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A Two-layer Game-based Incentive Mechanism for Decentralized Crowdsourcing

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***Abstract*—Decentralized crowdsourcing removes the dependence on a trusted centralized platform based on blockchain and ensures system stability through the consensus of miners. The lack of centralized supervision requires all kinds of system nodes to voluntarily participate while their behaviors are profit-driven and unpredictable, thus introducing challenges to system performance. Moreover, the nodes in a decentralized crowdsourcing system inherently observe little information about the system status; therefore, it is difficult for them to discover and adopt theoretically optimal strategies. Current literature still lacks an effective mechanism to motivate the participation of all types of nodes. To this end, this paper employs a two-layer game model to simulate the interactions in the decentralized crowdsourcing system for investigating the participation willingness of different system nodes. Specifically, we apply a Stackelberg game to model the interactions of a crowdsourcing requester and other nodes, where the requester decides its reward policy and the others respond by selecting their roles to play. In addition, the interaction of the bounded rational other nodes is further represented as an evolutionary game. After analyzing the game model, we further design an incentive mechanism to maximize the requester utility while motivating other nodes to actively participate in the crowdsourcing. Through experimental simulations, we verify the effectiveness of the proposed incentive mechanism.**

***Index Terms*—blockchain, crowdsourcing, evolutionary game, Stackelberg game, incentive mechanism**

I. Introduction

Blockchain supports distributed and data-driven autonomous management [1] by applying a consensus mechanism to get rid of a trusted central party. Advanced cryptography technology enables the blockchain with the characteristics of decentralization, immutability, traceability, transparency, anonymity. The properties of blockchain, such as decentralization, immutability, anonymity, and anonymity enable it to be widely applied in many scenarios, where decentralized crowdsourcing (DCS) is one of them [16] [17].

DCS contains three types of nodes: workers, miners, and requesters. The requesters would like to collect large-scale data by requesting DCS service, while the workers collect, process and store data. The miners collaborate to distributively maintain and manage the DCS system. The service quality and system security of DCS significantly rely on the massive engagement of workers and miners. However, current research supposes their active participation by default, which is apparently an unreasonable assumption since practical nodes are rational and profit-driven.

Incentive mechanism applies a variety of internal or external incentives to standardize and relatively immobilize the expected behavior of system nodes. In DCS, due to the lack of centralized control, the active participation and cooperative behavior of nodes is more necessary to ensure the security and sustainability of the system. However, the dynamic environment and unpredictable node behavior pose challenges to the performance of the system. Quality control is a hot spot in the crowdsourcing system, which should be more carefully considered in DCS because of the uncooperative behavior caused by node anonymity and distribution. Concretely, workers may send fake data and miners may refuse to generate and broadcast blocks. Therefore, a reasonable and feasible incentive mechanism is badly needed to encourage the active participation of all nodes and ensure their cooperative and trustworthy behavior for improving system performance.

Existing incentive mechanisms in DCS are mostly designed based on game theory [8] and auction theory [18] [9] with the goal of maximizing the requester utility, or apply service quality [12] or reputation [7] as an incentive to the cooperation of workers. Unfortunately, the incentive need of miners is totally missed in the existing works [6]–[12]. Moreover, the cryptocurrency-based incentive mechanisms are controversial for the uncertainty of its practical value.

We are confronting several challenges due to the diversity and complexity of decentralized scenarios when addressing the above problems in existing DCS incentive mechanisms. On one hand, zero trust between a large number of distributed nodes impedes their active participation, which is essential to the successful deployment of DCS. The incomplete information of bounded rational nodes greatly complicate node interaction. Therefore, it is extremely difficult to select an appropriate model for capturing the node interaction and further analyze the process of node strategy selection. On the other hand, the introduction of miners into DCS makes the design of an incentive mechanism convoluted. The participation of massive rational miners and workers, which contribute to the security and service quality of DCS, requires the requesters to pay additional rewards, compared with a centralized solution. Undoubtedly, the requesters hope to pay the rewards as low as possible for profit maximization.

To overcome these challenges, this paper employs the game theory to construct an incentive mechanism for motivating various system nodes to actively participate in DCS while maximizing the requester utility. Firstly, we design the utility functions of various nodes to build a proper economic model. Secondly, we apply a two-layer game to model the interactions of all system nodes, where a Stackelberg game [3] is adopted to simulate the interaction of a requester and other nodes and an evolutionary game [2] is applied to model the strategy evolution of the other nodes. Thirdly, we employ a backward induction to analyze this two-layer game, based on the game theoretical analysis, we propose an incentive mechanism that can maximize the requester utility and motivate other nodes to actively work as miners and workers.

The rest of this paper is organized as follows. Section II reviews existing incentive mechanisms in DCS. Section III presents the system model and economic model of DCS, according to which we design our two-layer game-based incentive mechanism in Section IV. Section V presents experimental results and the last section concludes this paper.

II. Related Work

This section reviews existing literature about incentive mechanisms in DCS and concludes their shortcomings.

Cheng et al. [6] and Xu et al. [7] both adopted reputation-based incentives for workers. Kadadha et al. [10] employed smart contracts to establish a fair and transparent incentive mechanism. However, these three incentive mechanisms do not consider the incentives to requesters and miners. An et al. [12] designed the rewards of workers and miners to be distributed according to their contributions without considering the requester incentive. Considering long-term high-quality sensor data collection under budget constraints, Hu et al. [8] proposed a three-stage Stackelberg game to maximize the utilities of both requesters and workers. To motivate worker participation in data collection and sharing, an auction-based quality-driven incentive mechanism is proposed in [9]. Lai et al. [11] designed a reverse auction-based incentive mechanism to motivate vehicles (workers) to participate in perceptual tasks while maximizing the requester utility. However, the incentive to miners is still missing. Yin et al. [14] developed a bidding mechanism based on time constraints and quality requirements to motivate vehicles to participate in sensing tasks. However, the implementation method and algorithm flow of the bidding mechanism are not specific. Li et al. [13] regulated that the rewards of workers are automatically allocated according to the evaluation results of their solutions while the evaluation scheme and reward distribution mechanism are not clear. Feng and Yan [15] designed that the rewards of both workers and miners are positively correlated with their credit values, so as to motivate each node to act honestly. However, the reward mechanism to miners is unclear and they did not consider to incent the requester.

To sum up, existing work unrealistically assumes that nodes are completely rational, which leads to a mismatch between theoretical analysis and practical strategy selection. Moreover, most incentive mechanisms ignore the incentive to miners; however, the miners play an important role in maintaining system security and reliability. To overcome these deficiencies, we aim to propose an incentive mechanism that can maximize the requester utility and motivate the active participation of workers and miners with bounded rationality.

III. System Model

In this section, we present the general procedure of DCS and summarize our research assumptions, based on which we further establish an economic model.

We consider a DCS with a requester and multiple nodes $\mathcal{N}$ that behave as workers and miners. The node acts as a worker and miner is called a hybrid node. The requester obtains high-quality task completion by providing appropriate remuneration to workers and miners. There are many types of worker nodes in mobile crowdsourcing system, such as data acquisition node, data storage node and data processing node. They collaborate to perform mobile crowdsourcing tasks according to protocol. Miner nodes collaborate to maintain and manage blockchain systems. Fig. 1 shows the structure of DCS and the procedure of DCS is as follows:

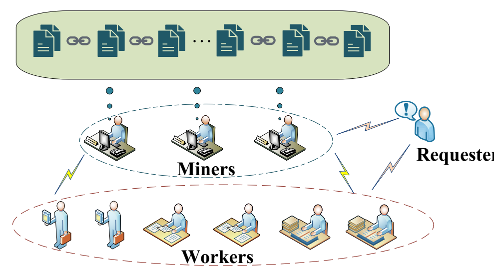

Fig. 1. Architecture of DCS.

A requester publishes its task request message while the miners that receive this message verify the validity of the task and broadcast the valid task through the blockchain. After receiving the task request, qualified workers selected by the requester perform the task and send their bids for this task. The workers can be further classified based on their functions and the task types. Then the task-completion quality of each worker is assessed by the miners. All the task related information are recorded in blocks. The miners generate and reach a consensus on blocks to ensure system security. All nodes do not trust with each other and they cannot be fully trusted.

This paper considers K types of sub-tasks, which is corresponding to K types of workers. We denote the total number of nodes of the j-th type of task as N_j. Each node $n_i \in \mathcal{N}$ has a quality attribute $\alpha_{j,i}$ as a worker and a contribution value $\theta_{j,i}$ as a miner for the j-th type of task.

A. Research Assumptions

Before concrete analysis, we summarize our research assumptions herein. To simplify our model, we assume that there is only one requester and its task is divided into multiple subtasks according to the task content. We assume the workers for the same subtask are homogeneous and each node can only perform one type of subtask considering their equipment constraints. The contribution of miners is related to their behavior in system maintenance and management. Each node will make rational behaviors dominated by its own interests. The work quality and contribution value will be verified by miners and recorded on the blockchain, thus no one can modify them.

B. Economic Model

Let $x_i \in \{M_j, W_j, H_j, A_j\}$ represent the strategy of node $n_i \in \mathcal{N}_j$, where M_j, W_j, H_j, A_j denote the strategy of being a miner, a worker, a hybrid node and not to participate, respectively. $I_{M_j}, I_{W_j}, I_{H_j}, I_{A_j}$ represent node sets that choose M_j, W_j, H_j, A_j. The requester provides reward $R_{T,j}$ at most for the j-th type of subtask, among which the reward proportion to workers is γ_j. Below are the node utility functions.

1) Miner: Considering the safety of the system jointly maintained by the miners, the reward of a miner depends on its relative contribution value, $\frac{\theta_{j,i}}{\sum\limits_{k \in I_{M_j}} \theta_{j,k}}$. According to the law of diminishing marginal cost [4], we use logarithmic function to model the relationship of the miner cost and its contribution value. Therefore, the utility of the j-th type of miners is:

$$E_{m,j} - C_{m,j}. \tag{1}$$

Herein, $E_{m,j} = R_{T,j} \times (1 - \gamma_j) \times \frac{\theta_{j,i}}{\sum\limits_{k \in I_{M_j}} \theta_{j,k}}$ and $C_{m,j} = \mu_j \times \log_2(1 + \theta_{j,i})$, where μ_j is the cost adjustment factor.

2) Worker: The reward of each node is distributed according to its work quality and the average reward. Based on the law of diminishing returns, a worker can get diminishing returns from unit work quality as its work quality increases. We adopts $\tanh$ [5] to construct the influence of work quality on reward. The utility of the j-th type of workers is:

$$E_{w,j} - C_{w,j}. \tag{2}$$

Herein, $E_{w,j} = \frac{R_{T,j} \times \gamma_j}{|I_{W_j}|} \times \frac{\tanh((\alpha_{j,i} - \overline{\alpha_j}) \times c_j) + 1}{2}$ and $C_{w,j} = \rho_j \times \alpha_{j,i}$. $\overline{\alpha_j}$ is the mean work quality of the j-th subtask and c_j is the worker reward regulation parameter. ρ_j represents the cost of the j-th type of worker with unit work quality.

3) Hybrid node: As miners will verify the work quality of workers, the hybrid node can make malicious verification to reduce the enthusiasm of other nodes to act as worker nodes and decrease the work quality of other worker nodes. To alleviate this situation, we set that the income of a hybrid node for acting as a worker and a miner will reduce considering its potential malicious behavior. The utility of the j-th type of hybrid nodes is:

$$\sigma_{j,1} \times E_{m,j} - C_{m,j} + \sigma_{j,2} \times E_{w,j} - C_{w,j}. \tag{3}$$

where $\sigma_{j,1}$ and $\sigma_{j,2}$ represent the attenuation factors of the miner income and the worker income, respectively.

4) Node that does not participate: This type of nodes has no income and without any cost, so its utility is 0.

5) Requester: The requester directly benefits from the completed task by paying rewards to the other nodes. At the same time, a high overall contribution value of all miner guarantees the credibility of work quality, which indirectly ensures the requester income. The requester gains diminishing marginal utility from work quality and obtains low benefit from the contribution values less than a certain threshold, thus, we use $\ln$ and $\cos$ to model the relationship of the requester income and the work quality as well as the contribution value, respectively. Therefore, the income of the requester is positively correlated with the work quality provided by worker nodes and the total contribution value provided by miner nodes. Let $\lambda_{j,1}$ and $\lambda_{j,2}$ be the income regulation parameters of the requester from the workers and miners, we can summarize the requester utility in (4).

IV. Two-layer Game-based Incentive Mechanism

A. Two-layer Game Model

According to the DCS workflow, we model the interaction between the requester and other nodes as a Stackelberg game. Considering that the other nodes are bounded rational, we use an evolutionary game to simulate their strategy selection.

1) Stackelberg game: In the first stage, the requester acts as a leader by setting its reward pricing with $R_{T,j}$ and γ_j. In the second stage, the other nodes respond to the requester strategy by choosing a role for maximizing their own utilities.

2) Evolutionary game: Considering the bounded rationality of other nodes, their role selection procedure is further modeled as an evolutionary game. In this game, population distribution is $I = (I_{M_j}, I_{W_j}, I_{H_j}, I_{A_j})$.

3) Two-layer game equilibrium: We employ a backward induction method to analyze the game equilibrium. We first analyze the strategy decisions of other nodes under fixed pricing parameters to investigate the evolutionary equilibrium. Then we analyze the influence of $R_{T,j}$ and γ_j on the evolutionary equilibrium and discover the Stackelberg equilibrium.

B. Evolutionary Equilibrium Analysis

We first study the node strategy selection process and then analyze the equilibrium state of the evolutionary game.

1) Game analysis: In each game stage, the nodes select their strategies based on current strategy population distribution at the current stage and the requester pricing strategy. We classify the nodes into risk-averse type and risk-appetite type according to their risk preference characteristics. To simplify the analysis, we assume that the same type node has the same risk preference characteristic. Specifically, the risk-averse node chooses the strategy with higher utility while the risk-appetite node would like stay with the current strategy to gamble.

We define the income obtained by predicting the node change in a strategy set as the risk return $f_{j,k}$, $k \in \{H, M, N, A\}$, which can be positive or negative. A large-scale strategy set poses great risks to its members while the risk return could be high. The risk return of a risk-averse node is 0 while that of a risk-appetite node is related to the node number in the strategy set and the utility of this strategy.

$$\sum_{j=1}^{K}\lambda_{j,1}\times\ln(1+\sum_{i\in I_{W_j}}\ln(1+\alpha_{j,i}))+\sum_{j=1}^{K}\lambda_{j,2}\times\frac{1}{2}\times(1-\cos(\frac{\pi}{N_j}\times\sum_{i\in I_{M_j}}\theta_{j,i}))-\sum_{j=1}^{K}(\sum_{i\in I_{W_j}/I_{H_j}}E_{w,j})$$
$$-\sum_{j=1}^{K}(\sum_{i\in I_{H_j}}\sigma_{j,1}\times E_{m,j}+\sigma_{j,2}\times E_{w,j})-\sum_{j=1}^{K}(\sum_{i\in I_{M_j}/I_{H_j}}E_{m,j}). \tag{4}$$

When $x_i = M_j$, if the sum of its utility and risk return is not less than 0, the node will choose to become a miner. To facilitate analysis, we assume that the node contribution values are independent and identically distributed random variables. Let $\overline{\theta_j}$ denote the mean contribution value of the j-th type of miners, then $\sum_{k\in I_{M_j}}\theta_{j,k} = \left|I_{M_j}\right| \times \overline{\theta_j}$. So the utility of the miner is:

$$R_{T,j}\times(1-\gamma_j)\times\frac{\theta_{j,i}}{\left|I_{M_j}\right|\times\overline{\theta_j}}-C_{m,j} \tag{5}$$

Therefore, when $x_i = M_j$, we have

$$R_{T,j}\times(1-\gamma_j)\times\frac{\theta_{j,i}}{\left|I_{M_j}\right|\times\overline{\theta_j}}-C_{m,j}+f_{j,M}\geq 0, \tag{6}$$

based on which we can derive the contribution value range of the miner group under different parameter settings.

When $x_i = W_j$, if the sum of its utility and risk return is not less than 0, the node become a worker. Similarly,

$$E_{w,j}-C_{w,j}+f_{j,W}\geq 0. \tag{7}$$

Therefore, the work quality range of the worker group under different parameter settings can also be obtained.

When (6) and (7) are both satisfied, the node will choose to be a hybrid node, namely $x_i = H_j$. If both of them are not satisfied, the node will choose not to participate with $x_i = A_j$.

We define $\Omega_{m,j}$, $\Omega_{w,j}$ and $\Omega_{h,j}$ as the contribution value range of miner group, the work quality range of worker group, and the contribution value and work quality range of hybrid group. Therefore, the population distribution of different strategies is described as follows:

$$\begin{cases} I_{M_j}=\{i\in\mathcal{N}_j|\theta_{j,i}\in\Omega_{m,j}\} \\ I_{W_j}=\{i\in\mathcal{N}_j|\alpha_{j,i}\in\Omega_{w,j}\} \\ I_{H_j}=I_{W_j}\cap I_{M_j}=\{i\in\mathcal{N}_j|(\theta_{j,i},\alpha_{j,i})\in\Omega_{h,j}\} \\ I_{A_j}=I_j-I_{M_j}\cup I_{W_j} \end{cases} \tag{8}$$

where $I_j = \{i \in \mathcal{N}_j|\theta_{j,i}\in(0,1], \alpha_{j,i}\in(0,1]\}$.

2) Evolutionary stable strategy: The game is divided into multiple stages. When the equilibrium is reached, no nodes will change their strategies from the next stage and the population distribution of each strategy will remain unchanged.

In our evolutionary game model, both players and their strategy sets are finite. According to the Nash existence theorem, there must be at least one Nash equilibrium. Therefore, the evolutionary game may have multiple equilibrium states. The initial node distribution can uniquely determine one stable equilibrium state. Therefore, given any initial node distribution, the system will eventually evolve to a unique and stable equilibrium state.

We denote the population distribution of different strategies at the equilibrium state as $I^*_{M_j}$, $I^*_{W_j}$, $I^*_{H_j}$, $I^*_{A_j}$. The node contribution value and the node work quality follow probability distributions F_1 and F_2 and their probability density functions are presented as f_1 and f_2 respectively. Therefore, the node number of each strategy can be expressed as follows:

$$\begin{cases} \left|I^*_{M_j}\right| = \int\limits_{\Omega^*_{m,j}} f_1(\theta_{j,i})d\theta_{j,i} \\ \left|I^*_{W_j}\right| = \int\limits_{\Omega^*_{w,j}} f_2(\alpha_{j,i})d\alpha_{j,i} \\ \left|I^*_{H_j}\right| = \iint\limits_{\Omega^*_{h,j}} f_1(\theta_{j,i})f_2(\alpha_{j,i})d\theta_{j,i}d\alpha_{j,i} \\ \left|I^*_{A_j}\right| = N_j - |I^*_{M_j}\cup I^*_{W_j}| \end{cases} \tag{9}$$

Herein, $\Omega^*_{m,j}$, $\Omega^*_{w,j}$ and $\Omega^*_{h,j}$ are determined by (6) and (7). Therefore, given the requester strategy and system parameters, $\Omega^*_{m,j}$, $\Omega^*_{w,j}$ and $\Omega^*_{h,j}$ can be determined with $I^*_{M_j}$ and $I^*_{W_j}$. Therefore, the equilibrium strategy can be obtained.

C. Equilibrium Analysis of Stackelberg Game

On the basis of the analysis of evolutionary game equilibrium mentioned above, we go back to the first stage of Stackelberg game and analyze the strategic choice of the requester node, so as to obtain the Stackelberg game equilibrium.

1) Game analysis: Based on the evolutionary equilibrium, the requester, as the leader, controls and adjusts its strategy to maximize its own utility and enable other nodes to assume diverse roles. According to (4), the requester utility maximization resembles an optimization problem constrained by the evolution state of other nodes, which can be expressed as (10), where the utility of the requester is denoted as $U(R_T,\gamma,I)$.

$$\begin{aligned} \max \quad & U(R_T,\gamma,I) \\ s.t. \quad & |I_{W_j}| = \eta_{w,j}(R_{T,j},\gamma_j), j\in\{1,2,\ldots,K\} \\ & |I_{M_j}| = \eta_{m,j}(R_{T,j},\gamma_j), j\in\{1,2,\ldots,K\} \\ & R_T\in[0,MAX] \\ & \gamma\in[0,1] \end{aligned} \tag{10}$$

$R_T = (R_{T,1}, R_{T,2}, \ldots, R_{T,K})$, $\gamma = (\gamma_1,\gamma_2,\ldots,\gamma_K)$, $\eta_{w,j}$ and $\eta_{m,j}$ are the mappings between $|I_{W_j}|$, $|I_{M_j}|$ and $R_{T,j}$, γ_j. MAX represents a finite value, which means that the requester is budget-constrained. Therefore, the optimal strategy of the requester can be obtained by solving (10).

2) Proof of equilibrium: Although it is difficult to clearly express the specific expression of $\eta_{w,j}$ and $\eta_{m,j}$ and we are unable to find the closed-form solution of (10), we can still try to prove the existence of this solution, that is, the existence of the equilibrium.

Combined with the distribution of the contribution value and the work quality, we can find that $U(R_T, \gamma, I)$ is a piecewise function of $R_{T,j}, \gamma_j, j \in \{1, 2, \ldots, K\}$. In each interval, which divides the piecewise function, $|I_{M_j}|$, $|I_{W_j}|$ and $|I_{H_j}|$ do not change and these intervals are all bounded. The partial derivative of $U(R_T, \gamma, I)$ with $R_{T,j}$ and γ_j are calculated as below.

$$\begin{aligned}\frac{\partial U}{\partial R_{T,j}} = &- \sum_{i \in I_{W_j}/I_{H_j}} \frac{\gamma_j}{|I_{W_j}|} \times \frac{\tanh((\alpha_{j,i} - \overline{\alpha_j}) \times c_j) + 1}{2} \\ &- \sum_{i \in I_{H_j}} \sigma_{j,2} \times \frac{\gamma_j}{|I_{W_j}|} \times \frac{\tanh((\alpha_{j,i} - \overline{\alpha_j}) \times c_j) + 1}{2} \\ &- \sum_{i \in I_{M_j}/I_{H_j}} (1 - \gamma_j) \times \frac{\theta_{j,i}}{\sum\limits_{k \in I_{M_j}} \theta_{j,k}} \\ &- \sum_{i \in I_{H_j}} \sigma_{j,1} \times (1 - \gamma_j) \times \frac{\theta_{j,i}}{\sum\limits_{k \in I_{M_j}} \theta_{j,k}} \end{aligned} \tag{11}$$

$$\begin{aligned}\frac{\partial U}{\partial \gamma_j} = &- \sum_{i \in I_{W_j}/I_{H_j}} \frac{R_{T,j}}{|I_{W_j}|} \times \frac{\tanh((\alpha_{j,i} - \overline{\alpha_j}) \times c_j) + 1}{2} \\ &- \sum_{i \in I_{H_j}} \sigma_{j,2} \times \frac{R_{T,j}}{|I_{W_j}|} \times \frac{\tanh((\alpha_{j,i} - \overline{\alpha_j}) \times c_j) + 1}{2} \\ &+ \sum_{i \in I_{M_j}/I_{H_j}} R_{T,j} \times \frac{\theta_{j,i}}{\sum\limits_{k \in I_{M_j}} \theta_{j,k}} \\ &+ \sum_{i \in I_{H_j}} \sigma_{j,1} \times R_{T,j} \times \frac{\theta_{j,i}}{\sum\limits_{k \in I_{M_j}} \theta_{j,k}} \end{aligned} \tag{12}$$

Hence, $\frac{\partial U}{\partial R_{T,j}}$ and $\frac{\partial U}{\partial \gamma_j}$ are constant. Therefore, $U(R_T, \gamma, I)$ is maximized on the boundary of the interval. The maximum value of $U(R_T, \gamma, I)$ can be obtained by comparing the maximum value of each interval. Thus, the existence of the Stackelberg equilibrium is proved.

D. Two-layer Game Equilibrium-based Incentive Mechanism

Combining the equilibrium analysis of the evolutionary game and Stackelberg game, we discover that the pricing parameters of the requester will influence the utilities of other nodes, thus resulting in different node strategy evolution. Furthermore, the requester utility is influenced by its pricing parameters and the evolution results of other nodes.

Therefore, only the requester provides reasonable $R_{T,j}$ and γ_j, can it make the other nodes to take an active part in the miner groups and worker groups while maximizing its own utility. Theoretically, according to (10), the corresponding relationship between the strategies of the other nodes at equilibrium and the pricing strategies $R_{T,j}$ and γ_j can be calculated. Thus, the values of $R_{T,j}$ and γ_j can be obtained according to the target of the requester, i.e., the specific desired number of miners and workers.

TABLE I
PARAMETER SETTINGS

Notation	Value	Notation	Value	Notation	Value
N	150	K	1	R_T	2000
γ	0.6	μ	8	c	5
ρ	2	λ_1	500	λ_2	100
σ_1	0.95	σ_2	0.9		

V. Experimental Evaluation

This section simulates the system evolution by describing how the evolutionary equilibrium changes with the pricing strategy and discussing the node distribution at equilibrium.

A. Experimental Settings

We consider a DCS with a requester and 150 other nodes. To simplify our experiments, we set $K = 1$, namely only one type of subtask exists. The contribution value and work quality of nodes are uniformly distributed on $(0, 1]$. Table I concludes the parameter settings of our economic model.

We aim to evaluate the performance of our incentive mechanism with some metrics. The strategy proportions at each game round are applied to evaluate the existence of equilibrium. The utilities of all system nodes at equilibrium is used to evaluate the achievement of individual rationality and fairness. Each node in the system is a rational stakeholder driven by individual interests. Individual rationality is to ensure that the utility of each node in the system is non-negative, so that they are willing to participate in the system. Meanwhile, the utility obtained by nodes of different work qualities or contribution values is used to assess the fairness. Nodes should receive rewards proportional to their contributions, so as to encourage them to contribute as much as possible.

We employ the work quality and contribution value threshold of each strategy at equilibrium to evaluate system sustainability. The contribution value of the miner node and the work quality of the worker node should be greater than a certain threshold, and the nodes with low contribution to the system should be screened out to ensure the sustainable development of the system.

B. Experimental Results and Analysis

Fig. 2 and Fig. 3 illustrate the influence of R_T on the number of workers and miners at equilibrium when $\gamma = 0.6$. It is worth noting that if the evolution results of other nodes still oscillate at the end of the game under the requester pricing parameter, we set the node number as -1 for simplification. According to Fig. 2, when R_T is small, it will lead to oscillations. When R_T increases to around 2000, almost all nodes choose to be a miner. The range of R_T which makes the worker node set stationary is much larger than that of the

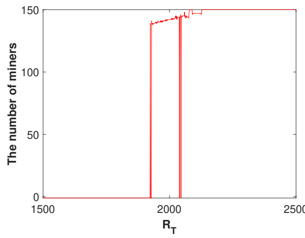

Fig. 2. The influence of R_T on the miner number at equilibrium.

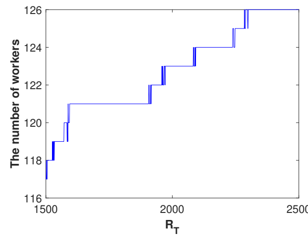

Fig. 3. The influence of R_T on the worker number at equilibrium.

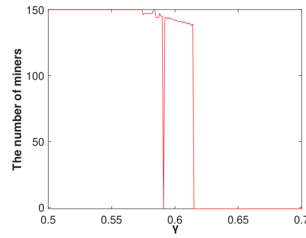

Fig. 4. The influence of γ on the miner number at equilibrium.

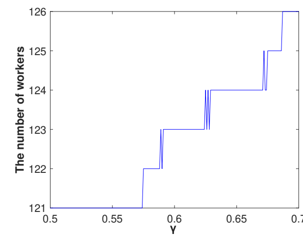

Fig. 5. The influence of γ on the worker number at equilibrium.

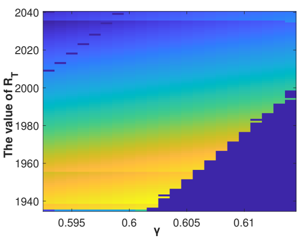

Fig. 6. The effect of different equilibrium states on the requester utility when adjusting R_T and γ.

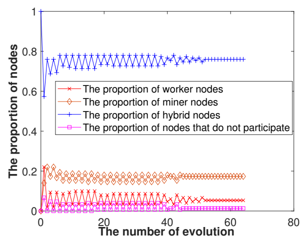

Fig. 7. Evolution of other nodes.

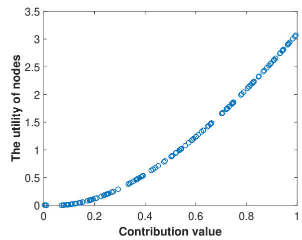

Fig. 8. The utility of miners after equilibrium is reached.

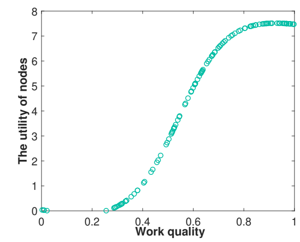

Fig. 9. The utility of workers after equilibrium is reached.

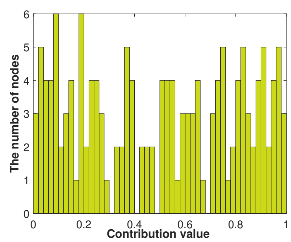

Fig. 10. Node distribution of the miner group in the initial state.

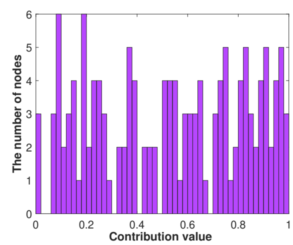

Fig. 11. Node distribution of miner group after equilibrium is reached.

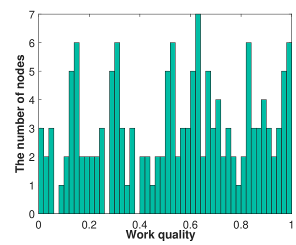

Fig. 12. Node distribution of the worker group in the initial state.

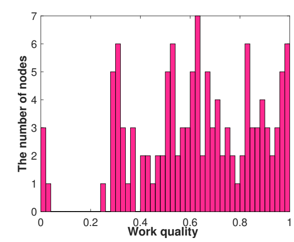

Fig. 13. Node distribution of worker group after equilibrium is reached.

miner node set in Fig. 3. Fig. 3 shows that the miner number grows in a step-wise fashion as R_T increases, which verifies that the miner number and worker number remain constant in the interval as the theoretical analysis of the requester utility maximization. Fig. 4 and Fig. 5 show the influence of γ on the number of workers and miners at equilibrium when R_T is 2000. Their stationary and piece-wise characteristics are similar to the relationship between the node number and R_T. Combining the results of Fig. 2 to and Fig. 5, the appropriate pricing parameters can be found to maximize the requester utility and motivate the participation of a large number of workers and miners. The above results show the existence of the bounded intervals that do not change with $|I_{M_j}|$, $|I_{W_j}|$ and $|I_{H_j}|$.

The relationship between the requester utility and R_T as well as γ is shown in Fig. 6. For easy observation, we set the requester utility with unstable evolution as 0. The more yellow the color block in the figure is, the higher the requester utility is. The maximum requester utility, which is non-negative, is obtained when $R_T = 1939$, $\gamma = 0.602$. The edge of color block in Fig. 6 is jagged because the step of $R_{T,j}$ and γ_j is discontinuous.

Fig. 7 describes the strategy evolution of other nodes under the parameters that maximize the requester utility, which reaches an equilibrium at the 52nd game round. At the beginning of the evolution, all nodes work as hybrid nodes. After that, each node compare the predicted utility of each strategy in the next stage and change their roles accordingly for the next stage. Fig. 8 and Fig. 9 respectively describe the utility of each node in the miner group and worker group under the parameters that maximize the requester utility. All nodes that choose to participate can gain non-negative utility, thus satisfying individual rationality. Furthermore, the node utility increases as the contribution value or work quality increases, thus satisfying fairness.

Fig. 10, Fig. 11 and Fig. 12, Fig. 13 show the node distribution of miners and workers at the initial and equilibrium state, respectively. Comparing Fig. 12 with Fig. 13, all the workers with work quality in the $[0.04, 0.24]$ and part of workers whose work qualities are in the $[0.02, 0.04]$ and $[0.24, 0.26]$

give up acting a worker after the game. The worker whose work quality is in $[0, 0.04]$ still chooses to be a worker after evolution, since its cost is very low and it does not change its strategy considering the risk return. We can similarly analyze the results in Fig. 10 and Fig. 11. From the above, we can conclude that our mechanism meets sustainability.

According to the above results and analysis, a large number of workers selected by our incentive mechanism have high work qualities, which can meet the needs of the requester. A large-scale miner group also ensures the system security. This verifies the feasibility and effectiveness of the pricing incentive mechanism.

VI. Conclusion

In this paper, we designed an incentive mechanism for DCS based on game theory, aiming to motivate the participation of both workers and miners while maximizing the requester utility. We employed a Stackelberg game to model the interactions of the requester and other nodes and applied an evolutionary game to model the strategy selection of the other nodes with bounded rationality. Furthermore, we designed an incentive mechanism for DCS to achieve our design goals. We theoretically proved the feasibility of our incentive mechanism and verify its effectiveness through experimental simulations. The results show that our incentive mechanism can motivate a large number of high-quality workers and miners to participate in the system while maximizing the requester utility. Regarding future work, we plan to expand our incentive mechanism by considering delay factors in the evolutionary game, which could affect the decisions of different nodes. We will also extend our experimental settings with $K > 1$ to evaluate the scalability of our method. Furthermore, we will further compare the performance of our incentive mechanism with existing ones to show the advance of this paper.

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References

[1] S. Nakamoto, "Bitcoin: A peer-to-peer electronic cash system," Decentralized Business Review, 2008.

[2] J. W. Weibull, Evolutionary game theory, MIT Press, 1995.

[3] R. Wang, F. Zeng, L. Yao and J. Wu, "Game-theoretic algorithm designs and analysis for interactions among contributors in mobile crowdsourcing with word of mouth," IEEE Internet of Things Journal, vol. 7, no. 9, pp. 8271-8286, Sept. 2020.

[4] X. Li and C. K. Hsee, "The Psychology of Marginal Utility," Journal of Consumer Research, Vol. 48, no. 1, pp. 169-188, Jun. 2021.

[5] H. W. Eves. Foundations and fundamental concepts of mathematics, Courier Corporation, 1997.

[6] J. Cheng et al., "A reputation incentive mechanism of crowd sensing system based on blockchain," In International Conference on Artificial Intelligence and Security, Springer, pp. 695-706, Jul. 2020.

[7] T. Xu et al., "A quality assessment model for blockchain-based crowdsourcing system," in IEEE 24th International Conference on Computer Supported Cooperative Work in Design, pp. 794-799, 2021.

[8] J. Hu, K. Yang, K. Wang and K. Zhang, "A blockchain-based reward mechanism for mobile crowdsensing," IEEE Transactions on Computational Social Systems, vol. 7, no. 1, pp. 178-191, Feb. 2020.

[9] W. Chen, Y. Chen, X. Chen and Z. Zheng, "Toward secure data sharing for the IoV: A quality-driven incentive mechanism with on-chain and off-chain guarantees," IEEE Internet of Things Journal, vol. 7, no. 3, pp. 1625-1640, Mar. 2020.

[10] M. Kadadha, H. Otrok, R. Mizouni, S. Singh and A. Ouali, "SenseChain: A blockchain-based crowdsensing framework for multiple requesters and multiple workers," Future Generation Computer Systems, vol. 105, pp. 650-664, Apr. 2020.

[11] C. Lai, M. Zhang, J. Cao and D. Zheng, "SPIR: A secure and privacy-preserving incentive scheme for reliable real-time map updates," IEEE Internet of Things Journal, vol. 7, no. 1, pp. 416-428, Jan. 2020.

[12] J. An et al., "PPQC: A blockchain-based privacy-preserving quality control mechanism in crowdsensing applications," IEEE/ACM Transactions on Networking, 2022, doi: 10.1109/TNET.2022.3141582.

[13] M. Li et al., "CrowdBC: A blockchain-based decentralized framework for crowdsourcing," IEEE Transactions on Parallel and Distributed Systems, vol. 30, no. 6, pp. 1251-1266, 1 Jun. 2019.

[14] B. Yin, Y. Wu, T. Hu, J. Dong and Z. Jiang, "An efficient collaboration and incentive mechanism for Internet of Vehicles (IoV) with secured information exchange based on blockchains," IEEE Internet of Things Journal, vol. 7, no. 3, pp. 1582-1593, Mar. 2020.

[15] W. Feng and Z. Yan, "MCS-Chain: Decentralized and trustworthy mobile crowdsourcing based on blockchain," Future Generation Computer Systems, vol. pp. 649-666, Jun. 2019.

[16] Y. Lu, Q. Tang and G. Wang, "ZebraLancer: Private and anonymous crowdsourcing system atop open blockchain," in IEEE 38th International Conference on Distributed Computing Systems, pp. 853-865, 2018.

[17] S. Han, Z. Xu, Y. Zeng and L. Chen, "Fluid: A blockchain based framework for crowdsourcing," in Proceedings of the 2019 International Conference on Management of Data, pp. 1921-1924, Jun. 2019.

[18] X. Liang, Z. Yan and R. Kantola, "GAIMMO: A Grade-driven Auction-based Incentive Mechanism with Multiple Objectives for Crowdsourcing Managed by Blockchain," IEEE Internet of Things Journal, 2022, doi: 10.1109/JIOT.2022.3155631.