$ since the tasks in $\mathcal{T}$ are distinct. Furthermore, the expectation $\mathbb{E}_{\mathcal{A} \subseteq \mathcal{T}}[\cdot]$ is caused by the variety of the set $\mathcal{A}$ of k requested tasks, and for convenience of notation, the subscript $\mathcal{A} \subseteq \mathcal{T}$ is omitted in the remainder of this paper, *i.e.,* this expectation is denoted as $\mathbb{E}[\cdot]$.

Finally, we aim for HERALD to be computational efficient which is defined as follows.

Definition 4. *An incentive mechanism is computationally efficient if it can be carried out in polynomial time.*

In short, our objectives are to ensure the proposed mechanisms are truthful and individual rationality, as well as have low social cost and low computational complexity.

4 Incentive Mechanism for Uncertain Scenario

In this section, we present an incentive mechanism for the uncertain scenario. It will be proved that our mechanism is individual rationality and truthfulness. Furthermore, we investigate its competitive ratios on expected social cost, which is shown in Theorem 3. Apart from the above properties, we also show its computational complexity in Proposition 1.

4.1 Design Rationale

When designing the incentive mechanism, we usually need to consider the number of tasks that arrive simultaneously since different numbers of tasks arrive simultaneously usually for different scenarios, and result in different mechanisms. In the offline scenario, all tasks arrive simultaneously such that the information of tasks is completely known by the smart contract a priori. However, in the uncertain scenario, due to the uncertain tasks, the number of tasks arriving simultaneously is also uncertain. The different numbers of the arrival of tasks follow a different probability distribution, which will be illustrated by the following simple example.

Example 1. In this example, the smart contract has a sensing task set $\mathcal{T} = \{\tau_1, \tau_2, \tau_3\}$ with three tasks, each of which arrives in the future with probability $\frac{1}{3}$, *i.e.,* the arrival of tasks follows a uniform distribution. If only one task arrives simultaneously in the future, it may be τ_1, τ_2, or τ_3 with the same probability of $\frac{1}{3}$. While, if two tasks arrive simultaneously in the future, they maybe $\{\tau_1, \tau_1\}$, $\{\tau_2, \tau_2\}$ and $\{\tau_3, \tau_3\}$ with the same probability $\frac{1}{9}$, and may be $\{\tau_1, \tau_2\}$, $\{\tau_1, \tau_3\}$ and $\{\tau_2, \tau_3\}$ with the same probability $\frac{2}{9}$. Furthermore, if three tasks simultaneously arrive in the future, they maybe $\{\tau_1, \tau_2, \tau_3\}$ with probability $\frac{2}{9}$; $\{\tau_1, \tau_1, \tau_1\}$, $\{\tau_2, \tau_2, \tau_2\}$ and $\{\tau_3, \tau_3, \tau_3\}$ with the same probability $\frac{1}{27}$; and may be $\{\tau_1, \tau_2, \tau_2\}$, $\{\tau_1, \tau_3, \tau_3\}$, $\{\tau_1, \tau_1, \tau_2\}$, $\{\tau_1, \tau_1, \tau_3\}$, $\{\tau_2, \tau_2, \tau_3\}$, and $\{\tau_2, \tau_3, \tau_3\}$ with the same probability $\frac{1}{9}$.

As shown in the example, different from the existing works, where the number of tasks arriving simultaneously is fixed, in the uncertain scenario, due to the uncertainty of tasks, the number of tasks varies. Therefore, we propose the HERALD, which is an adaptive incentive mechanism based on the different numbers of tasks arriving simultaneously. In particular, we need to input an assumed number to the HERALD, which is the number of tasks arriving simultaneously. Then, according to the different input numbers, HERALD will output different results of winner selection and payment determination.

4.2 Design Details

To collect the sensory data of the uncertain tasks, we define a *selection threshold* (ST) $T \geq 0$ in HERALD. In particular, let $T = 64\mathbb{E}[C_{\mathcal{OPT}}(\mathcal{A})]$, where $\mathcal{A}$ is the set of k possibly simultaneously arriving tasks from the sensing task set $\mathcal{T}$, and 64 is set for facilitating the proof mentioned later. HERALD works as follows.

Algorithm 1: HERALD in the Smart Contract

Input: The task set $\mathcal{T}$, worker set $\mathcal{W}$, workers' preferred task sets Γ_i, workers' bids b_i, the number k of tasks arriving simultaneously.
Output: The winner set $\mathcal{S}$, and payment $\overrightarrow{p}$;

$\mathcal{S} \leftarrow \emptyset$;
Smart contract calculates the selection threshold T;
`// Winner Selection Phase by Smart Contract:`
while $\mathcal{T} \neq \emptyset$ **do**
  for *each worker* $i \in \mathcal{W}$ **do**
    Calculate the cost-effectiveness (CF) $\frac{b_i}{|\Gamma_i \cap \mathcal{T}|}$;
    `// Type I Selection:`
    if $\exists i \in \mathcal{W},\ s.t\ \frac{b_i}{|\Gamma_i \cap \mathcal{T}|} \leq \frac{T}{|\mathcal{T}|}$ **then**
      Choose a worker $i \in \mathcal{W}$ with the minimum value of CF denoted as $\frac{b_i}{|\Gamma_i \cap \mathcal{T}|}$ among the workers whose CFs are less than $\frac{T}{|\mathcal{T}|}$;
    `// Type II Selection:`
    else
      Choose a worker $i \in \mathcal{W}$, whose bid b_i is the least and preferred task set contains at least one uncovered task;
    $\mathcal{S} \leftarrow \mathcal{S} \cup \{i\}$;
    $\mathcal{T} \leftarrow \mathcal{T} \backslash \Gamma_i$;
`// Payment Determination Phase by Smart Contract:`
for *each* $i \in \mathcal{S}$ **do**
  Define a *copy set* $\mathcal{T}_i \leftarrow \Gamma_i$;
  Build a *covering set* $\mathcal{W}_i = \{j | \forall j \in \mathcal{W} \backslash \{i\},\ \Gamma_j \cap \mathcal{T}_i \neq \emptyset\}$;
  Define a *replaced set* $\mathcal{R}_i \leftarrow \emptyset$;
  while $\mathcal{T}_i \neq \emptyset$ **do**
    Choose a worker $j \in \mathcal{W}_i$ with the minimum CF denoted as $\frac{b_j}{|\Gamma_j \cap \mathcal{T}_i|}$;
    $\mathcal{R}_i \leftarrow \mathcal{R}_i \cup \{j\}$;
    $\mathcal{T}_i \leftarrow \mathcal{T}_i \backslash \Gamma_j$;
  $p_i \leftarrow \max\{b_i, p_{\mathcal{R}_i}\}$ for $p_{\mathcal{R}_i} = \sum_{j \in \mathcal{R}_i} b_j$;
Return $\mathcal{S}$ and $\overrightarrow{p}$.

Winner Selection Phase: In each iteration, there exist two types of selections in HERALD, namely, *type I selection* and *type II selection*.

- *Type I Selection:* When there are some workers whose cost-effectiveness (CF) is less than or equal to $\frac{T}{|\mathcal{T}|}$, the smart contract selects a worker with the least CF as the winner. Note that, for worker i, if $\Gamma_i \cap \mathcal{T} = \emptyset$, then its CF $= +\infty$.
- *Type II Selection:* When the CFs of all workers are larger than $\frac{T}{|\mathcal{T}|}$, the smart contract selects a worker as the winner, whose bid is the least and preferred task set contains at least one uncovered task in $\mathcal{T}$.

It then adds the winner selected above to the winner set $\mathcal{S}$.

Payment Determination Phase: For each winner $i \in \mathcal{S}$, the smart contract defines a *copy set* $\mathcal{T}_i = \Gamma_i$ and builds a *covering set* $\mathcal{W}_i = \{j|\forall j \in \mathcal{W}\backslash\{i\},\ \Gamma_j \cap \mathcal{T}_i \neq \emptyset\}$. It then derives a *replaced set* denoted as $\mathcal{R}_i$ consisting of workers in $\mathcal{W}_i$ with the least CFs in each iteration such that $\Gamma_i \subseteq \cup_{j\in\mathcal{R}_i}\Gamma_j$. The payment to winner i is $p_i = \max\{b_i, p_{\mathcal{R}_i}\}$, where $p_{\mathcal{R}_i} = \sum_{j\in\mathcal{R}_i} b_j$.

Example 2. In this example, the smart contract has a task set $\mathcal{T} = \{\tau_1, \tau_2, \tau_3, \tau_4, \tau_5\}$ with five tasks and there are seven workers with the preferred task sets $\Gamma_1 = \{\tau_1, \tau_2\}$, $\Gamma_2 = \{\tau_2, \tau_3\}$, $\Gamma_3 = \{\tau_3, \tau_1, \tau_4\}$, $\Gamma_4 = \{\tau_4, \tau_5\}$, $\Gamma_5 = \{\tau_4\}$, $\Gamma_6 = \{\tau_2, \tau_5\}$ and $\Gamma_7 = \{\tau_2, \tau_4, \tau_5\}$, as well as the costs $c_1 = 1.4$, $c_2 = 1.8$, $c_3 = 2.8$, $c_4 = 2.6$, $c_5 = 3.1$, $c_6 = 3.3$ and $c_7 = 3.6$. Since the mechanism HERALD is truthful which will be proved later, the workers' real costs are equal to their bids, i.e., $b_i = c_i$. We assume that the arrival of tasks follows a uniform distribution. When the input number of tasks arriving simultaneously is set to 1, *i.e.,* only one task arrives at each time, the task may be τ_1, τ_2, τ_3, τ_4, or τ_5 with the same probability $\frac{1}{5}$. Then, it can be obtained that the selection threshold $T = 125.44$. As shown in Algorithm 1, the smart contract will carry out the **winner selection phase**. For the first iteration, after calculating the cost-effectiveness of all workers, it can be seen that the condition in Line 6 of HERALD is satisfied. Therefore, the smart contract carries to `type I selection` and selects worker 1 as the winner. Then, the second iteration is carried out, where the condition in Line 6 of HERALD still holds. Thus, the `type I selection` is carried out, and worker 4 is selected as a winner. With the same iteration, it can be obtained that the final winner set selected by the HERALD is $\mathcal{S} = \{1, 2, 4\}$. Then, the smart contract carries out the **payment determination phase**. In particular, for worker 1 whose covering set is $\mathcal{W}_1 = \{2, 3, 6, 7\}$, it can be seen that the corresponding replace set is $\mathcal{R}_1 = \{2, 3\}$. Therefore, the smart contract to worker 1 is $p_1 = 1.8 + 2.8 = 4.6$. After the similar steps, it can be obtained that the payments to worker 2 and worker 4 are $p_2 = 1.4 + 2.8 = 4.2$ and $p_4 = 3.6$.

Furthermore, when the input number of tasks arriving simultaneously is set to 2, the tasks may be $\{\tau_1, \tau_1\}$, $\{\tau_2, \tau_2\}$, $\{\tau_3, \tau_3\}$, $\{\tau_4, \tau_4\}$, $\{\tau_5, \tau_5\}$ with the same probability $\frac{1}{25}$, and $\{\tau_1, \tau_2\}$, $\{\tau_1, \tau_3\}$, $\{\tau_1, \tau_4\}$, $\{\tau_1, \tau_5\}$, $\{\tau_2, \tau_3\}$, $\{\tau_2, \tau_4\}$, $\{\tau_2, \tau_5\}$, $\{\tau_3, \tau_4\}$, $\{\tau_3, \tau_5\}$, $\{\tau_4, \tau_5\}$ with the same probability $\frac{2}{25}$. The selection threshold is $T = 181.248$. Then, the smart contract can carry out the **winner selection phase** and **payment determination phase** of HERALD sequentially to obtain the winner set and the corresponding payments.

Remark 1. It can be seen that when we fix the input number as the total number of tasks n in the task set of the smart contract, HERALD has a probability of $\frac{A_n^n}{n^n}$ degraded to an offline incentive mechanism, which means that the HERALD can be applied to more scenarios compared with the existing offline incentive mechanisms.

4.3 Analysis

In this subsection, we will prove that HERALD satisfies the properties mentioned in Sect. 3.3.

Theorem 1 **([26]).** *A mechanism is truthful if and only if*

1) The selection rule is monotone: If worker i wins by bidding b_i, she also wins by bidding $b_i' \leq b_i$;
2) Each winner is paid the critical value: Worker i would not win if she bids higher than this value.

Theorem 2. *HERALD is truthful.*

Proof. To prove the truthfulness of HERALD, we will show it satisfies the conditions mentioned in Theorem 1.

Monotone: For a worker i, once she wins by bidding b_i, we will show that she will also win by bidding $b_i' \leq b_i$ through the following two cases.

Case 1: In an iteration of the winner selection phase, when the CF of winning worker i satisfies $\frac{b_i}{|\Gamma_i \cap \mathcal{T}|} \leq \frac{T}{|\mathcal{T}|}$, it means that she has the minimum CF among all workers. Therefore, she will also win by bidding $b_i' \leq b_i$.

Case 2: In an iteration, when the CF of winning worker i satisfies $\frac{b_i}{|\Gamma_i \cap \mathcal{T}|} > \frac{T}{|\mathcal{T}|}$, it means that she has the minimum cost among workers and there is not any worker j with $\frac{b_j}{|\Gamma_j \cap \mathcal{T}|} \leq \frac{T}{|\mathcal{T}|}$. We then need to consider two subcases.

Subcase 2.1: When the bid $b_i' \leq b_i$ satisfies $\frac{b_i'}{|\Gamma_i \cap \mathcal{T}|} > \frac{T}{|\mathcal{T}|}$, it means that she will also win by bidding b_i' since b_i' is the minimum and there is not any worker j with $\frac{b_j}{|\Gamma_j \cap \mathcal{T}|} \leq \frac{T}{|\mathcal{T}|}$.

Subcase 2.2: When the bid $b_i' \leq b_i$ satisfies $\frac{b_i'}{|\Gamma_i \cap \mathcal{T}|} \leq \frac{T}{|\mathcal{T}|}$, it means that she will also win by bidding b_i' since she is the only worker with CF being less than or equal to T.

Critical Value: When a worker i wins, it can be seen that her payment is $p_i = \max\{b_i, p_{\mathcal{R}_i}\}$, where $p_{\mathcal{R}_i} = \sum_{j \in \mathcal{R}_i} b_j$. When worker i increases her bid b_i to $\widetilde{b}_i$ such that $\widetilde{b}_i \leq p_{\mathcal{R}_i}$, her payments are always the same. However, when $\widetilde{b}_i > p_{\mathcal{R}_i}$, we need to consider the following two cases in each iteration of the winner selection phase.

Case 1: When CF of worker i satisfies $\frac{\widetilde{b}_i}{|\Gamma_i \cap \mathcal{T}|} \leq \frac{T}{|\mathcal{T}|}$, we will prove that there is a worker k in $\mathcal{R}_i$ such that $\frac{b_k}{|\Gamma_k \cap \mathcal{T}|} \leq \frac{\widetilde{b}_i}{|\Gamma_i \cap \mathcal{T}|}$. We have $\frac{\widetilde{b}_i}{|\Gamma_i \cap \mathcal{T}|} \geq \frac{\sum_{j \in \mathcal{R}_i} b_j}{\sum_{j \in \mathcal{R}_i} |\Gamma_j \cap \mathcal{T}|}$. Then let worker k be the one with the minimum CF $\frac{b_k}{|\Gamma_k \cap \mathcal{T}|}$ in $\mathcal{R}_i$, which means that $\frac{b_k}{|\Gamma_k \cap \mathcal{T}|} \leq \frac{b_j}{|\Gamma_j \cap \mathcal{T}|}$ for $\forall j \in \mathcal{R}_i$, *i.e.*, $b_k |\Gamma_j \cap \mathcal{T}| \leq b_j |\Gamma_k \cap \mathcal{T}|$. Therefore, we have $b_k \sum_{j \in \mathcal{R}_i} |\Gamma_j \cap \mathcal{T}| \leq |\Gamma_k \cap \mathcal{T}| \sum_{j \in \mathcal{R}_i} b_j$, *i.e.*, $\frac{b_k}{|\Gamma_k \cap \mathcal{T}|} \leq \frac{\sum_{j \in \mathcal{R}_i} b_j}{\sum_{j \in \mathcal{R}_i} |\Gamma_j \cap \mathcal{T}|}$. Since $\frac{b_k}{|\Gamma_k \cap \mathcal{T}|} \leq \frac{\widetilde{b}_i}{|\Gamma_i \cap \mathcal{T}|}$, the smart contract will select worker k instead of worker i in this iteration.

Case 2: When CF of worker i satisfies $\frac{\widetilde{b}_i}{|\Gamma_i \cap \mathcal{T}|} > \frac{T}{|\mathcal{T}|}$, we need to consider two subcases.

Subcase 2.1: Once there exist some workers $j \in \mathcal{R}_i$ such that $\frac{b_j}{|\Gamma_j \cap \mathcal{T}|} \le \frac{T}{|\mathcal{T}|}$, the smart contract will select a worker k among them with the minimum CF instead of worker i.

Subcase 2.2: Once the CFs of all workers $j \in \mathcal{R}_i$ satisfies $\frac{b_j}{|\Gamma_j \cap \mathcal{T}|} > \frac{T}{|\mathcal{T}|}$, the smart contract will always find a worker k with the minimum bid b_k such that $b_k \le p_{\mathcal{R}_i} \le \widetilde{b}_i$, which means that the smart contract will not select worker i.

Therefore, the conclusion holds. □

Lemma 1. *HERALD is individual rationality.*

Proof. As proved in Theorem 2, each worker bids her real cost c_i. The individual rationality of HERALD is guaranteed by the fact that the payment to each winner i is $p_i = \max\{b_i, p_{\mathcal{R}_i}\} \ge b_i = c_i$. □

Apart from truthfulness and individual rationality, it will be seen that HERALD has low computational complexity.

Proposition 1. *The computational complexity of the HERALD is $\mathcal{O}(m^2+mn)$.*

Proof. To obtain the computational complexity of HERALD, we need to separately consider the winner selection phase and payment determination phase.

1) *Winner Selection Phase:* The main loop (Lines 4–11) of the winner selection phase terminates in the worst case after n iterations. In every iteration, it takes m times to carry out type I selection to find the worker with the minimum bidding price effectiveness (Lines 6–7), or type II selection to find the worker with the minimum bidding price (Lines 8–9). Therefore, the computational complexity of the winner selection phase is $\mathcal{O}(mn)$.
2) *Payment Determination Phase:* Similarly, the main loop (Lines 12–20) of the payment determination phase terminates at worst after m iterations. In each iteration, it takes m iterations to build a covering set (Line 14) and other n iterations to build a replaced set (Lines 16–19). Therefore, the computational complexity of the payment determination phase is $\mathcal{O}(m^2 + mn)$.

Combining the winner selection phase and payment determination phase, the computational complexity of HERALD is $\mathcal{O}(m^2 + mn)$. □

In the following parts, we will show the competitive ratio on expected social cost achieved by HERALD when the tasks in $\mathcal{T}$ arrive following a uniform distribution. To derive the competitive ratio on the expected social cost of HERALD, we consider the costs of type I selection and type II selection separately.

Lemma 2. *When the arrivals of tasks in the task set $\mathcal{T}$ follow a uniform distribution, the competitive ratio on expected social cost achieved by HERALD through type I selection is $\mathcal{O}(\ln n)$.*

Proof. Let $\mathcal{S}_I = \{1, \ldots, h\}$ be the workers selected by HERALD through type I selection in this order. Moreover, let $\widetilde{\mathcal{T}}_i$ denote the set of tasks whose sensory data is not collected just before worker i is selected. Since HERALD carries out type I selection, $c_i \le |\Gamma_i \cap \mathcal{T}_i| \frac{64\mathbb{E}[C_{\mathcal{OPT}}(\mathcal{A})]}{|\widetilde{\mathcal{T}}_i|}$, where $\mathcal{A}$ is a subset of k tasks possibly arriving simultaneously from $\mathcal{T}$. Hence, the social cost of workers in $\mathcal{S}_I$ can be bounded by

$$\sum_{i \in \mathcal{S}_I} c_i \le \sum_{i \in \mathcal{S}_I} \frac{64|\Gamma_i \cap \widetilde{\mathcal{T}}_i|\mathbb{E}[C_{\mathcal{OPT}}(\mathcal{A})]}{|\widetilde{\mathcal{T}}_i|} \le 64\mathbb{E}[C_{\mathcal{OPT}}(\mathcal{A})] \sum_{t=1}^{m} \frac{1}{t}, \tag{2}$$

which is at most $64\mathbb{E}[C_{\mathcal{OPT}}(\mathcal{A})] \ln n$. Therefore, the conclusion holds due to the property of expectation. □

It remains to bound the expected cost of workers selected by the type II selection. To show the expected social cost of workers selected by HERALD through type II selection, we need the following notations. Let $\mathcal{S}_{II} = \{1, \ldots, \ell\}$ be the workers selected by HERALD through type II selection in this order. Let $\widetilde{\mathcal{T}}_i$ be the set of tasks whose sensory data is not collected just before worker i is selected. Let $n_i = |\widetilde{\mathcal{T}}_i|$ and $k_i = n_i \frac{k}{n}$ be the number of tasks in $\widetilde{\mathcal{T}}_i$ and the expected number of requested tasks arriving from $\widetilde{\mathcal{T}}_i$, respectively. Denote by $\mathcal{A}_i$ the subset of $\mathcal{A}$ obtained by taking requested tasks only belonging to $\widetilde{\mathcal{T}}_i$. Furthermore, for any set of $\mathcal{A}$, let $\mathcal{S}^*(\mathcal{A})$ be the set of workers with the minimum social cost. Then, let $\mathcal{S}'(\mathcal{A}_i)$ be the subset of $\mathcal{S}^*(\mathcal{A})$ such that for each task $\tau_j \in \mathcal{A}_i$, the worker in $\mathcal{S}'(\mathcal{A}_i)$ has the preferred task set containing task τ_j and has the least cost among workers in $\mathcal{S}^*(\mathcal{A})$.

Lemma 3. *When the arrivals of tasks in the task set $\mathcal{T}$ follow a uniform distribution, the competitive ratio on expected social cost achieved by HERALD through type II selection is $\mathcal{O}(\ln mn)$.*

Proof. Recall that the set of workers selected by HERALD through type II selection is $\mathcal{S}_{II} = \{1, \ldots, \ell\}$. Set $k_{\ell+1} = 0$ and $c_0 = 0$ for notational convenience. Moreover, let j be $k_j \ge 8 \ln 2n$ but $k_{j+1} < 8 \ln 2n$. Hence, we see at most $8 \ln 2n$ tasks from $\widetilde{\mathcal{T}}_{j+1}$ in expectation. Since each of these tasks is carried out by a worker who does not cost more than the one carrying out it in $\mathcal{S}^*(\mathcal{A})$, the cost incurred by workers $j+1, \ldots, \ell$ is bounded by $8 \ln 2n\mathbb{E}[C_{\mathcal{OPT}}(\mathcal{A})]$. Then, the expected cost incurred by using the remaining workers $1, \ldots, j$ satisfies

$$\begin{aligned}
&\sum_{i=1}^{j} c_i \Pr[\mathcal{A} \cap (\Gamma_i \cap \widetilde{\mathcal{T}}_i) \ne \emptyset] \\
&\le \sum_{i=1}^{j} c_i \mathbb{E}[|\mathcal{A} \cap (\Gamma_i \cap \widetilde{\mathcal{T}}_i)|] \overset{\widetilde{\mathcal{T}}_{i+1} \subseteq \widetilde{\mathcal{T}}_i \setminus \Gamma_i}{\le} \sum_{i=1}^{j} c_i \mathbb{E}[|\mathcal{A} \cap (\widetilde{\mathcal{T}}_i \setminus \widetilde{\mathcal{T}}_{i+1})|] \\
&\le \sum_{i=1}^{j} c_i (k_i - k_{i+1}) \overset{c_0=0}{\le} \sum_{i=1}^{j} k_i (c_i - c_{i-1}) \overset{(a)}{\le} \sum_{i=1}^{j} 16\mathbb{E}[|\mathcal{S}'(\mathcal{A}_i)|] \ln m (c_i - c_{i-1}) \\
&= 16 \ln m \left(c_j \mathbb{E}[|\mathcal{S}'(\mathcal{A}_{j+1})|] + \sum_{i=1}^{j} c_i \left(\mathbb{E}[|\mathcal{S}'(\mathcal{A}_i)|] - \mathbb{E}[|\mathcal{S}'(\mathcal{A}_{i+1})|] \right) \right) \\
&\overset{(b)}{\le} 16 \ln m \left(\mathbb{E}[C(\mathcal{S}'(\mathcal{A}_{j+1}))] + \sum_{i=1}^{j} \left(\mathbb{E}[C(\mathcal{S}'(\mathcal{A}_i))] - \mathbb{E}[C(\mathcal{S}'(\mathcal{A}_{i+1}))] \right) \right) \\
&\le 16 \ln m \mathbb{E}[C_{\mathcal{OPT}}(\mathcal{A})],
\end{aligned} \tag{3}$$

where inequalities (a) and (b) hold based on the Lemma 3.5 and Lemma 3.4 in the reference [27] respectively. As mentioned before, $\sum_{i=j+1}^{\ell} c_i \Pr[\mathcal{A} \cap (\Gamma_i \cap \widetilde{\mathcal{T}_i}) \neq \emptyset] \leq 8 \ln 2n \mathbb{E}[C_{\mathcal{OPT}}(\mathcal{A})]$. Therefore, the expected cost incurred by workers $1, \ldots, \ell$ satisfies $\sum_{i=1}^{\ell} c_i \Pr[\mathcal{A} \cap (\Gamma_i \cap \widetilde{\mathcal{T}_i}) \neq \emptyset] \leq [8 \ln 2n + 16 \ln m] \cdot \mathbb{E}[C_{\mathcal{OPT}}(\mathcal{A})]$. Then we have $\frac{\sum_{i=1}^{\ell} c_i \Pr[\mathcal{A} \cap (\Gamma_i \cap \widetilde{\mathcal{T}_i}) \neq \emptyset]}{\mathbb{E}[C_{\mathcal{OPT}}(\mathcal{A})]} \leq \mathcal{O}(\ln mn)$, this proof is completed. □

Finally, by combining Lemma 2 and Lemma 3, we have the following theorem.

Theorem 3. *When the arrivals of tasks in the task set $\mathcal{T}$ follow a uniform distribution, the competitive ratio on expected social cost achieved by HERALD is $\mathcal{O}(\ln mn)$.*

According to Theorem 3, we can obtain the conclusion that HERALD achieves a low expected social cost, which means that it can be applied to many other scenarios with uncertain sensing tasks.

5 Performance Evaluation

In this section, we introduce the baseline methods, simulation settings, as well as simulation results of the performance evaluation of our proposed HERALD.

5.1 Baseline Methods

COst-effectiveNEss greedy auction (CONE): For the uncertain scenario, the smart contract only knows that the tasks in $\mathcal{T}$ arrive in the future with a probability distribution. Therefore, to collect sensory data for these tasks, the smart contract calculates the CF of each worker and selects worker i as a winner, whose CF $\frac{b_i}{|\Gamma_i \cap \mathcal{T}|}$ is the least among those of workers in each iteration. The smart contract then obtains the sensory data of worker i.

COSt greedY auction (COSY): For the uncertain scenario, to collect sensory data of these tasks, the smart contract compares the bids of workers and selects worker i as a winner, whose bid b_i is the minimum among those of workers and preferred task set Γ_i contains at least one uncovered task in each iteration. Then, the smart contract collects the sensory data of worker i.

The payment determination phases of both CONE and COSY are the same as HERALD. Clearly, CONE and COSY are truthful and individual rationality.

5.2 Simulation Settings

We show the evaluation parameters for different cases in Table 1, where c_i is the cost of worker i for executing her preferred task set Γ_i and $|\Gamma_i|$ is the number of tasks in the preferred task set. Furthermore, m, n are the numbers of workers in worker set $\mathcal{W}$ and sensing tasks in the task set $\mathcal{T}$, respectively. Additionally, k is the number of tasks possibly arriving simultaneously in the future in the

Table 1. Simulation Settings for HERALD.

Settings	Individual cost c_i	Number $\|\Gamma_i\|$ of preferred tasks	Number m of workers	Number n of sensing tasks	Number k of arriving tasks
I	$[5, 20]$	$[15, 20]$	$[70, 160]$	150	120
II	$[5, 20]$	$[15, 20]$	70	$[90, 180]$	$[60, 150]$
III	$[5, 10], [10, 15], [15, 20]$	$[20, 25]$	80	$[70, 160]$	$[50, 140]$
IV	$[15, 25]$	$[10, 15], [15, 20], [20, 25]$	$[60, 150]$	160	100

uncertain scenario. For the convenience of representation, k is briefly referred to as the number of arriving tasks.

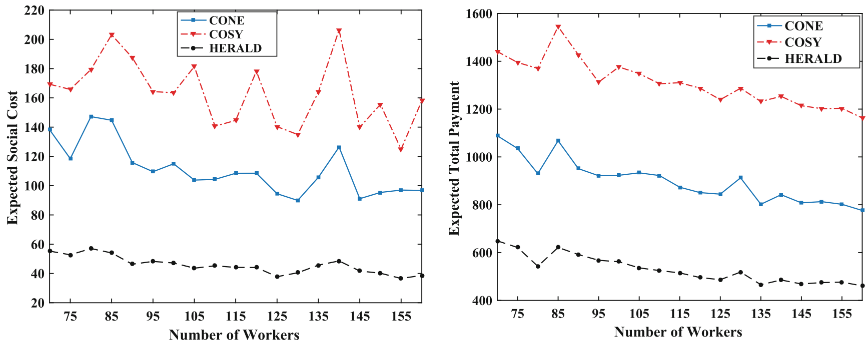
In our evaluation, for HERALD, we show the influences of the numbers of workers and sensing tasks on the expected social cost and expected total payment. Specifically, to evaluate the impact of the quantity m of workers in worker set $\mathcal{W}$, we increase it from 70 to 160 by fixing the number n of sensing tasks and the number k of arriving tasks to 150 and 120, respectively, *i.e.,* setting I. Furthermore, to evaluate the impact of the quantity n of sensing tasks, we vary it from 90 to 180 and increase the number k of arriving tasks from 60 to 150 with the quantity m of workers fixed to 70, *i.e.,* setting II. Additionally, in setting I and setting II, the cost c_i of worker i and the number of tasks in her preferred task set Γ_i are sampled uniformly and independently at random in the intervals $[5, 20]$ and $[15, 20]$, respectively.

Nextly, we investigate the impacts of worker's costs on the expected social cost and expected total payment obtained by HERALD, respectively. In particular, to evaluate the impacts of worker's cost c_i, we select it in three distinct intervals, *i.e.,* $[5, 10]$, $[10, 15]$ and $[15, 20]$ in setting III, respectively, where the number $|\Gamma_i|$ of tasks in preferred task set is sampled in the interval $[20, 25]$. Furthermore, in setting III, the number m of workers is fixed to 80, while the number n of sensing tasks and the number k of arriving tasks vary from 70 to 160 and 50 to 140, respectively.

Finally, we evaluate the impacts of the number of workers' preferred tasks on the expected social cost and expected total payment derived by HERALD, respectively. Specifically, we select the number $|\Gamma_i|$ of tasks in each preferred task set in three distinct intervals, *i.e.,* $[10, 15]$, $[15, 20]$ and $[20, 25]$ in setting IV, respectively, where the cost c_i of each worker is sampled in the interval $[15, 25]$. Furthermore, in setting IV, the number n of sensing tasks and the number k of arriving tasks are fixed to 160 and 100, respectively, while the number m of workers varies from 60 to 160.

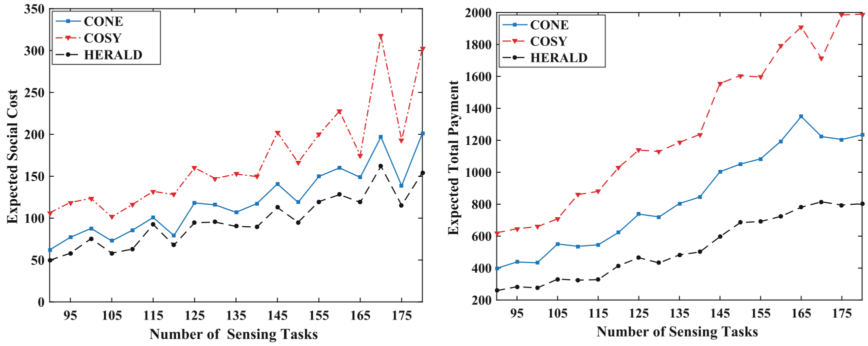
5.3 Simulation Results

In Fig. 3, we evaluate the impact of the number of workers. Specifically, Fig. 3(a) and Fig. 3(b) show the impact on the expected social cost and expected total payment derived by HERALD. It is shown that HERALD outperforms CONE and COSY. Interestingly, with the increasing number of workers, the expected social cost and expected total payment calculated by HERALD decrease. This is because with the increasing number of workers, for each task, the smart contract has more opportunities to collect sensory data from the worker whose cost is less.



(a) (b)

Fig. 3. (a) Expected social cost versus different numbers of workers for the uncertain scenario. (b) Expected total payment versus different numbers of workers for the uncertain scenario.

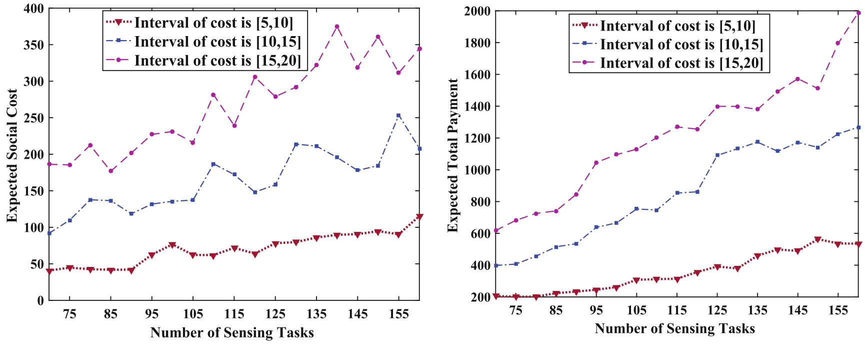


(a) (b)

Fig. 4. (a) Expected social cost versus different numbers of sensing tasks for the uncertain scenario. (b) Expected total payment versus different numbers of sensing tasks for the uncertain scenario.

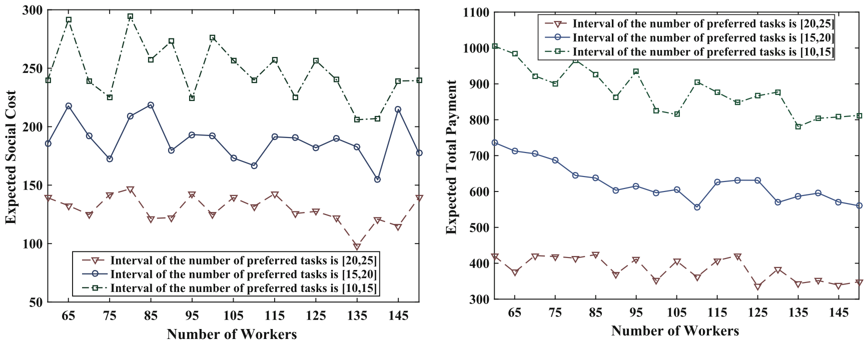
In Fig. 4, the impact of the number of tasks is also investigated. Specifically, Fig. 4(a) and Fig. 4(b) show the impact on the expected social cost and expected total payment derived by HERALD. Similarly, it can be seen that HERALD outperforms CONE and COSY. Additionally, with the increasing number of tasks, the expected social cost and expected total payment calculated by HERALD increase. This is because with the increasing number of tasks, the smart contract needs to collect sensory data from more workers.

In Fig. 5, we show the influence of the worker's cost. In particular, Fig. 5(a) and Fig. 5(b) plot the influence on the expected social cost and expected total payment obtained by HERALD. It can be seen that the higher worker's cost means the higher expected social cost and expected total payment in HERALD since the higher cost of the worker means that for the same tasks, the workers need more social cost and the smart contract needs more payment compared to the scenario with the lower cost of the worker.



(a) (b)

Fig. 5. (a) The impact of worker's cost on the expected social cost obtained by HERALD for uncertain scenario. (b) The impact of worker's cost on the expected total payment obtained by HERALD for uncertain scenario.



(a) (b)

Fig. 6. (a) The impact of the number of worker's preferred tasks on the expected social cost obtained by HERALD for uncertain scenario. (b) The impact of the number of worker's preferred tasks on the expected total payment obtained by HERALD for uncertain scenario.

We finally investigate the influence of the number of workers' preferred tasks in Fig. 6. In particular, Fig. 6(a) and 6(b) give the impact on the expected social cost and expected total payment obtained by HERALD. It can be observed that the more preferred tasks of each worker decrease the expected social cost and expected total payment in HERALD. This is because compared to the scenario with the less preferred tasks of each worker, the smart contract needs fewer workers to execute the requested tasks due to the more preferred tasks of each worker, which results in the less expected social cost and expected total payment in HERALD.

6 Conclusion

In this paper, we design an incentive mechanism, HERALD, for the uncertain tasks in MCS systems by using smart contracts. Specifically, the uncertain tasks arrive according to a probability distribution such that the smart contract does not have any information on the tasks. HERALD utilizes the decentralized nature of the blockchain to eliminate the system's reliance on third parties. It is proved that HERALD satisfies truthfulness, individual rationality, low computational complexity, and achieves an $\ln mn$ competitive ratio on expected social cost. Finally, HERALD's desirable properties are validated through theoretical analysis and extensive simulations.

Acknowledgement. This work is supported by the grant PAPRICAS: Programming technology foundations for Accountability, Privacy-by-design & Robustness in Context-aware Systems. Independent Research Fund Denmark.

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