GAIMMO: A Grade-Driven Auction-Based Incentive Mechanism With Multiple Objectives for Crowdsourcing Managed by Blockchain

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***Abstract*—Blockchain has been applied for decentralized crowdsourcing management by deploying a number of miners to reach a consensus on crowdsourced task allocation and payment decision. In a blockchain-based crowdsourcing system (BCS), incentive becomes essential to motivate the participation and cooperation of all system entities. However, existing literature scarcely investigates how to motivate heterogeneous crowdsourcers, workers, and miners simultaneously toward satisfying multiple objectives without the support of centralized management. In this article, we propose GAIMMO, a novel grade-driven auction-based incentive mechanism for BCS with multiple objectives in mind: crowdsourcer utility maximization, social welfare maximization, social grade maximization, and social cost minimization. Concretely, we propose a grade-based task sorting (GTS) algorithm to determine the service priority of heterogeneous crowdsourcers in order to motivate their cooperative behaviors, which consequently maximizes crowdsourcer utility when combining with the carefully designed utility functions of other system entities. We propose a grade-based utility function of workers and employ a hierarchical premium-based task assignment (PTA) algorithm to realize social welfare maximization, social grade maximization, and social cost minimization. We further propose a fixed-grade-sum and grade-based reward-sharing (FGSGRS) method to encourage fast block generation and motivate high-grade miners without damaging the profits of the crowdsourcers. We conduct simulation-based experiments to show the effectiveness and advance of our proposed incentive mechanism in stimulating the participation willingness of high-grade system entities and achieving the multiple objectives.**

***Index Terms*—Auction, blockchain, crowdsourcing, incentive mechanism, social cost, social welfare.**

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I. Introduction

CROWDSOURCING aggregates the intelligence of crowds to provide solutions to outsourced tasks [1], [2]. The entities that explore their idle resources for providing solutions to the tasks are called workers. The requester's outsourcing tasks are crowdsourcers that pay rewards to the contributed workers. Centralized crowdsourcing (CCS) relies on a centralized platform to allocate tasks to workers, as well as collect solutions and assign rewards to workers.

In crowdsourcing, task completion and system sustainability require enthusiastic participation of all system entities, especially the workers. To this end, numerous incentive mechanisms have been designed to attract crowdsourcing participants. A number of incentive mechanisms based on different auctions have been adopted to maximize the profits of the crowdsourcers [3], minimize their costs [4], and maximize the social welfare that is the sum of the profits of both the crowdsourcers and the workers [5]. Contract theory is widely applied to motivate workers to reveal their private information [6], [7]. In addition, researchers have proposed some grade-based incentive mechanisms to associate the behaviors of system entities to their grade values for motivating expected or cooperative behavior of the system entities, where the grade could be trust [8], [9], reputation [10]–[12], data, service quality [13]–[15], etc.

Existing grade-based incentive mechanisms are constructed for the CCS and depend on a reliable party to select workers, determine payments, and evaluate grade values. The reliable party is usually the crowdsourcing platform that is assumed to be trustworthy. However, such an assumption is impractical in practice. The platform could collude with crowdsourcers or workers. Moreover, even if the platform is honest, it is commonly the primary target of attackers and could suffer from single-point-of-failure problems and DDoS attacks.

Blockchain, a promising decentralized technology with immutability, auditability, and reliability, has been applied into crowdsourcing [16], [17]. The centralized platform in CCS is replaced by a blockchain-based crowdsourcing platform (BCP) that is managed by miners through consensus on task announcement, worker selection, and payment decision. In a blockchain-based crowdsourcing system (BCS), the miners verify the correctness and validity of crowdsourcing information for supporting its regular operations. Some researchers have employed the consensus of miners to guarantee the trustworthiness of grade evaluation in blockchain-based decentralized systems [18]–[20]. The proper execution and the security of BCS are inseparable from the participation of all system entities. Therefore, an incentive mechanism is crucially essential in BCSs.

Although game theory [21], auction theory [22]–[25], contract theory [26], and other methods [17], [27] have already been applied to design incentive mechanisms in BCSs, we identify the following practical problems. First, existing incentive mechanisms cannot guarantee fairness for all system entities. Some researchers have analyzed BCSs with heterogeneous crowdsourcers [23]–[26]. However, they offer the crowdsourcers with the same probability to obtain crowdsourcing services. This causes unfairness to high-grade crowdsourcers, especially when the capabilities of workers are not sufficient to provide services to all crowdsourcers. Herein, fairness follows the definition of distributional fairness in [28], which emphasizes that what an entity obtains should be proportional to what it has given or paid for. Second, existing grade-based incentive mechanisms seldom regard both grade values and utility-related economic elements as the parameters to be optimized at the same time [23], [26], [27]. However, optimizing the economic elements contributes to motivating the participation willingness of the system entities while optimizing the grade values produces a healthy and sustainable ecosystem. Therefore, it is valuable to optimize both parameters when applying a grade-based incentive mechanism. Third, the incentive to motivate the newly involved entity, namely, the miner, has not yet been properly designed [22], [23]. Although some researchers have noticed this problem, they just assumed the existence of a payment mechanism for the miners [29] or mentioned that the miners can obtain rewards from the crowdsourcers [30] without further investigation. Therefore, it is necessary to design a feasible incentive mechanism for the miners. In short, an effective incentive mechanism with multiple design objectives related to all system entities is highly expected for addressing the above open problems.

Unfortunately, we confront some challenges in solving the above problems. First, a crowdsourcer may have different types of tasks with different task requirements. Such crowdsourcer heterogeneity increases the difficulty of incentive mechanism design. Second, the tradeoff between multiple objectives is not easy to balance. The payments in BCSs are mainly offered by the crowdsourcers, therefore, the incentive mechanism should first satisfy the crowdsourcers by maximizing their utilities. The utilities of other system entities should also be guaranteed and their participation costs should be minimized in order to attract their involvement, which is essential for the success of BCSs. In addition, BCSs should recruit high-grade participants for ensuring system trustworthiness and liveness. The high-grade workers usually produce satisfactory task execution results to the crowdsourcers. The crowdsourcers need to pay relatively high payments to the high-grade workers while this may violate the objective of maximizing the utilities of the crowdsourcers. Third, the existence of miners in BCSs complicates the design of a proper payment strategy. The crowdsourcers prefer to pay relatively low payments to the miners. However, the number of participated miners will decrease without enough payments, which inherently influences the security of BCSs and eventually damages the utilities of all system entities. All these challenges motivate our work presented in this article.

In this article, we design GAIMMO, a novel grade-driven auction-based incentive mechanism for decentralized crowdsourcing in order to achieve multiple objectives: maximize the utilities of crowdsourcers, maximize social welfare, minimize social cost, and maximize social grade. Herein, the social welfare is the sum of the utilities of all system entities, the social grade refers to the sum of grade values of crowdsourcers, workers, and miners, and the social cost corresponds to the sum of the costs of workers and miners. First, we propose a grade-based task sorting (GTS) algorithm to determine the service priority of different crowdsourcers in order to motivate their cooperative behaviors for gaining high grades. We also sort the subtasks outsourced by the same crowdsourcer according to their requirements for guaranteeing task completion. Second, we propose a grade-based utility function of workers with truthfulness and employ a hierarchical premium-based task assignment (PTA) algorithm to assign suitable workers to each subtask according to their service priorities for balancing the objectives of social grade maximization and social cost minimization. Premium is the ratio between bid and grade value. Consequently, we maximize the social welfare by motivating the participation of high-grade workers with a grade-based utility function design when the social cost is minimized. Third, we further propose a fixed-grade-sum and grade-based reward-sharing (FGSGRS) method by setting that only the first several miners that find a block can be rewarded with shared proportions determined by their grades. In this way, we motivate miners to behave cooperatively for gaining high grades. In addition, we design the reward amount carefully to avoid damaging the profits of crowdsourcers. Specifically, the contributions of this article can be summarized as follows.

1) We propose GAIMMO for decentralized crowdsourcing participated by heterogeneous crowdsourcers, workers, and miners in order to achieve multiple objectives: crowdsourcer utility maximization, social welfare maximization, social cost minimization, and social grade maximization.
2) We investigate the functions of these objectives and conclude that the multiple objectives can be obtained by motivating high-grade system entities, minimizing social cost, and carefully scheduling the interest interactions between crowdsourcers and miners.
3) We design several auxiliary algorithms for the practical implementation of GAIMMO, conduct experiments to illustrate its feasibility, and emphasize its superiority through comparison with borderline methods.

The remainder of this article is organized as follows. Section II reviews existing incentive mechanisms in crowdsourcing systems. Section III presents the general procedure of BCS with an auction, along with research assumptions, our grade-based economic model, problem descriptions, and research goals. We present the details of GAIMMO and the auxiliary algorithms in Section IV, followed by our experimental settings and experimental results in Section V. Finally, we present our conclusion in the last section.

II. Related Work

This section reviews existing literature about incentive mechanisms in crowdsourcing systems and concludes their shortcomings, which motivates our research.

A number of incentive mechanisms are designed for the crowdsourcing systems participated by one crowdsourcer and multiple workers. Hu *et al.* [21] employed a three-stage Stackelberg game to model the interactions among a crowdsourcer, contract workers, and temporary workers in the BCS. The authors involved reputation values into the utility functions of the workers. The proposed reward mechanism maximizes the utilities of all players (i.e., the crowdsourcer and workers) and data quality with budget constraints and data quantity requirements. Chatzopoulos *et al.* [31] applied a combinatorial auction to model the interaction between a crowdsourcer and multiple workers. The BCP selects workers for each task according to the unit cost of workers, which minimizes the payment paid by the crowdsourcer to the workers. Similar to [21], this article does not mention how to motivate the miners. Kang *et al.* [26] employed the crowdsourcer to evaluate the data quality of workers through attack detection schemes. They applied a contract theory-based incentive mechanism to assist the crowdsourcer to select the optimal workers according to reputation value, which succeeds in maximizing the utilities of the crowdsourcers and the workers. However, the miners in this system are preselected edge nodes and the incentive to them is ignored. Different from [26], An *et al.* [27] enabled the miners to perform worker selection through a matching degree. The crowdsourcer is responsible for verifying the data quality of the workers through quality grading evaluation (QGE). The payments to the workers with different grades are also different. This incentive mechanism benefits the crowdsourcer with high-quality data. Gao *et al.* [34] employed blockchain as a method to guarantee the trustworthiness of worker selection and applied a deterministic encryption algorithm to encrypt reputation values stored on the blockchain to prevent side-channel attacks. Unfortunately, no incentive mechanism is applied to motivate participants.

Some researchers have designed incentive mechanisms for crowdsourcing with a centralized or blockchain-based platform and multiple workers, where the platform directly outsources tasks to workers. Huang *et al.* [32] applied a Stackelberg game to model the interaction of a centralized platform and workers. They investigated the influence of the quality heterogeneity of workers on the platform's profits when the number of workers is fixed. The authors discovered that a discriminatory reward policy contributes to high social welfare. Xiao *et al.* [35] proposed an incentive mechanism to resist the collusion of workers, the purpose of which is different from this article. Chen *et al.* [22] enabled the BCP to select workers for maximizing the social welfare and determined data quality-based rewards for the selected workers. Herein, the data quality is verified by the BCP through an expectation–maximization (EM) algorithm; thus, the incentive mechanism heavily relies on the truthfulness of the BCP and is not applicable in our scenario with heterogeneous crowdsourcers. In [33], a BCP adopts a hierarchical worker selection method, which first filters all workers according to their credibility and then selects the workers based on budgets and bids. The incentive mechanism provides the BCP with near-optimal profits and high data reliability.

We also discovered some incentive mechanisms designed for crowdsourcing with multiple crowdsourcers and multiple workers. Krishna and Lorenz [36] enabled centralized and trusted task allocators to analyze worker preferences and apply maximum likelihood and EM to designate tasks. Yu *et al.* [37] employed reverse combination auction to model the interactions between task publishers located in different places and vehicles, designed a worker selection method to guarantee the profits of the crowdsourcing platform. They applied virtual currency to encourage long-term participation and adopted the reputation to motivate workers to provide high-quality data. However, these two works were not conducted for blockchain-based systems. Wei *et al.* [23] applied the auction theory to design an incentive mechanism for motivating the participation of high-quality workers. The crowdsourcers also work as miners to manage the blockchain, evaluate the data quality of the workers, and select workers based on the weighted sum of bid, reputation, and data quality. Yin *et al.* [24] considered the heterogeneity of tasks and classified them as general tasks and emergent tasks. The worker selection methods are different for different kinds of tasks. The payments to the selected workers of different tasks are also different. The incentive mechanism for general tasks maximizes the profits of the crowdsourcers, while that for emergent tasks maximizes the profits of both the crowdsourcers and the workers as well as reduces the task processing time. Wang *et al.* [25] proposed a reverse auction-based incentive mechanism and enabled the BCP to choose workers with a hierarchical method. Specifically, the BCP first determines a candidate worker set according to the task-completion rates of workers and then selects some workers for minimizing the selected worker number and the costs. Furthermore, the rewards to the selected workers are calculated based on their credits and bids. Xu *et al.* [17] considered the task of each crowdsourcer to be related to location and service time period. The authors applied the optimization theory to help workers find their best strategies, which can achieve maximum service time, maximum payment from crowdsourcers, and minimum cost to perform the tasks. Unfortunately, this method is designed from the perspective of workers, which may not be compatible with a practical scenario that the crowdsourcers dominate the market. However, none of these papers [17], [23]–[25] considered the competition among the multiple crowdsourcers.

Table I compares existing incentive mechanisms in BCSs with ours. We summarize their shortcomings as follows.

1) *Shortcoming 1:* The competition among heterogeneous crowdsourcers is scarcely discussed. Many researchers only considered one crowdsourcer in their incentive mechanisms, which could confine the practical

TABLE I
COMPARISON AMONG RELATED WORK AND THIS ARTICLE

Reference	Heterogeneity of Crowdsourcers	Motivated Entities	Objectives	Applied Methods	S1	S2	S3
[21]	no	workers	maximize the utility of crowdsourcer maximize the utilities of workers maximize data quality	three-stage Stackelberg game	×	×	⋆
[31]	no	workers	minimize the payment of crowdsourcer	auction	×	×	−
[26]	yes	workers	maximize the utilities of crowdsourcers maximize the utilities of workers	contract theory reputation	×	×	×
[27]	no	−	obtain high-quality data	matching theory	×	×	×
[32]	no	workers	high social welfare maximize the platform's profit	Stackelberg game	×	×	×
[22]	no	workers	maximize social welfare obtain high-quality data at low cost	auction	×	×	⋆
[33]	no	workers	maximize the utility of crowdsourcer	auction	×	×	−
[23]	yes	workers	motivate high-quality workers	auction	×	×	×
[24]	yes	workers	maximize the utilities of crowdsourcers OR maximize the utilities of both	reverse auction	×	×	−
[25]	yes	workers	minimize selected worker number minimize the cost of workers	reverse auction	×	×	−
[17]	yes	workers	maximize service time of workers maximize the utilities of workers minimize the energy cost of workers	optimization	×	×	−
Our paper	yes	crowdsourcers workers miners	maximize the utility of crowdsourcers maximize social welfare maximize social grade minimize social cost	auction and grade	⋆	⋆	⋆

S1: Shortcoming 1; S2: Shortcoming 2; S3: Shortcoming 3
×: The paper suffers from the shortcoming
⋆: The paper overcomes the shortcoming
−: The paper does not need to consider the shortcoming

application of their methods. Even if some researchers have considered the multicrowdsourcer scenario, they pay little attention to the competition among the crowdsourcers, which is worth noting especially when the high-quality and low-cost resources (i.e., workers) are insufficient.

2) *Shortcoming 2:* The motivated entities in BCS are not comprehensive. Existing incentive mechanisms impractically assume that the crowdsourcers are honest and cooperative. However, their honest and cooperative behavior also need motivation in practical scenarios. Moreover, the blockchain technology introduces miners that play an important role in maintaining the security and reliability of the BCSs, while most papers seldom detail how to provide incentives to the miners.
3) *Shortcoming 3:* The grade values and the utility-related elements are not optimized simultaneously in the existing literature. The incentive mechanisms in [23] and [27] only maximize the grade values, data quality to be more exact, while ignore the practical profits of system entities. Although the incentive mechanisms in [21] and [22] are designed based on multiple objectives, they are suffering from the above two shortcomings.

III. System Model

In this section, we present the general procedure of BCS with an auction and summarize our research assumptions, based on which we further establish an economic model. Afterward, we describe our research problems and research goals.

Before further investigation, we specify the system with notations. The system consists of N crowdsourcers $\mathcal{C} = \{C_1, C_2, \ldots, C_N\}$, K workers $\mathcal{W} = \{W_1, W_2, \ldots, W_K\}$, and L miners $\mathcal{M} = \{M_1, M_2, \ldots, M_L\}$. A crowdsourcer C_n issues a task T_n with three subtasks that are a data collection subtask t_n^c, a data processing subtask t_n^p, and a data storage subtask t_n^s, and transfers some deposits d_n for their subtasks. The crowdsourcer C_n holds specific requirements Π_n to its task T_n. Each worker W_k submits bids $b_{n,k}^c$, $b_{n,k}^p$, and $b_{n,k}^s$ for subtasks t_n^c, t_n^p, and t_n^s according to its corresponding costs $c_{n,k}^c$, $c_{n,k}^p$, and $c_{n,k}^s$. The miners together maintain the BCP by verifying all transactions in the system, including the validity of task issuance, task bidding, payment, etc. A grade mechanism based on roles and subtasks is introduced to evaluate the performance of all system entities. Although the grade could be trust, reputation, or other parameters calculated based on historical behavior and other elements (e.g., criteria, standards, policies, and basic capabilities), the grade mentioned in this article is fixed to one kind, like trust value. Furthermore, the grade values of the workers for different subtasks are calculated based on the same grade evaluation theory, by considering proper inputs of a concrete evaluation method with context awareness. Specifically, a system entity possesses independent grade values for its crowdsourcer role, worker role, and miner role. Furthermore, each worker holds different grade values for different subtasks. After the task T_n is completed and confirmed on the block, the crowdsourcer C_n pays some payments to the workers that are calculated by the miners and rewards the miners that have participated in the transaction verification related to task T_n. The payments and rewards are calculated by a certain rule of the system designer.

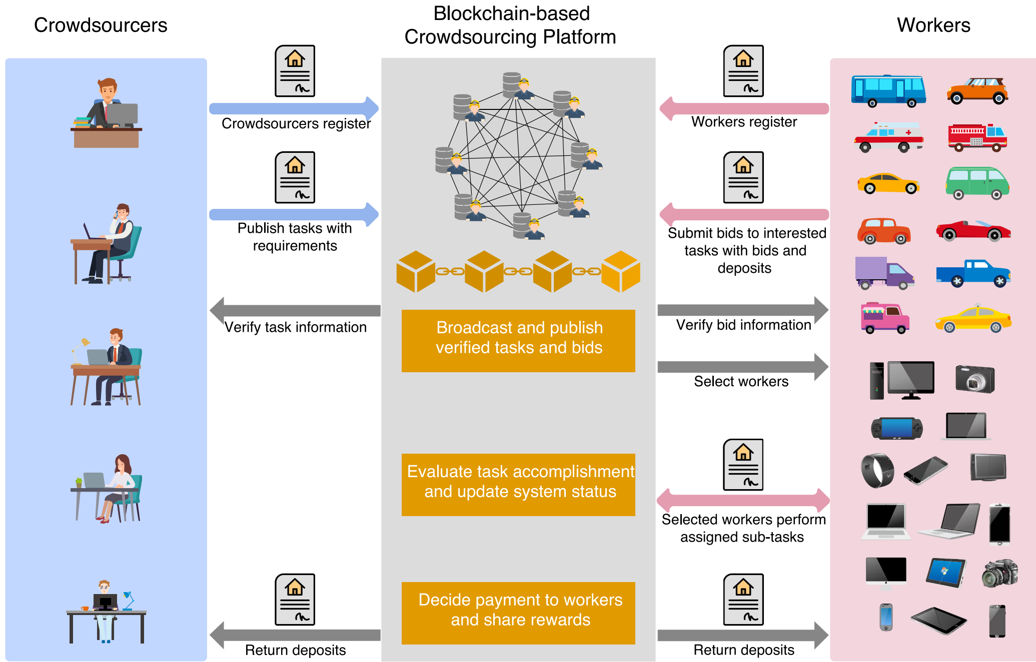

Fig. 1. Procedure of a BCS with auction.

Fig. 1 depicts the procedure of the system with an auction that is detailed as follows.

1) All system entities invoke a smart contract to register on the BCP.
2) Each crowdsourcer publishes its task/subtasks and requirements on the platform and transfers the secure deposits to the platform.
3) Miners verify the task issuance and deposit transferring transactions and publish verified tasks on the platform.
4) By browsing published tasks, each worker submits bids for interested subtasks and pays deposits. Specifically, a worker can bid for many subtasks and it should pay deposits for each subtask to suppress malicious bidding.
5) The miners verify the bid and deposit transactions to primarily exclude unqualified bids for avoiding unnecessary workloads. After that, the miners select workers for each subtask according to the requirements of the crowdsourcers and the goals of the platform.
6) The selected workers perform their assigned subtasks. Specifically, the selected data collecting workers first submit collected data to the selected data processing workers, which then upload the processed data to the selected data storage workers.
7) The miners verify the subtasks accomplishment and update the grade values for each system entity. The miners calculate the payment to the selected workers according to the payment structure designed by the system designer. The miners receive the rewards from the crowdsourcers according to a certain rule written on the smart contract by the system designer. Finally, the miners return the deposits to the crowdsourcers and workers after deducting their payments.

A. Research Assumptions

The following are the research assumptions of this article work.

System Assumption: The blockchain applied is a public blockchain that every entity can join as well as leave freely and they can adopt any role arbitrarily. We assume that there are sufficient numbers of crowdsourcers, workers, and miners in our investigated system. A solid grade evaluation model is applied, where the grade could be trust, reputation, etc. Furthermore, the grade is measured based on roles and subtasks, which means that an entity has different grade values with regard to their roles and a worker holds different grade values for different subtasks. The grade values are accessible to miners; therefore, the miners can easily make decisions on task assignment and payment calculation. We consider role-based utilities, rather than entity-based utilities. Hence, if an entity performs multiple roles (e.g., a crowdsourcer and miner) at the same time, we split it as different individuals (a crowdsourcer and a miner) and calculate utilities separately. Notably, even if an entity can perform many subtasks, we do not further split it when calculating the utility. The application of blockchain along with the grade mechanism has encouraged honest behaviors of all participants [19], [20]; therefore, the number of malicious participants can be greatly controlled and limited.

Crowdsourcer Assumption: We assume a crowdsourcer publishes one task at one time, which can be further divided into the data collection, data processing, and data storage subtasks. A crowdsourcer that published multiple tasks will be regarded as multiple crowdsourcers. An obvious requirement of the crowdsourcer is the lowest acceptable grade of workers for each subtask. Practical crowdsourcers generally have limited budgets, considering the task fulfillment cannot produce infinite profits to the crowdsourcers. We assume that the budget is a fraction of the task fulfillment profits and is determined by the requirement on grade.

Worker Assumption: We assume workers to take an active part in bidding since bidding is effortless and costless. If a worker is unwilling to participate in a subtask, it can set its bid as an unreasonable value. To ensure fairness and consider the practical capability of a worker, we assume that there is a limitation on the number of subtasks that a worker can conduct simultaneously. Furthermore, We assume the limitation number is known to each worker, since the worker is familiar with its ability and it can infer such a number from historical information. Without loss of generality, we advocate that a worker will not refuse an assigned task if it still has the capability to handle the task. We also assume that the worker will not accept the excess number of subtasks considering the risk of forfeiting deposits for uncompleted tasks.

B. Economic Model

We establish an economic model based on the system procedure as well as the research assumptions and produce the utility functions of all system entities in this section.

According to the crowdsourcer assumption, we consider that a crowdsourcer C_n holds different requirements for each subtask. We denote the requirements as $\Pi_n = \{\Theta_n^c, \Theta_n^p, \Theta_n^s, \psi_n^c, \psi_n^p, \psi_n^s\}$. Herein, Θ_n^c, Θ_n^p, and Θ_n^s are the minimum requirements of the grade values for the subtasks. ψ_n^c, ψ_n^p, and ψ_n^s represent the budgets of C_n for recruiting the data collection workers, data processing workers, and data storage workers, respectively. Table II summarizes the notations throughout this article for convenient reference.

TABLE II
NOTATIONS

Notation	Explanation
$\mathcal{C}, \mathcal{W}, \mathcal{M}$	The crowdsourcer/worker/miner set
N, K, L	The number of crowdsourcers/workers/miners
C_n	The n-th crowdsourcer
W_k	The k-th worker
M_l	The l-th miner
T_n	The task of crowdsourcer C_n
t_n^c, t_n^p, t_n^s	The data collection/processing/storage sub-task of crowdsourcer C_n
d_n	The deposit of task T_n
Π_n	The requirement of task T_n
$c_{n,k}^c, c_{n,k}^p, c_{n,k}^s$	The cost for W_k to perform t_n^c, t_n^p, t_n^s
$b_{n,k}^c, b_{n,k}^p, b_{n,k}^s$	The bid for W_k to perform t_n^c, t_n^p, t_n^s
$\Theta_n^c, \Theta_n^p, \Theta_n^s$	The minimum grade requirement of t_n^c, t_n^p, t_n^s set by crowdsourcer C_n
$\psi_n^c, \psi_n^p, \psi_n^s$	The budgets of t_n^c, t_n^p, t_n^s set by crowdsourcer C_n
$\theta_k^c, \theta_k^p, \theta_k^s$	The data collection/processing/storage grade value of worker W_k
$\tau_{n,k}^c, \tau_{n,k}^p, \tau_{n,k}^s$	The assignment indicator of t_n^c, t_n^p, t_n^s to W_k
θ_n	The grade value of crowdsourcer C_n
p_n^c, p_n^p, p_n^s	The task-completion profit of C_n brought by a worker with $\Theta_n^c, \Theta_n^p, \Theta_n^s$
R_n	The total rewards that C_n pays to the miners
U_n, U_k, U_l	The utility function of C_n, W_k, M_l
$f_{n,k}^a$	The payment to W_k for performing t_n^a
θ_l	The grade of miner M_l
c_l^n	The cost for M_l to verify all transactions related to crowdsourcer C_n
$\omega_{n,k}^c, \omega_{n,k}^p, \omega_{n,k}^s$	The premium of W_k when being selected to perform t_n^c, t_n^p, t_n^s
NUM_k	The maximum number of sub-tasks that worker W_k can perform simultaneously
$num(k)$	The number of sub-tasks that are assigned to W_k
Ξ	The requirement accumulated grades of miners to generate a new block
τ_l^n	The qualification of M_l to share rewards from C_n
γ_n	The fraction of payment paid to miners set by C_n

We introduce $\tau \in \{0, 1\}$ to indicate the assignment of subtasks. For example, $\tau_{n,k}^c = 1$ indicates that the subtask t_n^c is assigned to and accepted by the worker W_k. Considering that if no workers participate in the data collection subtask of crowdsourcer C_n, the data processing and storage subtasks of this crowdsourcer cannot be further performed. Therefore, the values of $\tau_{n,k}^p$ and $\tau_{n,k}^s$ are related to $\sum_k \tau_{n,k}^c$. Specifically, $\tau_{n,k}^p = 1$ if $\sum_k \tau_{n,k}^c > 0$ and the subtask t_n^p is assigned to W_k. The parameter $\tau_{n,k}^s$ shares a similar definition.

We apply the function $v()$ to represent the influence of a worker's grade value on the task-completion profit of a crowdsourcer. We set $(\partial v / \partial \theta_k^a) > 0$ and $(\partial^2 v / \partial \theta_k^{a2}) < 0$, where $a = c, p, s$. This setting is easy to understand and widely applied in the value function design [22]. A high-grade worker will bring the crowdsourcer high profits. When the grade value increases, the marginal profit will decrease. We adopt p_n^a to denote the profit brought by worker W_k whose grade value is Θ_n^a for completing the subtask t_n^a. Then $v(\Theta_n^a) = 1$. If $\theta_k^a > \Theta_n^a$, C_n can benefit more than p_n^a. Therefore, the task-completion profit brought by a worker with θ_k^a is $v(\theta_k^a) p_n^a$.

Crowdsourcer C_n needs to pay the selected workers of each subtask for their contributions. We denote $f_{n,k}^a$ as the payment to worker W_k, which is related to its grade value θ_n^a and all bids of the subtask. The crowdsourcer C_n also needs to pay a certain amount of rewards to the miners. If denote the rewards as R_n, we can conclude the utility function of C_n as follows:

$$U_n = \sum_k \sum_{a=\{c,p,s\}} \tau_{n,k}^a \big(v(\theta_k^a) p_n^a - f_{n,k}^a \big) - R_n. \tag{1}$$

Based on our crowdsourcer assumption, the value of p_n^a is determined with the following method. When the grade values of all recruited workers for t_n^s are Θ_n^a, the profits that C_n can obtain from all the recruited workers is linearly related to its budget ψ_n^a. Therefore

$$\sum_k \tau_{n,k}^a p_n^a = \alpha_n \psi_n^a \tag{2}$$

where $\alpha_n > 1$.

The worker W_k will obtain payments from every crowdsourcer C_n for performing different kinds of subtasks t_n^a. The utility function of W_k consists of all its received payments minus its costs for performing these subtasks. Hence, the utility function of W_k is presented as follows:

$$U_k = \sum_n \sum_{a=\{c,p,s\}} \tau_{n,k}^a \big(f_{n,k}^a - c_{n,k}^a \big). \tag{3}$$

We denote the reward-sharing function of miners as $g()$, which is positively related to the grade values of miners to ensure fairness. The function $g()$ is also related to τ_l^n, which indicates whether a miner M_l is qualified for being rewarded by the crowdsourcer C_n. We simply set

$$g(\theta_l, \tau_l^n) = \frac{\tau_l^n \theta_l}{\sum_l \tau_l^n \theta_l} \tag{4}$$

which satisfies $\sum_l g(\theta_l, \tau_l^n) = 1$. We conclude the expected utility function of M_l as follows:

$$U_l = \sum_n \left(g(\theta_l, \tau_l^n) R_n - c_l^n\right). \tag{5}$$

Notably, even if all system entities need to transfer security deposits, the deposits will be returned later on. Therefore, we exclude the deposits from our economic model.

C. Problem Description

We identify the following problems when designing a grade-driven auction-based incentive mechanism for BCSs with heterogeneous system entities.

First, the heterogeneity of crowdsourcers and workers and the diverse requirements of different subtasks complicate the procedure of worker selection. Concretely, a rational crowdsourcer prefers workers with high-grade values and low costs. Since the tasks are published on the blockchain, they can be bid with the same probability. However, considering the capability limitation, economic workers cannot provide services to all crowdsourcers. If the miners arrange workers for the tasks without considering the service priority of crowdsourcers, the most suitable workers for high-grade crowdsourcers may have been assigned to low-grade crowdsourcers, thus decreasing the willingness of high-grade ones to participate in the system. Therefore, we need to arrange the service priority of multiple crowdsourcers fairly. Moreover, a crowdsourcer outsources multiple subtasks and the service priority of these subtasks within the same crowdsourcer should also be considered. In addition, the match of workers and subtasks needs careful study with regard to the requirements of crowdsourcers, the capability of workers, and the profits of crowdsourcers. Specifically, miners should contemplate the fundamental tradeoff between high grade and low cost when selecting workers, since practical crowdsourcers are rational and profit driven.

Second, the incentive mechanism with multiple objectives is difficult to design. Crowdsourcers need to pay workers and reward miners for their contributions. They prefer to obtain services from high-grade system entities with low payments while the workers and miners would like to receive high payments with low costs. The interest conflict among them urges us to decide which objective should be satisfied first and how to balance the tradeoff between different objectives.

Third, involving miners as additional entities to be motivated increases the difficulty of effective and fair incentive mechanism design. Only rewarding one miner may not be the best approach since the majority cannot gain anything for a long period. Rewarding several miners could be a feasible alternative; however, we still face two challenges. The first one is how to set the amount of rewards. A small amount cannot provide enough incentives to the miners, and therefore may pose security problems to the system. A large amount may cause profit losses to the crowdsourcers. The second one is how to improve the willingness of high-grade miners, thus enhancing system security and efficiency.

D. Research Goals

For overcoming these problems, we propose our goals when designing a feasible incentive mechanism for BCSs.

Involving the incentive of miners complicates the design of utility functions. Our goal is to motivate the miners to verify transactions fast and guarantee the grade value of system entities at a high level without the profit loss of others.

The primary objective of our incentive mechanism is to provide crowdsourcers with satisfaction, since the crowdsourcers dominate BCSs as they decide whether to outsource tasks and control the payments to other system entities. From the view of the whole system, we aim to propose an incentive mechanism that can attract high-grade participants and suppress the willingness of low-grade system entities for guaranteeing long-term system development. Furthermore, the total costs for achieving these goals should be tolerable for building a green and sustainable system. We expect the workers and miners can also benefit from participating in BCSs. In general, we hope to first maximize crowdsourcer utility and then maximize social welfare and the social grade at a relatively low social cost.

Herein, social welfare refers to the sum of the utilities of all participants. After deduction, we conclude the formula of the social welfare based on our economic model as follows:

$$\begin{aligned} \mathrm{SW} &= \sum_n U_n + \sum_k U_k + \sum_l U_l \\ &= \sum_n \left(\sum_k \sum_a \tau_{n,k}^a \left(v(\theta_k^a) p_n^a - c_{n,k}^a \right) - \sum_l c_l^n \right). \end{aligned} \tag{6}$$

The parameters $f_{n,k}^a$ and R_n are eliminated from SW, and the final form of SW is the sum of task-completion profits of all crowdsourcers subtracts the costs of all workers and miners, which is defined as social cost, representing as follows:

$$\mathrm{SC} = \sum_n \left(\sum_k \sum_a \tau_{n,k}^a c_{n,k}^a + \sum_l c_l^n \right). \tag{7}$$

By comparing (6) and (7), we recognize that the satisfaction of social welfare maximization can be realized by motivating high-grade workers and minimizing the social cost.

We designate social grade as the sum of the grade values of the crowdsourcers, all selected workers, and rewarded miners, which is formalized as follows:

$$\mathrm{SG} = \sum_n \left(\theta_n + \sum_k \sum_a \tau_{n,k}^a \theta_k^a + \sum_l \tau_l^n \theta_l \right). \tag{8}$$

A high social grade represents the promising prospect of the system with sustainability.

It is possible for a rational worker to gain more profits if its bid is higher than its real cost, which will definitely damage the profits of crowdsourcers. Therefore, a feasible incentive mechanism should motivate workers to bid according to their real costs, which is called the requirement of truthfulness. Specifically, for any worker W_k with truthful bid

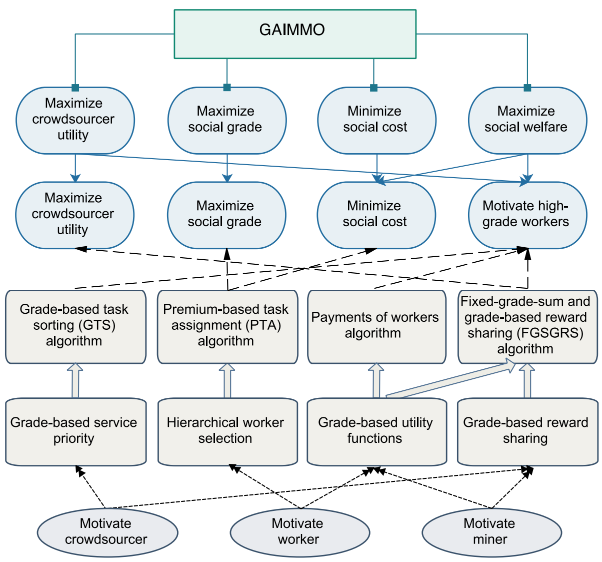

Fig. 2. Overview of GAIMMO.

$b^c_{n,k}$ and untruthful bid $\bar{b}^c_{n,k}$, the relationship between their corresponding payments satisfies $f^c_{n,k}(b^c_{n,k}) \geq f^c_{n,k}(\bar{b}^c_{n,k})$.

IV. Incentive Mechanism Design

This section presents the methods in our incentive mechanism to motivate crowdsourcers, workers, and miners, respectively, along with some auxiliary algorithms for implementing these methods. All of these methods are executed by miners with predefined policies.

A. Incentive Mechanism Overview

Fig. 2 overviews of our incentive mechanism GAIMMO. According to (1), the crowdsourcer utility can be maximized by selecting high-grade workers and delicately scheduling R_n. By investigating the equation of social welfare, we have recognized that social welfare maximization can be realized by motivating high-grade workers and minimizing social costs. The social grade maximization objective requires to motivate all high-grade system entities, including crowdsourcers, workers, and miners.

We propose a grade-based service priority method to motivate crowdsourcers with high-grade values and deploy it with a GTS algorithm. We employ grade-based payment to attract high-grade workers for maximizing the utilities of crowdsourcers. In addition, we present a hierarchical worker selection method by considering the balance of social grade maximization and social cost minimization. We introduce premium, which is the ratio of bid and grade, and design a PTA algorithm to deploy the hierarchical worker selection method. In order to motivate miners, we design an FGSGRS algorithm, which is carefully designed to avoid damaging the profits of crowdsourcers.

Before the concrete introduction of GAIMMO, we specify public information and private information in our model. First, the requirements of crowdsourcers are accessible to all authorized miners for worker selection and payment decisions.

Algorithm 1: GTS

Input: $\mathcal{C}$, $\{\theta_n\}$, $\{\Theta^c_n\}$, $\{\Theta^p_n\}$, $\{\Theta^s_n\}$
Output: Task sorting set $T.sort$

Initialization;
Sort $\mathcal{C}$ in the non-increasing order of $\{\theta_n\}$ as $\mathcal{C}'$;
$T.sort = \emptyset$;
for $C'_n \in \mathcal{C}'$ **do**
  Sort t^c_n, t^p_n, t^s_n in the non-increasing order of Θ^c_n, Θ^p_n, Θ^s_n as $T_n.sort$;
  $T.sort \leftarrow T.sort \cup T_n.sort$;
end

Second, the workers know their costs for performing subtasks. Third, the grade values of all system entities are attached to their pseudonyms and published on the blockchain and can be accessed by the public. Fourth, the task assignment and execution results that have been verified and confirmed are published on the blockchain, thus all system entities can observe.

B. Incentive of Crowdsourcers

Crowdsourcers are the direct beneficiary of BCSs and their incentives are commonly ignored in existing incentive mechanisms. However, their participation and cooperation are also essential for the success of BCSs. We propose a grade-based service priority method to motivate high-grade crowdsourcers and design the payment and reward policies of other system entities without sacrificing the profits of crowdsourcers.

When multiple crowdsourcers have published their tasks and requirements, the BCP needs to decide the order in which the crowdsourcing service is provided. We first sort all tasks $\{T_n\}$ according to the grade values of $\{C_n\}$. Concretely, the miners will select workers for the crowdsourcer with the highest grade value first; therefore, this crowdsourcer can obtain the services from highly matched workers with a high probability. In this way, the crowdsourcers are motivated to maintain their grade values at a high level for high-quality of service experience and expenditure savings.

According to our assumption, each crowdsourcer could have different lowest acceptable grade values for different subtasks. Therefore, we additionally sort the subtasks $\{t^c_n, t^p_n, t^s_n\}$ for each crowdsourcer C_n according to the descending order of the minimum grade requirements Θ^c_n, Θ^p_n, and Θ^s_n. The underlying reason is to avoid the possibility of task failures while increasing the matching degree of subtasks and workers. Concretely, we select workers for the subtask with the highest grade value requirement first to avoid that suitable workers have been assigned to the subtask with a lower grade value requirement and unexpected task failures happen.

GTS presents the deployment of the grade-based service priority method as shown in Algorithm 1. By inputting the grade values of crowdsourcers and the lowest acceptable grade value of each subtask into this algorithm, we can obtain the task sorting result, which is the service priority order.

After sorting all subtasks of all crowdsourcers and obtaining the order T.sort, the miners need to arrange suitable workers for each subtask according to the order, namely, decide the values for all $\tau_{n,k}^{a}, a = \{c, p, s\}$. The objective of crowdsourcer utility maximization is considered in the worker selection procedure. According to (1), the grade values of selected workers should maximize $v(\theta_k^a)p_n^a - f_{n,k}^a$. Therefore, the grade value θ_k^a and payment $f_{n,k}^a$ are two elements to be considered in worker selection. In addition, (1) shows that the rewards to miners reversely influence the utilities of crowdsourcers. We regulate the rewarding amount to miners to be a fraction of the payments to workers; therefore, the rewarding amount is relatively constant.

C. Incentives of Workers

The worker selection procedure and the structure of payment $f_{n,k}^a$ influence the incentives of workers.

Combining the requirements of each subtask with our research goals, the worker selection procedure aims at solving the following problems by determining the values for all $\tau_{n,k}^a$:

$$\text{maximize} \quad U_n, \text{SW}, \text{SG}, -\text{SC}$$

$$\text{s.t.} \quad \sum_k \tau_{n,k}^a f_{n,k}^a \le \psi_n^a \quad \forall n \tag{9}$$

$$\tau_{n,k}^a \theta_k^a \ge \tau_{n,k}^a \Theta_n^a \quad \forall n \tag{10}$$

$$\sum_n \sum_a \tau_{n,k}^a \le NUM_k \quad \forall k. \tag{11}$$

Condition (9) means that the payments to all workers that perform each subtask should not exceed the budget of each crowdsourcer. We enable (10) to represent that the selected workers should satisfy the minimum grade value requirements. The condition (11) shows the capability limitation of workers.

The main objective of crowdsourcers is to recruit the economical workers with high grade and low cost. In this case, they can recruit more workers with the given budget constraint, thus increasing the task-completion profits. In order to select the economical workers and balance the tradeoff between social grade maximization and social cost minimization, we define the ratio of the bid to grade as premium and introduce a parameter $\omega_{n,k}^a$ to quantify the premium of W_k in performing t_n^a, where

$$\omega_{n,k}^a = \frac{b_{n,k}^a}{\theta_k^a}, a = \{c, p, s\}. \tag{12}$$

A lower value of ω equates to a more economical worker.

In order to reduce the computational complexity of the worker selection procedure, we propose a hierarchical worker selection method to assign workers for each subtask in T.sort according to priority. Specifically, the miners first filter the available worker set and produce a candidate worker set for each subtask according to Θ_n^a. Then, they optimize the assignments by choosing the workers according to $\omega_{n,k}^a$ in the candidate worker set and the capabilities of these workers.

Overall, the miners apply Algorithm 2 to select workers for all subtasks in T.sort sequentially. They first initialize the number of subtasks that each worker W_k has conducted num(k) as 0. For each subtask, they exclude the workers in $\mathcal{W}$ with unqualified grade and produce the candidate worker

Algorithm 2: PTA

Input: $T.sort$, $\mathcal{W}$, $\{b_{n,k}^a\}$, $\{\psi_n^a\}$, $\{\theta_k^a\}$, $\{\Theta_n^a\}$, $\{NUM_k\}$
Output: $\{\tau_{n,k}^a\}$

Initialization: Set all $num(k) = 0$, $\mathcal{CW}_n^a = \emptyset$, $B_n^c = 0$, set all $\tau_{n,k}^a = 0$;
for $i = 1$ *to* $\mid T.sort \mid$ **do**
  if $T.sort(i) = t_n^a$ **then**
    for $k = 1$ *to* $\mid \mathcal{W} \mid$ **do**
      if $(\theta_k^a \ge \Theta_n^a) \wedge (W_k \in \mathcal{W})$ **then**
        add W_k into $\mathcal{CW}_n^a$;
      end
    end
    for $k' = 1$ *to* $\mid \mathcal{CW}_n^a \mid$ **do**
      calculate $\omega_{n,k'}^a \leftarrow \frac{b_{n,k'}^a}{\theta_{k'}^a}$;
    end
    sort $\mathcal{CW}_n^a$ according to the non-decreasing order of $\omega_{n,k'}^a$ as $\mathcal{CW}_n^a.sort$;
    set $NUM_n^a = \underset{\kappa}{argmax}\left\{\kappa \,|\, \frac{\psi_n^a}{\sum_{\bar{k}=1}^{\kappa}\theta_{\bar{k}}^a} \ge \omega_{n,\kappa}^a\right\}$, where $W_{\bar{k}} \in \mathcal{CW}_n^a.sort$;
    select the first NUM_n^a workers in $\mathcal{CW}_n^a.sort$ as the selected workers and formulate $\mathcal{SW}_n^a$;
    for $k_a = 1$ *to* NUM_n^a **do**
      find the k such that $\mathcal{SW}_n^a(k_a)$ is $\mathcal{W}(k)$;
      set $\tau_{n,k}^a = 1$;
      $num(k) \leftarrow num(k) + 1$;
      if $num(k) \ge NUM_k$ **then**
        $\mathcal{W} \leftarrow \mathcal{W} \setminus \{W_k\}$;
      end
    end
  end
end

set $\mathcal{CW}_n^a$. Then, they sort $\mathcal{CW}_n^a$ according to the nondecreasing order of $\omega_{n,k'}^a$ as $\mathcal{CW}_n^a$.sort. Considering that the selected worker number of t_n^a is decided by budget ψ_n^a, they set $\text{NUM}_n^a = \text{argmax}_\kappa\{\kappa|(\psi_n^a/[\sum_{\bar{k}=1}^{\kappa}\theta_{\bar{k}}^a]) \ge \omega_{n,\bar{k}}^a\}$, where $W_{\bar{k}} \in \mathcal{CW}_n^a$.sort. They select the first NUM_n^a workers in $\mathcal{CW}_n^a$.sort as the selected workers and formulate $\mathcal{SW}_n^a$. The workers whose capabilities are depleted after being selected will quit from the existing worker set for the next round.

To ensure the truthfulness of our incentive mechanism, namely, to motivate the workers to bid with their real costs, we design $f_{n,k}^a$ according to the following rule [38]:

$$f_{n,k}^a = \min\left\{\frac{\psi_n^a}{\sum_{W_{\bar{k}} \in \mathcal{SW}_n^a}\theta_{\bar{k}}^a}, \omega_{n,k+1}^a\right\} \times \theta_k^a. \tag{13}$$

The value of $f_{n,k}^a$ is irrelevant to $b_{n,k}^a$, thus W_k has no incentive to misreporting bids, which could further adversely influence its probability of being selected. In addition, $f_{n,k}^a$ is positively correlated with θ_k^a for motivating high-grade workers.

Algorithm 3: Payment of Workers

Input: C_n, $\mathcal{W}$, t_n^a, $\{\tau_{n,k}^a\}$, $\{\theta_k^a\}$, $\{b_{n,k}^a\}$
Output: $\{f_{n,k}^a\}$
for $a \in \{c, p, s\}$ **do**
  for $k = 1$ *to* K **do**
    if $\tau_{n,k}^a = 1$ **then**
      calculate $f_{n,k}^a$ according to (13);
    else
      $f_{n,k}^a = 0$;
    end
  end
end

Algorithm 4: Reward Allocation of Miners (FGSGRS)

Input: C_n, $\{f_{n,k}^a\}$, $\{\tau_{n,k}^a\}$, γ_n, $\mathcal{M}$, $\{\theta_l\}$, $\mathcal{SM}_n$, Ξ
Output: $\{\tau_l^n\}$, $\{g(\theta_l)\}$
Initialization: $\xi_n = 0$, set all $\tau_l^n = 0$;
$R_n = \gamma_n \sum_k \sum_{a=\{c,p,s\}} \tau_{n,k}^a f_{n,k}^a$;
for $i = 1$ *to* $\mid \mathcal{SM}_n \mid$ **do**
  while $\xi_n < \Xi$ **do**
    find l such that $\mathcal{SM}_n(i)$ is M_l;
    $\tau_l^n = 1$;
    $\xi_n \leftarrow \xi_n + \theta_l$;
  end
end
for $l = 1$ *to* L **do**
  $g(\theta_l, \tau_l^n) \leftarrow \frac{\tau_l^n \theta_l}{\sum \tau_l^n \theta_l}$;
  C_n pays $g(\theta_l, \tau_l^n) R_n$ to miner M_l;
end

D. Incentive of Miners

For reducing the reward variance of miners, we borrow the idea from mining pools and distribute the rewards among miners. Considering that only sharing rewards to the high-grade miners will cause centralization, we regulate that only the first several miners that involve all the transactions of C_n in their blocks will be rewarded by C_n.

We set that the first several miners, the sum of whose grade values exceeds Ξ, can share the rewards from C_n for motivating high-speed transaction verification and block generation. Any miner has the same probability to be rewarded by the same crowdsourcer when the miners have the same network and communication environment, that is not influenced by their grade values.

As explained in Section IV-B, we consider the reward to miners paid by C_n is a fraction of the total payments to workers. Therefore, the miners are motivated to verify the transactions related to high-grade workers as the high-grade workers are more likely to obtain high profits. Denoting the fraction as γ_n, the utility function of M_l can be formulated as follows:

$$U_l = \sum_n \left(g\left(\theta_l, \tau_l^n\right) \gamma_n \sum_k \sum_{a=\{c,p,s\}} \tau_{n,k}^a f_{n,k}^a - c_l^n \right). \quad (14)$$

Herein, $g()$ is a grade-based reward-sharing function; therefore, the high-grade miners are motivated to participate.

Besides, we provide Algorithm 4 to compute the reward to each miner based on the FGSGRS method. $\mathcal{SM}_n$ illustrates the set of miners that have found the blocks with T_n and these miners are organized in chronological order. We first initialize the parameter ξ_n as 0, which denotes the accumulated grade value of the miners that have verified all the transactions of C_n, and the qualification of all miners to share the reward $\{\tau_l^n\}$ as 0. We find the first several members in $\mathcal{SM}_n$ that make ξ_n exceeds Ξ. After identifying the order of these miners in $\mathcal{M}$, we assign $\{\tau_l^n\}$ as 1 to the corresponding M_l. The shared reward of each miner in $\mathcal{M}$ is calculated according to (4).

V. Experiment Evaluation

We conducted several experiments based on simulation-based data sets to evaluate the effectiveness of GAIMMO and compared our methods with some borderline methods. This section first describes our experiment settings, followed by the experiment results of GAIMMO. We also compared our three auxiliary algorithms with borderline methods, respectively, to evaluate the superiority of GAIMMO.

The experiment results of GAIMMO are presented in terms of the utilities of all system entities, the average grade, and average premium of the selected workers in the crowdsourcers with different grade values.

First, we compared our GTS algorithm with a random task sorting algorithm (*borderline method 1*) [37], [39], [40], which simulates the first-come–first-serve scenario for the service priority arrangement of crowdsourcers. The purpose of this comparative experiment is to evaluate the effectiveness of our grade-based service priority method in motivating high-grade crowdsourcers. Therefore, we documented the utility of crowdsourcers, the average grade of workers, and the average premium of workers in each crowdsourcer as the evaluation metrics.

Second, we measured our premium-based worker selection method with a grade-based worker selection method (*borderline method 2*) and a cost-based worker selection method (*borderline method 3*) [31], [33]. Borderline method 2 is widely applied when a grade mechanism exists while the other one is the method adopted in auction theory. Notably, the other methods, including the task sorting method and the payment allocation method, remain the same as in GAIMMO. We employed the utilities of crowdsourcers, social welfare, social cost, and social grade in each crowdsourcer as the evaluation metrics, which are the parameters to be optimized in Section IV-C.

Third, we analyzed the effectiveness of our FGSGRS method by comparing the utility of miners with that in a fixed-grade-sum and average reward-sharing (FGSARS) method (*borderline method 4*) and a fixed-miner-number and grade-based reward-sharing (FMNGRS) method (*borderline method 5*). We merely took the utility of miners as the evaluation metric, since it was the only

TABLE III
PARAMETER SETTINGS

Notation	Value	Notation	Value	Notation	Value
N	10	K	100	L	100
θ_n	[0.5,1)	θ_l	[0.5,1)	NUM_k	[5,9]
θ_k^a	[0.5,1)	$c_{n,k}^a$	[1,2]	α_n	2
ψ_n^c	40	ψ_n^p	30	ψ_n^s	30
Θ_n^c	0.6	Θ_n^p	0.65	Θ_n^s	0.7
γ_n	0.2	c_l^n	0.1	Ξ	20

parameter that was influenced by these reward-sharing methods.

A. Experimental Settings

We simulated a crowdsourcing system[1] as follows. The parameter settings are concluded in Table III.

We considered a system with ten crowdsourcers, 100 workers, and 100 miners. The grade values of each kind of system entity are uniformly distributed between 0.5 and 1. The value of 0.5 is typically the baseline. The entities with grade values that are below 0.5 behave badly and will hardly be selected by rational crowdsourcers. Therefore, they will be excluded from the system gradually and we do not consider them in our system. The capability of a worker is between 5 and 9. The values of $\Theta_n^a(a = c, p, s)$ are the same for all crowdsourcers; therefore, we can evaluate the influence of the grade values of the crowdsourcers by comparison easily. We regarded $\Theta_n^s > \Theta_n^p > \Theta_n^c$ to represent that the security of stored data is more important than the accuracy of data processing results while the quality of the collected data is the comparatively least important element. We can change the relationships among Θ_n^a to represent other scenarios. In our experiment, the primary difference between crowdsourcers is their grade values so that we can discover the influence of grade values of crowdsourcers on evaluation metrics.

Furthermore, we scheduled that the costs of the workers with the same grade for each subtask vary from 1 to 2. We configured this setting to involve the workers with different grade values and different costs, thus with different premiums. We assigned budgets ψ_n^c, ψ_n^p, and ψ_n^s with the value 40, 30, and 30 and set α_n as 2. The value of α_n only influences the task-completion profit of crowdsourcers, which should be the same when other incentive mechanisms are applied. Based on the values of these parameters, we can further calculate p_n^a according to (2).

We determined γ_n is 0.2 and set the value to be the same for every crowdsourcer since its value has little influence on our experimental results. We designed that the miners were equipped with the same mining cost but different grade values, therefore, we can identify the influence of their grade. The required accumulated grade of miners for generating a new block, Ξ, is a system default parameter and we considered it as 20. We instantiated $v(\theta_k^a)$ as follows:

$$v\left(\theta_k^a\right) = \begin{cases} 1 + \left(\theta_k^a - \Theta_n^a\right)^{\frac{1}{2}}, & \theta_k^a \geq \Theta_n^a \\ 1 - \left(\Theta_n^a - \theta_k^a\right)^{\frac{1}{2}}, & \theta_k^a < \Theta_n^a. \end{cases} \quad (15)$$

[1]The data sets can be found here: https://drive.google.com/drive/folders/1CVKEwiWzjkABDZ_e3HV9iVSFF4CXxMZt?usp=sharing.

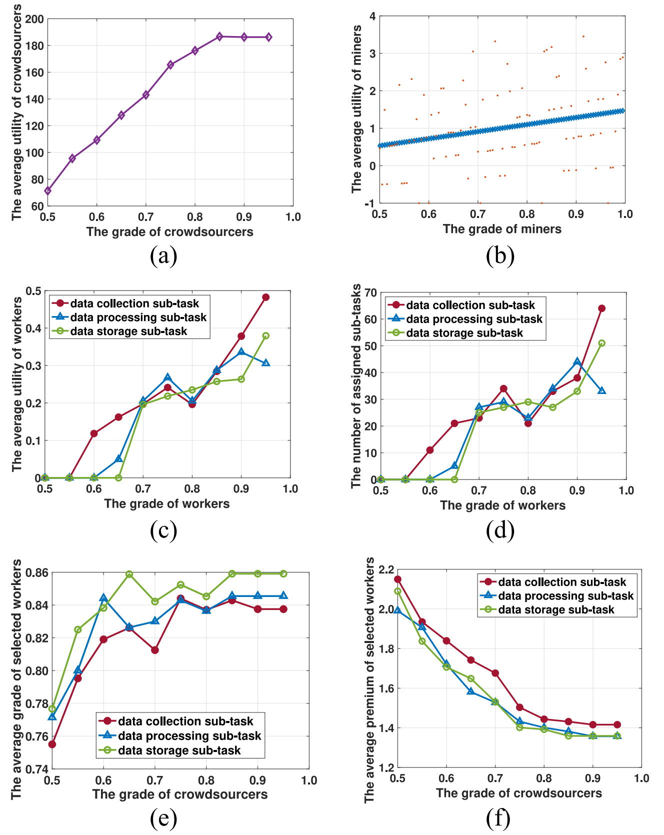

Fig. 3. Results of GAIMMO. (a) Average utilities of crowdsourcers. (b) Average utilities of miners. (c) Average utilities of workers for performing every subtask. (d) Total number of assigned subtasks to the workers. (e) Average worker grade of different subtasks in different crowdsourcers. (f) Average worker premium of every subtask in different crowdsourcers.

B. Experimental Results of GAIMMO

We first deployed the auxiliary algorithms of our incentive mechanism with the above parameter settings. The evaluation metrics in this experiments are the utilities of all system entities, the average grade, and average premium of selected workers in each crowdsourcer.

Fig. 3(a)–(c) shows the average utilities of all system entities. Specifically, the red dots in Fig. 3(b) represents the utility of each miner while the blue line is the fitted function curve of miners' utilities. We can find that a high-grade value enables each system entity to roughly obtain a high utility; therefore, our incentive mechanism can motivate them to behave cooperatively for keeping the grade value at a high level. Fig. 3(d) implies that normally a high-grade value means a large number of assigned subtasks. Combined with Fig. 3(c), we can conclude that a high-grade worker will obtain a high total utility. The average worker grade for each subtask generally increases with the rise of the crowdsourcer grade, as plotted in Fig. 3(e). Therefore, our GTS algorithm guarantees that a high-grade crowdsourcer can obtain services from high-grade

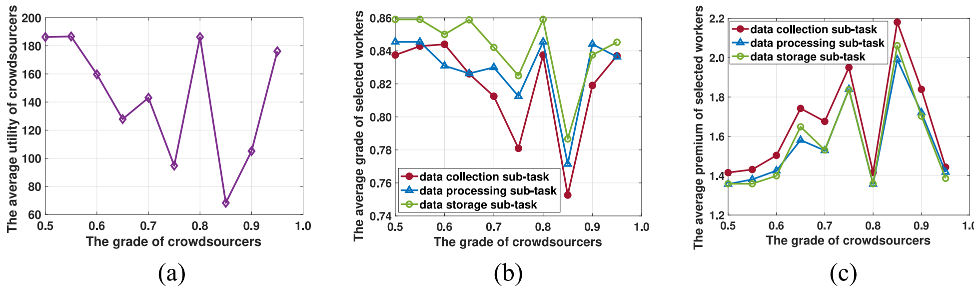

Fig. 4. Experimental results of borderline method 1. (a) Average utility of crowdsourcer. (b) Average worker grade of different subtasks in different crowdsourcers. (c) Average worker premium of every subtask in different crowdsourcers.

workers. Despite some downward trends in Fig. 3(e), the utilities of crowdsourcers never drop and the average premium of workers linearly decreases with the rise of the grade of crowdsourcers, as shown in Fig. 3(a) and (f), respectively.

To sum up, our incentive mechanism can successfully motivate system entities to behave cooperatively for maintaining their grade values at a high level. In the following sections, we will further compare these experimental results of GAIMMO with those of borderline methods to illustrate the advantages of our methods in achieving multiple objectives.

C. Comparison With Borderline Method 1

We compared the borderline method 1 with our grade-based service priority method, while keeping the other methods the same as in Section V-B. The evaluation metrics include the average utility of crowdsourcers, the average grade value, and the premium of selected workers.

Fig. 4 illustrates that these metrics fluctuate with the growth of the grade values of crowdsourcers. The reason is that the service is arranged to the crowdsourcers randomly while the crowdsourcers that are served earlier can have more choices so that they can select the most economical workers. By comparing Fig. 4 with Fig. 3(a), (e), and (f), we found that our incentive mechanism holds the advantages in promoting the crowdsourcers to maintain their grade values, which contributes to building a reliable system environment.

D. Comparison With Borderline Methods 2 and 3

The borderline methods 2 and 3 refer to two kinds of worker selection methods. The evaluation metrics are the parameters to be optimized by the worker selection method in Section IV-C.

Fig. 5(a) presents the utilities of crowdsourcers with different grade values. GAIMMO provides the highest utilities among these three methods when the grade of crowdsourcers is higher then 0.7. In addition, GAIMMO performs better than the cost-based worker selection method with regard to the crowdsourcer utility. Fig. 5(b) shows the social welfare in the crowdsourcers with different grade. In general, GAIMMO provides the highest social welfare for the participants in crowdsourcers with grade values higher than 0.65 and the grade-based worker selection method performs the best when the grade value is lower than 0.6. Fig. 5(c) demonstrates the social cost in each crowdsourcer. The social costs are relatively

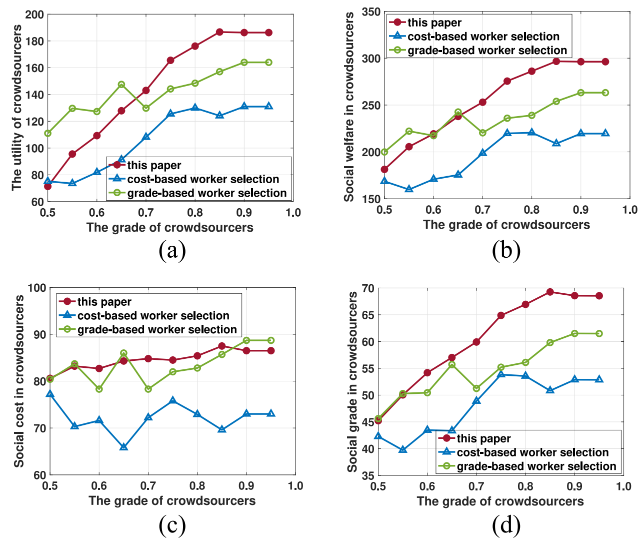

Fig. 5. Comparative results of our method and borderline methods 2 and 3. (a) Utilities of crowdsourcers. (b) Social welfare in crowdsourcers. (c) Social cost in crowdsourcers. (d) Social grade in crowdsourcers.

constant parameters with regard to the rise of the crowdsourcer grade since the budgets of the crowdsourcers are constant. The cost-based worker selection works best for each crowdsourcer as it is designed to select workers with small costs. Unfortunately, the social costs are the highest in almost all crowdsourcers when GAIMMO is applied. Fig. 5(d) displays the social grade in the crowdsourcers with different grade. We identified that the social grades of all crowdsourcers when the cost-based worker selection method is adopted are the smallest among all methods. Although the grade-based worker selection method assigns high-grade workers to each subtask, it fails to consider the cost of workers and cannot recruit more workers than GAIMMO. Consequently, GAIMMO accumulates a larger social grade for each crowdsourcer than the grade-based worker selection method.

To clearly compare the overall performance of our method and the comparative methods, we introduced a parameter

$$\mathrm{OP} = \beta_1 \overline{U_n} + \beta_2 \overline{\mathrm{SW}} + \beta_3 \overline{\mathrm{SG}} - \beta_4 \overline{\mathrm{SC}} \tag{16}$$

where $\beta_1 + \beta_2 + \beta_3 + \beta_4 = 1$ and $\overline{U_n}, \overline{\mathrm{SW}}, \overline{\mathrm{SG}}, \overline{\mathrm{SC}}$ are the normalized values. We assigned the value of $[\beta_1, \beta_2, \beta_3, \beta_4]$ as $[0.25, 0.25, 0.25, 0.25]$, $[0.3, 0.3, 0.2, 0.2]$, $[0.3, 0.25, 0.25, 0.2]$, and $[0.4, 0.3, 0.2, 0.1]$ to represent four

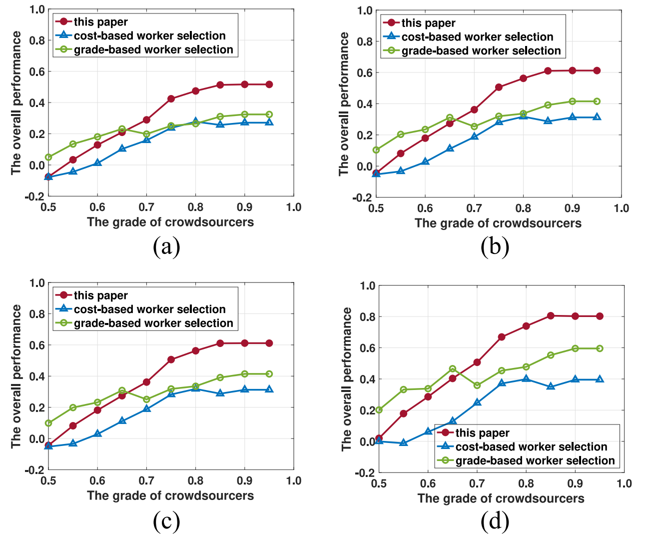

Fig. 6. Overall performance of our method and borderline methods 2 and 3. (a) $[\beta_1, \beta_2, \beta_3, \beta_4] = [0.25,0.25,0.25,0.25]$. (b) $[\beta_1, \beta_2, \beta_3, \beta_4] = [0.3,0.3,0.2,0.2]$. (c) $[\beta_1, \beta_2, \beta_3, \beta_4] = [0.3,0.25,0.25,0.2]$. (d) $[\beta_1, \beta_2, \beta_3, \beta_4] = [0.4,0.3,0.2,0.1]$.

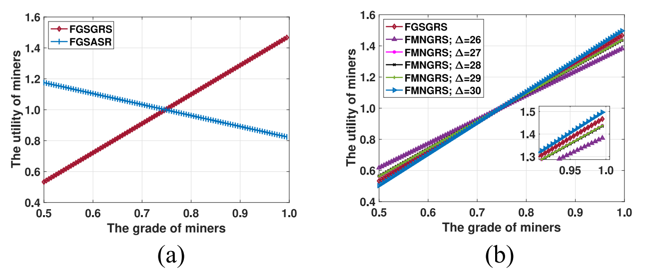

Fig. 7. Comparative results in terms of the utility of miners. (a) Between our method and borderline method 4. (b) Between our method and borderline method 5.

kinds objectives of the crowdsourcers and plotted the corresponding results in Fig. 6. We discovered that the overall performance of our method was generally better than the grade-based worker selection method when the grade of crowdsourcer is higher than 0.65. while the cost-based selection method performed worst under our system settings.

E. Comparison With Borderline Methods 4 and 5

The borderline methods 4 and 5 refer to two kinds of reward-sharing methods for the miners. Specifically, we employed the FGSARS method and the FMNGRS method as the borderline methods 4 and 5 and compared their performance in the utility of miners with our FGSGRS method, respectively.

Fig. 7(a) shows that the grade-based reward-sharing method (i.e., the line with diamonds) guarantees that a high-grade miner can obtain a high profit while the average sharing method (i.e., the line with vertical bars) has the opposite effect, when we consider to reward the first several miners when the sum of their grade values reaches a threshold. Fig. 7(b) depicts the results of grade-based reward-sharing methods in the contexts of fixed grade sum (i.e., the line with diamonds) and fixed miner number (i.e., all the other lines except the one with diamonds), respectively. The utilities of high-grade miners decrease with the rise of the fixed number of miners Δ to be rewarded. Similarly, the utilities of low-grade miners increase with the rise of the fixed number of miners, since the total rewards to the miners are stable and the small Δ means a large share. Furthermore, under our parameter settings, the high-grade miners can obtain more profits in our method (fixed grade sum) than in the fixed-miner-number method when $\Delta < 30$. Therefore, our method performs well in motivating the participation of the high-grade miners.

F. Discussion

The time complexity of Algorithm 1 is related to the number of crowdsourcers and the time complexity of the applied sorting algorithm, which is not specified in Algorithm 1. If the merge sort algorithm is applied, then the time complexity of Algorithm 1 becomes $O(N \log N)$, where N stands for the number of crowdsourcers. Algorithm 2 assigns $3N$ subtasks to K workers. The time complexity for the task assignment of each subtask is $O(K + k \log k)$, where k is the number of selected workers. Therefore, the time complexity of Algorithm 2 is $O(NK + Nk \log k)$. Algorithm 3 outputs the payments to all workers, the time complexity of which is $O(K)$. Algorithm 4 needs to find the order of rewarded miners, the time complexity of which is $O(lL)$. Herein, l refers to the number of rewarded miners. Algorithm 4 calculates the rewards to each miner with a time complexity is $O(L)$. Therefore, the overall time complexity of Algorithm 4 is $O(lL)$. In the future, we will continue to consider how to improve the efficiency of our algorithms and produce near-optimal task assignment results with formal proof.

This article focuses on discussing a crowdsourcing scenario that all subtasks can be completed. In the future, we will further investigate a more complicated scenario with scarce workers and mutual restriction among different subtasks during the fulfillment of a whole task.

VI. Conclusion

In this article, we proposed GAIMMO, which is a novel grade-driven auction-based incentive mechanism for BCS with heterogeneous system entities. GAIMMO aims to achieve multiple objectives, including crowdsourcer utility maximization, social welfare maximization, social grade maximization, and social cost minimization. Considering the dominance of crowdsourcers in BCS, we took crowdsourcer utility maximization as our primary objective. Specifically, we proposed the grade-based service priority method to motivate high-grade crowdsourcers and carefully designed the utility functions of other system entities for avoiding profit losses of the crowdsourcers as well as guaranteeing the truthfulness of bids. Then, we selected workers for each subtask according to the requirements of crowdsourcers and the capability of the workers. Meanwhile, we adopted the hierarchical PTA algorithm to balance the objectives of social welfare maximization, social grade maximization, and social cost minimization. We associated the utilities of miners with grade values for motivating them to behave cooperatively and proposed the FGSGRS method to encourage quick block generation without sacrificing the profits of crowdsourcers. The experimental results illustrated the effectiveness of our incentive mechanism in motivating all system entities to gain high-grade values and the achievement of multiple objectives.

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