Hindawi
Wireless Communications and Mobile Computing
Volume 2021, Article ID 5525791, 11 pages
https://doi.org/10.1155/2021/5525791

Research Article

Information Acquisition Incentive Mechanism Based on Evolutionary Game Theory

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Received 9 February 2021; Revised 8 July 2021; Accepted 2 August 2021; Published 17 August 2021

Academic Editor: Yin Zhang

Based on evolutionary game theory, this paper proposes a new information acquisition mechanism for intelligent mine construction, which solves the problem of incomplete information acquisition in the construction of new intelligent mining area and reduces the difficulty of information acquisition, which solves the problem of the imperfect mine information acquisition in the construction of a new smart mine regions and decreases the difficulty of a mine information acquisition. Based on the evolutionary game model, the perceptual incentive model based on group is established. The reliability of information collection is ensured by sharing and modifying the information collector. Through the analysis of the simulation results, it is found that the regional coverage model based on the cooperation in game theory and evolutionary game theory has a good effect on solving the bottleneck problem of the current intelligent mining area. This paper has an enlightening effect on the optimization of the mine information acquisition system. Through the improvement of the mine information acquisition system, the working efficiency of the information acquisition terminal can be effectively increased by 6%.

1. Introduction

Most of the mining companies in the world are traditional mining companies. They use the traditional mining information acquisition mechanism and the daily inspection information of the skilled workers as the daily operation indicators of the mine. However, the traditional production management method is often lack of the scientificalness and the intelligence, which leads to the low level of information and intelligence in mining regions.

The practical experience-oriented production leads to the increased uncertainty and the increased risks in the production process. This adversely affects the life safety of miners in the long-term underground work environment. In the actual management practice, there is no unified planning and management mechanism. Many workers are unable to use information collection equipment and are reluctant to collect information in the higher risk region. This directly leads to the incomplete information acquisition [1].

Meanwhile, the measurement error and the insufficient information coverage make it impossible to conduct the stable measures in a high-risk region. This implies the danger of the safety construction of the mining region. In addition, the knowledge level of workers in the traditional mining industry is relatively lower, and the level of informatization is different, and the learning ability of the equipment is not satisfied. In the actual information acquisition process, a lot of inaccurate information will be collected.

In addition, the corporate culture of the traditionally heavy industry company leads to the vicious competition among information collectors and the poor degree of information fusion. This leads to poor integration of information between regions.

In view of the above problems, in the actual situation of the existing enterprises, this paper tries to solve the problem that the enthusiasm of the staff to collect information is not high, and this is the basis of the intelligence and controllability of information. Combining the traditional incentive model with the game theory model, an improved incentive mechanism for encouraging employee to collect and share information in high-risk region through differentiated monetary rewards within a limited budget [2, 3]. Using this mechanism, the coverage of information collection region is maximized and the information errors caused by human factors are decreased. So, the system scheme of this paper is shown in Figure 1.

The chapters of this paper are as follows: the second part is literature review. The third part is the regional maximization incentive model. The fourth part is the evolutionary game incentive model. Finally, the fifth part is the conclusion.

2. Related Work

There are many researches on information acquisition mechanism based on evolutionary game theory.

Wang et al. (2020) used word-of-mouth crowdsourcing to design game theory algorithms to analyze the interactions between mobile contributors [4]. Based on the Stackelberg game, the behavior of the contributor is analyzed and the optimal strategy is found for the contributor. Two different modes of crowd-sourced task publishing are considered. One-time parallel publishing and multitime sequential publishing form two different market scenarios. Then, for these two cases, stage and multistage contributor game models are established, respectively. The inverse induction method is used to analyze each game, and the optimal strategy of the game is transformed into an optimization problem. Lagrange Multiplier and Karush Kuhn Tucker (KKT) methods are used to solve the optimization problem. Theoretically, the existence and uniqueness of Stackelberg equilibrium are proved.

Zeng et al. (2021) used the reputation incentive mechanism of the service cache and game theory analysis to perform edge calculations on the software-defined vehicles [5]. Contributions are measured by introducing reputation as the basis for each vehicle to provide a different quality of service. An incentive mechanism was designed using Stackelberg game modeling, and the optimal strategies of both sides of the game were analyzed by backward induction. In addition, the existence and uniqueness of the two-stage Stackelberg equilibrium is proved, and a genetic optimization algorithm is designed to quickly obtain the optimal strategy of both players in the game.

Shu et al. (2015) presented research on the extraction of integrated sensor ontology with global and local alignment [6]. He proposed to strengthen the communication mode between sensor networks in the Internet of Things and establish the semantic connection between sensor ontologies, which is essential in the communication field.

This study strengthens the communication mode between sensor networks in the Internet of Things and establishes semantic connection between sensor ontologies, which is essential in the communication field.

The research work of the initial incentive mechanism mainly focuses on the participatory perception system, some of whose research work is to improve the entertainment of the task. It is hoped that the participants can actively improve the sensory information by participating in the game. In the group-aware computing system, however, the most tasks are more urgent, and the more direct material rewards have a more positive effect on the employee's willingness to participate. Musthag and Ganesan (2013) used monetary incentives as the main means to stimulate information collectors [7]. For the monetary incentive, the currently main researches are divided into the static monetary incentives and the dynamic monetary incentives [8, 9]. The main difference is the variability of the incentive amounts and the adjustable basis for the currently specific situation.

2.1. Static Monetary Incentive Research. In the static monetary incentives, the number of rewards is predetermined according to some criteria, and the amount is the same throughout the perception process. Reddy et al. (2010) found that the amount of payment directly affected the employee's participation and the information accuracy through adjusting the incentive amount high, medium, and low [10]. Musthag and Ganesan (2013) considered the employee's psychological factors and hides a part of the reward amount. The number of rewards can be known only after the task is completed. This method can effectively invoke the employee's expectation to the reward amount and increase the enthusiasm of the employee. However, the method did not consider the individual deviation caused by the employee's own personal factors, and the detailed setting of the variables has not been described in detail. Then, the method cannot achieve a good regression in the more specific case.

2.2. Dynamic Monetary Incentive Research. Dynamic monetary incentives set a variable budget for each task, and the budget depends on the real-time conditions. Lee and Hoh (2010) showed that the problem with fixed pricing is to determine the right amount for each task, because from an economic point of view, high prices lead to an unworkable strategy, and low prices discourage employee participation [11]. Singla and Krause (2013) used an online learning mechanism that minimizes regret [12]. Luo and Liu (2014) proposed that the task publisher can select a winner from all the participants after the task is completed or after a certain time [13]. Zhang et al. (2015) expands to a Nash bargaining game model for the multiparticipant scenarios that is perceived by the mobile group intelligence [14]. However, there is no reasonable explanation for the specific evaluation method of the game model with the multiple participants and the model evaluation deviation caused by individual differences in the model evaluation.

Adeel et al. (2014) used the virtual markets in a mobile sensing environment where the profit of information transactions is between the sender and the receiver's sales price [15]. Singla and Krause (2015) proposed an equilibrium method based on the reverse auction theory. The final price would stabilize in an interval, and the final incentive would be stabilized [16]. However, this method is limited to specific scenarios.

For a wide region of scenarios and multiparticipant balance research, there is no deep discussion. The proposed balance has certain limitations. Shaw et al. (2011) and Yan et al. (2010) explored crowdsourcing as a recruiting mechanism [17, 18]. Tham and Luo (2014) proposed a strategy that measured the quality of information and the amount of time series information and motivated participants to continue

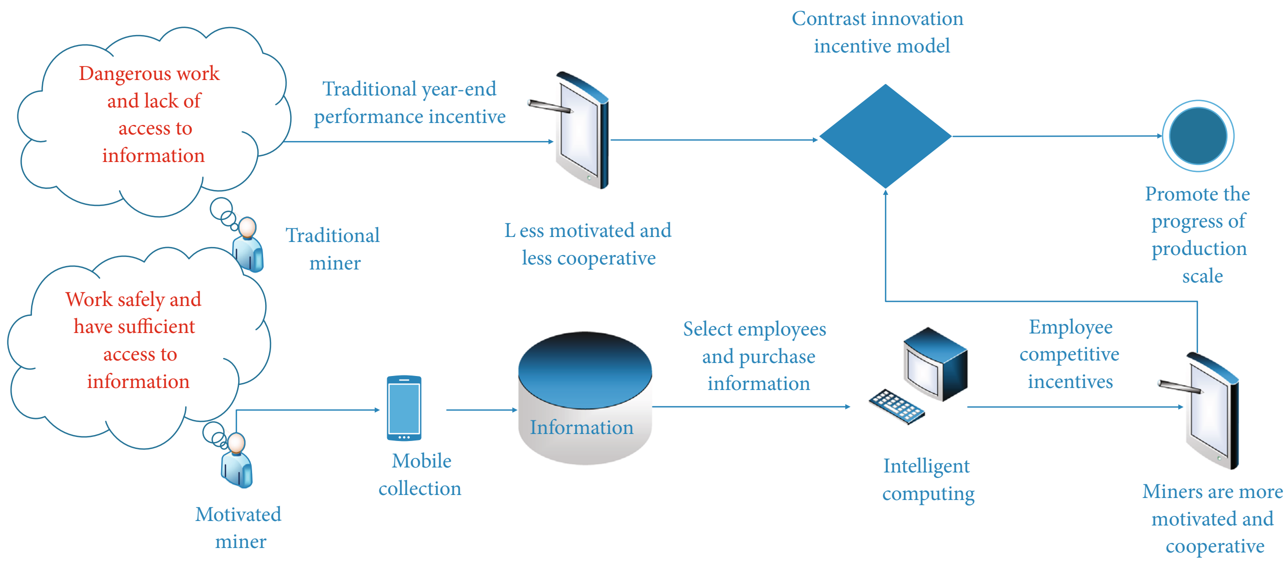

Figure 1: System scheme.

to participate and provide high quality information [19]. Balkanski and Hartline (2016) used Bayesian mechanism to implement the approximately optimal mechanism for achieving budget balance in a pricing incentive system [20]. Nan et al. (2014) presented a cross-space, multi-interaction-based dynamic incentive mechanism [21]. Singla and Krause (2013) presented an incentive mechanism based on the connection between reverse auctions and the multiarm bandit problem [22]. Denzis et al. (2005) used techniques from economics and psychology to address the problem of compensating people to get and use the relative information [23]. Feng et al. (2014) proposed an incentive mechanism that selects a representative subset of the participants with a constrained budget [24].

The current researches are mainly based on the theoretical models through setting simulation conditions and conducting experiments in an environment. This paper proposes the practical and feasible improvement scheme and focuses on the information acquisition incentive mechanism model. Furthermore, the game theory model is also used. In addition, the actual coal mining management is taken as the application example.

3. Region Maximization Incentive Mechanism

3.1. Reverse Auction Competing of the Evolution Game Theory. The information acquisition model collects information through the mobile employees with sensing and computing devices. The employee expenses a certain amount of personal costs in the process of participating in the information perception. Then, the knowledge gained and some equipment may be lost. In order to ensure the employee's participation in the process of information collection, it is necessary to establish a certain incentive mechanism, so that employees can get more returns and maximize the utility while paying the cost [25]. As a special game form in game theory, the auction model is often used to model the process of information collection in group perception [26]. Using the auction model, each employee has a price tag based on the cost of the information collection process. The information collection center acts as a buyer and purchases the information collected by the employee. For the information center, it aims at information buying with the lowest price and the maximum utility. For the employee, the collected information is sold at the highest price, that is, the payments are considered to maximize the utility.

Since the auction model is a low-cost transaction, the cost of purchasing the perceived information can be reduced. But at the same time, the employee exit, the incentive cost explodes, and the information quality need to be considered due to the auction failure. Therefore, the monetary incentives are a common method of returning employees [27].

For the price selection, this paper assumes that the information center selects the lowest price in the same type of information and rejects other quotations. In information selection, this section only considers the coverage of the information, that is, whether the current information overlaps with the existing information coverage region. The region coverage maximization incentive mechanism based on reverse auction is used for the region coverage and employee participation in group perception [28]. Considering the actual scenario, the employee's price tag is combined with the employee's perceived cost.

Under the limited budget of the platform service provider, the incentive mechanism aiming at the region coverage maximization algorithm is proposed, which reduces the possibility of overlapping the employee's perceived region of platform selection. At the same time, this method keeps employees involved, increases the perceived region of the selected employees of the platform, and collects more comprehensive sensory information to improve the perceived service quality. The reverse auction is the standard requirement of the information acquisition center, and it is a revolutionary and epoch-making technology [29]. The employee conducts the interactive real-time bidding through a dedicated network platform during the effective time. The bid at the end of the auction is the final quotation of each employee. The supply strength is given to a comprehensive evaluation, so that one or several of the most competitive employee are selected as the information collector.

3.2. Parameter Settings of the Reverse Auction Competing. In a fixed region where information collection is required, the group sensing system consists of information collection employees and information collection platforms [30]. In the initial state, N employees are randomly distributed in the specified region.

Assume that w_i represents the employee i. If each employee can perceive the same region, that is, the information amount is fixed for each employee to collect. With a radius of r, the circle represents the employee's perceived region. Then, the sensing region s_i of the employee i can be expressed as shown in Equation (1).

$$s_i = \pi r^2 (i = 1, 2, 3, \cdots, N). \tag{1}$$

The employee set $W = \{w_1, w_2, w_3 \cdots w_n\}$ is taken as the final information collection result. The information collection platform publishes information collection tasks based on the current production requirements and selects employee and purchases information from a centralized set of employees with a budget.

The reverse auction method is used to simulate the process of sensory information collection. The employee competes as a bidder in the reverse auction to sell the information. The service platform of the sole auctioneer selects the employee to purchase information from the optimal participating employee w_i in a certain standard. Then, the service platform notifies other unsuccessful employees to win or lose the result of this round of auction, and the winner obtains the price. As the income, the participating employee judges the next round state. If the employee exits, the service platform informs the exiting employee of the maximum price of the auction, and the exiting employee judges whether the next round of auction returns.

In the process of information auction, each employee has an initial bid price a_i and the cost c_i for acquiring information according to the individual situation.

This paper defines the employee participation cost as the sum of completing the information sensing and sending the sensory information. Because all employees have the same perceived region, the difference among the cost of participators is the difference in the transmission cost. If the communication fee for the employee to send the information is borne by the platform, the employee participation cost is mainly the power consumed. Referring to the path loss index in different environments, the propagation loss of the channel in the urban environment is proportional to the fourth power of the distance. The employee participation cost c_i is defined by Equation (2).

$$c_i = \alpha d_i^4 (i = 1, \cdots, N), \tag{2}$$

where α represents the price per unit distance and d_i represents the distance between the employee and the base station.

The information center publishes the information requirement with a low price. This may result in overlapping of the perceived region, that is, the information reported by the adjacent employees is the same, and the service platform wastes funds on the budget. On the other hand, the partial region information cannot be obtained, which reduces the coverage of the perceived information.

The regional coverage maximization algorithm can solve the above problem [31]. The goal is to make the selected employee's perception regions not overlap each other if the budget L is fixed.

If the employee w_1 be selected in the employee set W, define the number of employees who are aware of the scope of all employees in the participating employee u_i. The selected employee set w_1 as the overlapping region of the participating employees u_i. The employee-aware region overlap degree cdd_i is given by Equation (3).

$$cdd_i = \begin{cases} cdd_i + 1, & \text{If } d(u_i, u_j) < 2r, \\ 0, & \text{Otherwise,} \end{cases} \tag{3}$$

where $d(u_i, u_j)$ represents the distance between two employee centers, $u_i \subseteq W$, $u_j \subseteq W_1$.

The specific process is as follows:

(1) Let $W = \{u_1, u_2, \cdots u_N\}$, $W_1 = \varnothing$, loop counter $m = 0$

(2) The employee with the lowest price from the participating employees and W is selected as the winning employee in the selected employee set w_1

(3) Select an employee with the employee-aware region overlap degree $cdd_i = m$ and the lowest price in the selected employee set w_1 from the remaining set $w \setminus w_1$ into the selected employee set w_1, and subtract the employee from the budget L price

(4) Determine whether the budget L is exhausted. If there is still a budget, go to step (5); if the budget is exhausted, output the selected employee set w_1 and end the algorithm

(5) Judging the set $w \setminus w_1$, there is still employee overlap with the perceived region of the employee in w_1, $cdd_i = m$; if there is still, then carry out step (3) and step (4). If not, $m = m + 1$, and return to step (3), until the budget L is exhausted or the participating employees W are all selected. The selected employee set w_1 is obtained and the algorithm ends

When the platform selects the employee to end, all the employees in the winning employee set w_1 sell the sensory information set to the platform and obtain the price as the revenue. The failed employee is not selected by the platform in this round of auction, and the profit is zero. Participating in the total revenue earned by the employee statistics participating in the auction, when the total revenue is lower than the employee participation cost, the employee chooses to exit the next round of auction.

Since the participation cost c_i of the employee in the scenario is directly related to the distance d_i between the employee and the base station, the profit rate G_i^r is defined. The profit rate G_i^r of the participating employee u_i at the r round auction is given by Equation (4).

$$G_i^r = \frac{e_i^r}{p_i^{\prime} c_i}, \tag{4}$$

where e_i^r identifies the total revenue obtained by the employee u_i from the first round to the r round auction. If the employee u_i wins in the r round, then $e_i^r = e_i^{r-1} + b_1^r$, where b_1^r indicates the bid of the employee u_i in the rth round. If the employee u_i fails in the rth round, $e_i^r = e_i^{r-1}$. Indicating the total number of participations of the employee u_i from the first round to the r round auction, c_i represents the participation cost of the employee. $p_i^r c_i$ represents the total cost value of the employee u_i from the first round to the r round. For each round of auction, each employee participates in the employee to calculate the rate of return. If the employee's G_i^r is higher than a certain threshold, it means that the employee is still participating in the next round of auction, and the bid price is appropriately adjusted. If it is below a certain threshold, then the next round of this employee exits.

For the exiting employee u_k, the platform informs the r round maximum transaction price φ_r. The employee calculates its budget period yield EG_k^{r+1} in the $r+1$th round. The EG_k^{r+1} is given by Equation (5).

$$EG_k^{r+1} = \frac{e_k^r + \varphi_r}{\left(p_k^{\prime} + 1\right) c_k}. \tag{5}$$

The incentive mechanism is mainly composed of platform selection and employee judgment. The platform selection criterion based on the regional coverage maximization algorithm guarantees the regional coverage rate, and the employee judgment guarantees the employee participation in group perception. The employee first calculates the participation cost based on the distance of the base station, then sets the initial price in the auction according to the participation cost and participates in the auction. According to the regional coverage, the service platform acts as the auctioneer in the case of a fixed budget. The algorithm selects the employee to purchase the sensory information. Participating employees judge whether to continue to participate in the auction according to the rate of return. For the exiting employee, the platform will inform the maximum price in the second round of auction, and the exiting employee calculates the expected rate of return to determine whether to return to the auction.

3.3. Simulation Result Analysis. In a fixed region where information collection is required, the group sensing system consists of information collection employees and information collection platforms. In the initial state, N employees are randomly distributed in the specified region, and w_i is used to represent employee i. If each employee can perceive the same region, the amount of information that each employee can measure is certain. With a radius of r, the circle represents the employee's perceived region. Then, the sensing region of the employee i can be given by Equation (6).

$$s_i = \pi r^2 (i = 1, 2, 3, \cdots, N). \tag{6}$$

For example, the number of participating employees $N = 200$, budget $L = 4000$, and employee perceived radius $r = 16$. In the iterative process, the participating employees judge whether to participate in the next round of auction and adjust the price according to the rate of return after each auction.

As a result, the uncertainty of the employee's decision for the next round leads to the volatility and system of the participating employees' quotations. By exiting the employee to calculate the expected rate of return to determine whether to return, it is possible to ensure that the number of participants in the system is maximized. Therefore, the average incentive price of the selected employee converges after a certain number of auction iterations, and the employee price is finally stable, that is, the currently selected region. The relationship between iteration number and price relationship is shown in Figure 2.

As the platform chooses as much as possible, the sensing region does not overlap. The employee distribution diagram is shown in Figure 3.

As the perceived radius r increases, the degree of overlap of the employee's perceived region is higher. In the case of L fixed, the criterion for the platform to select employees is to select unselected employees with the selected employee's perceived region. If the perceived radius r of the employee is small, the employee perception region hardly overlaps or the degree of overlap is low. Since the employee participation cost is related to the distance from the base station, the employee price around the base station is low, and the service platform selects the employee around the base station to cause the purchase under a fixed budget. If the perceived radius r of the employee is large, the employee's perceived region overlaps a lot. In order to avoid overlapping of the selected employee's perceived region, the selected employees are dispersed in the target region, so the number of employees purchased under the same budget is small.

When the employee's perceived radius is the same, the greater the L, the larger the number of employees that can be purchased under different budgets L. The relationship between budget and selected employee is shown in Figure 4.

Analysis shows that the larger the budget of the service platform, the more employees choose to purchase. The service platform can purchase the perceptual information of all participating employees when the budget is large enough. Therefore, regardless of the employee radius r, the number of selected employees is equal to the number of participating employees when the budget is large enough. When the

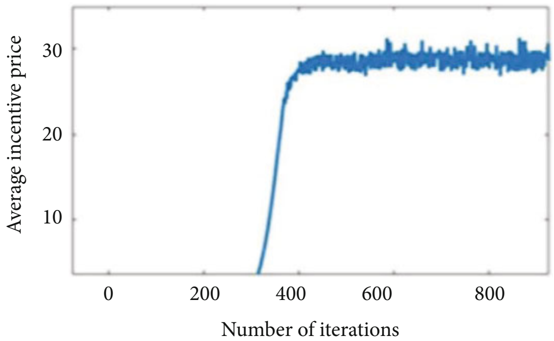

Figure 2: The relationship between iteration number and price relationship.

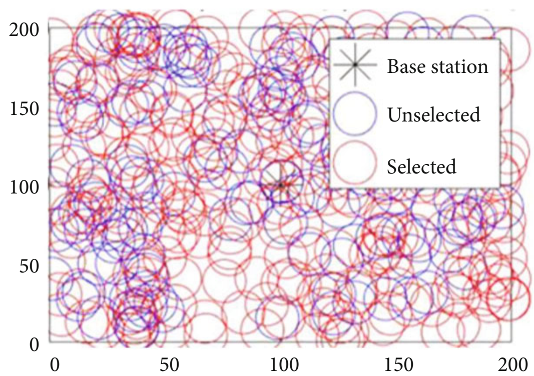

Figure 3: The diagram of employee distribution.

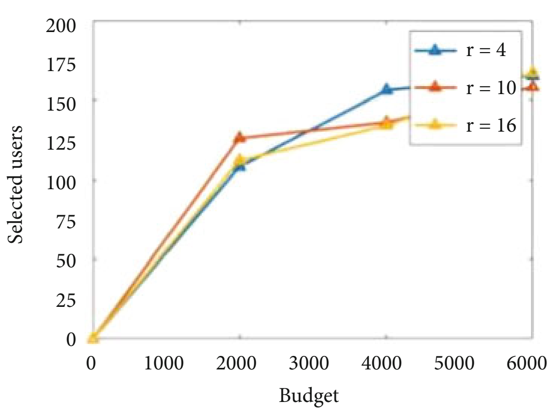

Figure 4: The relationship between budget and selected employee.

perceived radius r is small, the employee's perceived region hardly overlaps or the degree of overlap is low. Since the price of the employee around the base station is low, the service platform starts to select from the employees around the base station. As a result, the number of employees purchased under the fixed budget is large. The relationship between employee perception radius and the number of employees is shown in Figure 5.

4. Evolutionary Game Incentive Model

4.1. Game Strategy and Revenue Matrix. In the perception system, when only participant B selects the shared information, participant A obtains the perceptual information of participant B. Therefore, participant A obtains more accurate perceptual information through information processing and receives more rewards from the platform. For participant B, sharing information does not make it more rewarding. B's strategy in the next round of evolutionary games is uncertain, which may affect the enthusiasm of B cooperation [32]. In order to encourage participants to cooperate in the game and promote information exchange, it is necessary to set reward and punishment measures in the game model. This paper introduces the cooperation rate as an incentive penalty factor to promote the cooperation of participants [33]. According to the cooperation rate, the participant's game cost can be dynamically adjusted. The participant with high cooperation rate will reduce the game cost, which is a reward for the cooperation of the participants. On the contrary, participants with low cooperation rates will increase the cost of the game, which is also to increase the cooperation rate through punishment. Assuming that the evolutionary game of w round has been experienced in the recent time period, the cooperation rate of each round of participants can be expressed as $\{x_1, x_2, x_3, \cdots x_w\}$, then the cooperation rate of the most recent period is given by Equation (7).

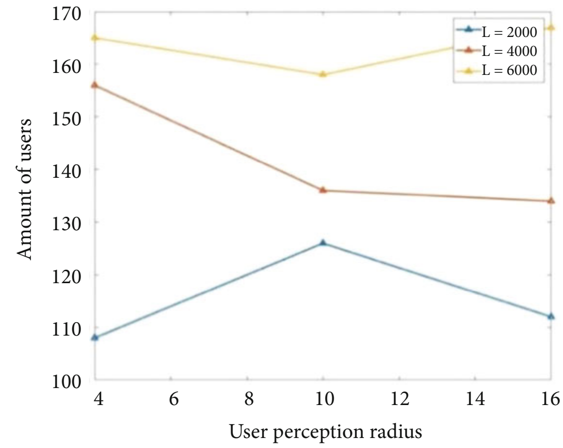

Figure 5: The relationship between employee perception radius and the number of employees.

$$z = \frac{1}{w}\sum_{k=1}^{\infty} x_k y(k), \tag{7}$$

where $y(k) \in [0, 1]$ is the attenuation function, so the adjustment coefficient β of the game cost t can be expressed by Equation (8).

$$\beta = 1 + \eta - z, \tag{8}$$

where $0 < \eta < 1$. When the cooperation rate is 1, the game cost $\beta t = \eta t$; when the cooperation rate is 0, the game cost is $\beta t = \eta t$ currently. In the actual scenario, the company's budget is not unlimited. The participant's return is the amount paid by the information platform to the participant, that is, the total expenditure of the service platform is the total return sum of all participants. Define α to adjust the income $s + \Delta s$ to control the amount of payment. The income adjustment coefficient α can be expressed by Equation (9).

$$\alpha = 1 + \frac{u_{th} - u_j^{\text{total}}}{u_{th}}, \tag{9}$$

where u_{th} is the platform budget, u_j^{total} is the total expenditure of the platform after the j-round game.

The main idea of the evolutionary game is "survival of the fittest," that is, it should encourage behaviors that promote the evolution of the system and impose penalties on behaviors that hinder the evolution of the system. Define the employee's revenue as the fitness in the evolution, continuously generate high-yield employees, and eliminate low-yield employees. After a round of evolutionary game, each participant calculates its income. If the return is higher than the average of employee's return, the system will increase its number of games in the next round of evolution. On the contrary, if the employee's return is lower than the average of employee's return, the number of games will be reduced in the next round of games. Let $f_{i,j+1}$ denote the number of players in the $j + 1$ round, then the equation of $f_{i,j+1}$ is given by Equation (10).

$$f_{i,j+1} = f_{i,j} + f_{i,j} \frac{u_{i,j} - \bar{u}_j}{u_{i,j}}, \tag{10}$$

where $f_{i,j}$ represents the number of games in the jth round of the participants, $u_{i,j}$ represents the participant's return in j round,-$\bar{u}_j = u_j^{m_i} / m_j$ is the jth round average revenue of the employee, and m_j represents the number of participants in the jth round. In order to survive, participants in different strategies constantly adapt to the environment during the evolutionary game, and each participant updates their strategy with a certain probability. Copy rules, also known as proportional imitation rules, mean that when a round of evolutionary games ends, participants randomly imitate another participant with a certain probability. The participant update policy rule is defined by Equation (11).

$$P(\pi_A \longrightarrow \pi_B) = \begin{cases} \delta, & u_n > u_A, \\ 0, & u_n \le u_A, \end{cases} \tag{11}$$

where π_A and π_B represent the strategies of participants A and B, u_A and u_B represent the returns of participants A and B, and δ is the probability coefficient. The above formula indicates that when the benefit of B is greater than the return of A, the probability of adopting B's strategy is an update of its own strategy.

Assuming that the total number of participants in the system is m, each participant has two game strategy choices, shared or not shared. u_{th} represents the budget set by the service platform. The median income $s + \Delta s$ and the game cost t

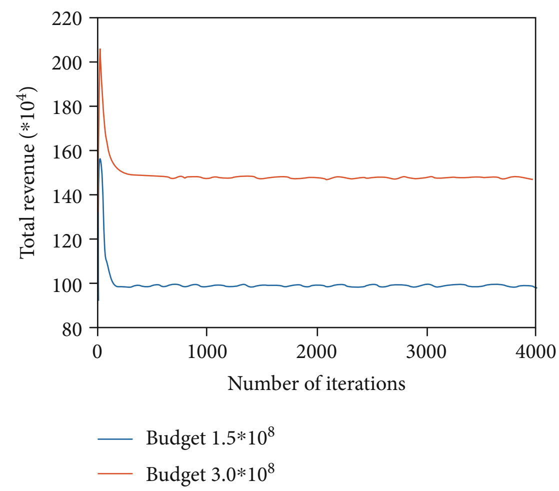

Figure 6: System stability.

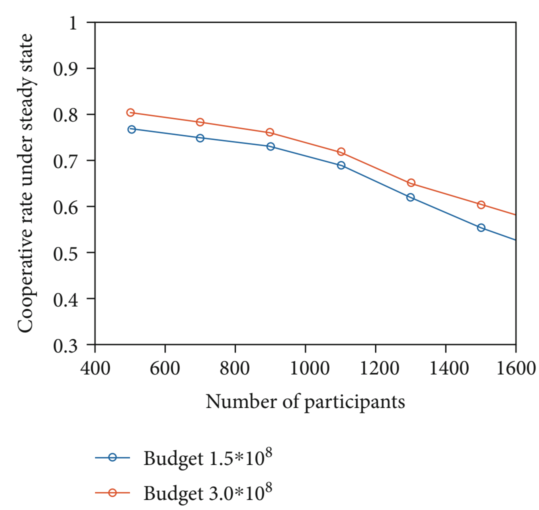

Figure 7: Relationship between cooperation rate and number of participants in steady state of the system.

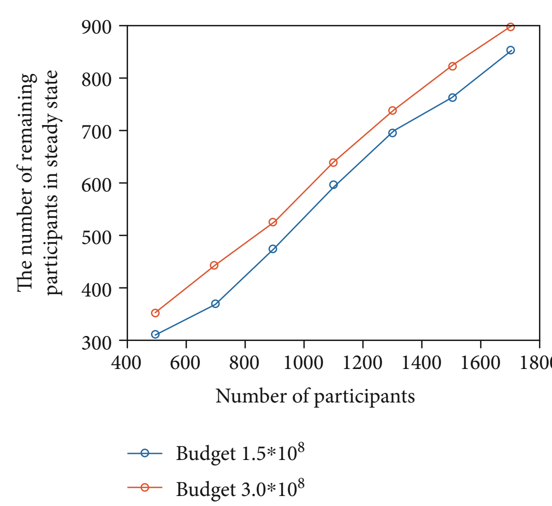

Figure 8: Relationship between remaining participants and number of participants in steady state.

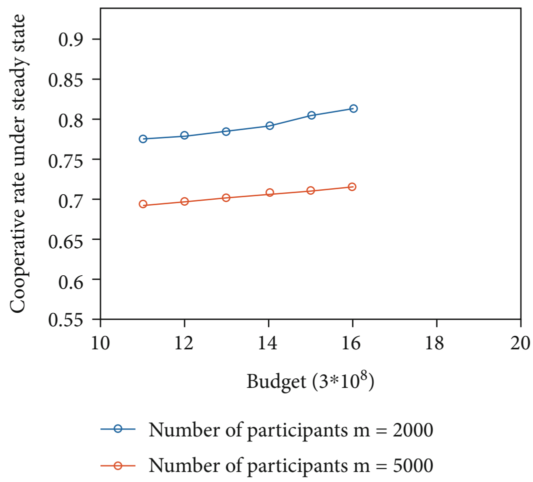

FIGURE 9: Relationship between cooperation rate and the budget.

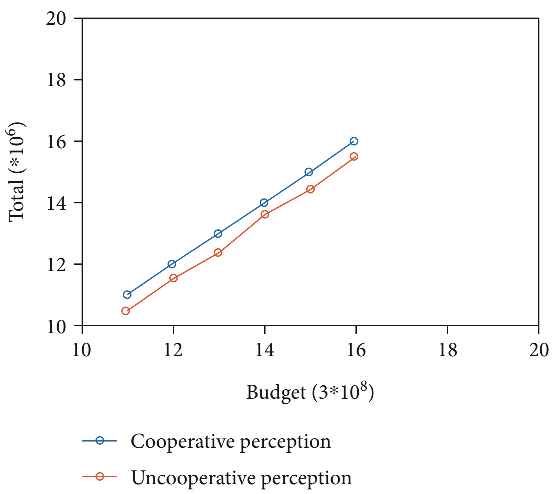

FIGURE 10: The income changes after the introduction of the cooperation mechanism.

of the initial return matrix are all positive integers. The initial cooperation rate of each participant is 0.5, and the initial number of games is f. Each participant performs f-games with other m-1 participants, respectively. This process is called a round of evolution. After a round of game, calculate the income of each participant, so that the income of i participants in the jth game is s_i^j, the cost is t_i^j, then the total return is $u_{i,j}^{\text{total}} = s_i^j - t_i^j$. The total employee income is $u_j^{\text{total}} = \sum_{i=1}^{m} u_{i,j}^{\text{total}}$, and the average return is $\bar{u}_j = (1/m)\sum_{i=1}^{m} u_{i,j}^{\text{total}}$. Then, adjust α and β, update the return matrix $s + \Delta s$ and t, and calculate the number of times each participant plays in the next round. If it is 0, exit the game until the system reaches stability.

4.2. Simulation Result Analysis. This paper first analyzes the stability of the system and simulates the iterative curve of the total revenue of the system steady state under the $u_{th} = 3.0 \times 10^8$ and $u_{th} = 1.5 \times 10^8$, respectively. The algorithm uses α to adjust the income to achieve control over the budget amount. As shown in the simulation results, the total revenue of the employee does not exceed the total budget of the platform. Adjusting the parameter $\alpha > 1$, the next round of $s + \Delta s \longrightarrow \alpha(s + \Delta s)$ will increase with the number of iterations. In the early stage of the game, the employee's income increases. When $\alpha < 1$, the employee's income can be reduced.

By constantly adjusting the parameters, the employee can get the maximum benefit within the budget and finally stabilize at a fixed value. At the moment, the system is stable, and the employee income can be recorded as a stable income. The system stability is shown in Figure 6.

Under the budget of $u_{th} = 3.0 \times 10^8$ and $u_{th} = 1.5 \times 10^8$, the relationship between the cooperation rate and the number of participants in the steady state is discussed in this paper. When the number of participants in the system increases, the budget of the platform is fixed. The competition among participants increases with the increase of people, resulting in a significant decline in the cooperation rate.

Relationship between cooperation rate and number of participants in steady state of the system is shown in Figure 7.

In the case of a fixed number of participants, the increase in budget promotes cooperation among participants, so the cooperation rate increases with the budget when the system reaches stability. By introducing a reward factor, as the number of participants increases, the number of reputation participants in steady state also increases, which is indicating that the system is efficient. By encouraging more participants to join the information sharing, employee engagement can effectively increase.

Under the budget of $u_{th} = 3.0 \times 10^8$ and $u_{th} = 1.5 \times 10^8$, the relationship between remaining participants and number of participants in steady state of the system is shown in Figure 8.

Finally, in the condition of the system reaching a steady state, the relationship between the cooperation rate and the budget is simulated. It can be seen from the simulation results that the increase of the budget promotes the cooperation between the participants, so the cooperation rate becomes larger as the budget increases. The relationship between cooperation rate and the budget in system steady state is shown in Figure 9.

In the case of a fixed budget, the greater the number of participants, the more intense the competition between them. Therefore, the cooperation rate under steady state is reduced. In the process of evolutionary game, the fitness is the employee's benefit. The participants in the group continuously improve their strategies and learn from the high-yield partners. Therefore, when the system reaches a stable state, the number of employees who choose to cooperate will increase a lot. The total employee income is maximized within the budget, which increases the total revenue of the employee compared to the perception of noncooperation.

When the number of participants is $m = 2000$ and $m = 5000$, the income change after the introduction of the cooperation mechanism is shown in Figure 10.

Considering the limited number of employees and possible experimental deviations, this paper conducted a relevant robustness test at the end of the experiment, trying to pass multiple and diverse parameters. This model simulation

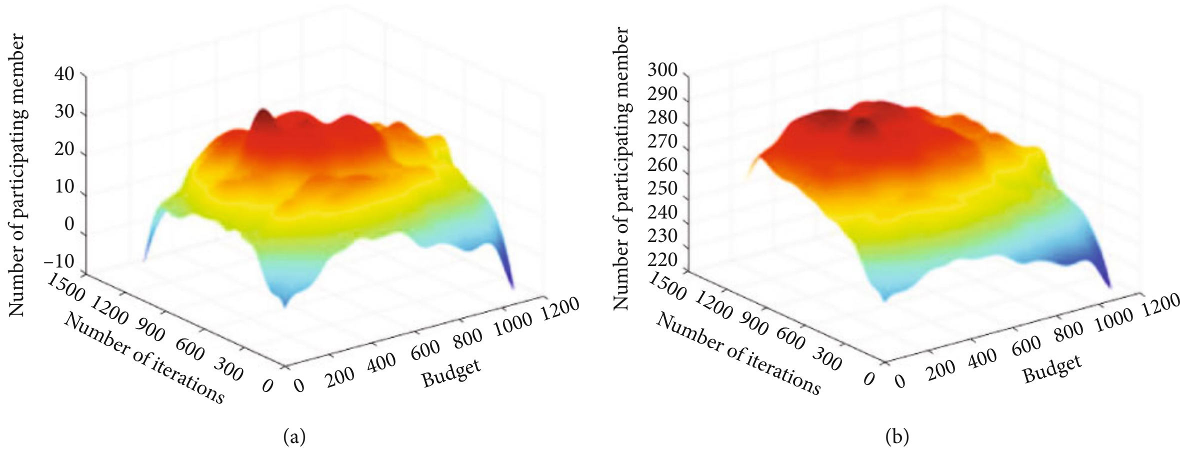

Figure 11: Multivariate simulation results.

eliminates the deviation of experimental results caused by a single parameter change. Therefore, this paper will run a simulation in a linearly increasing of the employees' number, iterations, and the budget.

By changing the employees' and iterations' number, increasing the budget accordingly, the effectiveness of model simulation can be effectively improved. Therefore, based on the simulation effort model proposed in this paper, it can be found that budget control and employee number control are both important parameters for completing game equilibrium. By effectively improving the incentive budget and the number of participating employees in actual production, the incentive model is guaranteed to achieve maximum utility. Multivariate simulation results are shown in Figure 11.

Based on the above analysis results, the proposed algorithm effectively improves the incentive mode. Compared with traditional year-end result incentives, competitive incentives enable first-line miners to achieve good competition and cooperation in their daily work and increase the enthusiasm of employees. Therefore, the incentive algorithm proposed in this paper is feasible and consistent with the actual situation, which can better promote the work efficiency of employees and the reform of corporate strategic management.

5. Conclusions

The experimental results show that after the introduction of incentive mechanism, the budget required by the enterprise is 6% lower than that of the traditional enterprise, the cooperative relationship between employees is more stable, and the enthusiasm of employees will be further improved. Therefore, multiple conclusions can be drawn.

(1) Company can maximize the scope of information collection by effectively establishing incentives. Under a limited budget, aiming at maximizing regional coverage, the reverse auction principle is used to motivate information collectors collecting information from remote regions

(2) Through the evolutionary game model, this paper introduces the concept of reward factor by simulating the cooperative game behavior and strategy update behavior of workers in the collection process. This method encourages all information collectors sharing information by providing additional subsidies to information sharers and solves problem of inaccurate information collection

(3) Considering that the algorithm proposed in this paper is costly in practice, this paper carries out further feasibility tests. By selecting the information of the same type of mining enterprises, it is found that the management reform can effectively promote the progress of production scale. Therefore, it can be inferred that the management reform proposed in this paper is reasonable in practice and effective at solving the current production problems caused by improper management

The future development of information acquisition incentive mechanism in intelligent mine construction mainly includes two aspects: the first is the theoretical system, which further innovates the existing theories and expands the scope of application of theories. Second, the application of the incentive mechanism, to further improve the technology needed in the incentive mechanism, the incentive mechanism will be better applied in practice, become an important link in the construction of intelligent mines.

Data Availability

The data used to support the findings of this study have not been made available because data privacy.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This paper is supported by the National Natural Science Fund grant no. 51804249.

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