Efficient Group Collaboration for Sensing Time Redundancy Optimization in Mobile Crowd Sensing

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Efficient Group Collaboration for Sensing Time Redundancy Optimization in Mobile Crowd Sensing

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Abstract—In mobile crowd sensing (MCS), complex tasks often require collaboration among multiple workers with diverse expertise and sensors. However, few studies consider the sensing time redundancy of multiple workers to complete a task collaboratively, and the subjective and objective collaboration willingness of participating workers in forming collaboration groups for different tasks. If solely focusing on enhancing workers' willingness to collaborate, it cannot guarantee the minimum time redundancy within the collaboration group, resulting in a decrease in the group's efficiency. Similarly, if only aiming to reduce sensing time redundancy among the workers in the collaboration group, it may lead to a loss of workers' willingness to collaborate, and the diminished motivation among workers will consequently reduce the group's efficiency. To address these challenges, this paper proposes EGC-STRO, a method for forming efficient collaboration groups in MCS that optimizes sensing time redundancy while balancing the workers' cooperation willingness as constraints. First, this method proposes an evaluation indicator to select workers who meet their reward expectations, i.e., objective collaboration willingness, and uses an incentive mechanism based on bargaining game to maximize the overall interests. Furthermore, subjective collaboration willingness is defined and a collaboration worker selection algorithm is designed. The algorithm adds workers who meet both subjective and objective willingness requirements to the candidate set and selects workers with the smallest sensing redundancy time in the worker candidate set to join the final collaboration group. Simulation results demonstrate that compared with the baseline methods, our proposed EGC-STRO increases the worker engagement by about 5%-20%, increases the task coverage by 6%-25%, increases the platform utility by 17%-50%, and increases the worker utility by 20%-60%.

***Index Terms*—Bargaining game, Collaboration group, Incentive mechanism, Mobile crowd sensing, Sensing time redundancy.**

I. INTRODUCTION

Mobile Crowd Sensing (MCS) [1] is a novel and prominent paradigm of data acquisition, that can realize reasonable allocation and adequate coverage of sensing tasks. This paradigm takes advantage of mobile devices carried by workers to sense and collect information from the surrounding environment anytime and anywhere. Unlike the traditional way of deploying fixed sensors to collect data, MCS can be more flexible in meeting the demands of large-scale sensing applications, such as road and traffic detection [2]-[3], environment monitoring [4]-[6], and mobile social recommendation [7]-[9].

In MCS, one-task-to-one-worker scenarios (where each task requires only one worker to execute) have been widely considered by researchers [10]-[12]. With the development of MCS, tasks have become increasingly complex and tend to require multiple workers to cooperate. Thus, worker collaboration methods have emerged [13]-[15], which break down one whole task into smaller subtasks and recruit multiple workers to perform these smaller subtasks in a collaboration group. To promote collaboration sensing quality and reduce collaboration sensing costs, many factors have been considered, such as skill differences [16]-[19], collaboration probability [20], and collaboration costs related to time and computation [21]-[24]. However, most existing collaboration methods have neglected the sensing time redundancy problem, among workers, thus suffering from the data redundancy problem obtained during the overlapping sensing time in a collaboration

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group. That is, when a collaboration worker group of multiple workers performs the same sensing task, the sensing time redundancy caused by the overlapping working time between workers will reduce high sensing costs and low sensing efficiency. Moreover, when considering the collaborations, the existing methods fail to take into account whether the subjective or objective collaboration willingness of workers to participate in sensing tasks meets their expected threshold, which may potentially affect the utility of the workers and the platform. For instance, consider a round-the-clock noise monitoring project where a significant number of participants coincidentally converge in one area of the city without proper organization or coordination. This situation would inevitably lead to redundant data and elevated monitoring expenses, caused by overlapping sensing duration. Therefore, joint consideration of the willingness of the collaboration workers and reducing their sensing time redundancy is a new challenging problem in group collaboration.

To overcome the above challenge, an efficient collaboration group formation model for sensing time redundancy optimization in MCS is proposed, i.e., ECG-STRO. In ECG-STRO, we first proposed objective collaboration willingness and subjective collaboration willingness as two key indicators to evaluate the willingness of a worker and to select the workers whose metric values meet the predetermined threshold to join the candidate worker set. On the one hand, the tradeoff between reward and cost for a task affects whether a worker is willing to join the collaboration group of the task, which can be referred to as the objective collaboration willingness of the worker. Therefore, this paper proposes an evaluation index, i.e., objective collaboration willingness, as one of the key two metrics to select a set of candidate workers that meet revenue expectations. In ECG-STRO, to evaluate the workers' objective collaboration willingness and maximize the interests of the platform and workers, the bargaining game incentive mechanism is proposed to simulate the interaction between the platform and workers, and Nash equilibrium is solved as the solution for the optimal task pricing problem. If the optimal task price of a worker is achieved to serve a certain task, i.e., the optimal reward, is higher than the worker's expected reward threshold, the worker is considered willing to participate in the task, and the optimal task price is denoted as the important indicator for joining the candidate set.

On the other hand, the task preferences of workers are the primary factors in forming the collaboration group, which can be referred to as the subjective collaboration willingness of workers. Therefore, another evaluation index is proposed, more details are given in Section IV B. Then, for the selection of the workers of the candidate set, it is necessary to meet threshold conditions of both the objective and the subjective collaboration willingness. Furthermore, in ECG-STRO, to reduce sensing time redundancy and form an efficient collaboration group that meets workers' objective and subjective willingness indicators, a novel collaboration group selection algorithm is proposed based on the minimization of the time redundancy among the workers in the obtained candidate worker set, to finally form a collaboration group.

The main contributions of this paper are summarized as follows:

1) In this paper, ECG-STRO is proposed to minimize sensing time redundancy while considering subjective and objective cooperation willingness as constraints. In ECG-STRO, we innovatively propose objective and subjective cooperation willingness as two key indicators to preliminary select a candidate worker set for further sensing time redundancy minimization. A bargaining game based incentive mechanism is proposed to evaluate the objective willingness, while the subjective collaboration willingness is evaluated based on workers' browsing frequency and browsing intensity.
2) Based on the proposed indicators, a candidate worker set can be formed to narrow down the search scope for the optimal sensing time redundancy solution. This set comprises workers who meet both the objective and subjective cooperation willingness thresholds. To further minimize sensing time redundancy within the collaboration group, ECG-STRO is proposed to minimize sensing time redundancy within the candidate set.
3) The experiments and comparison with two baseline algorithms show the effectiveness of ECG-STRO. The task coverage is increased by at best 25% due to the reduction of time redundancy, and the worker engagement is increased by at best 20%. Due to the incentive mechanism, the worker utility is increased by at best 60%, and the platform utility is increased by at best 50%.

The remainder of this paper is organized as follows. Section II summarizes existing related studies. Section III introduces the proposed system model and problem definition. A bargaining game incentive mechanism and an optimization model based on sensing time redundancy analysis are discussed in Section IV. Section V gives the performance evaluation via analysis of the simulation results. Finally, conclusions are drawn in Section VI.

II. RELATED WORK

A. *Incentive Mechanism based on Game Theory in MCS*

Currently, considering the limited capabilities and selfishness of workers, how to attract them to participate in sensing activities and improve the system efficiency of MCS is a challenging problem.

Some studies have proposed the usage of game theory to study the interaction between workers in MCS systems. In literature [25], the interactions between the requester and the sensors were formulated as a two-stage Stackelberg differential game model while considering the average behavior of sensors to solve the dynamic task pricing problem. The authors of [26] studied the problem of designing a suitable incentive mechanism combined with data quality under social influence. The authors of [27] considered the nondeterministic mobility of mobile users, where the platform only has the probability distribution about users' mobility. They designed an effective mechanism to collect high-quality data to maximize the expected social welfare.

The above works only consider a single sensing task in a single sensing time slot. Further, the authors of [28] studied the multi-leader-multi-follower Stackelberg game based on deep reinforcement learning (DRL) to solve the problem of assigning sufficient and profitable incentives to multiple task originators and multiple sensing users in MCS. In literature [29], a tripartite evolutionary game model of crowdsourcing workers, crowdsourcing platforms, and task requesters was proposed. The model focuses on the evolutionary stability strategies and evolutionary trends of different participants. The authors of [30] established a public environment sensing model based on evolutionary game theory. Employing the Word-of-Mouth mode and Stackelberg game theory, in [31], the authors proposed the optimal strategies in mobile crowdsourcing focusing on profit-maximization. However, it overlooks the optimization of reducing sensing time redundancy and balancing cooperation willingness in efficient group formation.

In the research of this paper, workers are generally rational and want to get more rewards. Similarly, the platform is also rational and wants to obtain the worker's sensing data with less payment. There is a conflict between these two sides. This conflict is essentially a pricing problem. Rubinstein-Stahl Bargaining Game is a theory that can describe the process of unlimited complete information bargaining and transform the above pricing problem into a bargaining model [32]. It is used for reference in this paper to design the incentive mechanism.

B. Collaboration Sensing in MCS

Collaboration sensing is a paradigm based on teamwork, in which workers with different abilities (or skills) are recruited to form collaboration groups and work together to complete complex tasks.

To promote the quality of collaboration sensing, some researchers focus on analyzing the ability complementarity of workers. The authors of [16] designed a novel low-complexity collaboration mobile crowdsourcing recruitment approach relying on Graph Neural Networks (GNNs) to shrink the workers' search space and exploit a metaheuristic genetic algorithm to select appropriate workers. The authors of [17] proposed a hybrid approach in which requesters can hire a team with the required expertise and social connections to collaborate on tasks. The authors of [18] developed two team-building strategies for the collaboration MCS framework to form virtual teams according to four criteria: professional level, the strength of social relations, cost of recruitment, and confidence level of recruiters. The authors of [19] aim to make opportunistic crowd sensing via the collaboration of workers with different abilities to detect urban phenomena.

To further promote collaboration quality, in addition to ability complementarity, other factors must be considered, such as the collaboration probability among workers, collaboration cost on time, or computation. The authors of the literature [20] studied the Deadline-sensitive User Recruitment problem and proposed a probabilistic collaboration mobile crowd sensing method where mobile users perform sensing tasks with certain probabilities, and multiple users may be recruited collaboratively to perform a common task. The authors of [21] proposed two heuristic algorithms: CB-greedy and CB-local, based on greedy strategy and local search technique to solve the problem of cost-effective and budget-balanced task allocation problem in worker collaboration. In literature [22], CrowdTracking was proposed as a crowd-tracking system where people can collaboratively keep track of the moving vehicle by taking photos, especially in places where video cameras are insufficient. In literature [23], the purpose of collaboration sensing is to reduce both network traffic and computation in the cloud. The authors of [24] focused on the workload of team members in a cost- and quality-effective way and introduced the BeTogether middleware to solve the problem of worker workload balance.

However, among the existing collaboration sensing methods, there is rare research to consider sensing time complementarity. Most existing collaboration sensing methods have neglected to sense time overlap among workers and suffered the data redundancy problem. Our work aims to minimize the sensing time redundancy between workers in a collaboration group.

III. System Model And Problem Formulation

The system model of this paper includes an MCS system model, which defines the scenario of the entire MCS system, an incentive game model, which defines the incentive mechanism between workers and the platform, and a collaboration group selection model to ensure efficient group collaboration. The notations used in this paper are summarized in Table I.

TABLE I
NOTATIONS USED

Notations	Description
Γ, π_j	Task set and the jth task
W, w_i	Worker set and the ith worker
s_{π_j}, e_{π_j}	The start and end time of the jth task
$s_{w_i \to \pi_j}$	The start time of w_i executing π_j
$e_{w_i \to \pi_j}$	The completion time of w_i executing π_j
$\mathbb{W}_{w_i \to \pi_j}$	The subjective collaboration willingness of w_i executing π_j
$\mathcal{R}_{w_{ji}}$	The remuneration paid to w_i after completing π_j
$cost_i^j$	Consumption during the execution of π_j by w_i
$U_{w_i}^{\pi_j}$	The objective collaboration willingness and worker utility of w_i executing π_j
$O_{(w_i, w_{i+1})}^{\pi_j}$	Sensing redundancy time between w_i and w_{i+1}
θ	The objective collaboration willingness threshold
$\varkappa$	The subjective collaboration willingness threshold
U_p	The platform utility
R_p	The revenue the platform obtains from suppliers
P	The revenue paid by the platform to workers
$cost_p$	The platform consumption
S	The Social Welfare

MCS System Model

From the platform side, whether workers can be selected to join the same collaboration group for a task depends on the tradeoff between the reward and the cost for the task (which is related to the task pricing) and the time complementarity of their available sensing time. From the worker side, whether a worker is willing to join a collaboration group for a task depends on the task types that the workers are interested in (their subjective collaboration willingness) and the tradeoff between reward and cost for the task (their objective collaboration willingness).

Fig. 1 shows the system model of EGC-STRO, which consists of service providers, a platform, and a large number of workers participating in sensing tasks. First, the service providers submit requests to the sensing platform, and the platform publishes these requests to workers as sensing tasks (Steps 1-2), while using the incentive mechanism based on the bargaining game to calculate workers' optimal rewards as the objective collaboration willingness (Step 3). Then, the subject collaboration willingness, which represents workers' task interests, and the objective collaboration willingness, are used as constraints. Workers who meet the constraint threshold are selected to join the candidate set (Step 4). Furthermore, an algorithm to form a collaboration group based on sensing time redundancy is used to complete the sensing task and upload sensing data to the platform (Step 5). Ultimately, the platform delivers data to the service provider and gets a reward (Steps 6-8).

Step 3 in Fig. 1 represents the first stage of EGC-STRO, which is based on the incentive mechanism of the bargaining game to maximize social welfare and derive workers' objective willingness to cooperate. Steps 4 and 5 correspond to the second stage, which involves the collaboration group selection algorithm focused on minimizing time redundancy. In these steps, the candidate set is filtered based on subjective and objective collaboration willingness, and the algorithm is employed to identify efficient collaboration groups from the candidate set.

Service providers: Individuals or groups with specific requests can act as service providers to purchase sensing data from the platform according to their application requirements. Service providers hope to purchase high-quality and reliable sensing data at a reasonable price and apply the acquired sensing data to various fields to provide various application services.

Platform: The platform releases sensing tasks to workers or collaboration groups according to the needs of service providers, receives the perception information uploaded by workers or collaboration groups, and pays remuneration. The platform publishes the sensing task set $\Gamma = \{\pi_1, \dots, \pi_j, \dots, \pi_m\}$ to the worker set $W = \{w_1, \dots, w_i, \dots, w_n\}$.The attributes of the task π_j include the starting time s_{π_j} of the task π_j, and the completion time e_{π_j} of the task π_j.

Workers: Workers select tasks from the platform according to their interests and upload information about their sensing characteristics to the platform. Workers can also form cooperative groups to complete tasks together, which can increase efficiency. The task preferences of workers are primary factors in collaboration group formation, which reflect the subjective collaboration willingness of workers. The attributes of worker w_i related to task π_j include its starting time $s_{w_i \to \pi_j}$ to execute the task π_j, its completion time $e_{w_i \to \pi_j}$to execute the task π_j and its subjective collaboration willingness $\mathbb{W}_{w_i \to \pi_j}$ to execute the task π_j.

Candidate Set: The platform selects workers to form the candidate collaboration worker set, in which the workers' indicators of both the subjective and the objective cooperative willingness are higher than the thresholds, respectively.

Collaboration Groups: The platform unilaterally assigns the task to a group of workers based on the optimization algorithm to form the final collaboration group.

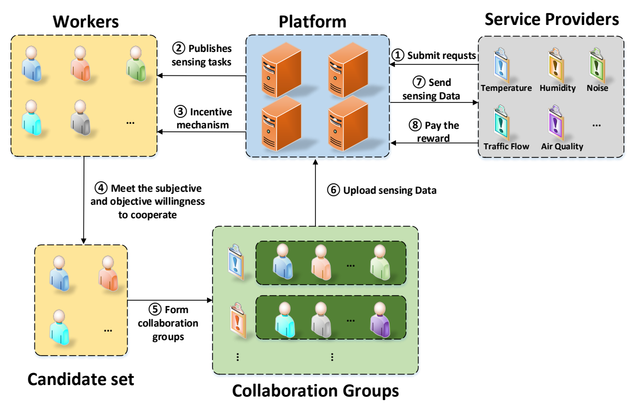

Fig. 1. System of collaboration MCS.

From the platform side, whether workers can be selected to join the same collaboration group for a task depends on the tradeoff between reward and cost for the task (which is related to the task pricing) and the complementarity between their available sensing time. From the worker side, whether a worker is willing to join a collaboration group for a task depends on the task types that the workers are interested in (their subjective collaboration willingness) and the tradeoff between reward and cost for the task.

B. *Incentive Model between Workers and Platform*

The purpose of the incentive mechanism in this paper is to increase the benefits of workers and the platform, motivate more workers to participate in collaboration, and increase workers' objective willingness to collaborate. Therefore, we use optimal social welfare to represent the incentive model, which includes worker utility and platform utility.

Worker utility: For the worker w_i, the MCS platform pays remuneration $\mathcal{R}_{w_{ji}}$ according to the completion of the task π_j. During the execution of the task, the worker consumption is recorded as $cost_i^j$. Therefore, the worker utility function is

$$U_{w_i}^{\pi_j} = \mathcal{R}_{w_{ji}} - cost_i^j. \tag{1}$$

In this paper, we assume the above worker utility as the worker's objective collaboration willingness.

Platform utility: For the MCS platform, its utility depends on the service provider, the remuneration paid to workers and the platform's consumption $cost_p$,

$$U_p = R_p - P - cost_p, \tag{2}$$

where R_p represents the revenue the platform obtains from suppliers, P represents the remuneration paid by the platform to workers, it is equal to the sum of the wages of all workers.

The formal definition of social welfare is

$$\mathrm{S} = \left(\sum\nolimits_{w_i \epsilon W_{\pi_j}, \pi_j \epsilon \Gamma} U_{w_i}^{\pi_j}\right) + U_p, \tag{3}$$

where w_i represents the ith worker in the candidate set W_{π_j} for executing the jth task, π_j represents the jth task in the task set Γ.

In the game, both users and the platform hope to maximize their utility and play games around the optimization of social welfare. This problem can be described as a social welfare maximization problem, defined as follows,

$$\max \quad \mathrm{S}, \tag{4}$$

$$\text{s.t.} \quad U_{w_i}^{\pi_j} \geq 0 \; and \; U_p \geq 0\,. \tag{5}$$

We use the Rubinstein-Stahl bargaining game to solve the social welfare maximization problem to improve workers' objective collaboration willingness for a collaboration group in Section IV.

C. *Problem Formulation*

In our collaboration group formation model, we comprehensively consider the following factors and the optimization objective, which include:

Objective collaboration willingness: the objective collaboration willingness $U_{w_i}^{\pi_j}$, i.e. worker utility, which represents the objective collaboration willingness of worker w_i to perform task π_j, and is determined by the remuneration paid to the worker by the platform after an ongoing bargaining game between the platform and the worker. It will be addressed in Section IV and obtained by Eq. (22).

Subjective collaboration willingness: the subjective collaboration willingness $\mathbb{W}_{w_i \to \pi_j}$, which represents the subjective collaboration willingness of worker w_i to perform task π_j, and is determined by the worker's interest in the task, i.e., the browsing intensity. It will be addressed in Section IV and obtained by Algorithm 1.

Sensing time redundancy of the collaboration group: it is the total time that consists of multiple sensing time overlapping periods when a group of workers to collaborate a task, denoted as O_{π_j}. We assume that a task is completed by relay from w_1 to w_n. There may be a sensing time overlapping period in working time between the two workers w_i and w_{i+1}, which leads to the repeated generation of sensing data and reduces sensing efficiency. The optimization goal of this paper is to minimize the sensing time redundancy time to perform a task More details will be addressed in Section IV.

To form an efficient collaboration group, we try to select workers who meet the thresholds of their reward expectations and browsing interests (i.e., subjective and objective collaboration willingness) and minimize the sensing time redundancy of the collaboration group. That is, for the task π_j, the objective willingness of the work w_i to collaborate $U_{w_i}^{\pi_j}$ must exceed the set threshold θ, and the subjective willingness to collaborate $\mathbb{W}_{w_i \to \pi_j}$ must exceed the set threshold $\varkappa$. The selection of collaboration workers aims to minimize the sensing redundancy time. To achieve this, we have developed a model by considering the above main optimization objective and the constraints. We can efficiently form collaboration groups for different tasks with minimal redundancy time, maximizing efficiency during the MCS activities. Thus, the problem is formulated as follows,

$$\min \sum_{i=0}^{p} O_{(w_i, w_{i+1})}^{\pi_j}\,, \tag{6}$$

$$\text{s.t.} \quad O_{(w_i, w_{i+1})}^{\pi_j} \geq 0 \; and \; 0 \leq i \leq p\,, \tag{7}$$

$$U_{w_i}^{\pi_j} \geq \theta, \tag{8}$$

$$\mathbb{W}_{w_i \to \pi_j} \geq \varkappa, \tag{9}$$

where, $O_{(w_i, w_{i+1})}^{\pi_j}$ represents the sensing time overlapping period between the work $\mathrm{w_i}$ and the work $\mathrm{w_{i+1}}$ in the collaboration group when they collaborate on the task π_j. θ represents the objective collaboration willingness threshold, and $\varkappa$ represents the subjective collaboration willingness threshold. Workers who satisfy both of the aforementioned thresholds are chosen to be members of the candidate collaboration worker set, and the final collaboration group members are further selected by minimizing the sensing time redundancy from the candidate set.

The specific implementation algorithm for the collaboration group formation model is described in Section IV of our research.

IV. Method Of EGC-STRO

A. *Incentive Mechanism Based on Bargaining Game*

In this section, we first analyze the total cost of a collaboration group and then design an incentive mechanism based on the Rubinstein-Stahl bargaining game to improve workers' objective collaboration willingness for a collaboration group.

The sensing cost for worker w_i to complete task π_j comprises time and energy costs. Assuming that the sensing power of w_i is p_{w_i}, its available sensing time to execute task π_j is $e_{w_i \to \pi_j} - s_{w_i \to \pi_j}$, and its sensing cost for task π_j can be expressed as follows:

$$cost_{w_i \to \pi_j}^{time} = e_{w_i \to \pi_j} - s_{w_i \to \pi_j}, \tag{10}$$

$$cost_{w_i \to \pi_j}^{energy} = p_{w_i} cost_{w_i \to \pi_j}^{time}, \tag{11}$$

$$cost_{w_i \to \pi_j}^{sense} = \rho cost_{w_i \to \pi_j}^{time} + \sigma cost_{w_i \to \pi_j}^{energy}\,, \tag{12}$$

where $cost_{w_i \to \pi_j}^{time}$, $cost_{w_i \to \pi_j}^{energy}$ and $cost_{w_i \to \pi_j}^{sense}$ are the time cost, energy cost and sensing cost, respectively. ρ and σ are positive proportion factors, such that $\rho + \sigma = 1$.

In our incentive mechanism, the platform is regarded as the buyer of sensing data and the workers in the collaboration groups are the sellers of sensing data. The buyer's bottom line price for task π_j is $\mathcal{P}_{buy}^{\pi_j}$, which represents the highest purchase price acceptable to the buyer and can be expressed as:

$$\mathcal{P}_{buy}^{\pi_j} = \varphi_{\pi_j}\left(e_{\pi_j} - s_{\pi_j}\right), \tag{13}$$

where φ_{π_j} refers to the maximum cost per unit of time spent on task π_j, estimated by the platform.

Similarly, the seller $(w_i \to \pi_j)$'s bottom line price for task π_j is $\mathcal{P}_{sell}^{w_i\to\pi_j}$, which represents the lowest selling price acceptable to the seller and can be expressed by the following formula:

$$\mathcal{P}_{sell}^{w_i\to\pi_j} = \left(1 - \mathbb{W}_{w_i\to\pi_j}\right) \cdot cost_{w_i\to\pi_j}^{sense}, \tag{14}$$

where $cost_{w_i\to\pi_j}^{sense}$ represents the actual cost of the worker w_i to execute task π_j.

The Rubinstein-Stahl bargaining process can be modeled as a game of splitting a piece of cake between two sides. It is assumed that $\mathcal{P}_{sell}^{w_i\to\pi_j}$ is higher than $\mathcal{P}_{buy}^{\pi_j}$, and the "cake" is the difference between $\mathcal{P}_{buy}^{\pi_j}$ and $\mathcal{P}_{sell}^{w_i\to\pi_j}$. This can be expressed as:

$$Z = \mathcal{P}_{sell}^{w_i\to\pi_j} - \mathcal{P}_{buy}^{\pi_j} > 0. \tag{15}$$

In our bargaining game model, after the seller makes an offer in the first round if the buyer accepts the offer, a deal will be made, and the game ends; otherwise, it will enter into the second round.

In the second round, the buyer makes an offer, and the seller can also accept or reject this offer. If one side's offer is accepted by the other side during a round, the deal will be finalized, and the game will come to an end. However, if the offer is not accepted, the next round will commence, and the other side will have the opportunity to make an offer in the subsequent round. This process repeats until an offer is acceptable to both sides. Suppose the proportional share set in the rth round is $\eta_r = \{\eta_{sell}^r,\ \eta_{buy}^r\}$. η_{sell} represents the seller w_i's proportional share and η_{buy} represents the buyer's proportional share, $\eta_{sell} + \eta_{buy} = 1,\ \eta_{sell} \geq 0,\ \eta_{buy} \geq 0$. This bargaining game aims to get a set of proportional shares $\{\eta_{sell}^*,\ \eta_{buy}^*\}$ acceptable to both the buyer and the seller.

Then the utility functions of the buyer and seller can be expressed as

$$U_{sell}^r = \lambda_{sell}^r \eta_{sell}^r Z, \tag{16}$$

$$U_{buy}^r = \lambda_{buy}^r \eta_{buy}^r Z, \tag{17}$$

where $\lambda_{sell} \in [0,1]$ represents the seller's discount factor, which is related to the average subjective willingness to collaborate of workers in W; and $\lambda_{buy} \in [0,1]$ represents the buyer's discount factor, which is related to the numbers of all optional collaboration groups for task π_j in the platform. The discount factor is the discount rate of the next round to the current round.

For example, if a seller makes an offer η_{sell} in the current round, the offer η'_{sell} of the next round can only be discounted to be equal to the $\lambda_{sell}\eta_{sell}$ and less than η_{sell} of the current round. The discount factor is essentially determined by the bargaining workers' patience, which reflects the material cost and time cost of the bargaining process.

As the number of rounds increases, the game cost becomes higher, which will reduce the utility value of both the buyer and the seller. Therefore, both sides should accept a reasonable offer as soon as possible.

Since the bargaining game is a dynamic game with complete information, the Nash equilibrium of the game can be obtained [33]. The final price accepted by both the buyer and the seller is given as follows:

$$\eta_{sell}^* = \frac{1 - \lambda_{buy}}{1 - \lambda_{buy}\lambda_{sell}}, \tag{18}$$

$$\eta_{buy}^* = \frac{\lambda_{buy}(1 - \lambda_{sell})}{1 - \lambda_{buy}\lambda_{sell}}. \tag{19}$$

According to the above formulas, the optimal reward $\mathcal{R}$ given by the platform from the task π_j to the worker w_i can be expressed as follows:

$$\mathcal{R}_{w_{ji}} = \mathcal{P}_{sell}^{w_i\to\pi_j} + \eta_{sell}^* Z. \tag{20}$$

To stimulate the objective collaboration willingness of workers, maximize the interests of the workers in the collaboration group, and calculate the objective collaboration willingness U of each worker to collaborate on the task through the bargaining game, Algorithm 1 is designed. The calculated objective collaboration willingness will be used as a constraint to select workers to the candidate collaboration worker set who meet the threshold of objective collaboration willingness.

Algorithm 1 Incentive Mechanism Based on Bargaining

Input: $\varphi, \Gamma, W, \lambda_{buy}, \lambda_{sell} \in [0,1]$.
Output: $\mathcal{R} = \{\mathcal{R}_{w_{11}}, \ldots \mathcal{R}_{w_{ji}}, \ldots \mathcal{R}_{w_{mn}}\}, U$.

```
η*_sell = (1−λ_buy) / (1−λ_buy λ_sell)
for each π_j in Γ do
    P_buy^{π_j} = φ_{π_j}(e_{π_j} − s_{π_j})
    for each w'_i in W do
        P_sell^{w_i→π_j} = (1 − W_{w_i→π_j}) · cost_{w_i→π_j}^{sense}
        Z = P_sell^{w_i→π_j} − P_buy^{π_j}
        R_{w_ji} = P_sell^{w_i→π_j} + η*_sell Z
    end for
    R ← R ∪ R_{w_ji}, C ← C ∪ cost_i^j
end for
U = R − C
Return R, U
```

The inputs of Algorithm 1 include the maximum cost per unit time φ, the task set Γ, the worker set W, the discount factor

λ_{buy} and λ_{sell}.

In the process of traversing Γ in the outer loop (Lines 2-10) in Algorithm 1, we calculate $\mathcal{P}_{buy}^{\pi_j}$ (Line 3). In the process of traversing W in the inner loop (Lines 4-8), we calculate $\mathcal{R}_{w_{ji}}$ (Line 7) caused by $\mathcal{P}_{sell}^{w_i \to \pi_j}$(Line 5) and Z(Line 6). The output of Algorithm 1 is the optimal reward $\mathcal{R}$. The optimal reward obtained through the game serves as the objective willingness of workers to collaborate, providing an indicator for the subsequent generation of candidate sets.

The time complexity of Algorithm 1 is caused by n times of the inner loop and m times of the outer loop. Therefore, the time complexity of Algorithm 1 is $O(|m * n|)$, where n is the number of workers and m is the number of tasks.

B. Optimization Model based on Sensing Time Redundancy Analysis

In the collaboration group, the formation process of both the task preferences of workers (which reflects the subjective collaboration willingness of workers) and the sensing time redundancy among workers are considered. We will discuss these two factors, respectively.

1) Evaluation of Subjective Collaboration Willingness

Recent studies in [34] and [35] show that the task preferences of a worker are closely related to its browsing behaviors including browsing content, duration and frequency (all actions of a worker while interacting with the tasks).

To accurately obtain the real-time preferences of a worker, we analyzed its browsing history over a preset statistical period. An example distribution diagram of the browsing duration of worker w_i on task π_j is shown in Fig. 2.

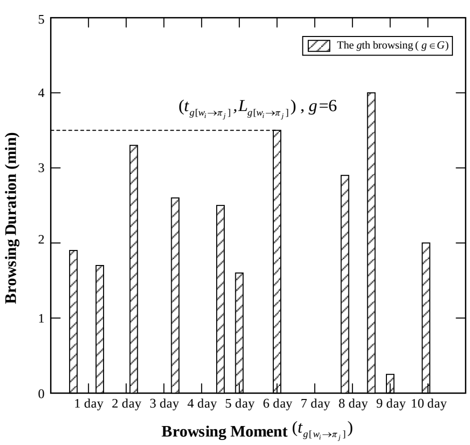

Fig. 2. Distribution diagram of browsing duration of worker w_i on task π_j.

Within the total statistical time period $[0, T_b]$ (it ranges from the beginning to the end of worker w_i's browsing history, for instance, in Fig. 2, the total statistical time period lasts 10 days), $L_{g[w_i \to \pi_j]}$ is the gth browsing duration at the sampling starting moment $t_{g[w_i \to \pi_j]}$ for worker w_i on task π_j.

Within $[0, T_b]$, the browsing duration of worker w_i at different sampling starting moments have different weights $\omega\left(t_{g[w_i \to \pi_j]}\right)$, which can be defined as $\omega\left(t_{g[w_i \to \pi_j]}\right) = t_{g[w_i \to \pi_j]}/T_b$, that is, if a sampling starting moment is closer to T_b, its corresponding browsing duration of worker w_i will have greater weight. For $L_{g[w_i \to \pi_j]}$, the browsing intensity $BI(t_{g[w_i \to \pi_j]})$ is

$$BI\left(t_{g[w_i \to \pi_j]}\right) = L_{g[w_i \to \pi_j]} \cdot \omega\left(t_{g[w_i \to \pi_j]}\right) = \frac{L_{g[w_i \to \pi_j]} \cdot t_{g[w_i \to \pi_j]}}{T_b}, \quad (21)$$

therefore, for a worker w_i with G times of browsing, his intensity of interest in task π_j, namely its subjective collaboration willingness to execute task π_j, is

$$\mathbb{W}_{w_i \to \pi_j} = \sum_{g=1}^{G} BI\left(t_{g[w_i \to \pi_j]}\right) = \sum_{g=1}^{G} \frac{L_{g[w_i \to \pi_j]} \cdot t_{g[w_i \to \pi_j]}}{T_b}. \quad (22)$$

The subjective collaboration willingness calculated by key factors such as the browsing intensity of workers' browsing tasks will be used as another constraint to select workers to join the candidate collaboration worker set who meet their threshold of subjective collaboration willingness.

2) Sensing Time Redundancy Analysis

In this section, we take the process of selecting p workers continuously from the candidate collaboration worker set W_{π_j} to form a final collaboration group P_{π_j} for task π_j as an example to illustrate the details of sensing time redundancy optimization.

The worker w_i has his sensing time interval when takes part in the task π_j as one collaboration group member, and the start time the end time for the worker w_i for the task π_j is $s_{w_i \to \pi_j}$ and $e_{w_i \to \pi_j}$. The task π_j has its own start and end time, i.e., s_{π_j} and e_{π_j}. The start and end time of the task is independent of the sensing time of workers. When the time for workers to perform the task ends, they will withdraw from the sensing task ahead of time. The total available sensing time of group P_{π_j} must cover the time span required by task π_j. For group P_{π_j}, its sensing time redundancy to execute task π_j is caused by the following three situations:

As shown in Fig. 3(a), if there exists an overlap between the available sensing time of workers w_i' and w_{i+1}' (who are selected to successively execute the task π_j , the sensing time redundancy for them will be calculated as $O_{(w_i', w_{i+1}')}^{\pi_j} = e_{w_i' \to \pi_j} - s_{w_{i+1}' \to \pi_j}$.

As shown in Fig. 3(b), if the available sensing time of the first selected worker w_1' to join group P_{π_j} covers the starting time of task π_j (i.e.,$s_{w_1' \to \pi_j} < s_{\pi_j} < e_{w_1' \to \pi_j}$), the sensing time redundancy will be the waiting time from the start sensing time of worker w_1' to the start time to execute task π_j at s_{π_j}, which is called the “head”, and denoted by $hd_{w_1' \to \pi_j}$.

As shown in Fig. 3(c), if the available sensing time of the last selected worker w_p' to join the group P_{π_j} covers the completion time to execute the task π_j (i.e., $s_{w_p' \to \pi_j} < e_{\pi_j} < e_{w_p' \to \pi_j}$), the sensing time redundancy will be the time span from e_{π_j} to the completion time of worker w_p' to finish its sensing state at $e_{w_p' \to \pi_j}$, which is called the "tail", and denoted by $tl_{w_p' \to \pi_j}$.

To sum up, we define the total sensing time redundancy caused by the above three situations in the time span of the task π_j as the sensing time redundancy O_{π_j} of group P_{π_j}, which may include one $hd_{w_1' \to \pi_j}$, one $tl_{w_p' \to \pi_j}$, and multiple $O^{\pi_j}_{(w_i',w_{i+1}')}$, as shown in Fig. 4 Therefore, O_{π_j} will be calculated as followings

$$O_{\pi_j} = hd_{w_1' \to \pi_j} + \sum_{i=1}^{p-1} O^{\pi_j}_{(w_i',w_{i+1}')} + tl_{w_p' \to \pi_j}. \quad (23)$$

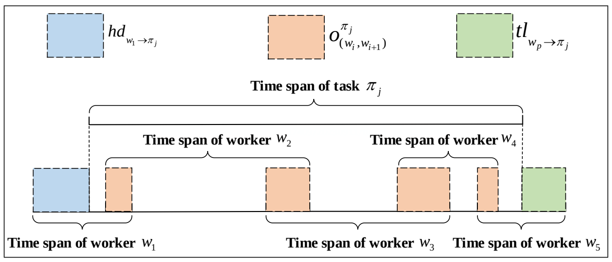

Fig. 4. An example of calculating O_{π_j}

We provide an optimization model to minimize the ratio of sensing time redundancy in the collaboration worker selection process as given below:

$$minimize \quad \frac{O_{\pi_j}}{e_{\pi_j} - s_{\pi_j}}, \quad (24)$$

$$s.t. \quad \mathbb{W}_{w_i' \to \pi_j} \geq \varkappa \left(w_i' \in P_{\pi_j}\right), \quad (24a)$$

$$U^{\pi_j}_{w_i'} \geq \theta \left(w_i' \in P_{\pi_j}\right), \quad (24b)$$

$$e_{w_p' \to \pi_j} - s_{w_1' \to \pi_j} \geq e_{\pi_j} - s_{\pi_j}, \quad (24c)$$

$$s_{w_1' \to \pi_j} \leq s_{\pi_j}, \quad (24d)$$

$$e_{w_1' \to \pi_j} > s_{\pi_j}, \quad (24e)$$

$$e_{w_p' \to \pi_j} \geq e_{\pi_j}, \quad (24f)$$

$$s_{w_p' \to \pi_j} < e_{\pi_j}, \quad (24g)$$

$$x_i \neq 1 \; and \; x_{i+1} \neq 1 (x_i \epsilon \{0,1\}), \quad (24h)$$

where O_{π_j} in (24) , as calculated by Eq. (23), represents the sensing time redundancy in the task execution process of group P_{π_j} . The constraint (24a) indicates that the subjective collaboration willingness of all members in collaboration group P_{π_j} must be greater than the subjective collaboration willingness threshold $\varkappa$ $(0 \leq \varkappa \leq 1)$. The constraint (24b) indicates that the objective cooperation willingness of all members in the collaboration group P_{π_j} must be greater than the threshold $\theta (0 \leq \theta \leq 1)$. The constraint (24c) indicates that the total available sensing time of the collaboration group P_{π_j} to execute task π_j cannot be less than the time span of task π_j. The constraints (24d)–(24e) indicate that the available sensing time of the first selected worker to execute task π_j cannot be outside the time span of task π_j, and the constraints (24f)–(24g) indicate that the available sensing time of the last selected worker to execute task π_j cannot be outside the time span of task π_j. (24h) represents whether w_i is selected, $x_i = 0$ means not selected, and $x_i = 1$ means selected.

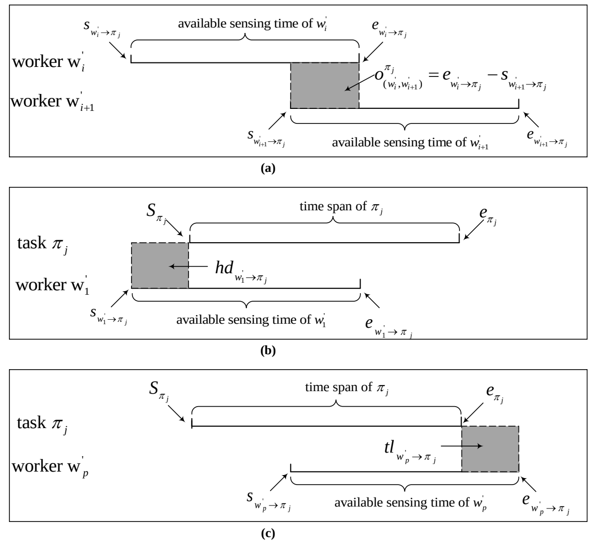

Fig. 3. Schematic diagram of three situations of sensing time redundancy.

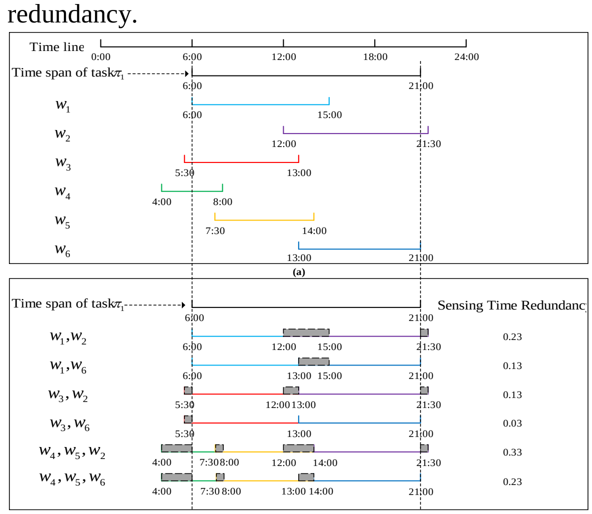

Fig. 5. An example of a collaboration group

Fig. 5 shows an example of collaboration group formation. Fig. 5(a) shows the time span of task π_1 and the available sensing time of six workers $\{w_1, w_2, w_3, w_4, w_5, w_6\}$ to execute task π_1. Fig. 5(b) shows various optional collaboration groups that meet the requirements of task π_1. According to their corresponding sensing time redundancy, we find that the collaboration group $P_{\pi_1} = \{w_3, w_6\}$ has the minimum sensing time redundancy of 0.03. Therefore, it is the optimal collaboration group for task π_1.

To search for the optimal collaboration group with the minimum sensing time redundancy for task π_j from worker set W, Algorithm 2 is proposed.

Algorithm 2 Collaboration Worker Selection

Input: W, π_j, $\varkappa$, θ.

Output: P_{π_j}.

Initialization:

$hd_{min} \leftarrow \infty$, $\mathcal{F} \leftarrow 0$ ($\mathcal{F}$ is used to store current worker),
$O_{min} \leftarrow \infty$, $\mathcal{M} \leftarrow 0$, $W_{\pi_j} \leftarrow \emptyset$ (W_{π_j} is the candidate set),
$\mathbb{W}_{w_i \to \pi_j}$, $U_{w_i}^{\pi_j}$.
// Step 1: form candidate set
1: **for** $i \leftarrow 1$ **to** n **do**
2: **if** $\mathbb{W}_{w_i \to \pi_j} \geq \varkappa$, $U_{w_i}^{\pi_j} \geq \theta$ **then**
3: Append w_i into W_{π_j}
4: end if
5: end for
// Step 2: selection of workers from the candidate set
6: **for** $i \leftarrow 1$ **to** $W_{\pi_j}.size()$ **do**
7: **if** $\boldsymbol{x_i} = 0$, $s_{c_i \to \pi_j} \leq s_{\pi_j} < e_{c_i \to \pi_j}$ **then**
8: **if** $hd_{c_i \to \pi_j} < hd_{min}$ **then**
9: $\mathcal{F} = c_i$
10: $hd_{min} = hd_{c_i \to \pi_j}$
11: end if
12: end if
13: end for
14: Append $\mathcal{F}$ into P_{π_j} and $\boldsymbol{x_i} = 1$ and $e_{c_* \to \pi_j} = e_{c_i \to \pi_j}$
15: **while** $e_{c_* \to \pi_j} \leq e_{\pi_j}$ *and* $s_{c_i \to \pi_j} \geq s_{\pi_j}$ **do**
16: **for** $k \leftarrow 1$ ($k \neq i$) **to** $W_{\pi_j}.size()$ **do**
17: $O = e_{c_* \to \pi_j} - s_{c_k \to \pi_j}$
18: **if** $x_k = 0$, $s_{c_k \to \pi_j} \leq e_{c_* \to \pi_j}$, $O < O_{min}$ **then**
19: $\mathcal{M} = c_k$
20: $O_{min} = e_{c_* \to \pi_j} - s_{c_k \to \pi_j}$
21: end if
22: end for
23: Append $\mathcal{M}$ into P_{π_j} and $x_{\mathcal{M}} = 1$ and $e_{c_* \to \pi_j} = e_{\mathcal{M} \to \pi_j}$
24: end
25: **Return** P_{π_j}

Lines 1-5 represent the selection of workers. The workers who meet the subjective and objective collaboration willingness thresholds will be selected into the candidate set.

In the process of traversing the candidate set (Lines 6-13 of Algorithm 2), we calculate the "head" ($hd_{c_i \to \pi_j}, c_i \in W_{\pi_j}$) caused by each worker and select the worker who causes the minimum "head" and has enough subjective and objective collaboration willingness to join the group P_{π_j} (Line 14) as the first selected worker. Lines 15–24 are used for selecting other workers and tail workers to join the collaboration group P_{π_j}.

The starting time of the selected worker to execute task π_j must be before the completion time to execute task π_j, and the sensing time overlap between the two successively selected workers ($e_{c_* \to \pi_j} - s_{c_{i'} \to \pi_j}$) should be the minimum (Line 17). As long as the completion time of the current last selected worker c_* to execute task π_j ($e_{c_* \to \pi_j}$) in the collaboration group P_{π_j} is less than or equal to the completion time of the task π_j (e_{π_j}), Algorithm 2 proceeds to find the next worker suitable to join the collaboration group P_{π_j}. We assume there are enough workers in the candidate work set to be selected to execute the task successively and the cases that negative overlapping sensing time of two workers among the candidate set are ignored in this paper.

In the collaboration group selection algorithm, the time redundancy caused by overlapping working time is indeed a crucial consideration.

When selecting the tail worker for a collaboration group, the algorithm prioritizes the overlap time with the previous worker rather than the time beyond the end of the task. By ignoring the time beyond the task end, the algorithm streamlines the selection process and ensures the enhanced utilization of resources within the collaboration group, resulting in increased effectiveness.

In Algorithm 2, the time complexity of Step 1 and Step 2 is $O(n)$ and $O(n * m)$, respectively. Where n is the number of workers and m is the number of tasks. Therefore, the time complexity of Algorithm 2 is at the level of $O(n^2)$.

V. Performance Evaluation

In this section, simulations are conducted to compare the proposed EGC-STRO with the Stochastic Team Formation Algorithm (STFA) [17], and the Incentive Mechanism based on Reputation for collaborative sensing (IMR) [36]. STFA is a stochastic algorithm that exploits workers' social networks to recruit a suitable collaboration group for tasks according to a certain probability. IMR is a collaboration sensing method based on a reputation incentive mechanism, which collaborates by combining workers with similar reputation values that meet the threshold value. The time complexity of STFA is O(n), and the time complexity of IMR is $O(n^3)$. STFA and IMR can be compared with the proposed mechanism regarding worker engagement, task coverage, platform utility and worker utility.

A. Simulation Setup

All simulations are conducted on a Windows 10 PC with an Intel Core i7 2.2 GHz processor and 16 GB of memory. The specific data sets of tasks and workers are generated by a pseudo-random number generator and are preprocessed accordingly. Simulation results are averaged across 1000 iterations for each test under the same simulation settings.

To investigate the influence of the numbers of workers and tasks on the performance of EGC-STRO and baseline methods, when the number of workers n is set as 200, the number of tasks m is varied from 25 to 500. When the number of tasks m is set as 200, the number of workers n is varied from 25 to 500. Five task types are assumed in the simulations.

The starting time of tasks and the starting time of workers to execute tasks are generated according to the specified probability model: the probabilities of the starting time points ranging from 0:00 to 6:00 and from 18:00 to 24:00 are both 0.1, and the probability of the starting time points ranging from 6:00 to 18:00 is 0.8.

The highest budget per unit of time φ is set to 2. The sensing power of the worker's device p_i is set to 1.

To study the influence of the discount factor on the optimal rewards of workers, the worker utility of the system is measured by varying the ratio between discount factors of the buyer and seller $\lambda_{sell}/\lambda_{buy}$, where λ_{buy} is set as a fixed value of 0.6.

Performance Metrics

In the simulations, we use worker engagement, task coverage, platform utility and worker utility to measure the performance of different methods. Worker engagement and worker utility can reflect the performances from the side of workers. Task coverage and platform utility can reflect the performances from the side of the platform aspect.

1) ***Worker Engagement:***

It is defined as $r_{worker} = \frac{par}{n}$, i.e., the ratio of the engagement number of workers par to the total number of workers n.

2) ***Task Coverage:***

It is defined as $r_{task} = \frac{cov}{m}$, i.e., the ratio of the number of tasks covered by workers cov to the total number of tasks m.

3) ***Platform Utility:***

It is an important metric to evaluate the budget feasibility of the incentive mechanism, and is defined as $U_{plat} = b - p$, where b is the total budget of the platform, and p is the total compensation paid to all workers.

4) ***Worker Utility:***

The sum of the utilities of all the workers, i.e., $par \times U_{worker} = r - c$, where U_{worker} is the worker's average utility, r is the total reward of all workers, and c is the total compensation of all workers.

C. Worker Engagement

As can be seen from Fig. 6, the proposed EGC-STRO has higher worker engagement than IMR for different values of m and n. This is due to the proposed EGC-STRO having an effective incentive mechanism, which makes the workers' objective willingness to collaborate higher than the other two baseline methods and therefore increases worker engagement. As the number of tasks and the number of workers increases, the worker engagement of EGC-STRO tends to stabilize.

The proposed EGC-STRO considers the complementarity of sensing time compared to IMR, so more workers with shorter available sensing time can be motivated to participate in the task.

For different values of m, the difference between EGC-STRO and STFA is small when m is small, and the worker engagement of EGC-STRO is much higher than that of STFA as m increases. This is because the advantage of EGC-STRO is more obvious when the number of tasks is fixed and the number of workers is larger.

For different values of n, the worker engagement of EGC-STRO is higher than that of STFA when n is small, and as n increases, the worker engagement of EGC-STRO does not differ much from that of STFA. This is because with the same number of tasks, the more the number of workers, the closer the worker engagement is to the fixed value.

As shown in Fig. 6(a), worker engagement in the three methods increases with the increase of m. This is because when the number of workers n is fixed and the number of tasks m increases, the chance for workers to join collaboration groups will increase. Fig. 6(b) shows that, when n ranges from 25 to 500, worker engagement in the three methods decreases with the increase of n. This is because, under the condition that the number of tasks m is fixed and the number of workers n increases, there will be more idle workers. Compared with other algorithms, the EGC-STRO increases worker engagement by 5% and 20% at best under the condition of different numbers of workers and tasks in Fig. 6.

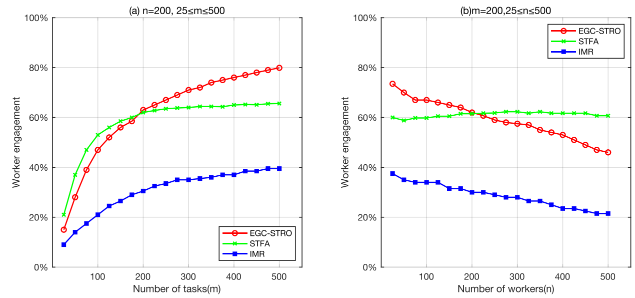

Fig. 6. Comparison of worker engagement.

D. Task Coverage

As shown in Fig. 7, the task coverage rate of the proposed EGC-STRO is significantly better than the other baseline methods, especially IMR, for different values of m and n. This is because the proposed EGC-STRO can reduce the sensing time redundancy of workers, which makes workers perform more tasks in a limited time and greatly improves the efficiency of workers, that is, it enables workers to perform more tasks in a preset time period. Moreover, an effective incentive mechanism makes the objective collaboration willingness of workers higher than the other two baseline methods, which increases worker participation and indirectly increases task coverage. As the number of tasks and the number of workers increases, the task coverage of EGC-STRO tends to stabilize.

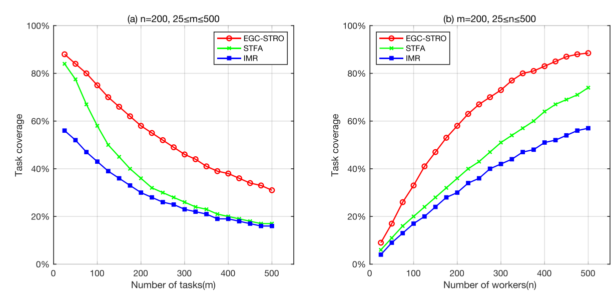

Fig. 7. Comparison of task coverage.

As illustrated in Fig. 7(a), the task coverage of all three methods declines as the value of m increases. Notably, as m grows substantially larger, the task coverage decreases very little. This is because the redundancy of workers leads to higher task coverage when n is fixed m is small, and as m increases, there are more unassigned tasks due to the lack of workers, which leads to lower task coverage.

From Fig. 7(b), it can be observed that the task coverage of the three methods increases with the increasing n. This is because the increase in the number of workers n makes there are sufficient workers to complete the rationed tasks, which directly reduces the number of unassigned tasks, resulting in higher task coverage. As the number of workers increases, the task coverage of the three methods converges to the same value. Compared with other algorithms, EGC-STRO increases task coverage by 6% and 25% at best under the condition of different numbers of workers and tasks in Fig. 7.

E. Platform Utility

As can be seen from Fig. 8, the method in this paper has a higher platform utility than the two baseline methods. The reason is that the other collaboration sensing methods have the problem of sensing time redundancy, and their platforms bear the cost of sensing time redundancy in the process of pricing with collaboration groups, and there is no effective incentive mechanism to minimize the cost of the platform, resulting in lower platform utility. As the number of tasks and the number of workers increases, the platform utility of EGC-STRO tends to stabilize.

In Fig. 8(a), the platform utilities of the three methods increase with the number of tasks, and the growth rate remains stable. This is because, with a sufficient number of workers, the more tasks provided, the more tasks workers can perform, and the more transactions between the collaboration group and the platform, and thus the platform utility increases accordingly.

In Fig. 8(b), the average platform utility increases with the number of workers for all methods. When the number of workers increases in the interval [25,200], the platform utility increases significantly. The platform utility tends to level off when the number of workers exceeds 200. This is because when the number of workers reaches 200, the fixed number of tasks prevents the remaining workers from engaging in sensing collaboration, thus reaching saturation. If there are no more tasks to perform, no more transactions can be generated, the utility of the platform will not increase and tends to converge. Compared with other algorithms, the EGC-STRO increases platform utility by 17% and 50% at best under the condition of different numbers of workers and tasks in Fig .8.

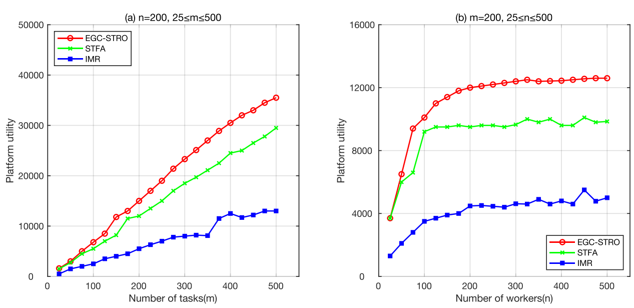

Fig. 8. Comparison of platform utility.

F. Worker Utility

As shown in Fig. 9(a) and Fig. 9(b), the worker utility of all three methods increases as the number of tasks or workers increases. However, the proposed EGC-STRO has greater worker utility than the other baseline methods. This is because the method is more effective in motivating workers with shorter available sensing time to join the collaboration group, thus increasing the probability of executing large-span tasks. Moreover, the number of workers involved in sensing activities in the proposed EGC-STRO is relatively more significant compared to other methods, thus generating a relatively larger worker utility. In addition, because the bargaining game incentive mechanism of the proposed EGC-STRO makes workers' objective willingness to collaborate increase, more workers will be willing to join the collaboration group for collaboration sensing, which will have a certain impact on the overall utility of workers. As the number of tasks and the number of workers increases, the worker utility of EGC-STRO tends to stabilize.

As shown in Fig. 9(a), as the number of tasks increases, the probability of workers being able to match the appropriate sensing task also increases, thus increasing worker utility. As shown in Fig. 9(b), the worker utility increases for all three methods as the number of staff increases, which is because the increase in the number of staff leads to an increase in the probability of performing the task.

Fig. 9(c) and Fig. 9(d) show the worker utilities of the proposed EGC-STRO with different discount factors for different numbers of tasks and workers for the buyer (platform) and the seller (worker), respectively. The buyer's discount factor is set to a fixed value of 0.6, and the seller's discount factor is set to 0.3, 0.6, and 0.9 for all the proposed EGC-STRO algorithms, respectively.

Fig. 9 shows that the more significant the seller's discount factor is, the larger the worker's utility will be. This is because when the seller's discount factor is more significant than the buyer's discount factor, the worker's utility is greater. In this case, the worker will be more patient in the bargaining game and therefore, their cost loss in the bargaining game will be smaller, and they can be rewarded closer to the bid price. Compared with other algorithms, the EGC-STRO increases worker utility (social welfare) by 20% and 60% at best under the condition of different numbers of workers and tasks in Fig. 9.

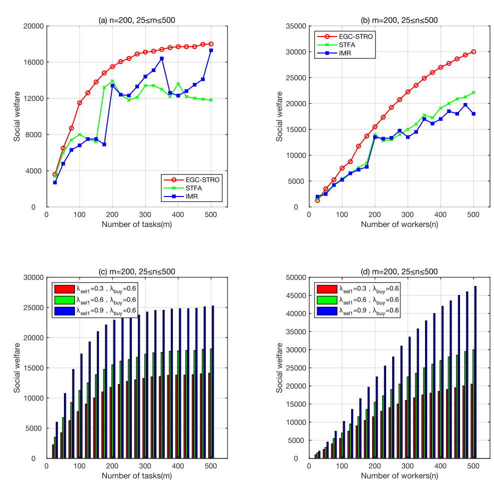

Fig. 9. Comparison of worker utility.

VI. CONCLUSION

To attract more workers to participate in collaboration, reduce sensing data redundancy and improve the effectiveness of collaboration sensing, EGC-STRO is proposed in this paper. First, EGC-STRO incorporates an incentive mechanism to select employees based on their reward expectations, which is referred to as their objective willingness to collaborate. This mechanism utilizes the principles of a bargaining game to maximize the overall interests of the workers. By applying the concept of subgame perfect Nash equilibrium, EGC-STRO ensures that workers receive optimal rewards that align with their objective willingness to collaboration. Additionally, EGC-STRO introduces a collaboration worker selection model that takes into account the subjective willingness to collaborate of the employees. When selecting workers for collaboration, the algorithm first identifies workers who meet both the subjective and objective preference thresholds and adds them to the candidate set. From this candidate set, the collaboration workers are then chosen sequentially based on the criterion of minimizing sensing redundancy time, thereby promoting the formation of efficient collaboration groups and potentially guarantee the worker and platform utilities. The experimental results show that compared with the other two baseline methods, EGC-STRO is efficient in terms of worker engagement, task coverage, platform utility, and worker utility. In future work, we will consider real-world datasets to further validate the algorithm and study worker collaboration scenarios from a spatial complementarity perspective.

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