Mobile Crowdsensing Ecosystem with Combinatorial Multi-Armed Bandit-Based Dynamic Truth Discovery

Jia Liu, *Senior Member, IEEE,* Jianbo Shao, *Graduate Student Member, IEEE,* Min Sheng, *Senior Member, IEEE,* Yang Xu, *Senior Member, IEEE,* Tarik Taleb, *Senior Member, IEEE* and Norio Shiratori, *Life Fellow, IEEE*

***Abstract*—Mobile crowdsensing (MCS) has emerged as a popular and promising paradigm for solving challenging problems by utilizing collective wisdom and resources. However, the system architecture and operational rules for MCS have not been well-defined, and obtaining accurate and reliable results from conflicting data collected by workers is difficult due to discrepancies in sensor quality and privacy protection requirements. In this paper, we combine the methodologies of Dynamic Truth Discovery (DTD), Combinatorial Multi-Armed Bandit (CMAB), and Multi-Attribute Reverse Auction to develop a novel MCS ecosystem, with the objective of maximizing the sensing accuracy-aware utility under the budget constraint. We first establish the data collection model by jointly considering the task completion duration as well as the deviation caused by both endogenous errors and privacy protection-oriented injected noise. Then, we theoretically evaluate the accuracy of truth discovery and quantify the contribution of each worker to MCS to form the worker selection criterion. As the qualities of workers are initially unknown, the platform faces the exploration-exploitation dilemma. Therefore, we apply CMAB to transform the worker recruitment problem into a combinatorial arm-pulling problem and elaborately design an Upper Confidence Bound (UCB) algorithm to achieve a desirable exploration-exploitation tradeoff. Moreover, we design an auction-based payment method for the platform, stimulating workers to provide their quoted price honestly while enabling individual rationality. Extensive simulations and comparison results demonstrate the feasibility and effectiveness of our proposed MCS ecosystem.**

***Index Terms*—Mobile crowdsensing, truth discovery, combinatorial multi-armed bandit, critical payment, regret upper bound.**

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Jia Liu and Yang Xu are with the School of Computer Science and Technology, Xidian University, Xi'an 710071, China (e-mail: {liujia,yxu}@xidian.edu.cn).

Jianbo Shao is with the Department of Computer Science and Technology, Shanghai University of Finance and Economics, Shanghai 200433, China (email: jianboshao.sufe.cs@gmail.com).

Min Sheng is with the State Key Laboratory of Integrated Service Networks, Institute of Information Science, Xidian University, Xi'an 710071, China (e-mail: msheng@mail.xidian.edu.cn).

Tarik Taleb is with the Faculty of Electrical Engineering and Information Technology of the Ruhr University Bochum, Bochum, Germany (e-mail: tarik.taleb@rub.de).

Norio Shiratori with the Research and Development Initiative, Chuo University, Tokyo 112-8551, Japan (e-mail: norio.shiratori.e8@tohoku.ac.jp).

I. Introduction

In recent years, there has been a notable surge in the prevalence of mobile devices equipped with precision processors, advanced communication capabilities, and an array of sensors. This technological advancement has paved the way for the emergence of "Mobile Crowdsensing (MCS)", a novel approach that harnesses the collective knowledge of a large group of individuals armed with mobile devices to perform sensing tasks [1]–[3]. MCS offers a highly efficient and cost-effective solution for gathering and analyzing sensory data across a diverse range of scenarios, such as intelligent transportation [4], real-time environmental monitoring [5], and noise mapping [6], to name a few. Currently, various MCS applications, including OpenSignal [7], Boss [8], and Gigwalk [9], have been developed to address intricate sensing problems that would be challenging for traditional sensor networks.

The effectiveness of MCS largely relies on the accuracy of data gathered by workers. However, the acquisition of reliable sensory data is a daunting challenge in the face of real-world limitations, including a dearth of detection capabilities, untrustworthy sources, and unpredictable subjective factors. For instance, the quality of sensors used by workers varies, resulting in different levels of errors in their sensory data. In some cases, workers may engage in the falsification of information rather than executing prescribed tasks, in order to economize on time, energy, or battery life [10]. Consequently, data obtained from individual workers are likely to be unreliable, underscoring the necessity of collecting and aggregating data from a crowd of workers to yield more accurate results on the platform. To enhance the precision of aggregated data, a weighted aggregation mechanism called *Truth Discovery* that assigns higher weights to workers with superior data quality is more desirable than naive methods, such as averaging, which treats all workers equally [11], [12].

However, the full potential of truth discovery in MCS systems has not been fully realized. First, the open nature of MCS systems leads to high worker mobility, resulting in a significant disparity in worker quality. Therefore, selecting high-quality participants to perform tasks is critical for the platform to ensure the quality of the gathered data. The existing literature on worker recruitment problems in MCS systems generally assumes that workers' quality information is readily available, but this assumption is untenable in reality as it is implausible for workers to have accurate self-assessments [13], [14]. In fact, accurately inferring workers' sensing qualities from their sensory data is a challenging task for the platform. To address this problem, we propose a *combinatorial multi-armed bandit*-based scheme in this paper. Second, the sensing task value usually exhibits temporal variability, such as traffic flow monitoring and air quality measurement, whereas truth discovery is typically applied to static data aggregation [15]. As workers require a certain amount of time to complete sensing tasks, the sensing data collected by the platform may become outdated, causing the aggregated data to deviate from the current true value of the task. Therefore, the platform should consider task execution efficiency when selecting workers.

On the other hand, the utilization of mobile devices and the potential privacy leakage during the data collection process can impose costs on workers participating in an MCS system. To attract rational workers, the platform must provide sufficient monetary rewards to compensate for the workers' costs. However, since cost information is often private and sensitive, workers may have the motivation to strategically manipulate their reported costs to receive higher rewards [16]. Designing effective incentive mechanisms to encourage honest reporting of costs during the workers' recruitment is therefore another crucial challenge in MCS systems. Previous research has focused on incentive mechanism design when worker quality information is known, but this is often not the case in practice [17], [18].

A. Contributions of Our Work

Motivated by the preceding discussions, in this paper, we aim to establish an MCS ecosystem consisting of a platform and a team of workers with unknown qualities, to perform time-sensitive sensing tasks under a certain budget. The worker's cost could be reported strategically and the platform recruits workers in multiple time slots to capture the temporal dynamics of tasks' values. The platform assesses the quality of workers by measuring their task completion time and deviation from the ground truth, and strives to recruit high-quality workers based on these criteria. In particular, the deviation from the ground truth originates from two aspects. On the one hand, endogenous errors in the workers' sensors lead to inaccurate data perception. On the other hand, the data collected by the sensors often contains workers' sensitive privacy information, and thus workers deliberately inject a certain degree of noise to perturb the sensory data for privacy protection.

Due to the initial lack of understanding about workers' quality, the platform tentatively recruits workers to perform tasks and acquires such knowledge accordingly. The platform then uses the gained knowledge to select the optimal group of workers for subsequent task execution. These two processes are called exploration and exploitation, respectively [19], [20]. During the continuous worker recruitment process, the platform's excessive exploration may consume significant costs associated with learning about workers' quality, thereby impeding the utilization of high-quality workers. Conversely, over-exploitation can hinder the platform from gaining adequate knowledge about workers' quality and limit the potential benefits from better workers' participation. Therefore, our goal is to design an incentive mechanism that addresses this dilemma between exploration and exploitation, enabling the platform to achieve higher accuracy of aggregated data within a budget constraint, while ensuring that workers truthfully disclose their costs for participating in MCS. To sum up, we are faced with the following challenges:

- Identifying an appropriate worker selection criterion that fully considers task completion time and deviation from the ground truth to ensure the accuracy of truth discovery.
- Determining a suitable tradeoff between exploration and exploitation within a limited budget.
- Designing reasonable payment schemes that incentivize workers to participate in MCS and report their costs truthfully.

To overcome the aforementioned challenges, we develop in this work a novel yet efficient MCS ecosystem, which combines the methodologies of *Truth Discovery*, *Combinatorial Multi-Armed Bandit (CMAB)*, and *Multi-Attribute Reverse Auction*. We first mathematically model the task completion time and deviation from the ground truth for workers, and analyze the accuracy of the truth discovery algorithm. Then, we apply CMAB to transform the worker recruitment problem into a combinatorial arm-pulling problem, where workers and their sensing quality are treated as arms and associated rewards, respectively, allowing us to balance the exploration-exploitation tradeoff and optimize the worker group for subsequent tasks. To solve this problem, we employ a well-defined Upper Confidence Bound (UCB) index for greedy arm selection to obtain the maximal rewards. Additionally, we design a payment mechanism in the multi-attribute reverse auction so that workers can truthfully report the level of injected noise and the corresponding costs.

The contributions of this paper are four-fold:

- *Novel Mobile Crowdsensing Ecosystem Design:* To the best of our knowledge, this is the first work that establishes an MCS ecosystem with the privacy-preserving dynamic truth discovery, where CMAB and multi-attribute reverse auction are combined to dynamically select workers without prior knowledge of their quality, while guaranteeing high truth discovery accuracy as much as possible.
- *Truth Discovery Accuracy Analysis:* Jointly considering the task completion duration as well as the deviation caused by both endogenous errors and privacy protection-oriented injected noise, we theoretically evaluate the accuracy performance of truth discovery in terms of α-error probability. We reveal the inherent relationship between the upper bound of α-error probability and workers' individual attributes, thus paving the way for the worker selection criterion design in the MCS ecosystem.
- *Worker Recruitment and Payment Scheme:* By integrating multi-attribute reverse auction into the UCB algorithm, we design a CMAB-based greedy algorithm to recruit workers and compute payments for their participation, which effectively addresses the issue of exploration-exploitation tradeoff. Besides, we theoretically prove that

workers can achieve truthfulness and individual rationality in each round of MCS, while the platform could realize approximate utility maximization under a budget constraint.

- *Extensive Numerical Simulations and Comparisons:* The numerical comparison simulations with a variety of parameter settings demonstrate the feasibility and effectiveness of our proposed MCS ecosystem.

B. Paper Organization

The remainder of this paper is organized as follows. We introduce related work in Section II and an overview of the proposed MCS ecosystem in Section III. Section IV presents the details of the data collection model and truth discovery algorithm in the MCS ecosystem, as well as analyzes the crowdsensing accuracy and formulates the utility maximization problem. We elaborate on the design of worker selection and payment mechanism in Section V and prove some good properties of the proposed MCS ecosystem in Section VI. Section VII presents the simulation results, followed by the conclusion in Section VIII.

II. Related Work

Fueled by the proliferation of smart mobile devices, recent years have witnessed a rapid growth of flexible and economic MCS applications [21]–[25]. Due to incomplete views, background noises, and malicious or privacy protection purposes, the sensory data submitted by different workers for the same task may be inconsistent. Ascertaining truthful values from conflicting sensory data is thus a critical challenge in MCS systems. Truth discovery [26]–[28], as an effective technique to jointly identify accurate information from noisy or contradictory sensory data, has been attracting considerable research attention. For example, Zhi *et al.* [29] presented a dynamic truth discovery model using hidden Markov and Kalman filtering to capture truth dynamics, infer source dependency, and handle missing data. Fu *et al.* [30] proposed a decentralized truth discovery design for resource-limited networks using joint maximum likelihood estimation and provided two randomized algorithms for accelerated truth finding. Xiao *et al.* [31] proposed an algorithm to solve the truth discovery task by formulating it as a joint maximum likelihood estimation problem and provided theoretical analysis on convergence and consistency. Although the aforementioned efforts have greatly facilitated the development of truth discovery technology, they are still inapplicable to scenarios where the ground truth varies over time. To this end, in this work, we divide the continuous time into multiple time slots and dynamically estimate the truth value in each time slot, thereby capturing the evolutionary trend of the task ground truth over time.

In MCS systems, privacy is one of the critical concerns for participating workers. Existing protocols often fall short in terms of providing sufficient privacy protection while also incurring heavy computation and communication overheads. To tackle these problems, Zhang *et al.* [32] developed two secure and efficient truth discovery schemes for stable and frequently moving users, respectively, which utilize homomorphic Paillier encryption to ensure strong privacy. Tang *et al.* [33] devised two privacy-preserving and lightweight truth discovery protocols, which delink workers from their data and reduce each worker's overheads by leveraging perturbation technology. In [34], a privacy-preserving truth discovery scheme was proposed, which employs a randomizable matrix and encryption mechanisms to safeguard the privacy of tasks and data. While these works have made significant progress in terms of privacy protection, they have not yet considered integrating incentive mechanisms into truth discovery, which is necessary for stimulating sufficient worker participation.

Therefore, another line of related work is a series of incentive mechanisms recently developed by the research community in order to incentivize worker participation in MCS systems [35]–[37]. Specifically, Peng *et al.* [35] introduced a quality-aware incentive mechanism that compensates workers based on their contribution to MCS tasks. Dai *et al.* [36] developed a distributed many-to-many matching model for MCS tasks and workers, with a stable matching algorithm that ensures individual rationality, stability, and convergence while achieving at least half of optimal system efficiency. Liu *et al.* [37] proposed a behavioral economics-based incentive mechanism to improve user engagement in mobile crowdsensing by accelerating capital deposit accumulation, promoting cooperative behavior, and mitigating the effect of diminishing marginal utility. Note that these works assumed that workers' quality information is known in advance, which is somewhat idealistic in reality. To overcome this limitation, researchers have conducted thorough investigations by utilizing numerous learning-based approaches, including deep reinforcement learning [38], federated learning [39], and multi-armed bandits (MAB) [20], [40], [41].

Regarding research works on MAB, Gao *et al.* [20] assigned importance weights to each crowdsensing task and modeled the worker recruitment with different qualities as an MAB problem. Then, an UCB-based algorithm was proposed to maximize the total weighted quality of tasks under a limited budget. In [40], the worker selection in the context of crowdsourcing was modeled as an MAB problem. A new metric for worker selection was designed based on the concept of entropy in information theory, and a minimum entropy upper confidence bound algorithm was developed to balance the exploration and exploitation in worker selection. Taking into account workers' context information (i.e., extrinsic ability and intrinsic ability), Wu *et al.* [41] modeled the worker selection in crowdsensing as a context-aware MAB problem and designed a modified Thompson sampling algorithm to maximize the sum of workers' service qualities. However, these works have not comprehensively considered the challenges in practical MCS scenarios. On the one hand, they primarily focused on selecting high-quality workers but tended to neglect the heterogeneity among workers' data in reality (conflicting data may exist) and the timeliness of task ground truth (the ground truth is time-varying). To this end, this paper integrates dynamic truth discovery (DTD) into MCS, capturing the temporal variability of task truth by selecting workers to submit data in multiple rounds, such that a novel worker selection criterion is deduced with the objective of maximizing the ground truth discovery accuracy. On the other hand, the previous works failed to account for the dishonest behavior (untruthful cost reporting) of strategic workers, which is inconsistent with reality. In this paper, we integrate the multi-attribute reverse auction into the system and introduce a well-designed payment mechanism that ensures worker participation and honest cost reporting.

Regarding the underlying physical techniques of mobile crowdsensing, reading relevant literature on the signal processing aspect can be very helpful. For example, Nordio *et al.* [42] analyzed the performance of several reconstruction/estimation techniques based on linear filtering, and obtained the MSE as well as the asymptotic expression in the case where the number of field-harmonics and the number of sensors grow to infinity. Reise *et al.* [43] developed a novel distributed architecture for sampling and reconstructing time-varying non-bandlimited physical fields in wireless sensor networks. Taking into account both signal properties and sampling properties, Zabini *et al.* [44] analyzed multi-dimensional random sampling with uncertainties, deriving the optimal interpolator function and obtaining asymptotic results.

In summary, this work is distinguishable from the existing ones in the sense that we propose a novel CMAB-based dynamic truth discovery mechanism for developing an MCS ecosystem, with well-defined worker selection criteria that maximize the accuracy of truth discovery to the fullest extent, and an auction-based payment rule that ensures truthfulness and individual rationality. In the MCS ecosystem, we address for the first time the dynamic truth discovery problem with unknown prior knowledge of worker quality, while learning workers' characteristics via a multi-armed bandits approach. Furthermore, a more challenging problem that the platform needs to simultaneously learn two variables related to worker quality, i.e., endogenous errors and task duration, is also overcome in this work.

The main notations used in this paper are summarized in Table I. Throughout this paper, except for the numerical superscripts on symbols related to power, such as ${\xi^t_{i,n}}^2$ and ${\sigma_{i,n}}^2$ in the following, all other superscripts on mathematical symbols denote an index rather than an exponent.

TABLE I
MAIN NOTATIONS.

Notation	Description
$\mathcal{I}$	Set of workers
$\mathcal{N}$	Set of sensing tasks
B	Platform's budget
x_n^{truth}	Ground truth of task n
$x_n^{\text{truth}(s_t)}$	Ground truth of task n in round t
$\mathcal{K}^t$	Set of selected workers in round t
$x_{i,n}^t$	Raw sensory data of worker i for task n in round t
$\tilde{x}_{i,n}^t$	Perturbed data of worker i for task n in round t
$y_{i,n}^t$	Endogenous error of worker i for task n in round t
$z_{i,n}^t$	Injected random noise of worker i for task n in round t
$\boldsymbol{\sigma}_i$	Privacy protection level adopted by worker i
D	Number of times that worker data is sampled
τ_i^t	Task completion duration of worker i in round t
$\hat{x}_n^t$	Platform's estimated ground truth for task n in round t
$u^t(\mathcal{K}^t)$	Platform's utility in round t
R	Fixed income received by the platform
β	Unit economic loss parameter
b_i	Quoted price of worker i
c_i	True cost of worker i
$p_i^t(b_i)$	Corresponding payment for the selected worker i in round t
$v_i^t(b_i)$	Utility of the selected work i with the quoted price b_i
$\text{Reg}(B)$	Platform's regret with the total budget B
q_i^t	Quality of worker i in round t
$\bar{q}_i^t$	Combinatorial empirical mean of worker $i$os quality
$\ddot{q}_i^t$	UCB term of $\bar{q}_i^t$
Q_i^t	Combinatorial confidence radius of q_i^t
RCR_i^t	Revenue-Cost-Ratio of worker i in round t

III. System Overview

Consider a typical mobile crowdsensing (MCS) ecosystem consisting of a platform and I workers. The platform has N sensing tasks to be accomplished, with a total budget B supplied for this purpose. The set of workers and the set of sensing tasks are dentoed by $\mathcal{I} = \{1, 2, \cdots, I\}$ and $\mathcal{N} = \{1, 2, \cdots, N\}$, respectively. Each task n is associated with a ground truth (i.e., accurate real-time state information), which is denoted as x_n^{truth}, and we consider that the evolution of the ground truth with respect to time s follows an unknown function $x_n^{\text{truth}(s)}$. The platform recruits workers to sense the evolutionary ground truth $x_n^{\text{truth}(s)}$ at multiple time points, denoted as $\{s_1, s_2, \cdots\}$, where the time interval between s_t and s_{t+1} is referred to as round t. We assume that workers sense the ground truth at the beginning of each round. In other words, worker i observes $x_n^{\text{truth}(s_t)}$ and acquires the sensory data $x_{i,n}^t$ in round t.

The heterogeneity in workers' quality can lead to differences in the accuracy of sensory data, which is typically attributed to two main factors. On the one hand, the quality of workers' devices is uneven, leading to different data quality. On the other hand, as the sensory data collected by workers may reveal private information that they do not want to disclose, injecting noise into the raw data becomes necessary. Workers with different sensitivity to privacy information will inject different levels of noise. In this paper, we consider that workers have no knowledge of the quality of their equipment and are only able to control the level of injected noise.

In our developed MCS ecosystem, prior to initiating multiple rounds of sensing tasks, workers submit their desired economic compensation and the level of injected noise, in the form of bids, to the platform. Then, during the execution process of the MCS ecosystem, the platform purchases the sensory data from workers according to the submitted bids. In the first round, as the platform lacks prior knowledge of the quality of workers' sensory data, it selects all workers to perform sensing tasks. In each subsequent round, to avoid wasting the limited budget on low-quality workers, the platform applies a certain selection mechanism, which is based on workers' historical performance, to determine a group of workers (referred to as the *winning worker set*) to perform sensing tasks. Formally, we use $\mathcal{K}^t$ to denote the set of selected workers in round t, where $|\mathcal{K}^1| = I$ and $|\mathcal{K}^t| = K$ for $\forall t > 1$. In each round t and for each task n, after collecting the corresponding sensory data from all selected workers, the platform aggregates the data by using the truth discovery algorithm [45], to produce an estimated result, denoted as $\hat{x}_n^t$.

The considered MCS ecosystem and its operational process are illustrated in Fig. 1. In the following sections, we will elaborate on the details of the MCS ecosystem as well as the

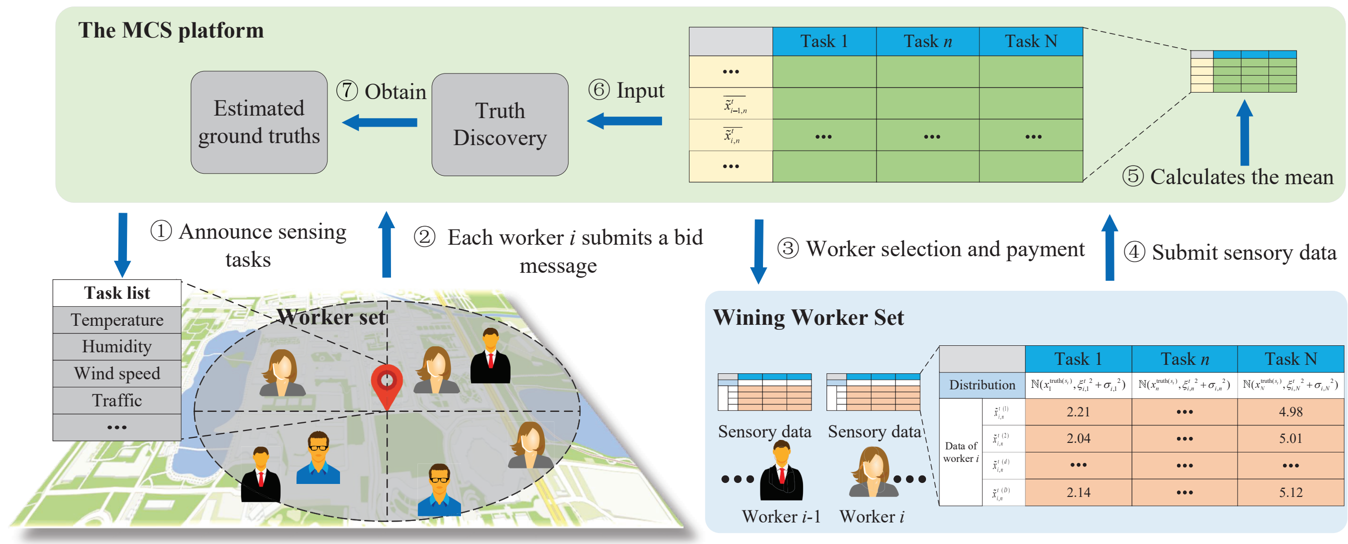


Fig. 1. MCS ecosystem and its operational process.

worker selection scheme and corresponding payment strategy.

IV. Design Details and Problem Formulation

In this section, we introduce in detail the data collection scheme and the truth discovery algorithm utilized within our MCS ecosystem. Additionally, we analyze the crowdsensing accuracy theoretically and formulate the utility maximization problem for the MCS platform.

A. Data Collection

1) Data Sensing Model: Due to inherent characteristics of workers, such as pixel density, sensor accuracy, and data collection habits, endogenous errors exist between the raw sensory data and the ground truth. Formally, in round t, the raw sensory data of worker i for task n can be represented as

$$x_{i,n}^t = x_n^{\text{truth}(s_t)} + y_{i,n}^t, \tag{1}$$

where $x_n^{\text{truth}(s_t)}$ is the ground truth for task n at time s_t and $y_{i,n}^t$ denotes the endogenous error. We assume that $y_{i,n}^t$ follows a Gaussian distribution $\mathbb{N}(0, {\xi_{i,n}^t}^2)$, where $\xi_{i,n}^t$ is sampled from an unknown distribution with an unknown expectation ξ_i that could represent worker i's error level. We define the utmost amplitude of workers' error level as $A^\xi \triangleq \sup_{\forall i,n,t} \xi_{i,n}^t - \inf_{\forall i,n,t} \xi_{i,n}^t$.

For privacy protection purposes, workers will obfuscate their raw sensory data by injecting a certain level of noise. Let $\tilde{x}_{i,n}^t$ denote the perturbed data of worker i for task n in round t, we have

$$\tilde{x}_{i,n}^t = x_{i,n}^t + z_{i,n}^t, \tag{2}$$

where $z_{i,n}^t$ is the injected random noise that is sampled from a Gaussian distribution[1] $\mathbb{N}(0, {\sigma_{i,n}}^2)$. $\sigma_{i,n}$ reflects the privacy protection level adopted by worker i for task n and $\boldsymbol{\sigma}_i = \{\sigma_{i,1}, \sigma_{i,2}, \cdots, \sigma_{i,N}\}$ is the privacy protection vector of worker i for all tasks. According to Eq. (1) and Eq. (2), worker i's perturbed data $\tilde{x}_{i,n}^t$ follows the Gaussian distribution $\mathbb{N}(x_n^{\text{truth}(s_t)}, {\xi_{i,n}^t}^2 + {\sigma_{i,n}}^2)$.

To process the randomness of workers' perturbed data, the platform requires each worker to submit its sensory data D times for each task in each round. That is to say, in each round t, the platform obtains D samples from $\mathbb{N}(x_n^{\text{truth}(s_t)}, {\xi_{i,n}^t}^2 + \sigma_{i,n}^2)$, denoted as $\{\tilde{x}_{i,n}^{t\,(d)}\}_{d=1}^D$, for $\forall i \in \mathcal{K}^t$ and $\forall n \in \mathcal{N}$. Then, the platform takes the mean of $\{\tilde{x}_{i,n}^{t\,(d)}\}_{d=1}^D$ as the input of the truth discovery algorithm, i.e.,

$$\overline{\tilde{x}_{i,n}^t} = \frac{\sum_{d=1}^D \tilde{x}_{i,n}^{t\,(d)}}{D}. \tag{3}$$

2) Task Duration Model: In our MCS system, to economize on the scarce communication resources, we assume that each winning worker submits $D \cdot N$ data items to the platform disposable in each round. Let τ_i^t denote the task completion duration, i.e., the time interval between the start time of round t and the data submission time of worker i, which is endogenously heterogeneous for many reasons, e.g., device, network signal, personal preference, etc. Therefore, we consider τ_i^t is sampled from an unknown distribution with an unknown expectation τ_i. Let $A^\tau \triangleq \sup_{\forall i,t} \tau_i^t - \inf_{\forall i,t} \tau_i^t$ denote the utmost amplitude of τ_i^t. After waiting $\tau^t \triangleq \max\{\tau_i^t | i \in \mathcal{K}^t\}$ seconds, the platform can receive the data from by all winning workers and then aggregates them to produce the result $\hat{x}_n^t$. Note that at this moment, the ground truth has evolved into $x_n^{\text{truth}(s_t+\tau^t)}$, so the platform can only use $\hat{x}_n^t$ to approximate $x_n^{\text{truth}(s_t+\tau^t)}$, as shown in Fig. 2. We assume that the platform can get the maximum slope of $x_n^{\text{truth}(s)}$ through historical statistics, denoted as $L = \max\{\frac{\partial x_n^{\text{truth}(s)}}{\partial s} | \forall s\}$.

[1]In most cases, random noise satisfies the Central Limit Theorem and thus follows the Gaussian distribution. Gaussian noise conforms to the principle of linear superposition, i.e., it is additive in nature and often called additive Gaussian noise. Additive Gaussian noise is a very typical noise that is widely used in many areas such as signal processing and statistics [46], [47].

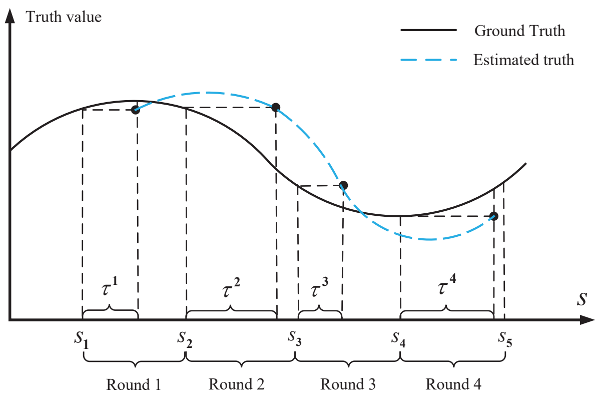


Fig. 2. Truth evolution.

B. Truth Discovery

For a specific crowdsensing task, truth discovery can correct conflicting data $\{\tilde{x}_{i,n}^t | i \in \mathcal{K}^t\}$ provided by a set of workers and generate a corresponding estimated result $\hat{x}_n^t$. Although different truth discovery algorithms achieve this goal in different ways, their basic principles are the same. The general procedure of truth discovery is summarized in Algorithm 1.

Algorithm 1 Truth Discovery Algorithm

Input: Mean of sensory data from K workers for N tasks, i.e., $\overline{\tilde{x}_{i,n}^t}$ for $\forall i \in \mathcal{K}^t$ and $\forall n \in \mathcal{N}$.

Output: Estimated ground truth for N tasks in round t, $\{\hat{x}_n^t\}_{n=1}^N$.

```
Initialize workers' weights {w_i}_{i=1}^K;
while Convergence criterion is not satisfied do
  // Truth Inference
  for all n ∈ N do
    Update the estimated ground truth x̂_n^t based on
    workers' current weights using Eq. (4);
  end for
  // Weight Estimation
  for all i ∈ K^t do
    Update the weight w_i based on current estimated
    ground truth using Eq. (5);
  end for
end while
```

In our MCS ecosystem, the platform will first calculate the average value $\overline{\tilde{x}_{i,n}^t}$ of the submitted data according to Eq. (3) and takes it as the input of Algorithm 1. The truth discovery algorithm initializes the weights of workers, and then iteratively conducts truth inference and weight estimation until satisfying a pre-defined convergence criterion [48], shown as follows.

Truth Inference: In this step, the algorithm produces an inferred value $\hat{x}_n^t$ for each task n based on the currently estimated worker weights. Formally, there is

$$\hat{x}_n^t = \frac{\sum_{i=1}^K w_i \cdot \overline{\tilde{x}_{i,n}^t}}{\sum_{i=1}^K w_i}, \tag{4}$$

where w_i denotes the weight of worker i.

Weight Estimation: This step updates the worker weights $\{w_i | i \in \mathcal{K}^t\}$ based on the inferred ground truth $\hat{x}_n^t$. Formally, there is

$$w_i = g\left(\sum_{n=1}^N f_{\text{loss}}\left(\overline{\tilde{x}_{i,n}^t}, \hat{x}_n^t\right)\right), \tag{5}$$

where $g(\cdot)$ is some monotonically decreasing function, and $f_{\text{loss}}(\cdot)$ represents a function that measures the distance between $\overline{\tilde{x}_{i,n}^t}$ and $\hat{x}_n^t$. Specifically, we apply the commonly-used absolute loss function in this paper. Although different truth discovery algorithms may adopt different functions $g(\cdot)$ and $f_{\text{loss}}(\cdot)$, they share the same underlying principle that higher weights are assigned to workers whose data are closer to the inferred ground truth.

C. Accuracy Analysis

Definition 1 (Mean Absolute Error): When the winning worker set in round t is $\mathcal{K}^t$, $\text{MAE}(\mathcal{K}^t)$ denotes the mean absolute error (MAE) between the estimated truth $\hat{x}_n^t$ and the real-time ground truth $x_n^{\text{truth}(s_t+\tau^t)}$, which can be expressed as

$$\text{MAE}(\mathcal{K}^t) \triangleq \frac{1}{N}\sum_{n=1}^N |\hat{x}_n^t - x_n^{\text{truth}(s_t+\tau^t)}|. \tag{6}$$

Definition 2 (α-Error Probability): Given $0 < \alpha < 1$, we define α-error probability as the probability that MAE is no less than a threshold α. Let $p_{er}(\alpha)$ denote the α-error probability, which can be expressed as

$$p_{er}(\alpha) \triangleq Pr\left\{\text{MAE}(\mathcal{K}^t) \geq \alpha\right\}. \tag{7}$$

MAE is a commonly-used metric to measure the crowdsensing accuracy, and we have the following theorem regarding the upper bound of α-error probability $p_{er}(\alpha)$.

Theorem 1: α-error probability of the truth discovery algorithm in round t is upper bounded by

$$p_{er}(\alpha) \leq \frac{\sum_{i=1}^K \{L\tau_i^t + \sqrt{\frac{2}{\pi D}} \frac{\sum_{n=1}^N \xi_{i,n}^t}{N} + \bar{\sigma}_i + LA^\tau\}}{\alpha}, \tag{8}$$

where $\bar{\sigma}_i = \frac{1}{N}\sum_{n=1}^N \sigma_{i,n}$.

Proof: According to Algorithm 1, the MAE between the estimated truth $\hat{x}_n^t$ and the real-time ground truth satisfies

$$\begin{aligned}
&\frac{1}{N}\sum_{n=1}^N |\hat{x}_n^t - x_n^{\text{truth}(s_t+\tau^t)}| \\
&= \frac{1}{N}\sum_{n=1}^N \left|\frac{\sum_{i=1}^K w_i \cdot \overline{\tilde{x}_{i,n}^t}}{\sum_{i=1}^K w_i} - x_n^{\text{truth}(s_t+\tau^t)}\right| \\
&= \frac{1}{N}\sum_{n=1}^N \left|\frac{\sum_{i=1}^K w_i (\overline{\tilde{x}_{i,n}^t} - x_n^{\text{truth}(s_t+\tau^t)})}{\sum_{i=1}^K w_i}\right| \\
&\leq \frac{1}{N}\frac{\sum_{n=1}^N \sum_{i=1}^K w_i |\overline{\tilde{x}_{i,n}^t} - x_n^{\text{truth}(s_t+\tau^t)}|}{\sum_{i=1}^K w_i} \\
&= \frac{1}{N}\frac{\sum_{i=1}^K w_i (\sum_{n=1}^N |\overline{\tilde{x}_{i,n}^t} - x_n^{\text{truth}(s_t+\tau^t)}|)}{\sum_{i=1}^K w_i} \\
&\leq \sum_{i=1}^K \frac{1}{N}\sum_{n=1}^N |\overline{\tilde{x}_{i,n}^t} - x_n^{\text{truth}(s_t+\tau^t)}|.
\end{aligned} \tag{9}$$

By applying the inequality $|a-b| \le |a-c| + |c-b|$ for any real numbers a, b and c, we have

$$|\overline{\tilde{x}_{i,n}^t} - x_n^{\text{truth}(s_t+\tau^t)}| \le \big[|\overline{\tilde{x}_{i,n}^t} - x_n^{\text{truth}(s_t+\tau_i^t)}| + |x_n^{\text{truth}(s_t+\tau_i^t)} - x_n^{\text{truth}(s_t+\tau^t)}|\big]. \tag{10}$$

Substituting (10) into (9) yields

$$\begin{aligned} &\frac{1}{N}\sum_{n=1}^{N}|\hat{x}_n^t - x_n^{\text{truth}(s_t+\tau^t)}| \\ &\le \sum_{i=1}^{K}\frac{1}{N}\sum_{n=1}^{N}\Big[|\overline{\tilde{x}_{i,n}^t} - x_n^{\text{truth}(s_t+\tau_i^t)}| \\ &\quad + |x_n^{\text{truth}(s_t+\tau_i^t)} - x_n^{\text{truth}(s_t+\tau^t)}|\Big] \\ &\le \sum_{i=1}^{K}\frac{1}{N}\sum_{n=1}^{N}\Big[|\overline{\tilde{x}_{i,n}^t} - x_n^{\text{truth}(s_t+\tau_i^t)}| + LA^\tau\Big] \end{aligned} \tag{11}$$

From Eq. (3), we have that $\overline{\tilde{x}_{i,n}^t}$ follows the Gaussian distribution $\mathbb{N}(x_n^{\text{truth}(s_t)}, \frac{{\xi_{i,n}^t}^2+\sigma_{i,n}^2}{D})$. Thus, $\overline{\tilde{x}_{i,n}^t} - x_n^{\text{truth}(s_t+\tau_i^t)}$ follows the Gaussian distribution $\mathbb{N}(\mu(s_t,\tau_i^t), {v_{i,n}}^2)$, where $\mu(s_t,\tau_i^t) \triangleq x_n^{\text{truth}(s_t)} - x_n^{\text{truth}(s_t+\tau_i^t)}$, and ${v_{i,n}}^2 \triangleq \frac{{\xi_{i,n}^t}^2+\sigma_{i,n}^2}{D}$. Then, we can obtain the expectation of $|\overline{\tilde{x}_{i,n}^t} - x_n^{\text{truth}(s_t+\tau_i^t)}|$ in (12), shown at the bottom of this page, where $\Phi(\cdot)$ is the Cumulative Density Function (CDF) of the standard Gaussian distribution. Note that L is the maximum slope of $x_n^{\text{truth}(s)}$, there is $\mu(s_t,\tau^t) \le L\tau^t$. Therefore, given any $0<\alpha<1$, we have

$$\begin{aligned} &p_{er}(\alpha) \triangleq Pr\left\{\frac{1}{N}\sum_{n=1}^{N}|\hat{x}_n^t - x_n^{\text{truth}(s_t+\tau^t)}| \ge \alpha\right\} \\ &\le Pr\left\{\sum_{i=1}^{K}\frac{1}{N}\sum_{n=1}^{N}\Big[|\overline{\tilde{x}_{i,n}^t} - x_n^{\text{truth}(s_t+\tau_i^t)}| + LA^\tau\Big] \ge \alpha\right\} \\ &\le \frac{\mathbb{E}\left\{\sum_{i=1}^{K}\frac{1}{N}\sum_{n=1}^{N}[|\overline{\tilde{x}_{i,n}^t} - x_n^{\text{truth}(s_t+\tau_i^t)}| + LA^\tau]\right\}}{\alpha} \\ &\text{(Markov's Inequality)} \\ &= \frac{\sum_{i=1}^{K}\frac{1}{N}\sum_{n=1}^{N}\left\{\mathbb{E}[|\overline{\tilde{x}_{i,n}^t} - x_n^{\text{truth}(s_t+\tau_i^t)}|] + LA^\tau\right\}}{\alpha} \\ &\le \frac{\sum_{i=1}^{K}\frac{1}{N}\sum_{n=1}^{N}\left\{\mu(s_t,\tau_i^t) + \sqrt{\frac{2({\xi_{i,n}^t}^2+\sigma_{i,n}^2)}{\pi D}} + LA^\tau\right\}}{\alpha} \\ &\le \frac{\sum_{i=1}^{K}\frac{1}{N}\sum_{n=1}^{N}\left\{L\tau_i^t + \sqrt{\frac{2}{\pi D}}(\xi_{i,n}^t + \sigma_{i,n}) + LA^\tau\right\}}{\alpha} \\ &= \frac{\sum_{i=1}^{K}\{L\tau_i^t + \sqrt{\frac{2}{\pi D}}\frac{\sum_{n=1}^{N}\xi_{i,n}^t}{N} + \bar{\sigma}_i + LA^\tau\}}{\alpha}. \end{aligned} \tag{13}$$

■

According to Theorem 1, the upper bound of α-error probability is proportional to $L\tau_i^t + \sqrt{\frac{2}{\pi D}}\frac{\sum_{n=1}^{N}\xi_{i,n}^t}{N} + \bar{\sigma}_i$, which indicates that a worker with lower $L\tau_i^t + \sqrt{\frac{2}{\pi D}}\frac{\sum_{n=1}^{N}\xi_{i,n}^t}{N} + \bar{\sigma}_i$ has less effect on the increase in MAE. That is, this worker contributes more to the MCS accuracy. Let $q_i^t \triangleq L\tau_i^t + \sqrt{\frac{2}{\pi D}}\frac{\sum_{n=1}^{N}\xi_{i,n}^t}{N}$ represent the quality of worker i in round t, we can obtain that the platform should choose workers with smaller $q_i^t + \bar{\sigma}_i$. However, $q_i^t + \bar{\sigma}_i$ is not available in advance when selecting workers because it contains random variables τ_i^t and $\xi_{i,n}^t$. Therefore, we will refer to its expectation, i.e., $\mathbb{E}\{q_i^t + \bar{\sigma}_i\} = L\tau_i + \sqrt{\frac{2}{\pi D}}\xi_i + \bar{\sigma}_i \triangleq q_i + \bar{\sigma}_i$, to form a worker recruitment criterion, which will be elaborated in Section V-A.

D. Problem Formulation

In order to incentivize the platform to consistently update the latest truth, our MCS ecosystem regulates that the platform can receive fixed income R (for example, in the form of subscription fees earned from users browsing the platform updated information) after each round of updates. On the other hand, we consider that the error between the updated estimation and the actual ground truth has a negative effect on the platform's utility, with a larger error resulting in a decreased utility. Hence, the platform's utility $u^t(\mathcal{K}^t)$ in round t can be expressed as

$$u^t(\mathcal{K}^t) = R - \beta \cdot \text{MAE}(\mathcal{K}^t), \tag{14}$$

where β represents the unit economic loss parameter due to the decrease in crowdsensing accuracy.

Let b_i denote the quoted price from worker i for performing a round of crowdsensing tasks. Please note that this quoted price is submitted to the platform by every worker in the form of a bid, prior to the whole MCS process being initiated. Let $p_i^t(b_i)$ denote the corresponding payment for the selected worker i in round t and $\mathcal{P}^t = \{p_i^t(b_i) | i \in \mathcal{K}^t\}$ denote the payment vector. When a worker is not selected, the payment is 0. Let c_i denote the true cost of worker i caused by performing a round of crowdsensing tasks, with the assumption that this cost falls within a specific range for all workers, i.e., $c_{\text{min}} \le c_i \le c_{\text{max}}$, for $\forall i \in \mathcal{I}$. Then, the utility $v_i^t(b_i)$ of the selected work i with the quoted price b_i is given by

$$v_i^t(b_i) = p_i^t(b_i) - c_i. \tag{15}$$

The goal of the platform is to maximize its utility under budget constraint B. Let $\omega(B)$ represent the number of rounds of crowdsensing that the platform can perform under budget constraint B. Accordingly, when determining the set of workers to execute crowdsensing tasks in each round, i.e., $\{\mathcal{K}^1, \mathcal{K}^2, \cdots\}$, the platform should consider reducing the MAE as much as possible, while also saving on payments to increase the number of rounds of crowdsensing $\omega(B)$. In the following,

$$\mathbb{E}[|\bar{x}_{i,n}^t - x_n^{\text{truth}(s_t+\tau_i^t)}|] = \mu(s_t,\tau_i^t) \cdot \left\{2\Phi\left[\frac{\mu(s_t,\tau_i^t)}{v_{i,n}}\right] - 1\right\} + \frac{2v_{i,n}}{\sqrt{2\pi}}\exp\left\{-\frac{\mu(s_t,\tau_i^t)^2}{2{v_{i,n}}^2}\right\}. \tag{12}$$

if there is no ambiguity, we use ω and $\omega(B)$ interchangeably. Then, the platform utility maximization (PUM) problem can be formulated as

$$\text{PUM:} \max_{\{\mathcal{K}^1,\mathcal{K}^2,\cdots\}} \sum\nolimits_{t=1}^{\omega(B)} u^t(\mathcal{K}^t), \tag{16a}$$

$$\text{s.t.} \quad \sum\nolimits_{t=1}^{\omega(B)} \sum\nolimits_{i\in\mathcal{K}^t} p_i^t(b_i) \leq B, \tag{16b}$$

$$|\mathcal{K}^1| = I, \tag{16c}$$

$$|\mathcal{K}^t| = K, \ \forall t > 1. \tag{16d}$$

In the following section, we will address the PUM problem by devising appropriate strategies for worker selection and payment. We expect the MCS ecosystem to possess some desirable properties, and for this purpose, we introduce the following definitions.

Definition 3 (Truthfulness): For each work i with a true cost c_i and a quoted price b_i, let $v_i^t(c_i) = p_i^t(c_i) - c_i$ and $v_i^t(b_i) = p_i^t(b_i) - c_i$ denote worker i's utility for the truthful and untruthful bids, respectively. The truthfulness property requires that the following inequality holds for $\forall b_i \geq 0$:

$$v_i^t(c_i) \geq v_i^t(b_i). \tag{17}$$

The truthfulness of the MCS ecosystem can guarantee that each strategic worker will report its true cost as the quoted bid price, since an untruthful bid price will not lead to a better payoff.

Definition 4 (Individual Rationality): Consider that each worker in our MCS ecosystem is rational, its utility in each round should be no less than 0, i.e., $v_i^t(b_i) \geq 0$; otherwise, workers are unwilling to participate in the MCS ecosystem.

Remark 1: It is worth emphasizing that truthfulness and individual rationality (IR) are necessary conditions for the MCS ecosystem to sustainably operate effectively. If truthfulness is not satisfied, workers may resort to strategies of reporting costs untruthfully, inducing the platform to pay higher cost compensations to earn greater utility. This not only reduces the platform's profits but also encourages emulation by other workers, severely deteriorating the operational efficiency and environment of the MCS ecosystem. If IR is not satisfied, workers will decline participation in the MCS ecosystem, rendering it unable to operate at all. In the subsequent sections, we will validate the truthfulness and IR of the proposed MCS ecosystem through both theoretical analysis and experimental simulations.

Definition 5 (Regret): Regret refers to the difference between the total achieved utility of the optimal policy that has knowledge of the expected error ξ_i and task completion duration τ_i of workers in advance, and the utility achieved by the proposed solution in the case where these values are unknown. Let $\text{Reg}(B)$ denote the regret with the total budget B, which is expressed as

$$\text{Reg}(B) = \frac{B \cdot u^*}{C^*} - \sum\nolimits_{t=1}^{\omega(B)} u^t, \tag{18}$$

where $u^* = u(\mathcal{K}^*)$ and $C^* = \sum_{i\in\mathcal{K}^*} b_i$ represent the utility and payment of the optimal policy in a round, respectively, and $\mathcal{K}^*$ denotes the corresponding optimal set of workers.

V. CMAB-DTD Framework for MCS

In this section, we first present how to determine the winning worker set for each round of crowdsensing tasks, and then explain how to calculate payment for each selected worker, followed by a summary of the entire CMAB-based dynamic truth discovery (CMAB-DTD) framework for MCS.

A. Winning Worker Set Determination

In order to select high-quality workers, we have incorporated the multi-attribute reverse auction mechanism in our ecosystem to intensify competition among workers and reduce the platform's cost. The multi-attribute reverse auction involves the platform issuing a call for sensing tasks to attract eligible workers. During the auction process, workers are required to submit multi-dimensional information (price and privacy protection preferences) in their bids, competing to become the winner and receive the payment (details regarding worker selection and payment calculation will be introduced later). Specifically, before initiating multiple rounds of crowdsensing tasks, each worker i submits a bid message to the platform, denoted as

$$Bid_i = \{\boldsymbol{\sigma}_i, b_i\}, \tag{19}$$

where $\boldsymbol{\sigma}_i$ and b_i are worker i's quoted privacy protection vector and price for performing the crowdsensing tasks, respectively. Note that c_i is the true cost of worker i, and a strategic worker may not bid truthfully, i.e., $b_i \neq c_i$. Based on the bid messages, in each round of crowdsensing, the platform determines the winning worker set $\mathcal{K}^t$ and calculates the payment $\mathcal{P}^t$ to all selected workers, so as to maximize its utility under the budget constraint, as formulated in the PUM problem (16).

We propose a budget-constraint K-arm CMAB model to solve the PUM problem. In this model, each worker represents an arm, and the worker's sensing quality is the associated reward. Recruitment is treated as pulling arms. K workers are recruited in each round, and the sensing quality of each worker can be learned accordingly. The main challenge lies in this model is the platform's lack of knowledge about workers' sensing qualities, forcing it to recruit workers provisionally to conduct sensing tasks (exploration) and then adjust the winning worker group based on the learned knowledge (exploitation).

As mentioned previously, exploration and exploitation are two important but opposite considerations when selecting winning workers, and the platform needs to balance these two processes so as to maximize its utility. To this end, we adopt the concept of Upper Confidence Bound (UCB), whose core idea is always to have optimism in the face of uncertainty [49]. Specifically, for an arbitrary round t, we estimate each worker's error ξ_i and task completion duration τ_i based on the knowledge learned from previous rounds. Let κ_i^t be the number of times that worker i is selected until round t. Note that within a single round, the platform can learn the error up to N times but the task completion duration only once. Let η_i^t denote the number of times that error ξ_i has been learned until round t, then $\eta_i^t = N \cdot \kappa_i^t$. Let $\bar{\xi}_i^t$ and $\bar{\tau}_i^t$ be the empirical mean of error and task duration of worker i until round t, respectively, and the combinatorial empirical mean of worker i's quality can be denoted as $\bar{q}_i^t \triangleq L\bar{\tau}_i^t + \sqrt{\frac{2}{\pi D}}\bar{\xi}_i^t$. If worker i is selected in round t, then $\bar{\tau}_i^t$, $\bar{\xi}_i^t$, κ_i^t, η_i^t are updated as follows:

$$\begin{cases} \bar{\tau}_i^t = \frac{\bar{\tau}_i^{t-1}\kappa_i^{t-1}+\tau_i^t}{\kappa_i^{t-1}+1}, \\ \bar{\xi}_i^t = \frac{\bar{\xi}_i^{t-1}\eta_i^{t-1}+\sum_{n\in\mathcal{N}}\xi_{i,n}^t}{\eta_i^{t-1}+N}, \\ \kappa_i^t = \kappa_i^{t-1}+1, \\ \eta_i^t = \eta_i^{t-1}+N. \end{cases} \tag{20}$$

Otherwise, these parameters remain unchanged from the previous round.

According to the UCB policy of combinatorial multi-armed bandits [20], [50], the UCB terms of task duration and error are $A^\tau\sqrt{\frac{(K+1)\ln(t)}{\kappa_i^t}}$ and $A^\xi\sqrt{\frac{(K+1)\ln(\sum_{j\in\mathcal{I}}\eta_j^t)}{\eta_i^t}}$, respectively. Therefore, the UCB term of $\bar{q}_i^t$, denoted as $\ddot{q}_i^t$, can be expressed as

$$\ddot{q}_i^t = \bar{q}_i^t - Q_i^t, \tag{21}$$

where $Q_i^t = \left\{(K+1)[L^2\frac{(A^\tau)^2\ln(t)}{\kappa_i^t} + \frac{2(A^\xi)^2\ln(\sum_{j\in\mathcal{I}}\eta_j^t)}{\eta_i^t\pi D}]\right\}^{\frac{1}{2}}$ is the combinatorial confidence radius of worker i's quality q_i^t in round t [51]. The minus sign in Eq. (21) is due to the fact that a smaller q_i^t indicates better quality of worker i.

In each round of worker selection, the platform calculates the Revenue-Cost-Ratio (RCR) of each worker as

$$\mathrm{RCR}_i^t = \frac{\frac{R}{K} - (\ddot{q}_i^{t-1} + \bar{\sigma}_i)}{b_i}, \tag{22}$$

where $\frac{R}{K} - (\ddot{q}_i^{t-1} + \bar{\sigma}_i)$ represents the average revenue brought to the platform by worker i, and b_i is the quoted price of worker i. Then, the platform selects the top K workers as the winner set.

Note that the platform can only obtain the perturbed data from workers, but cannot directly observe the error term $\xi_{i,n}^t$. Hence, we make an unbiased estimation for $\xi_{i,n}^t$ as follows:

$$(\xi_{i,n}^t)^2 + \sigma_{i,n}^2 \approx \frac{1}{D-1}\sum_{d=1}^D \left(\tilde{x}_{i,n}^{t\,(d)} - \overline{\tilde{x}_{i,n}^t}\right)^2, \tag{23}$$

$$\Rightarrow \xi_{i,n}^t \approx \sqrt{\frac{1}{D-1}\sum_{d=1}^D \left(\tilde{x}_{i,n}^{t\,(d)} - \overline{\tilde{x}_{i,n}^t}\right)^2 - \sigma_{i,n}^2}. \tag{24}$$

B. Worker Payment Calculation

Next, we move on to devising payment rules that incentivize the selected workers to truthfully report their costs, while also ensuring their individual rationality.

We regard round 1 as the initialization phase, where the platform selects all workers (i.e., $\mathcal{K}^1 = \mathcal{I}$) to initialize the parameters η_i^1, $\bar{\xi}_i^1$, κ_i^1, $\bar{\tau}_i^1$, $\bar{q}_i^t$ and $\ddot{q}_i^1$. In addition, the platform adopts $c_{\max}$ as the payment to every worker. Consequently, each worker's payment in round 1 is no less than its true cost, indicating that the worker's utility is non-negative and the property of individual rationality is satisfied. Then, the platform updates the remaining budget as $B - I\cdot c_{\max}$.

After the initialization phase, the platform selects K workers in each round until the budget exhausts. Specifically, at the beginning of each round t, the platform can acquire the value of $\ddot{q}_i^{t-1}$ for $\forall i \in \mathcal{I}$. The platform ranks workers in decreasing order according to the value of RCR_i^t and selects the top K workers to compose the winning worker set $\mathcal{K}^t$. To guarantee truthfulness, the platform calculates the corresponding payment $\mathcal{P}^t$ using the idea of critical payment [50]. Formally, there is

$$p_i^t(b_i) = \min\left\{\frac{\frac{R}{K} - (\ddot{q}_i^{t-1} + \bar{\sigma}_i)}{\frac{R}{K} - (\ddot{q}_{K+1}^{t-1} + \bar{\sigma}_{K+1})}\cdot b_{K+1}, c_{\max}\right\}. \tag{25}$$

The critical payment of a winning worker i should be calculated based on the bid of the $(K+1)$-th worker, i.e., $\frac{\frac{R}{K}-(\ddot{q}_i^{t-1}+\bar{\sigma}_i)}{\frac{R}{K}-(\ddot{q}_{K+1}^{t-1}+\bar{\sigma}_{K+1})}\cdot b_{K+1}$. The $\min\{\cdot\}$ ensures that the payment will not exceed the maximum cost.

We will demonstrate later that the payment method in (25) can ensure the selected workers' truthfulness and individual rationality simultaneously. The process of worker selection and payment in round t is summarized in Algorithm 2.

C. CMAB-DTD Framework

Integrating the truth discovery (Algorithm 1) and the worker selection and payment (Algorithm 2), we develop the CMAB-DTD framework for MCS, outlined in Algorithm 3. In the initialization phase, i.e., Steps 1-3, the platform selects all workers in round 1 (i.e., $\mathcal{K}^1 = \mathcal{I}$), obtains the estimated ground truth in this round, and assigns a payment of $p_i^1 = c_{\max}$ to each worker. This ensures that each worker's utility is greater than 0, thus satisfying individual rationality. Next, the platform can calculate parameters $\xi_{i,n}^1$, τ_i^1, η_i^1, κ_i^1, $\bar{\xi}_i^1$, $\bar{\tau}_i^1$, $\bar{q}_i^1$, $\ddot{q}_i^1$, and $B^1 = B - I\cdot c_{\max}$, in which B^t means the remaining budget after round t. After the initialization phase, in Step 6, the platform performs Algorithm 2 to recruit workers and calculate payments, and then obtains $\mathcal{K}^t$, $\mathcal{P}^t$. Next, as shown in Steps 7-9, if the total payment in this round exceeds the remaining budget, the process will terminate. Else, the platform will update budget B^t in Step 10. In Step 11, the platform obtains the perturbed sensory data $\{\tilde{x}_{i,n}^{t\,(d)}\}_{i,d,n=1}^{K,D,N}$ from K wining workers, while observing their task duration τ_i^t and calculating the error $\xi_{i,n}^t$. In step 12, the platform calculates the mean of each worker's submitted data $\overline{\tilde{x}_{i,n}^t}$. Then the platform performs Algorithm 1 to obtain the estimated ground truth $\{\hat{x}_n^t\}_{n=1}^N$ in round t.

Algorithm 2 Worker Selection and Payment

Input: $\xi_{i,n}^{t-1}$, τ_i^{t-1}, η_i^{t-1}, κ_i^{t-1}, $\bar{\xi}_i^{t-1}$, and $\bar{\tau}_i^{t-1}$
Output: $\mathcal{K}^t$, $\mathcal{P}^t$

1: Calculate $\bar{q}_i^{t-1} = L\bar{\tau}_i^{t-1} + \sqrt{\frac{2}{\pi D}}\bar{\xi}_i^{t-1}$;
2: Calculate $\ddot{q}_i^{t-1} = \bar{q}_i^{t-1} - Q_i^{t-1}$ according to (21);
3: Calculate RCR_i^t according to (22);
4: Sort the workers $\mathcal{I}$ by RCR values: $\mathrm{RCR}_{i_1}^t \geq \cdots \geq \mathrm{RCR}_{i_j}^t \geq \cdots \geq \mathrm{RCR}_{i_I}^t$;
5: Select the top K workers into the winning worker set $\mathcal{K}^t$;
6: Compute the payments $p_i^t(b_i)$ for each selected worker in $\mathcal{K}^t$ according to (25);
7: Update the parameters η_i^t, κ_i^t, $\bar{\xi}_i^t$, $\bar{\tau}_i^t$ according to (20);

Algorithm 3 CMAB-DTD Framework for MCS

Input: $\mathcal{I}$, $\mathcal{N}$, $\boldsymbol{Bid}$, K, B

Output: $\{\hat{x}_n^t\}_{n=1}^N$, $\mathcal{K}^t$, $\mathcal{P}^t$

Initialize $t=1$, $\mathcal{K}^t=\emptyset$, $p_i^t(b_i)=0$, $\forall i \in \mathcal{I}$;
The platform selects all workers in the first round, i.e., $\mathcal{K}^1=\mathcal{I}$, and determine the payment for selected workers, i.e., $p_i^1=c_{\max}$, to obtain $\{\hat{x}_n^1\}_{n=1}^N$;
Calculate parameters $\xi_{i,n}^1$, τ_i^1, η_i^1, κ_i^1, $\bar{\xi}_i^1$, $\bar{\tau}_i^1$, $\bar{q}_i^1$, $\ddot{q}_i^1$, and $B^1=B-I\cdot c_{\max}$
while $true$ **do**
    $t=t+1$;
    Perform **Algorithm 2** to obtain $\mathcal{K}^t$, $\mathcal{P}^t$;
    if $\sum_{i\in\mathcal{K}^t} p_i^t(b_i) \geq B^{t-1}$ **then**
        break;
    end if
    Update $B^t=B^{t-1}-\sum_{i\in\mathcal{K}^t} p_i^t(b_i)$;
    The platform obtains sensory data from K workers $\{\tilde{x}_{i,n}^{t\,(d)}\}_{i,d,n=1}^{K,D,N}$. In the meantime, the platform observes their task duration τ_i^t and calculates the error $\xi_{i,n}^t$;
    The platform calculates the mean of each worker's submitted data $\overline{\tilde{x}_{i,n}^t}$;
    Perform **Algorithm 1** to obtain $\{\hat{x}_n^t\}_{n=1}^N$;
end while

VI. Performance Analysis

In this section, we analyze the regret upper bound, truthfulness, and individual rationality of the proposed MCS ecosystem.

A. Upper Bound on Regret

We use the superscript $*$ to indicate the corresponding identifications of the optimal policy. Let $\bar{a}_i^t=\frac{R}{K}-(\bar{q}_i^{t-1}+\bar{\sigma}_i)$ and $a_i=\frac{R}{K}-(q_i+\bar{\sigma}_i)$. Then, we define the smallest and largest possible differences of RCR value and the largest possible difference of revenue among all non-optimal winner sets $\mathcal{K}^t \neq \mathcal{K}^*$ as follows:

$$\begin{aligned}
\Delta_{\max} &= \textstyle\sum_{i\in\mathcal{K}^*}\frac{a_i}{b_i}-\min_{\mathcal{K}^t\neq\mathcal{K}^*}\sum_{i\in\mathcal{K}^t}\frac{a_i}{b_i},\\
\Delta_{\min} &= \textstyle\sum_{i\in\mathcal{K}^*}\frac{a_i}{b_i}-\max_{\mathcal{K}^t\neq\mathcal{K}^*}\sum_{i\in\mathcal{K}^t}\frac{a_i}{b_i},\\
\bigtriangledown_{\max} &= u^*-\min_{\mathcal{K}^t\neq\mathcal{K}^*}u^t.
\end{aligned}\tag{26}$$

Moreover, we use a notation ϕ_i^t to denote the counter for the worker i after the initialization phase (i.e., $t>1$), in which the counter ϕ_i^t is updated as follows: when $\mathcal{K}^t\neq\mathcal{K}^*$, there is

$$i=\arg\min_{j\in\mathcal{K}^t}\phi_j^t, \quad \phi_i^t=\phi_i^t+1. \tag{27}$$

Here, if multiple workers satisfy the condition, we select any one worker randomly. When the winning worker set in a round is not the optimal set, the worker with the smallest counter ϕ_i^t will be incremented by 1, which indicates that the sum of the counter $\sum_i^I \phi_i^t$ is equal to the total times that the non-optimal worker set to be recruited. Next, we will focus on the upper bound of the counter ϕ_i^ω.

Lemma 1: For any worker $i\in\mathcal{I}$, the expectation of the counter ϕ_i^ω is upper bounded by

$$\begin{aligned}
\mathbb{E}\{\phi_i^\omega\} \leq{}& \frac{4K^2(K+1)L^2A^{\tau^2}}{(c_{\min}\Delta_{\min})^2}\ln\omega\\
&+\frac{8K^2(K+1)A^{\xi^2}}{(c_{\min}\Delta_{\min})^2\pi DN}\ln(\omega KN)+1+\frac{K\pi^2}{3}\\
={}&\varphi_1\ln\omega+\varphi_2\ln(\omega KN)+\varphi_3,
\end{aligned}\tag{28}$$

where

$$\begin{cases}
\varphi_1=\dfrac{4K^2(K+1)L^2A^{\tau^2}}{(c_{\min}\Delta_{\min})^2},\\
\varphi_2=\dfrac{8K^2(K+1)A^{\xi^2}}{(c_{\min}\Delta_{\min})^2\pi DN},\\
\varphi_3=1+\frac{K\pi^2}{3}.
\end{cases}\tag{29}$$

Proof: In each round t, one of the following cases must happen: 1) the optimal set of workers, i.e., $\mathcal{K}^*$, is selected; 2) a non-optimal set of workers is selected, i.e., $\mathcal{K}^t\neq\mathcal{K}^*$. In the first case, the counter ϕ_i^t will not change, while in the second case, the counter ϕ_i^t will be updated according to Eq. (27). Let $\Phi_i^t\in\{0,1\}$ denote the indicator that ϕ_i^t is incremented at round t, where $\Phi_i^t=1$ means that ϕ_i^t is incremented, and $\Phi_i^t=0$ otherwise. Then, we have

$$\begin{aligned}
\phi_i^\omega &= \sum_{t=2}^{\omega}\mathbb{I}\{\Phi_i^t=1\}=\vartheta+\sum_{t=2}^{\omega}\mathbb{I}\{\Phi_i^t=1,\phi_i^t\geq\vartheta\}\\
&\leq\vartheta+\sum_{t=1}^{\omega}\mathbb{I}\{\sum_{i\in\mathcal{K}^{t+1}}\mathrm{RCR}_i^t\geq\sum_{i\in\mathcal{K}^*}\mathrm{RCR}_i^t,\phi_i^t\geq\vartheta\}\\
&\leq\vartheta+\sum_{t=1}^{\omega}\mathbb{I}\{\max_{\vartheta\leq\kappa_{i(1)},\cdots,\kappa_{i(K)}\leq t}\sum_{j=1}^{K}\mathrm{RCR}_{i_{(j)}}^t\\
&\qquad\geq\min_{1\leq\kappa_{i^*(1)},\cdots,\kappa_{i^*(K)}\leq t}\sum_{j=1}^{K}\mathrm{RCR}_{i^*_{(j)}}^t\}\\
&\leq\vartheta+\sum_{t=1}^{\omega}\sum_{\kappa_{i(1)}=\vartheta}^{t}\cdots\sum_{\kappa_{i(K)}=\vartheta}^{t}\cdots\sum_{\kappa_{i^*(1)}=1}^{t}\cdots\sum_{\kappa_{i^*(K)}=1}^{t}\\
&\qquad\mathbb{I}\{\sum_{j=1}^{K}\mathrm{RCR}_{i_{(j)}}^t\geq\sum_{j=1}^{K}\mathrm{RCR}_{i^*_{(j)}}^t\},
\end{aligned}\tag{30}$$

where $i(j)$ and $i^*(j)$ denote the j-th nonzero element in $\mathcal{K}^{t+1}$ and $\mathcal{K}^*$, respectively. According to the definitions of ϕ_i^t and κ_i^t, we have $\kappa_i^t\geq\phi_i^t$ for $\forall i\in\mathcal{I}$ and $\forall t\geq 1$.

Next, we focus on the bound of $\sum_{j=1}^K\mathrm{RCR}_{i_{(j)}}^t \geq \sum_{j=1}^K\mathrm{RCR}_{i^*_{(j)}}^t$. Then, for the following event

$$\sum_{j=1}^{K}\frac{\bar{a}_{i_{(j)}}^t+Q_{i_{(j)}}^t}{b_{i_{(j)}}}\geq\sum_{j=1}^{K}\frac{\bar{a}_{i^*_{(j)}}^t+Q_{i^*_{(j)}}^t}{b_{i^*_{(j)}}},\tag{31}$$

we can get that at least one of the following cases must be true (which is based on the proof by contradiction):

$$\sum_{j=1}^{K}\frac{\bar{a}_{i^*_{(j)}}^t}{b_{i^*_{(j)}}}\leq\sum_{j=1}^{K}\frac{a_{i^*_{(j)}}-Q_{i^*_{(j)}}^t}{b_{i^*_{(j)}}},\tag{32}$$

$$\sum_{j=1}^{K}\frac{\bar{a}^t_{i_{(j)}}}{b_{i_{(j)}}}\geq\sum_{j=1}^{K}\frac{a_{i_{(j)}}+Q^t_{i_{(j)}}}{b_{i_{(j)}}},\tag{33}$$

$$\sum_{j=1}^{K}\frac{a_{i^*_{(j)}}}{b_{i^*_{(j)}}}<\sum_{j=1}^{K}\frac{a_{i_{(j)}}+2Q^t_{i_{(j)}}}{b_{i_{(j)}}}.\tag{34}$$

Next, we need to obtain the upper bound of the probabilities of Eq. (32) and Eq. (33). By applying the Chernoff-Hoeffding bound, we have

$$\begin{aligned}&Pr\left\{\sum_{j=1}^{K}\frac{\bar{a}^t_{i^*_{(j)}}}{b_{i^*_{(j)}}}\leq\sum_{j=1}^{K}\frac{a_{i^*_{(j)}}-Q^t_{i^*_{(j)}}}{b_{i^*_{(j)}}}\right\}\\&\leq\sum_{j=1}^{K}Pr\{\bar{q}^t_{i^*_{(j)}}\geq q^t_{i^*_{(j)}}+Q^t_{i^*_{(j)}}\}\\&\leq Ke^{-2\kappa^t_{i^*_{(j)}}Q^t_{i^*_{(j)}}{}^2}=Kt^{-2(K+1)}.\end{aligned}\tag{35}$$

We can also similarly prove that

$$Pr\left\{\sum_{j=1}^{K}\frac{\bar{a}^t_{i_{(j)}}}{b_{i_{(j)}}}\geq\sum_{j=1}^{K}\frac{a_{i_{(j)}}+Q^t_{i_{(j)}}}{b_{i_{(j)}}}\right\}\leq Kt^{-2(K+1)}.\tag{36}$$

Next, we will choose a certain ϑ to make the event defined in (34) impossible. Note that at the end of round t, $\sum_{j\in\mathcal{I}}\eta^t_j=tKN$. Based on the fact that $\frac{\eta^t_i}{N}=\kappa^t_i\geq\phi^t_i\geq\vartheta$, we have

$$\begin{aligned}&\sum_{j=1}^{K}\frac{a_{i^*_{(j)}}}{b_{i^*_{(j)}}}-\sum_{j=1}^{K}\frac{a_{i_{(j)}}}{b_{i_{(j)}}}-2\sum_{j=1}^{K}\frac{Q^t_{i_{(j)}}}{b_{i_{(j)}}}\\&\geq\Delta_{\min}-2\sum_{j=1}^{K}\frac{\sqrt{(K+1)(L^2\frac{(A^\tau)^2\ln t}{\kappa^t_i}+\frac{2(A^\xi)^2\ln(\sum_{j\in\mathcal{I}}\eta^t_j)}{\eta^t_i\pi D})}}{b_{i_{(j)}}}\\&\geq\Delta_{\min}-2\sum_{j=1}^{K}\frac{\sqrt{(K+1)(L^2\frac{(A^\tau)^2\ln t}{\vartheta}+\frac{2(A^\xi)^2\ln(tKN)}{\vartheta\pi DN})}}{c_{\min}}\geq0.\end{aligned}\tag{37}$$

We can conclude that Eq. (37) will always hold if ϑ satisfies the following condition:

$$\vartheta\geq\varphi_1\ln\omega+\varphi_2\ln(\omega KN).\tag{38}$$

Substituting (38) into (30), we can obtain that

$$\begin{aligned}&\mathbb{E}\{\phi^\omega_i\}\leq\lceil\varphi_1\ln\omega+\varphi_2\ln(\omega KN)\rceil\\&\quad+\sum\nolimits_{t=1}^{\infty}(t-\vartheta+1)^Kt^K2Kt^{-2(K+1)}\\&\leq\varphi_1\ln\omega+\varphi_2\ln(\omega KN)+1+2K\sum\nolimits_{t=1}^{\infty}t^{-2}\\&\leq\varphi_1\ln\omega+\varphi_2\ln(\omega KN)+\varphi_3.\end{aligned}$$

■

According to Lemma 1, the upper bound of counter ϕ^ω_i is highly related to the number of total rounds ω. Here, we define another payment computation method in the case where the expected quality are known in advance. That is, according to the selection criterion $\text{RCR}_i=\frac{a_i}{b_i}$, let $p_i(b_i)=\frac{a_i\cdot b_{K+1}}{a_{K+1}}\geq b_i$ be the payment for each winning worker i. Thus, the total payment in each round, denoted as $C^\star$, is determined as

$$C^\star=\sum\nolimits_{i\in\mathcal{K}^*}\frac{a_i\cdot b_{K+1}}{a_{K+1}}\geq\sum\nolimits_{i\in\mathcal{K}^*}b_i=C^*.\tag{39}$$

Then, for the maximum number of rounds ω, we have the following lemma.

Lemma 2: The maximum number of crowdsensing task execution rounds under the budget B, i.e., ω, is bounded by

$$\begin{aligned}&\frac{B}{C^\star}-\varphi_5\big((\varphi_1+\varphi_2)\ln(\frac{3B}{C^*}+\varphi_4)+\varphi_2\ln(KN)+\varphi_3\big)\\&\leq\omega\leq\frac{3B}{C^*}+\varphi_4,\end{aligned}\tag{40}$$

where

$$\begin{cases}\varphi_4=\dfrac{3Ic_{\max}}{Kc_{\min}}(\varphi_1\ln(\dfrac{3Ic_{\max}\varphi_1}{Kc_{\min}})\\\quad+\varphi_2\ln(\dfrac{3INc_{\max}\varphi_2}{c_{\min}})-\varphi_1-\varphi_2),\\\varphi_5=\dfrac{Ic_{\max}}{C^\star}.\end{cases}\tag{41}$$

Proof: We first let $\omega^*(B)$ denote the stopping round of the optimal solution under the budget B. Since the optimal solution knows the expected quality of all workers in advance and the bids submitted by each strategic worker are fixed, the optimal set of workers selected in each round is determined, i.e., $\mathcal{K}^*$. Then, the payment for each winning worker can be determined and the total payment in one round can be calculated as $C^*=\sum_{i\in\mathcal{K}^*}b_i$. Thus, the number of total rounds is fixed, i.e., $\omega^*(B)=\lfloor\frac{B}{C^*}\rfloor$, and further we have the following results:

$$\frac{B}{C^*}-1\geq\omega^*\leq\frac{B}{C^*}.\tag{42}$$

Then, we first analyze the relationship between $\omega^*(B)$ and $\omega(B)$. According to the payment computation, we get that the payment for each winning worker is greater than its true cost. Thus, the total payment in each round is greater than the value $K\cdot c_{\min}$ and we have $\omega(B)\leq\frac{B}{Kc_{\min}}$. Then, there is

$$\begin{aligned}\omega&\leq\omega^*+\omega(\sum\nolimits_{i\notin\mathcal{K}^*}\kappa_i(\omega)\cdot c_{\max})\\&\leq\omega^*+c_{\max}\cdot\omega(\sum\nolimits_{i=1}^{I}\phi^\omega_i)\\&\leq\omega^*+\frac{I\cdot c_{\max}}{K\cdot c_{\min}}\mathbb{E}\{\phi^\omega_i\}\\&\leq\frac{B}{C^*}+\frac{I\cdot c_{\max}}{K\cdot c_{\min}}\big(\varphi_1\ln\omega+\varphi_2\ln(\omega KN)+\varphi_3\big).\end{aligned}\tag{43}$$

According to the inequality $\ln x\leq x-1$ for $\forall x>0$, we have the following results:

$$\begin{aligned}&\ln(\frac{Kc_{\min}}{3Ic_{\max}\varphi_1}\omega)\leq\frac{Kc_{\min}}{3Ic_{\max}\varphi_1}\omega-1\\&\Rightarrow\ln\omega\leq\frac{Kc_{\min}}{3Ic_{\max}\varphi_1}\omega-1+\ln(\frac{3Ic_{\max}\varphi_1}{Kc_{\min}}).\end{aligned}\tag{44}$$

$$\begin{aligned}&\ln(\frac{c_{\min}}{3INc_{\max}\varphi_2}\omega KN)\leq\frac{c_{\min}}{3INc_{\max}\varphi_2}\omega KN-1\\&\Rightarrow\ln(\omega KN)\leq\frac{Kc_{\min}}{3Ic_{\max}\varphi_2}\omega-1+\ln(\frac{3INc_{\max}\varphi_2}{c_{\min}}).\end{aligned}\tag{45}$$

By substituting Eq.(44) and Eq.(45) into Eq.(43), we have

$$\begin{aligned}\omega &\le \frac{B}{C^*} + \frac{I\cdot c_{\max}}{K\cdot c_{\min}}\big(\varphi_1 \ln\omega + \varphi_2 \ln(\omega KN) + \varphi_3\big)\\ &\le \frac{B}{C^*} + \frac{2\omega}{3} + \frac{Ic_{\max}}{Kc_{\min}}\big(\varphi_1 \ln(\frac{3Ic_{\max}\varphi_1}{Kc_{\min}})\\ &\qquad + \varphi_2 \ln(\frac{3INc_{\max}\varphi_2}{c_{\min}}) - \varphi_1 - \varphi_2\big)\\ \Rightarrow \omega &\le \frac{3B}{C^*} + \frac{3Ic_{\max}}{Kc_{\min}}\big(\varphi_1 \ln(\frac{3Ic_{\max}\varphi_1}{Kc_{\min}})\\ &\qquad + \varphi_2 \ln(\frac{3INc_{\max}\varphi_2}{c_{\min}}) - \varphi_1 - \varphi_2\big)\\ &= \frac{3B}{C^*} + \varphi_4.\end{aligned} \tag{46}$$

Next, we focus on the lower bound of $\omega(B)$. Here, we divide B into two parts: B^* and $B^\dagger$, in which B^* means the budget is used to select the optimal set of workers and $B^\dagger$ indicates the remaining budget spent on pulling the non-optimal sets of workers. Then, we use $\omega^\star(B)$ to denote the total rounds in which the budget B is given and the payment is calculated by $p_i(b_i) = \frac{a_i \cdot b_{K+1}}{a_{K+1}}$. Hence, we get $\omega^\star(B) \le \omega^*(B)$ and $\frac{B}{C^\star} - 1 \le \omega^\star(B) \le \frac{B}{C^\star}$. Since $\omega^\star(B)$ and $\omega(B)$ are based on the same payment computation method, we have

$$\begin{aligned}&\omega(B) = \omega(B^* + B^\dagger) \ge \omega^\star(B^*)\\ &\ge \omega^\star(B - \textstyle\sum_{i\notin\mathcal{K}^*} \kappa_i(\omega)\cdot c_{\max})\\ &\ge \omega^\star(B - c_{\max}\cdot \textstyle\sum_{i=1}^{I} \phi_i^\omega)\\ &\ge \omega^\star(B - Ic_{\max}(\varphi_1 \ln\omega + \varphi_2 \ln(\omega KN) + \varphi_3))\\ &\ge \frac{B - c_{\max}I(\varphi_1 \ln\omega + \varphi_2 \ln(\omega KN) + \varphi_3)}{C^\star} - 1.\end{aligned} \tag{47}$$

According to (46) and (47), we have

$$\begin{aligned}\omega &\ge \frac{B}{C^\star} - \frac{Ic_{\max}}{C^\star}\big(\varphi_1 \ln(\frac{3B}{C^*} + \varphi_4)\\ &\qquad + \varphi_2(\ln(KN(\frac{3B}{C^*} + \varphi_4))) + \varphi_3\big)\\ &\ge \frac{B}{C^\star} - \varphi_5\big((\varphi_1+\varphi_2)\ln(\frac{3B}{C^*} + \varphi_4) + \varphi_2 \ln(KN) + \varphi_3\big).\end{aligned}$$

This completes the proof. ■

Theorem 2: The regret of our MCS ecosystem with the CMAB-DTD framework is bounded by $\mathcal{O}\big(IK^3 \ln(B + IK^2 \ln(IK^2))\big)$.

Proof: According to the definition of regret, Lemma 1 and Lemma 2, we have the following results:

$$\begin{aligned}&\mathrm{Reg}(B) = \frac{Bu^*}{C^*} - \textstyle\sum_{t=1}^{\omega} u^t\\ &= \frac{Bu^*}{C^*} - \omega u^* + \omega u^* - \textstyle\sum_{t=1}^{\omega} u^t\\ &\le \frac{Bu^*}{C^*} - \omega u^* + \textstyle\sum_{i=1}^{I} \phi_i^\omega \triangledown_{max}\\ &\le \frac{Bu^*}{C^*} - \omega u^* + I\triangledown_{\max}\big(\varphi_1 \ln(\frac{3B}{C^*} + \varphi_4)\\ &\quad + \varphi_2(\ln(KN(\frac{3B}{C^*} + \varphi_4))) + \varphi_3\big)\\ &\le \frac{Bu^*}{C^*} - (\frac{B}{C^\star} - \varphi_5\big((\varphi_1+\varphi_2)\ln(\frac{3B}{C^*} + \varphi_4)\\ &\quad + \varphi_2 \ln(KN) + \varphi_3\big))u^* + I\triangledown_{\max}\big(\varphi_1 \ln(\frac{3B}{C^*} + \varphi_4)\\ &\quad + \varphi_2(\ln(KN(\frac{3B}{C^*} + \varphi_4))) + \varphi_3\big)\\ &\le (u^*\varphi_5 + I\triangledown_{\max})(\varphi_1+\varphi_2)\ln(\frac{3B}{C^*} + \varphi_4)\\ &\quad + (u^*\varphi_2 + I\triangledown_{\max})\ln(KN) + (u^* + I\triangledown_{\max})\varphi_3.\end{aligned} \tag{48}$$

This completes the proof. ■

B. Truthfulness

Theorem 3: The proposed MCS ecosystem satisfies the property of truthfulness.

Proof: Based on the Myerson's theorem [52], an auction mechanism is truthful if and only if it satisfies two conditions: 1) the winning worker selection process is monotonic; 2) each winning worker is paid the critical value. First, we can easily prove that our winning worker selection is monotonic in each round. For each bid price b_i, if worker i can win the auction with b_i in round t, it must also win when submitting a smaller value. This conclusion is based on the greedy selection criterion $\frac{\frac{R}{K} - (\ddot{q}_i^{t-1} + \bar{\sigma}_i)}{b_i}$.

Next, we prove that the CMAB-DTD scheme also satisfies the second condition. There are two cases of the relationship between the payment p_i^t and the bid price b_i. In the first case, when worker i bids less than or equal to the obtained payment, i.e., $b_i \le p_i^t$, worker i still wins and receives the same payment. In the second case, when worker i bids greater than the obtained price, i.e., $b_i > p_i^t$, RCR_i can be written as

$$\mathrm{RCR}_i = \frac{\frac{R}{K} - (\ddot{q}_i^{t-1} + \bar{\sigma}_i)}{b_i} < \frac{\frac{R}{K} - (\ddot{q}_i^{t-1} + \bar{\sigma}_i)}{p_i^t}. \tag{49}$$

According to Eq. (25), the payment obtained by worker i is $p_i^t = \frac{\frac{R}{K} - (\ddot{q}_i^{t-1} + \bar{\sigma}_i)}{\frac{R}{K} - (\ddot{q}_{K+1}^{t-1} + \bar{\sigma}_{K+1})} b_{K+1}$, and substituting it into (49), we have

$$\begin{aligned}\mathrm{RCR}_i = \frac{\frac{R}{K} - (\ddot{q}_i^{t-1} + \bar{\sigma}_i)}{b_i} &< \frac{\frac{R}{K} - (\ddot{q}_{K+1}^{t-1} + \bar{\sigma}_{K+1})}{p_i^t}\\ &= \mathrm{RCR}_{K+1}.\end{aligned} \tag{50}$$

Now we find that worker i fails and worker $K+1$ wins. That is, p_i^t precisely represents the critical value for worker i, and if the bid price exceeds this critical value, worker i will fail. Therefore, the proposed MCS ecosystem guarantees truthfulness. ■

C. Individual Rationality

Theorem 4: The proposed MCS ecosystem satisfies the property of individual rationality.

Proof: For worker i, if the bid price b_i does not win the auction in round t, the corresponding payoff is 0; otherwise, the payoff will be $p_i^t(b_i) - c_i$. Here, we have $p_i^t(b_i) = \min\left\{\frac{\frac{R}{K}-(\ddot{q}_i^{t-1}+\bar{\sigma}_i)}{\frac{R}{K}-(\ddot{q}_{K+1}^{t-1}+\bar{\sigma}_{K+1})}b_{K+1}, c_{\max}\right\}$. Since the bid price b_i is prior to b_{K+1} in round t, we get $\mathrm{RCR}_i^t \geq \mathrm{RCR}_{K+1}^t$, i.e., $\frac{\frac{R}{K}-(\ddot{q}_i^{t-1}+\bar{\sigma}_i)}{b_i} \geq \frac{\frac{R}{K}-(\ddot{q}_{K+1}^{t-1}+\bar{\sigma}_{K+1})}{b_{K+1}}$. Then, there is $b_i \leq \frac{\frac{R}{K}-(\ddot{q}_i^{t-1}+\bar{\sigma}_i)}{\frac{R}{K}-(\ddot{q}_{K+1}^{t-1}+\bar{\sigma}_{K+1})}b_{K+1} = p_i^t(b_i)$. Furthermore, due to the truthfulness of the worker selection and payment mechanism, we have $b_i = c_i$ for $\forall i \in \mathcal{I}$. Therefore, we get $c_i \leq \frac{\frac{R}{K}-(\ddot{q}_i^{t-1}+\bar{\sigma}_i)}{\frac{R}{K}-(\ddot{q}_{K+1}^{t-1}+\bar{\sigma}_{K+1})}b_{K+1} = p_i^t(b_i)$, i.e., $p_i^t(b_i) - c_i \geq 0$ holds true in every round.

This completes the proof. ■

VII. Experimental Simulations

A. Experimental Methodology

Comparison Algorithms: Note that our CMAB-DTD framework takes into account multiple unknown variables, distinguishing it from most existing MCS systems that only consider a single variable and therefore cannot be directly used for comparison. Consequently, we have developed three comparison algorithms, called "Optimal", "ϵ-first", and "Random". "Optimal" means that the algorithm knows the expected qualities of all workers in advance, and always selects the same top-K workers with the highest qualities in each round. The Random algorithm does not know the expected qualities and will randomly select K workers in every round. "ϵ-first" will randomly select K workers using $\epsilon \cdot B$ budget (pure exploration phase), and greedily select the top-K workers with the highest qualities by using the remaining $(1-\epsilon)\cdot B$ budget (pure exploitation phase). In the ϵ-first algorithm, we set $\epsilon \in \{0.1, 0.5\}$.

Simulation Settings: In our simulations, we assume that there are 2 real-time sensing tasks (e.g., temperature and humidity) that the platform requires to observe the ground truth, and accordingly, 60 workers are willing to participate in these tasks (i.e., $I = 60$, $N = 2$). Without loss of generality, we assume that the ground truth functions of the two real-time sensing tasks changing with time s are $x_1^{\text{truth}(s)} = sin(0.1\cdot s) + 2$ and $x_2^{\text{truth}(s)} = 0.1 \cdot s$, respectively. We set the value of $\xi_{i,n}^t$ following a Gaussian distribution, with the mean generated from the uniform distribution $\mathbb{U}(0.1, 2)$ and a constant of 0.05 for the standard deviation. The random noise injected by worker i, i.e., $\boldsymbol{\sigma}_i = \{\sigma_{i,1}, \sigma_{i,2}, \cdots, \sigma_{i,N}\}$, is sampled from the uniform distribution $\mathbb{U}(0.1, 2)$. The workers' submission time τ_i^t is also set according to a Gaussian distribution, with the mean generated from the uniform distribution $\mathbb{U}(0.1, 2)$ and a constant of 0.05 for the standard deviation. Since each worker has different privacy sensitivity and sensing costs, we randomly generate the cost of each worker from the uniform distribution $\mathbb{U}(1, 2)$. Furthermore, we set $K = 20$, $R = 200$, $\beta = 1$, $D = 5$, $L = 0.1$ in default. When computing the weight in the truth discovery algorithm, $g(\cdot)$ is set to its optimal form, that is,

$$g(\cdot) = -\log\left(\frac{\sum_{n=1}^{N} f_{\text{loss}}\left(\overline{\tilde{x}_{i,n}^t}, \hat{x}_n^t\right)}{\sum_{i=1}^{K}\sum_{n=1}^{N} f_{\text{loss}}\left(\overline{\tilde{x}_{i,n}^t}, \hat{x}_n^t\right)}\right).$$

The underlying principle behind this form can be found in [25], [53], [54], which is not the focus of this paper. $f_{\text{loss}}(\cdot)$ can be set to any form capable of measuring distance, with little impact on truth discovery accuracy. We will adopt the most commonly used forms, i.e., the absolute value function and squared difference function, to illustrate their impact on truth discovery accuracy.

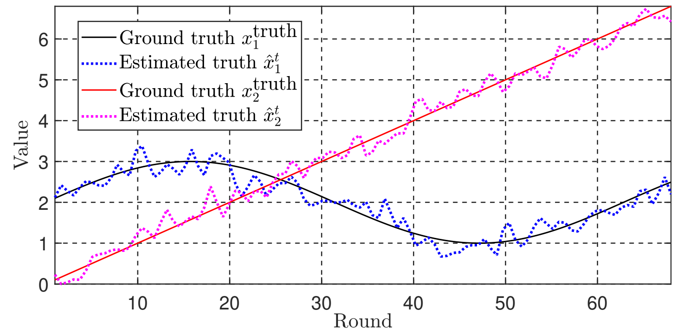


Fig. 3. Estimated truth versus ground truth.

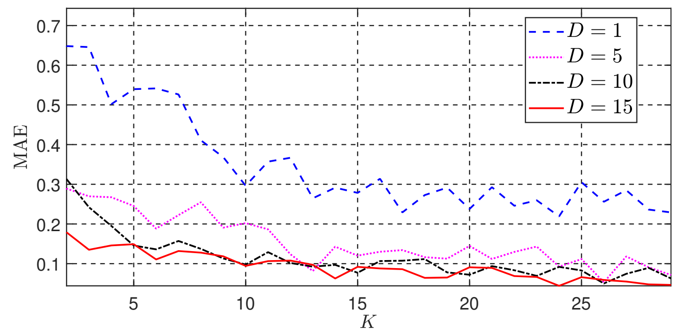


Fig. 4. Impact of selected worker quantity on the accuracy of mobile crowdsensing.

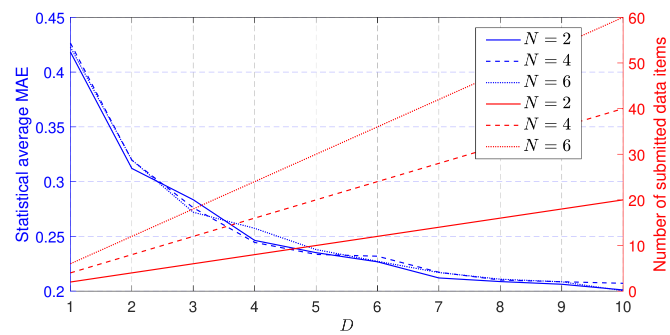
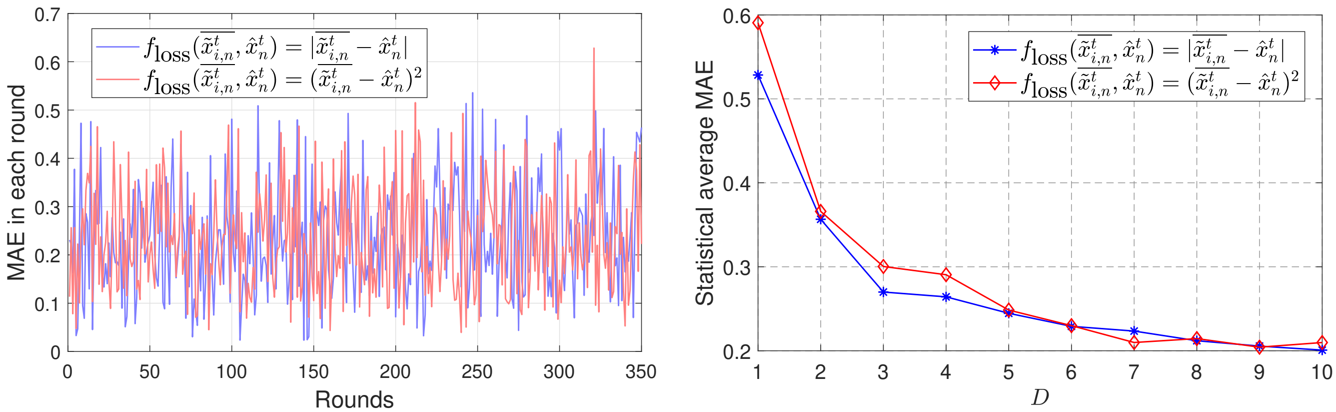


Fig. 5. Impact of number of samples on the system performance.

B. Experimental Results

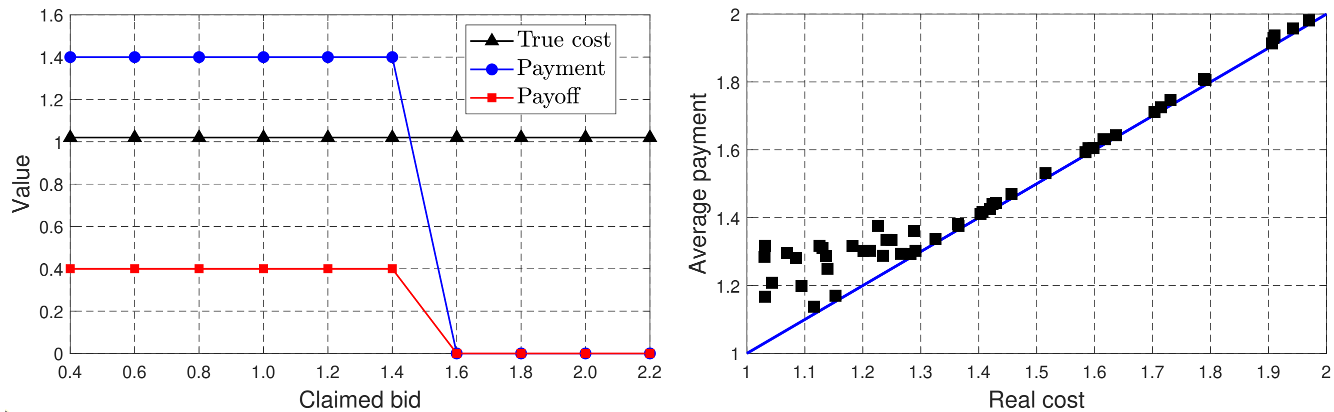
1) Performance Evaluation:



(a) MAE in each round under different f_{loss} functions.

(b) Statistical average MAE versus D under different f_{loss} functions.

Fig. 6. The impact of different f_{loss} functions on the accuracy of mobile crowdsensing.



(a) Truthfulness.

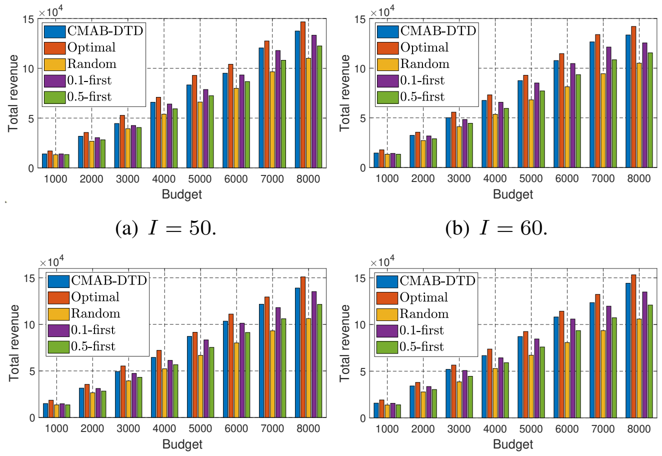
(b) Individual rationality.

Fig. 7. Truthfulness and individual rationality.

We first summarize in Fig. 3 the comparison between the estimated truths $\{\hat{x}_n^t\}_{n=1}^2$ obtained by the CMAB-DTD framework in the developed MCS ecosystem and the real ground truths $\{x_n^{\text{truth}(s)}\}_{n=1}^2$ in every round, where we set the budget $B = 2000$. From Fig. 3, it can be observed that for both the two sensing tasks, the estimated values in each round are close to the corresponding ground truths and exhibit small fluctuations around them. Additionally, the estimated value curve fits well with the changing trend of the ground truth. This indicates that the MCS ecosystem we have developed based on the CMAB-DTD framework, is capable of effectively estimating time-varying ground truth values even if their characteristics are unknown.

We plot Fig. 4 to show how the number of selected workers K influences the accuracy performance of the MCS ecosystem in terms of the mean absolute error (MAE), where we set the budget $B = 2000$ and the number of data samples $D \in \{1, 5, 10, 15\}$. We can observe from Fig. 4 that as the number of workers increases, the MAE generally shows a decreasing trend. This is because when more workers are selected in each round, there is a greater chance of selecting high-quality workers (who have lower injected noise, smaller endogenous errors, and faster data submission), thereby improving the sensing accuracy in each round and reducing the overall MAE. Furthermore, the increase in the number of data samples D can result in an improvement in the MAE. This is because the sensing data of worker i follows the Gaussian distribution $\mathbb{N}(x_n^{\text{truth}(s_t)}, {\xi_{i,n}^t}^2 + \sigma_{i,n}^2)$, and as more data samples are submitted, the probability that the mean value is close to the ground truth increases, leading to a more accurate estimated truth by the platform. However, it should be noted that when D is relatively large, the improvement in MAE diminishes gradually. Therefore, considering communication costs and privacy protection requirements, the data sampling size should not be set excessively large.

Fig. 5 illustrates the impact of the number of samples D on the performance of the MCS ecosystem. It can be observed that as D increases, the statistical average MAE gradually decreases, indicating an improvement in MCS accuracy. This is consistent with the intuition that an increase in D tends to reduce the randomness of perturbed data submitted by workers, leading the average to converge toward the expectation. However, it is worth noting that as D increases, the decrease in MAE slows down, showing an obvious behavior of



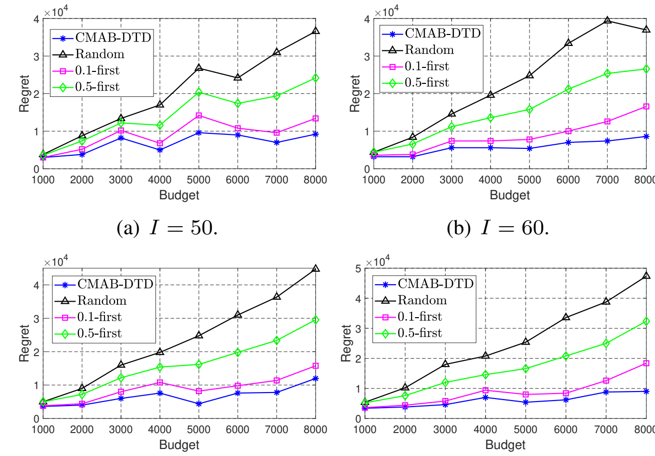
(a) $I = 50$.

(b) $I = 60$.

(c) $I = 70$.

(d) $I = 80$.

Fig. 8. Variation of platform's total revenue as budget increases.



(a) $I = 50$.

(b) $I = 60$.

(c) $I = 70$.

(d) $I = 80$.

Fig. 9. Variation of regret as budget increases.

diminishing marginal returns. On the other hand, the number of data items submitted from workers to the platform increases linearly with D, resulting in a linear growth of system communication resource (such as bandwidth and energy) consumption, posing greater challenges for resource-constrained applications. Therefore, D should be set reasonably according to application requirements to achieve an appropriate tradeoff between MCS accuracy and system communication efficiency.

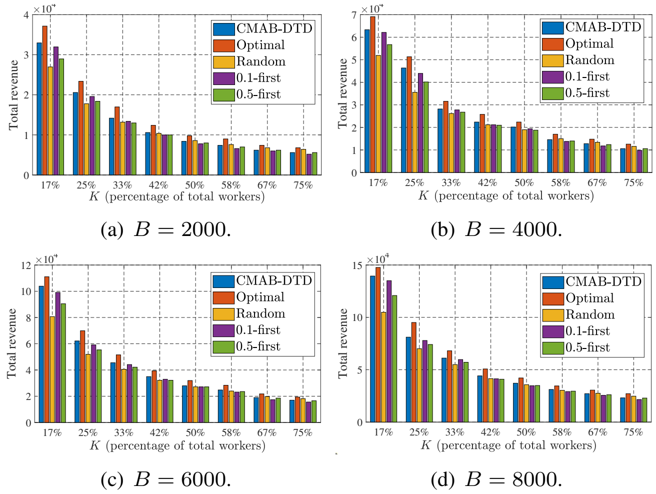
In Fig 6, we examine the impact of different forms of distance function $f_{\text{loss}}(\cdot)$ on the MAE of the CMAB-DTD algorithm, where we set $B = 4000$, $K = 10$, and the form of $f_{\text{loss}}(\cdot)$ as the absolute value function and squared difference function. From Fig. 6(a), we can observe that the MAE values fluctuate randomly in each round, and their ranges and trends are very similar under different $f_{\text{loss}}(\cdot)$ functions. In Fig. 6(b), we present the relationship between the MAE and D under different $f_{\text{loss}}(\cdot)$ functions. To mitigate the impact of randomness, we conduct 100 experiments at each $D \in \{1, 2, \cdots, 10\}$, and take the statistical average value as the Y-axis. Similar to the behavior in Fig. 5, the MAE decreases as D increases and exhibits diminishing marginal returns. Fig. 6(b) shows that the variation of MAE and the convergence point remain largely consistent across different $f_{\text{loss}}(\cdot)$ functions, indicating that the form of $f_{\text{loss}}(\cdot)$ has little impact on the accuracy of the CMAB-DTD algorithm. Therefore, an important insight we obtain from Fig 6 is that we can apply a simple form of the $f_{\text{loss}}(\cdot)$ function to measure the distance between the mean value of submitted data and the inferred value.

Next, we evaluate the economic properties of the proposed MCS ecosystem. We present the results in Fig. 7(a) to demonstrate the truthfulness of selected workers in each round of sensing tasks. In an arbitrary round, we randomly choose a worker and change its bid value while ensuring that all other settings of the ecosystem remain unchanged. From Fig. 7(a), it can be observed that the true cost of the worker is approximately 1.0, and the critical payment is around 1.4. When the claimed bid is lower than the critical payment, the worker can win with a corresponding payoff of approximately 0.4, which remains constant regardless of bid fluctuations. However, once the bid exceeds the critical payment, the worker's payoff becomes 0, indicating its failure in the worker selection mechanism. We validate the individual rationality of the MCS ecosystem in Fig. 7(b). Specifically, we record the payment received by each worker participating in the sensing tasks in each round. After the budget is exhausted, we calculate the average payment for each worker and summarize the results in Fig. 7(b). It can be observed that the average payment for each participating worker in the MCS ecosystem is higher than its true cost. It demonstrates that the proposed MCS ecosystem satisfies individual rationality, which is consistent with the theoretical analysis.

2) Performance Comparison:

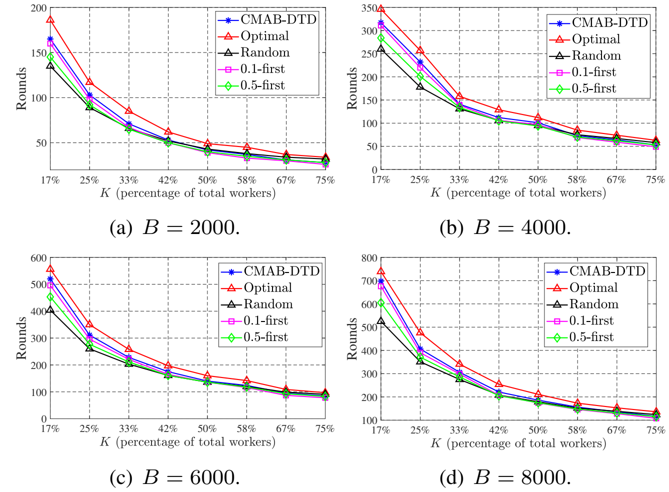
We compare the performance behaviors of the MCS ecosystem in terms of the platform's total revenue and regret in Fig. 8 and Fig. 9, respectively, under different algorithms as the budget increases. In line with intuition, Fig 8 illustrates that the platform's total revenue under all algorithms will be consistently improved with the increase in budget B. The performance of the proposed CMAB-DTD algorithm is significantly superior to that of the 0.1-first, 0.5-first, and random algorithms. Remarkably, the total revenue achieved by the CMAB-DTD algorithm is comparable to that of the Optimal algorithm, which possesses prior knowledge of the workers' quality. It indicates that the CMAB-DTD algorithm indeed achieves a good exploration-exploitation tradeoff, enabling efficient selection of high-quality workers for each round of sensing tasks.

From Fig. 9, we can observe that the regret of all algorithms exhibits a general increasing trend as the budget increases. This is because a larger budget allows the platform to perform more rounds of sensing tasks. In each round, as long as the winning worker set determined by the algorithm differs from that of the Optimal algorithm, regret will be incurred. Consequently, the total regret accumulates gradually as the number of rounds increases. However, the rate of cumulative regret under the CMAB-DTD algorithm is significantly lower



(a) $B = 2000$. (b) $B = 4000$. (c) $B = 6000$. (d) $B = 8000$.

Fig. 10. Variation of platform's total revenue as the number of selected workers increases.



(a) $B = 2000$. (b) $B = 4000$. (c) $B = 6000$. (d) $B = 8000$.

Fig. 11. Variation of total executable sensing rounds as the number of selected workers increases.

compared to the other three algorithms. This is attributed to the CMAB-DTD algorithm's ability to learn worker quality effectively based on historical results. In subsequent rounds, the winning worker set selected by the CMAB-DTD algorithm can closely approximate that of the Optimal algorithm. In addition, comparing the results under different total numbers of workers I, it can be observed that the regret of the other three algorithms has an obvious increment when I becomes larger. This is because the winning worker set selected from a larger pool of workers differs more from the winning worker set of the Optimal algorithm. In contrast, the CMAB-DTD algorithm maintains a relatively stable regret value, indicating its ability to efficiently learn the quality of workers and select high-quality workers for performing sensing tasks.

Next, we compare the performance behaviors of the MCS ecosystem in terms of the platform's total revenue and total executable sensing rounds in Fig. 10 and Fig. 11, respectively, under different algorithms as the number of selected workers increases. We fix the total number of workers I and gradually increase the proportion of selected winning workers, i.e., K/I. Fig. 10 shows that as the number of selected workers in each sensing round K increases, the total revenue that can be achieved by the platform under all algorithms exhibits a decreasing trend. This is because as the number of workers executing sensing tasks increases, the platform needs to increase the payment in each round, resulting in a decrease in the total number of rounds that can be performed within a fixed budget, as demonstrated by the behaviors in Fig. 11. Additionally, we can also observe that increasing the budget B leads to gains in the platform's total revenue, which is consistent with the results in Fig. 8. Fig. 11 shows that, under the fixed budget B, the CMAB-DTD algorithm always achieves a higher total number of rounds ω for performing sensing tasks, compared to the 0.1-first, 0.5-first, and random algorithms. This indicates that the CMAB-DTD algorithm not only has an advantage in selecting high-quality workers but also possesses a cost-effective payment rule.

VIII. Conclusion

In this paper, we have developed a mobile crowdsensing (MCS) ecosystem and presented detailed designs of the system architecture, operational process, worker selection, and payment determination. The proposed MCS ecosystem aims to maximize the platform's sensing accuracy-aware utility within a limited budget while also attracting workers' truthful participation. Taking into account the endogenous sensing errors, privacy-preserving noise injection, and the duration of completing sensing tasks, we have established a comprehensive model for the data collection process. Based on this model, the truth discovery accuracy was analyzed theoretically and the criterion for assessing the quality of workers was quantified mathematically. We exploited the CMAB approach to transform the worker recruitment problem into a combinatorial arm-pulling problem, and accordingly, an UCB algorithm has been meticulously designed to strike a balance between exploration and exploitation. Moreover, we have applied the multi-attribute reverse auction method to incentivize workers to provide truthful price quotes while ensuring their individual rationality. The developed MCS ecosystem has been thoroughly evaluated through simulations and comparison analyses, demonstrating its feasibility and effectiveness. This paper offers valuable insights and practical strategies for the advancement of MCS ecosystems, facilitating the utilization of collective wisdom and resources to effectively tackle complex problems.

In the MCS ecosystem proposed in this paper, the number of selected workers per round is fixed. Although the fixed number of selected arms is a consistent setting in all MAB-related literature to our knowledge, considering its variability would be an intriguing issue. On one hand, we consider that the unfixed number of workers will greatly expand the applicability of MAB, enabling it to cope with various scenarios involving changes in the available arm set, performance requirements, and cost constraints. On the other hand, the unfixed number of workers will pose greater challenges in establishing worker selection criteria, computing the cumulative value of worker quality, and ensuring fairness. We believe this is a highly challenging yet promising research direction, and we will delve deeper into it in our future work.

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Jia Liu (Senior Member, IEEE) received the B.E. degree from the School of Telecommunications Engineering, Xidian University, Xi’an, China, in 2010, and received the Ph.D. degree from the School of Systems Information Science, Future University Hakodate, Japan, in 2016. His research interests include wireless systems security, space-air-ground integrated networks, Internet of Things, 6G, etc. He has published over 70 academic papers in premium journals and conferences. He received the 2016 and 2020 IEEE Sapporo Section Encouragement Award.

Jianbo Shao (Graduate Student Member, IEEE) received the B.E. degree and M.S. degree from the School of Economics and Management, Xidian University, Xi’an, Chian, in 2020 and 2023, respectively. He is currently working toward the Ph.D. degree with the Department of Computer Science and Technology, Shanghai University of Finance and Economics. His research interests include intelligence analysis, blockchain, game theory, network economics, and so on.

Min Sheng (M’03, SM’16) joined Xidian University in 2000, where she is currently a Full Professor and the Director of the State Key Laboratory of Integrated Services Networks. She is also the Vice Chair of the IEEE Xi’an Section. She has published over 200 refereed papers in international leading journals and key conferences in the areas of wireless communications and networking. Her current research interests include space-terrestrial integration networks, intelligent wireless networks, and mobile ad-hoc networks. She received the China National Funds for Distinguished Young Scientists in 2018. She is an Editor for IEEE Communications Letters and IEEE Transactions on Wireless Communications.

Yang Xu (Senior Member, IEEE) received the B.E. degree from the School of Telecommunications Engineering and the Ph.D. degree from the Department of Communication and Information Systems, Xidian University, Xi’an, China, in 2006 and 2014, respectively, where she is currently an associate professor with the School of Computer Science and Technology. She has published over 50 academic papers in premium journals and conferences. Her research interests include wireless communications security, mobile crowdsensing, network economics, space-air-ground integrated networks, routing protocol design, etc.

Tarik Taleb (Senior Member, IEEE) received the B.E. degree (with distinction) in information engineering and the M.Sc. and Ph.D. degrees in information sciences from Tohoku University, Sendai, Japan, in 2001, 2003, and 2005, respectively. He is currently a Full Professor at Ruhr University Bochum, Germany. He was a Professor with the Center of Wireless Communications, University of Oulu, Oulu, Finland. He is the founder of ICTFICIAL Oy, and the founder and the Director of the MOSA!C Lab, Espoo, Finland. From October 2014 to December 2021, he was an Associate Professor with the School of Electrical Engineering, Aalto University, Espoo, Finland. Prior to that, he was working as a Senior Researcher and a 3GPP Standards Expert with NEC Europe Ltd., Heidelberg, Germany. Before joining NEC and till March 2009, he worked as Assistant Professor with the Graduate School of Information Sciences, Tohoku University, in a lab fully funded by KDDI. From 2005 to 2006, he was a Research Fellow with the Intelligent Cosmos Research Institute, Sendai. Taleb has been directly engaged in the development and standardization of the Evolved Packet System as a member of the 3GPP System Architecture Working Group. His current research interests include AI-based network management, architectural enhancements to mobile core networks, network softwarization and slicing, mobile cloud networking, network function virtualization, software-defined networking, software-defined security, and mobile multimedia streaming.

Norio Shiratori (Life Fellow, IEEE) received his Ph.D. degree from Tohoku University in 1977. He became an Assistant Professor and Associate Professor at the Research Institute of Electrical Communication, Tohoku University, in 1977 and 1984, respectively. In 1990, he was promoted to Full Professor at the School of Engineering, Tohoku University. In 1993, he commenced his role as Full Professor at the Research Institute of Electrical Communication, Tohoku University. In 1997, Prof. Shiratori became a Visiting Professor at UCLA (University of California, Los Angeles). In 1998, he was elevated to the status of IEEE Fellow. In 2004, Prof. Shiratori assumed the role of Japan representative for the International Federation for Information Processing (IFIP). In 2009, he served as the President of the Information Processing Society of Japan.

In 2010, following his retirement from Tohoku University, Prof. Shiratori took on the positions of Professor Emeritus at Tohoku University and Board Member at Future University Hakodate. In the same year, he became the Chair of the IEEE Sendai Section. In 2012, he was appointed as a Professor at the Global Information and Telecommunication Institute, Waseda University. In 2013, Prof. Shiratori assumed the role of Vice Chair of the IEEE Japan Council. Recognizing his significant contributions, he was honored with the title of IEEE Life Fellow in 2017. Since 2017, he has been serving as a Professor at Research and Development Initiative, Chuo University.

Prof. Shiratori has published over 15 books and over 600 refereed papers in computer science and related fields. He is a fellow of the Japan Foundation of Engineering Societies (JFES), the Information Processing Society of Japan (IPSJ), and the Institute of Electronics, Information and Communication Engineers (IEICE). He was a recipient of the Minister of MEXT Award from the Japanese Government in 2016, the Science and Technology Award from the Ministry of Education, Culture, Sports, Science, and Technology (MEXT) in 2009, the IEICE Achievement Award in 2001, the IEICE Contribution Award in 2011, the IPSJ Contribution Award in 2008, the IEICE Honorary Member in 2012, the IPSJ Honorary Member in 2013, IPSJ Memorial Prize Winning Paper Award in 1985, the IPSJ Best Paper Award in 1997, the IEICE Best Paper Award in 2001, the IEEE 5th SCE01 Best Paper Award in 2001, the IEEE ICPADS 2000 Best Paper Award in 2000, and the IEEE 12th ICOIN Best Paper Award.