

# Two-Stage Game Design of Payoff Decision-Making Scheme for Crowdsourcing Dilemmas

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**Abstract**—Crowdsourcing uses collective intelligence to finish complicated tasks and is widely applied in many fields. However, the crowdsourcing dilemmas between the task requester and the task completer restrict the efficiency of system severely, e.g., the cooperation dilemma leads to the failure in the interactions and the quality of service dilemma results in the inability of task completer to provide high-quality service. Current research usually focuses on solving only one aforementioned dilemma and fails to integrate perfectly with the service architectural pattern of crowdsourcing systems. In this article, combined with the crowdsourcing interaction phase, we limit the objects that cause dilemma and propose a two-stage game payoff decision-making scheme (TGPD) to overcome these shortcomings. To solve the cooperation dilemma between the requester and the crowdsourcing platform, we first propose a dynamic payment method based on the reputation-quality rules for the task requester, and then develop a cos-evaluation algorithm to estimate platform's cost, last design a co-determine algorithm to determine whether the platform adopts a cooperative strategy. To address the quality of service dilemma between the crowdsourcing platform and the workers, we first present an auction-screening method to estimate the reasonable recruitment range of workers which can be optimized by the result of cos-evaluation algorithm, and then use a reward distribution method to motivate workers to complete tasks with high quality and on time. The experimental results indicate that our new scheme successfully increases the worker's and platforms' payoffs at the same time, improves the accuracy of screening workers, enhances the worker's quality of service, and decreases the platform's cost.

**Index Terms**—Cooperation dilemma, quality of service dilemma, two-stage game, dynamic payment, auction screening.

## I. INTRODUCTION

CROWDSOURCING [1], [2] is a distributed problem-solving model, which can be described as a requester outsources the task that used to be done by a full-time staff to the public in a voluntary manner through open crowdsourcing platforms, and screens high-quality workers to complete tasks together through service bidding. A large number of application requirements have spawned many large-scale online job recruitment and task distribution management platforms. These platforms have created enormous economic benefits [3]. Also, the crowdsourcing system is applied to the computer application area due to its unique problem-solving patterns, such as machine learning and natural language processing. Machine learning technology can use the crowdsourcing platform to mark data tags [4]. A commercial internet crowdsourcing platform may have millions of data markers distributed around the world, who can do a lot of data tagging in a few days or even hours at a low price [5]. However, the crowdsourcing dilemmas between the task requester and the task completer in the crowdsourcing applications restrict the efficiency of system severely, e.g., the cooperation dilemma and the quality of service dilemma. The former is likely to cause the requester and the crowdsourcing platform cannot interact with each other, and the latter results in the task not being completed in a timely and high-quality manner. Therefore, solving these two problems is the key to promote the efficient application of crowdsourcing system.

The cooperation dilemma is caused by the non-cooperation between the task requester and the completer, such as the crowdsourcing platform charges the requesters fee, but does not complete the task for it or the requester accepts tasks submitted by the crowdsourcing platform without paying it. At present, the cooperation dilemma is alleviated by the incentive mechanisms which divide into the non-monetary incentive mechanisms and the monetary incentive mechanisms. The non-monetary incentive mechanisms increase the task completers' inner satisfaction by improving their reputation, credit, or social status to ease the conflict between him and the requester. However, the selection of reward in these mechanisms often varies from person to person, which is hard to set a proper reward for satisfying the needs of different task completers. The monetary incentive mechanisms provide

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rewards in the form of micro-payment [6] to task completers for alleviating the conflict. However, these mechanisms are prone to free-riding and false-reporting problems. In recent years, some scholars have introduced the game theory to the monetary incentive mechanisms. They use some appropriate game models to construct the interactions between the task requesters and the completers, and determine their equilibrium strategies to alleviate the conflict between them. Besides, such schemes can improve the quality of service to a certain extent.

The emergence of crowdsourcing makes a large number of complex problems to be solved. However, previous studies have shown that although workers with different backgrounds can complete tasks, they are more likely to make mistakes when they are assigned problems they are not good at, resulting in a lower quality of service [7]–[11]. Therefore, we need to pay attention to workers' quality of service and solve this dilemma which arises when some task completers fraud or delay in submitting results. Some researchers further improve the quality of service of crowdsourcing tasks by recruiting high-quality workers, designing efficient incentive schemes, and improving the characteristics of the crowdsourcing tasks. The task requesters recruit high-quality workers with the necessary skills, attitudes, or advanced training to complete the task. However, due to the various types of tasks handled by the platform, it is hard to design different recruitment criteria for different tasks to recruit high-quality workers. Also, designing an efficient incentive mechanism is an effective measure to improve service quality. However, the design of incentive schemes for quality of service are mostly used for specific problems and are not universal. Moreover, Improving the characteristics of the crowdsourcing tasks can enhance quality of service. However, the large number of empirical studies show that the existing crowdsourcing platforms do not effectively guarantee the completion quality and the output quality of the crowdsourcing tasks [12].

To address the above problems, combined with the crowdsourcing interaction phase, we limit the scenario in which the dilemma occurs, and propose a *two-stage game payoff decision-making scheme (TGPD)*. The overall modeling framework of this scheme is shown in Fig. 1. The interactions between the requesters and the crowdsourcing platform can be modeled as the first-stage game, and the problem of cooperation dilemma is transformed into how to promote cooperation between the parties involved. Similarly, the interactions between the crowdsourcing platform and the workers can be modeled as the second-stage game, and the problem of quality of service dilemma is transformed into how to motivate workers to improve the quality of service. The major contributions of this article are as follows:

(1) To solve the cooperation dilemma, we design a *cooperation promotion solution (CP)*. We first propose a dynamic payment method based on the reputation-quality rules for the requesters, and then develop a cos-evaluation algorithm to estimate platforms cost, last design a co-determine algorithm for the crowdsourcing platform to determine whether the crowdsourcing platform plays a cooperative strategy. Using the *CP* can encourage the requesters with low reputation to choose the cooperative strategy for increasing their reputation, and the enhancement of the requester's reputation can further promote the crowdsourcing platform to play the cooperative strategy.

(2) To address the quality of service dilemma, we design a *quality of service improvement solution (QI)*. We present an

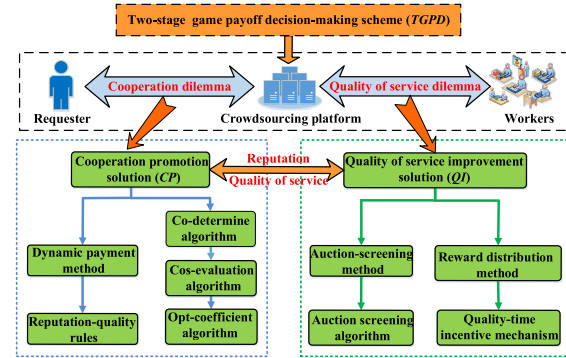


Fig. 1. The overall modeling framework of *TGPD* scheme.

auction-screening method based on a grey interval estimation model to estimate the worker's reasonable recruitment range which can be optimized by combing with the estimated result of the cos-evaluation algorithm. Besides, to further improve the quality of service, we use a quality-time incentive mechanism based on the quality of service level and the task completion time.

(3) This article derives that (a) the crowdsourcing platform should provide minimum quality reward and time reward in order to maximize its payoff while encouraging workers to complete tasks with assured quality and time; (b) to complete tasks for the maximum reward, the worker should provide the shortest completion time and the minimum level of quality of service on the basis of meeting requirements. Through the detailed analysis of five indicators, experimental results demonstrate the effectiveness of the proposed solutions, e.g., *CP*, *QI*.

The remainder of this article is organized as follows: Section II describes the background and some related work, and Section III gives the problem definition. We propose a two-stage game payoff decision-making scheme in Section IV. Section V deduces the process of determining the optimal strategy of workers and the crowdsourcing platform. Section VI presents the experimental results and analysis of the performance of our cooperation dilemma solution and quality of service dilemma solution. Finally, Section VII gives concluding remarks with possible extensions and directions for future research.

## II. RELATED WORK

This section describes the current research status in terms of addressing the problems of cooperation dilemma and quality of service dilemma.

### *Mechanisms for Solving the Cooperation Dilemma*

The non-monetary incentive mechanisms and the monetary incentive mechanisms are two cooperative promotion frameworks [13]. The former increases the task completer's inner satisfaction by improving its reputation, credit, or social status to ease the conflict between players. Some researchers create the rating protocol [14] to encourage players to adopt cooperative strategies. Lu *et al.* [15] created a new social optimal rating protocol for price and reputation plan, which encourage layers to contribute more to gain even higher rewards. However, these mechanisms emphasize personalization and need to meet the preferences of each player. While the others, the design of non-monetary incentive mechanism consisting

of a reward and punishment reputation system [16] can also achieve the purpose of promoting cooperation among players. Liu *et al.* [17] modified the penalty function of the game model according to the cooperation rate of players and established an effective incentive mechanism. However, these mechanisms are complicated and not always efficient. Monetary rewards will make the task completer more active when other incentive measures are invalid [18]. Therefore, there are some scholars use monetary incentives to promote cooperation between task requesters and completers, such as price-based multicast video distribution system [19], crowdsourcing perceptive incentive mechanism [20], and crowdsourcing perception incentive mechanism [21]. However, the traditional monetary incentive is effective for short-term status, it is not beneficial for the long-term development of the crowdsourcing system and might cause an enormous economic burden to the task requesters. In recent years, some researchers introduce game theory to the monetary incentive mechanisms. The two-person game models are often used to define the expected reward of mobile phone users [22]. Hu *et al.* [23] used the iterated prisoner's dilemma to analyze the worker's hostile attack issue and proposed a solution based on zero-determinant strategy [24] to promote cooperation between users. However, the incentive schemes based on traditional game theory often imply the assumption that the players are rational and cannot fully adapt to the environment of crowdsourcing systems.

#### *Mechanisms for Solving the Quality of Service Dilemma*

Recruiting high-quality workers and designing incentive schemes are two typical methods to improve the quality of service. Task requesters can screen workers [25] with the skills, preparation, and attitude needed to complete the task. Retelny *et al.* [26] selected experts among task completers to form a team to solve complex tasks. Ren *et al.* [27] proposed a novel matrix completion technique based data collection scheme to select the proper workers to complete tasks. However, designing different recruitment criteria for different tasks is currently a major challenge in recruiting high-quality workers due to many types of tasks handled by the platform. Taking incentive strategies are the most common way to improve the quality of service [28]. Koutsopoulos *et al.* [29] proposed a stochastic incentive scheme, which could balance the total cost of all users under the premise of participants successfully carrying out their tasks. Peng *et al.* [30] proposed an incentive mechanism based on the performance payment of workers. However, the selection of reward forms in incentive strategies needs to meet the different preferences of each task completers, it is difficult to achieve. Also, some researchers improve the quality of service of task completers by improving the characteristics [31] of crowdsourcing tasks. Guo *et al.* [32] showed that the introduction of occasional breaks, such as playing games or reading comics, can improve task completers' quality of service. Li *et al.* [33] studied how to dynamically instantiate and allocate work on a limited budget to maximize the quality of crowdsourcing tasks. However, most of the quality of service improvement schemes focus on a single specific quality aspect, and the design techniques are only applicable to proprietary platforms. Therefore, designing, building, and maintaining an efficient quality of service improvement scheme remain a challenging issue.

TABLE I

THE PAYOFF MATRIX OF THE REQUESTER AND THE PLATFORM

Platform \ Requester	<i>C</i>	<i>D</i>
<i>C</i>	$U - c_p, R - U$	$\vartheta * U - c_p, R - \vartheta * U$
<i>D</i>	$\vartheta * U, -\vartheta * U$	0, 0

To sum up, current researches usually focus on solving only one dilemma and fail to integrate perfectly with the trinity of structure within the crowdsourcing system. The platform is the bridge connecting two dilemmas and playing a dual role in these dilemmas, that is, the platform is the completer in the cooperation dilemma and the requester in the service quality dilemma. Therefore, this article sets the task completer to charge the requester based on its quality of service, and proposes the cooperation promotion solution and quality of service improvement solution respectively to solve these two problems.

### III. TWO-STAGE GAME MODEL

We assume that crowdsourcing platforms are reliable and the feedback information they provide to requesters is reliable. A crowdsourcing platform can get accurate information about specific requesters from other crowdsourcing platforms, such as their clients' reputation.

According to the first-stage game between the requester and the crowdsourcing platform, the problem of cooperation dilemma is transformed into how to promote cooperation between the parties involved. Assume the requester has two actions: *Cooperation*, i.e., *C*, means that the crowdsourcing platform submits the result of the task to the requester and the requester pays the retainage to it as promised; *Defection*, i.e., *D*, means that the crowdsourcing platform submits the result of the task but the requester does not pay the retainage to it. The crowdsourcing platform has two actions: *Cooperation*, i.e., *C*, means that the crowdsourcing platform accepts the requester's task and recruits workers for it to complete the task; *Defection*, i.e., *D*, means that the crowdsourcing platform accepts the requester's task, but does not recruit workers for it to complete tasks. The payoff matrix of two players is shown in Table I, where the column represents the platform's strategies, the row represents the requester's strategies.

Where  $U$  refers to the payoff obtained by the crowdsourcing platform to complete the task,  $c_p$  refers to the cost of the crowdsourcing platform to complete the task,  $R$  refers to the payoff obtained by the requester to complete tasks, and  $\vartheta$  refers to the ratio of the deposit paid to the total amount,  $0 < \vartheta < \frac{1}{2}$ ,  $\vartheta * U$  refers to the requester who pays the deposit.

As shown in Table I, when the crowdsourcing platform plays *C* and the requester plays *C*, the crowdsourcing platform will obtain the payoff  $U$  at the cost of  $c_p$ , and the requester will obtain the payoff  $R$  at the cost of  $U$ . The crowdsourcing platform plays *C*, whereas the requester plays *D*, the crowdsourcing platform will obtain the payoff  $\vartheta * U$  at the cost of  $c_p$ , and the requester will obtain the payoff  $R$  at the cost of  $\vartheta * U$ . When the crowdsourcing platform plays *D* and the requester plays *C*, the platform will obtain the payoff  $\vartheta * U$ , and the requester will obtain the payoff  $-\vartheta * U$ . The crowdsourcing platform plays *D*, whereas the requester plays *D*, the crowdsourcing platform will obtain the payoff 0, and the requester will obtain the payoff 0. Assume  $\vartheta * U - c_p > 0$ , it can be seen from Table I, there is a

pure strategy Nash equilibrium (the crowdsourcing platform  $D$ , the requester  $D$ ) in the game, and this equilibrium is caused by the cooperation dilemma between the requester and the crowdsourcing platform. We assume that the probability of the requester plays  $C$  is  $p$ , the probability of playing  $D$  is  $1-p$ , and then the expected payoff of the crowdsourcing platform playing  $C$  and  $D$  are:

$$\begin{aligned} E_c &= p * (U - c_p) + (1 - p)(\vartheta * U - c_p) \\ E_d &= p * \vartheta * U \end{aligned} \quad (1)$$

In view of the rationality and selfishness of crowdsourcing platform, cooperative strategies will be adopted only when the payoff of platform outweighs the payoff of its defection strategies. That is,

$$\begin{aligned} p * (U - c_p) + (1 - p)(\vartheta * U - c_p) &> p * \vartheta * U \\ p &> \frac{c_p - \vartheta * U}{(1 - 2\vartheta)U} \end{aligned} \quad (2)$$

From Eq. (2), it can be known that when the probability of requester playing  $C$  is higher than  $\frac{c_p - \vartheta U}{(1 - 2\vartheta)U}$ , the rational crowdsourcing platform will play  $C$ . But the parameter  $U$ ,  $p$ , and  $c_p$  are unknown in the interactions between two players. Therefore, once the three unknown parameters are determined, it can be determined whether the crowdsourcing platform will play  $C$ . Similarly, to maximize his payoff, the crowdsourcing platform hopes that the requester will play  $C$ . As we all know, if the crowdsourcing platform wants to promote cooperation with requesters, it is a good option to charge the requesters based on their reputation and the quality of service.

Similar to the first-stage game, we won't go into the details of the second-stage game. And the quality of service dilemma is transformed into how to motivate the workers to improve the quality of service.

#### IV. TWO-STAGE GAME PAYOFF DECISION-MAKING SCHEME

This section describes in detail the **cooperation promotion solution (CP)** and the **quality of service improvement solution (QI)**.

##### A. Cooperation Promotion Solution (CP)

This section discusses how to solve the cooperation dilemma from the perspective of the requester and the crowdsourcing platform respectively.

1) *The Requester Cooperation Promotion:* Requester's payment rules based on the requester's reputation and the crowdsourcing platform's quality of service can be categorized according to following two different occasions: the crowdsourcing platform will charge a higher amount if the requester's reputation is low and a lower amount if reputation is high. Meanwhile, to attract long term requester with a high reputation, requesters with high reputation can decide payment amount according to the platform's quality of service. Therefore, the requester's actual payment  $U$  is determined by

$$U = \eta * (\delta + e^{r_0 * p})^\varpi + \beta * \log(\omega + \sum_{i=1}^N \text{quality}_i) \quad (3)$$

where  $r_0$  is the reputation threshold of requesters,  $p$  is the requester's comprehensive reputation,  $N$  is the number of workers,  $\text{quality}_i$  is the crowdsourcing platform's quality of

service, that is, the worker's quality of service. There are two different occasions: if requester's reputation value  $p$  is lower than threshold value  $r_0$ , the requester's payment according to his reputation, setting  $\beta = 0$ ,  $\eta$  is used to adjust the requester pay value,  $\delta$  is used to adjust the changing trend of payment function,  $\varpi$  is used to adjust the convergence of payment function. Otherwise, setting  $\eta = 0$ ,  $\beta$  is used to adjust the requester pay value,  $\omega$  is used to adjust the changing trend of payment function.

To attract old customers, the crowdsourcing platform adopts the payment method of price reduction and amount increase. For example, to attract the requester with high reputation to submit the task, the requester pays according to the crowdsourcing platform's quality of service level, and the price is lower than the minimum price paid by the requester according to his reputation. Therefore, the above two payment rules should satisfy the following condition:

$$\eta * (\delta + e^{r_0 * p})^\varpi \geq \beta * \log(\omega + \sum_{i=1}^N \text{quality}_i) \quad (4)$$

According to the analysis of the above payment rules, the crowdsourcing platform should evaluate its quality of service level and the requester's reputation. The quality of service provided by the crowdsourcing platform is workers' quality of service. We use fuzzy logic rules to evaluate the workers' quality of service level in three aspects, i.e., task completion time ( $T$ ), worker's reputation ( $R$ ), and task complexity ( $C$ ). We first chose fuzzy membership functions to define a subordinated degree, the fuzzy input set (i.e.,  $T$ ,  $R$ , and  $C$ ) is composed of two levels: low ( $L$ ), high ( $H$ ). And the fuzzy output set (i.e., quality ( $Q$ )) is composed of four levels: bad ( $B$ ), medium ( $M$ ), well ( $W$ ), and excellent ( $E$ ). And then, we use the triangular membership as the fuzzy membership functions, as follows:

(i). Triangle membership function of reputation and task complexity:

$$\begin{aligned} L(z) &= \begin{cases} \frac{0.6 - z}{0.6}, & z \in (0, 0.6) \\ 0, & \text{others} \end{cases} \\ H(z) &= \begin{cases} \frac{z - 0.45}{0.55}, & z \in (0.45, 1) \\ 0, & \text{others} \end{cases} \end{aligned} \quad (5)$$

(ii). Triangle membership function of task completion time:

$$\begin{aligned} L(t) &= \begin{cases} \frac{t - 0.4}{0.6}, & t \in (0.4, 1) \\ 0, & \text{others} \end{cases} \\ H(t) &= \begin{cases} \frac{0.6 - t}{0.6}, & t \in (0, 0.6) \\ 0, & \text{others} \end{cases} \end{aligned} \quad (6)$$

(iii). Triangle membership function of quality of service:

$$\begin{aligned} E(s) &= \begin{cases} 0, & s \in (0, 0.6) \\ \frac{s - 0.6}{0.4}, & s \in (0.6, 1) \end{cases} \quad W(s) \\ &= \begin{cases} \frac{s - 0.5}{0.15}, & s \in (0.5, 0.65) \\ \frac{0.8 - s}{0.15}, & s \in (0.65, 0.8) \\ 0, & \text{others} \end{cases} \end{aligned} \quad (7)$$

$$B(s) = \begin{cases} \frac{0.4-s}{0.4}, & s \in (0, 0.4) \\ 0, & s \in (0.4, 1) \end{cases}$$

$$M(s) = \begin{cases} \frac{s-0.3}{0.2}, & s \in (0.3, 0.5) \\ \frac{0.6-s}{0.1}, & s \in (0.5, 0.6) \\ 0, & \text{others} \end{cases} \quad (8)$$

Combined with social control theory, we set fuzzy logic rules which establish a mapping function from  $T \times R \times C$  to  $Q$ , as shown in Table II. Finally, we defuzzify the output set to obtain the real value of the platform's quality of service level by using the centroid calculation method [34].

The player's reputation indicates the possibility that the player will complete a task, and the reputation can be calculated based on the inferential transfer of reputation with analogous tasks [35]. The concept of reputation is context-dependent [36]–[37]. Reputation is unique to a specific task, which further explains the probability of completing this task. Considering various factors such as ability, willingness, and social interaction, a variety of methods to evaluate the value of reputation are proposed. One of the most common ways is that the trustor uses his experience to evaluate the reputation based on the trustee's past performance on a specific task. However, once the task is different, the corresponding reputation cannot be inferred by this method.

A previous task  $t_k$  contains multiple characteristics  $\{\alpha_1(t_k), \alpha_2(t_k), \dots, \alpha_n(t_k)\}$ , where  $\alpha_j(t_k)$  denotes the  $j^{\text{th}}$  characteristic of task  $t_k$ . If the characteristics  $\{\alpha_1(t'_k), \alpha_2(t'_k), \dots, \alpha_j(t'_k)\}$  are extracted from multiple previous tasks  $\{t_1, t_2, \dots, t_n\}$  to compose a new type of task  $t'_k$ , we can calculate the reputation of a requester for completing this new task based on previous reputation values and an inference function  $g$ .

$$DR(t'_k) = g(DR(t_1), DR(t_2), \dots, DR(t_n)) \quad (9)$$

As different characteristics have different importance in the task, each characteristic needs to be weighted to reflect the above situation. The inference function can be given as:

$$DR(t'_k) = \sum_{i=1}^j w_i(t'_k) \frac{\sum_{i=1}^n w_i(t_k) DR(t_k)}{\sum_{i=1}^n w_i(t_k)} \quad (10)$$

where  $\alpha_i(t'_k) = \alpha_i(t_k)$ ,  $w_i(t'_k)$  is the weight factor of the  $i^{\text{th}}$  characteristic in new task  $t'_k$ . And  $\frac{\sum_{i=1}^n w_i(t_k) DR(t_k)}{\sum_{i=1}^n w_i(t_k)}$  refers to the

weighted average of existing reputation to characteristic  $a_i(t')$  in task  $t'_k$ . Eventually,  $DR(t'_k)$  is obtained as a weighted sum of these estimations of the characteristics that compose task  $t'_k$ . In order to effectively evaluate the requester's reputation, this article defines the requester's comprehensive reputation  $p$  as

$$p = \gamma DR + (1 - \gamma) \sum_{i \in pl(i)} \frac{IR_i * DR}{\sum_{i \in pl(i)} IR_i} \quad (11)$$

where  $\gamma$  is the weight coefficient of current crowdsourcing platform towards other platforms, whose value is in the range of  $0 \leq \gamma \leq 1$ .  $DR$  refers to requester's direct reputation based on current crowdsourcing platform.  $IR_i$  refers to requester's

TABLE II  
FUZZY LOGIC RULES FOR QUALITY OF SERVICE LEVEL

Time		Reputation		Complexity		Quality of service			
L	H	L	H	L	H	B	M	W	E
✓			✓		✓				E
✓			✓	✓					E
	✓		✓		✓				W
	✓		✓	✓					W
✓		✓			✓				M
✓		✓		✓					M
	✓	✓			✓				B
	✓	✓		✓					B

indirect reputation based on the information given by other crowdsourcing platforms.  $pl(i)$  refers to the crowdsourcing platform set that has interacted with current requester.

### 2) The Crowdsourcing Platform Cooperation Promotion:

From  $p > \frac{c_p - \partial U}{(1-2\partial)U}$ , it can be known that it is necessary to determine the payoff  $U$  and the cost  $c_p$  of crowdsourcing platform to complete the task for determining whether the crowdsourcing platform will play  $C$ . Therefore, this article proposes a co-determine algorithm to determine whether the rational crowdsourcing platform will play  $C$ . In this algorithm, the crowdsourcing platform first calculates the direct reputation  $DR$  and indirect reputation  $IR_i$  of the requester, and then obtains the comprehensive reputation  $p$ , that is, the probability of the requester playing  $C$ . Secondly, calculating the payoff  $U$  of crowdsourcing platform to complete the task, that is, the cost of requester completing the task with the crowdsourcing platform, and using the cos-evaluation algorithm to predict the cost  $c_p$  of platform to complete the task. Finally, determining whether the inequality  $p > \frac{c_p - \partial U}{(1-2\partial)U}$  holds, that is, whether the crowdsourcing platform will play  $C$ , as shown in co-determine algorithm.

In this article, we use the ADF test [38] and the KPSS test [39] to analyze the stationarity of data series. If the analysis results of the two methods are inconsistent, we will use the difference of  $n$ -th order process data series until the two test methods pass at the same time. Therefore, the crowdsourcing platform's historical cost data set can be regarded as a wide stationary time series. Since it is generally impossible to determine the distribution function of a wide stationary time series, the eigenvectors of the time series can be used to describe it, such as mean function, covariance function, autocorrelation function, and partial correlation function. The **Auto Regressive Moving Average (ARMA)** is a commonly used model to describe stationary sequences. According to [40], we can predict the cost of completing the same type of task for the  $l^{\text{th}}$  based on historical cost of the  $(l-1)^{\text{th}}$  of the crowdsourcing platform with

$$\begin{aligned} \hat{X}_{l,h|l-1} - \mu_{l-1,h} &= G((H_{l,h})^2 Q_{l-1,h,4} + (H_{l,h}) F_{l,h,4} \xi_{l,h}) \\ &= G((H_{l-1,h}) (\sum_{m=0}^{\infty} (H_{l-1,h})^m F_{l,h,4} \xi_{l-m-1,h})) \end{aligned} \quad (12)$$

where  $l$  is the  $l^{\text{th}}$  completion of the task,  $h$  is the type of task,  $F_{l,h}$  is a matrix formed by moving average coefficients,  $F_{l,h} = (1, b_{l,h,1}, b_{l,h,2}, \dots, b_{l,h,d-1})^T \in R^d$ ,  $\xi_{h,l}$  is the interference vector in the prediction process,  $X_{l,h}$  is the cost of the platform

to complete the task,  $\mu_{l,h}$  is the average payoff of workers,  $G$  is a standard matrix,  $G = (1, 0, 0 \dots, 0) \in R^d$ ,  $H_{l,h}$  is a matrix formed by moving autoregressive coefficients,

$$H_{l,h} = \begin{pmatrix} a_{l,h,1} & 1 & 0 & \dots & 0 \\ a_{l,h,2} & 0 & 1 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ a_{l,h,d-1} & 0 & 0 & \dots & 1 \\ a_{l,h,d} & 0 & 0 & \dots & 0 \end{pmatrix} \in R^{d \times d}$$

where  $Q_{l,h}$  is the cost matrix of the crowdsourcing platform,  $L$  is the total number of times that a task has been completed,  $p$  and  $q$  are the order of the ARMA model,  $d = \max(p, q + 1)$ . And then, we use the equation  $X'_{l,h} = \lambda * X_{l-1,h} + (1 - \lambda) * \hat{X}_{l,h|l-1}$  to further optimize the estimated results of ARMA model. In which,  $\hat{X}_{l,h}$  is the result of ARMA,  $X_{l-1,h}$  refers to the  $(l - 1)^{th}$  actual cost of hiring workers for the crowdsourcing platform, and  $X'_{l,h}$  is the optimized result. As we all know, the optimization parameters  $\lambda$  has a significant impact on the accuracy of the prediction model. It is critical to determine the optimal  $\lambda$  and minimize the prediction error. Therefore, we used the improved gold-cutting search method to determine  $\lambda$ , as shown in opt-coefficient algorithm.

However, even if the crowdsourcing platform adopts the above strategy, some short-sighted requesters may betray the crowdsourcing platform for high payoffs. To solve this problem, this article designs an extremely severe punishment mechanism, which can prompt such requesters to choose cooperative strategy after the ideological game. If the requester betrays the crowdsourcing platform, the platform will decrease the requester's reputation and notify other relevant crowdsourcing platforms about the requester's betrayal. The reputation penalty function is described as follows:

$$p = \frac{1}{\max\{f(x)\}} * f(x), x \geq 0 \quad (13)$$

where  $f(x) = (x_{max} - x)^3 + 1$ ,  $x$  is the requester's betrayal time,  $x_{max}$  refers to the platform can accept the maximum number of requester's betrayal time.

To sum up, the cooperation dilemma can be solved by three algorithms. The call relationship between these algorithms can be described as follows: the co-determine algorithm calls cos-algorithm to estimate the cost of tasks completed by workers, and then the cos algorithm calls the opt-coefficient algorithm to optimize the result of cost estimation, based on the results of the first two steps, the crowdsourcing platform use co-determine algorithm to make decisions.

### B. Quality of Service Improvement Solution (QI)

After the crowdsourcing platform accepts the task, it will publish the task online. Two issues need to be determined: workers' recruitment and reward distribution. The platform's total cost is divided into two parts, the quotation from workers and the reward.

1) *Auction-Screening Method*: The worker picks up tasks that he is interested in and gives crowdsourcing platform his quotation. Normally several workers will compete for one task, therefore the crowdsourcing platform needs to pick up the right worker. To obtain the workers' rational quotation interval, this article proposed an auction-screening algorithm. In this algorithm, we define the gray distance  $d_{\zeta_u}(q, q'_u(o))$  analogy

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#### Co-determine Algorithm

---

**Input**: the type of task  $h$ , the completion times of task  $l$

**Output**: the strategy of the platform playing

- 01: Initialize platform charging parameters  $\eta$ ,  $\delta$ ,  $\varpi$ ,  $r_0$ , and  $\beta$
  - 02: Calculate  $DR$ ,  $IR_i$ ,  $p$ ,  $U$
  - 03: Estimate  $c_p$  according to the **Co-evaluation Algorithm** step
  - 04: **If**  $p > \frac{c_p - \partial U}{(1 - 2\delta)U}$
  - 05: The platform choose to play strategy  $C$
  - 06: **Else**
  - 07: The platform choose to play strategy  $D$
- 

#### Cos-evaluation Algorithm

---

**Input**: the number of worker  $N$ , the moving autoregressive coefficient

matrix  $H_{l,h}$ , the cost matrix of platform  $Q_{l,h}$

**Output**: the cost estimation  $c_p$

- 01: Initialize  $p$  and  $q$ ,  $\xi_{h,l}$ ,  $G$ ,  $H_{l,h}$ , and  $F_{l,h}$
  - 02: Calculate  $\lambda^*$  according to the **Opt-coefficient Algorithm** step
  - 03: Predict the  $l^{th}$  cost  $c_p$  of platform with
  - 04:  $\hat{X}_{l,h|l-1} - \mu_{l-1,h} = G((H_{l,h}) (\sum_{m=0}^{\infty} (H_{l-1,h})^m F_{l,h} \xi_{l-m-1,h}))$
  - 05:  $c_p = \lambda^* * X_{l-1,h} + (1 - \lambda^*) * \hat{X}_{l,h|l-1}$
- 

#### Opt-coefficient Algorithm

---

**Input**: the result of ARMA  $\hat{X}_{l,h}$ , the  $(l - 1)^{th}$  actual cost of hiring workers for the platform  $X_{l-1,h}$

**Output**: Optimization parameter  $\lambda^*$

- 01: Divide the elements of  $[0, 1]$  into 10 sub-intervals, which are re-
  - presented by  $\lambda_1, \lambda_2, \dots, \lambda_{10}$
  - 02: Select a sub-interval  $\lambda_i \in (a, b)$  to find the optima  $\lambda^*$ , where  $a$
  - and  $b$  are the left and right endpoints of the  $i^{th}$  interval
  - 03: Calculate two test point  $\lambda_i$  and  $\lambda'_i$  with
  - 04:  $\lambda_i = 0.618a + 0.382b$
  - 05:  $\lambda'_i = 0.382a + 0.618b$
  - 06: **If**  $|\lambda_i - \lambda'_i| < \delta$  &&  $\delta = 0.01$ :
  - 07:  $\lambda^* = \frac{\lambda_i - \lambda'_i}{2}$
  - 08: **Else**:
  - 09:  $X'_{l,h} = \lambda_i * X_{l-1,h} + (1 - \lambda_i) * \hat{X}_{l,h|l-1}$
  - 10:  $f(\lambda_i) = \frac{1}{L} \sum_{l=1}^L \left| \frac{X_{l,h} - X'_{l,h}}{X_{l,h}} \right| \times 100\%$
  - 11:  $X'_{l,h} = \lambda'_i * X_{l-1,h} + (1 - \lambda'_i) * \hat{X}_{l,h|l-1}$ ,
  - 12:  $f(\lambda'_i) = \frac{1}{L} \sum_{l=1}^L \left| \frac{X_{l,h} - X'_{l,h}}{X_{l,h}} \right| \times 100\%$
  - 13: **If**  $f(\lambda_i) > f(\lambda'_i)$ :
  - 14:  $a = \lambda_i, \lambda_i = \lambda'_i, b = b$
  - 15: **Else**:
  - 16:  $a = a, \lambda_i = \lambda'_i, b = \lambda_i$
- 

with the calculation method of correlation coefficient, and use *grey interval estimation model (GIE)* to estimate worker's quotation grey confidence interval of grey confidence level  $\alpha$  to calculate the workers' rational price range  $[q_0, q_1]$  based on the historical quotation of workers of the same type of task, as shown in auction screening algorithm. This process is as follows:

**Step 1.** We define the workers' quotations as  $q_i = \{q_1(1), \dots, q_1(m), \dots, q_n(1), \dots, q_n(m)\}$ . And then sort the data in the set according to the ascending order by row and column in the matrix  $Q$ . By deleting all data at the edge of

the matrix  $Q$ , we obtain the following matrix  $Q'$ ,

$$Q' = \{q'_2(o), \dots, q'_{n-1}(o)\}$$

$$= \begin{bmatrix} q'_2(2) & q'_3(2) & \dots & q'_{n-1}(2) \\ q'_2(3) & q'_3(3) & \dots & q'_{n-1}(3) \\ \vdots & \vdots & \ddots & \vdots \\ q'_2(m-1) & q'_3(m-1) & \dots & q'_{n-1}(m-1) \end{bmatrix} \quad (14)$$

where  $o = 2, \dots, m-1$ , thus, the comparative sequence can be described as  $q'_i = \{q'_2(2), \dots, q'_2(m-1), \dots, q'_{n-1}(2), \dots, q'_{n-1}(m-1)\}$ . The maximum number of elements in each column can be seen as a reference value. These values compose a reference sequence  $q_{max} = \{q'_u(m-1), u = 2, \dots, n-1\}$ . We then standardize the above matrix and obtain the following matrix:

$$Q'' = \{q'_2(o), \dots, q'_{n-1}(o)\}$$

$$= \begin{bmatrix} 1 & \frac{q'_3(2)}{q'_2(2)} & \dots & \frac{q'_{n-1}(2)}{q'_2(2)} \\ 1 & \frac{q'_3(3)}{q'_2(3)} & \dots & \frac{q'_{n-1}(3)}{q'_2(3)} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & \frac{q'_3(m-1)}{q'_2(m-1)} & \dots & \frac{q'_{n-1}(m-1)}{q'_2(m-1)} \end{bmatrix} \quad (15)$$

**Step 2.** Calculate the correlation coefficient  $\zeta_u(q_{max}, q'_u(o))$  for each column of  $Q''$ , in which,  $o = 2, \dots, m-1, u = 2, \dots, n-1$ , (16), as shown at the bottom of the next page, where  $\rho$  represents the distinguishing coefficient in the range of  $[0,1]$ ,  $\rho = 0.5$ . Normalizing the correlation coefficient  $\zeta_u(q_{max}, q'_u(o))$  to obtain  $r_u$ , and re-normalizing  $r_u$  to obtain the correlation degree  $w_u = \frac{r_u}{\sum_{u=2}^{n-1} r_u}$ . Taking the mean

$\bar{q} = \{\bar{q}_u, u = 2, \dots, n-1\}$  of each element of the matrix  $Q'$  and calculate the grey estimate value  $q = \sum_{u=2}^{n-1} w_u * \bar{q}_u$ . Combined with correlation coefficient  $\zeta_u(q_{max}, q'_u(o))$ , we define data sample and estimation value  $q$ 's grey distance  $d_{\zeta_u}(q, q'_u(o))$  as follows:

$$d_{\zeta_u}(q, q'_u(o)) = \frac{\min_{u=2}^{n-1} \{\min_{o=2}^{m-1} \{|q - q'_u(o)|\}\} + \rho \max_{u=2}^{n-1} \{\max_{o=2}^{m-1} \{|q - q'_u(o)|\}\}}{|q - q'_u(o)| + \rho \max_{u=2}^{n-1} \{\max_{o=2}^{m-1} \{|q - q'_u(o)|\}\}} \quad (17)$$

**Step 3.** Define grey confidence as  $\alpha$  in the range of  $\frac{1}{5} \leq \alpha \leq 1$ . If  $d_{\zeta_u}(q, q'_u(o)) \geq \alpha$ , we obtain worker's quotation grey confidence interval that satisfies grey confidence  $\alpha$ . Choosing the result of the Cos-evaluation algorithm to optimize this interval, and then we can get the worker's rational quotation interval  $[q_0, q_1]$ .

**Step 4.** Workers choose the task and submit their quotations  $q_i$  to the platform. As long as  $q_i \in [q_0, q_1]$ , the worker will have the chance to get the task. Considering the feasibility of workers' quotations, the crowdsourcing platform needs to evaluate the workers' reputation and their enthusiasm to complete tasks, for example, whether the worker can complete tasks as soon as possible or not. First, sort the workers in ascending order according to their reputation, and then sort them in descending order according to the quoting time. The crowdsourcing platform will try to give the task to those who have high reputation and need less time to complete tasks.

### Auction screening Algorithm

**Input:** the workers' historical quotations set  $Q$ , the distinguishing coefficient  $\rho$ , and the confidence coefficient  $\alpha$  [t]

**Output:** The quotations range of the workers  $[q_0, q_1]$

01: Transform the historical quotations sample set  $Q$  to the matrix  $Q'$

02: Determine the reference sequence  $q_{max}$

03: Standardize the matrix  $Q'$

04: Calculate the correlation coefficient  $\zeta$  with

$$05: \zeta = \frac{\min_{u=2}^{n-1} \{\min_{o=2}^{m-1} \{|q'_u(m-1) - q'_u(o)|\}\} + \rho \max_{u=2}^{n-1} \{\max_{o=2}^{m-1} \{|q_{max} - q'_u(o)|\}\}}{|q'_u(m-1) - q'_u(o)| + \rho \max_{u=2}^{n-1} \{\max_{o=2}^{m-1} \{|q_{max} - q'_u(o)|\}\}}$$

06: Normalize  $\zeta$  to correlation degree  $w_u$

07: Calculate the grey estimate  $q$  of the workers' quotation with

$$08: q = \sum_{u=2}^{n-1} w_u * \bar{q}_u$$

09: Calculate the quotations range of the workers  $[q_0, q_1]$  with

$$10: d_{\zeta_u}(q, q'_u(o)) = \frac{\min_{u=2}^{n-1} \{\min_{o=2}^{m-1} \{|q - q'_u(o)|\}\} + \rho \max_{u=2}^{n-1} \{\max_{o=2}^{m-1} \{|q - q'_u(o)|\}\}}{|q - q'_u(o)| + \rho \max_{u=2}^{n-1} \{\max_{o=2}^{m-1} \{|q - q'_u(o)|\}\}}$$

11:  $d_{\zeta_u}(q, q'_u(o)) \geq \alpha$

Calculations on worker's reputation and requester's reputation are similar.

2) *Reward Distribution Method:* We made a quality-time incentive mechanism to further encourage workers to complete tasks with high quality and in time. We defined the reward function according to quality of service and task completion time as follows:

$$R_{q_i} = \text{sign}(quality_i - quality_0) * \frac{quality_i}{\sum_{z=1}^N quality_z} * Q \quad (18)$$

$$R_{t_i} = \text{sign}(time_i - time_0) * \frac{e^{-time_i}}{\sum_{z=1}^N e^{-time_z}} * T \quad (19)$$

where,  $\text{sign}(quality_i - quality_0)$  and  $\text{sign}(time_i - time_0)$  are defined as follows:

$$\text{sign}(quality_i - quality_0) = \begin{cases} 1, & quality_i - quality_0 \geq 0 \\ -1, & quality_i - quality_0 < 0 \end{cases} \quad (20)$$

$$\text{sign}(time_i - time_0) = \begin{cases} 1, & time_0 - time_i \geq 0 \\ -1, & time_0 - time_i < 0 \end{cases} \quad (21)$$

where  $quality_0$  and  $time_0$  separately refer to the threshold values of quality of service and task completion time set by crowdsourcing platform.  $R_{q_i}$  and  $R_{t_i}$  separately refer to the quality of service reward and task completion time reward for worker  $i$  who successfully completes the task.  $Q$  and  $T$  separately refer to the amount of the first two variables. To sum up, the worker's quality of service can be guaranteed by choosing the candidate set of rational workers based on the auction-screening method. The reward distribution method can further encourage workers to complete the tasks with assured quality and time.

In conclusion, this article designs unique charging rules to make a reasonable connection between these two dilemmas. In the cooperation dilemma solution, the crowdsourcing platform needs to evaluate the quality of service level of the workers and charge the requesters based on the evaluation results.

The fees are also used for the crowdsourcing platform to pay rewards to the workers who complete the tasks. In the quality of service dilemma solution, the platform needs to estimate the cost of recruiting workers to complete the decision-making task which can further compress the recruitment range of high-quality workers.

## V. OPTIMAL STRATEGY FOR WORKERS AND CROWDSOURCING PLATFORM

Each player wants to maximize their own payoff because of inherent nature. The requester's payment can be calculated based on the reputation-quality rules. Therefore, it has become an urgent issue to determine the optimal strategy of workers and the crowdsourcing platform respectively.

The payoff of worker  $i$  is,

$$R_{w_i} = x_i + R_{q_i} + R_{t_i} - c \quad (22)$$

$$R_{w_i} = x_i + \text{sign}(quality_i - quality_0) * \frac{quality_i}{\sum_{z=1}^N quality_z} * Q + \text{sign}(time_i - time_0) * \frac{e^{-time_i}}{\sum_{z=1}^N e^{-time_z}} * T - time_i * b \quad (23)$$

where,  $c = time_i * b$ ,  $b$  is the time unit cost to complete tasks,  $time_i$  is the time for worker  $i$  to complete the task.  $N$  is the number of workers,  $t$  is the maximum amount of time that the worker spends completing a task. According to above analysis, we divided the results into the following four cases.

- i)  $\begin{cases} quality_0 \leq quality_i \leq 1 \\ time_0 \leq time_i \leq t \end{cases}$
- ii)  $\begin{cases} 0 \leq quality_i \leq quality_0 \\ time_0 \leq time_i \leq t \end{cases}$
- iii)  $\begin{cases} quality_0 \leq quality_i \leq 1 \\ 0 \leq time_i \leq time_0 \end{cases}$
- iv)  $\begin{cases} 0 \leq quality_i \leq quality_0 \\ 0 \leq time_i \leq time_0 \end{cases}$

For case i), the payoff of worker  $i$  is,

$$R_{w_i} = x_i + \frac{quality_i}{\sum_{z=1}^N quality_z} * Q - \frac{e^{-time_i}}{\sum_{z=1}^N e^{-time_z}} * T - time_i * b \quad (24)$$

That is,

$$R_{w_i} = x_i + \frac{quality_i}{\sum_{z=1}^{N \neq i} quality_z + quality_i} * Q$$

$$- \frac{e^{-time_i}}{\sum_{z=1}^{N \neq i} e^{-time_z} + e^{-time_i}} * T - time_i * b \quad (25)$$

Compute the first derivative of  $R_{w_i}$  regarding  $quality_i$  and  $time_i$  respectively.

$$\begin{cases} R_{w_{quality_i}} = \frac{Q}{\left(\sum_{z=1}^N quality_z\right)^2} - \frac{Q * quality_i}{\left(\sum_{z=1}^N quality_z\right)^2} \\ R_{w_{time_i}} = \frac{T * e^{-time_i}}{\sum_{z=1}^N e^{-time_z}} - \frac{T * e^{-2 * time_i}}{\left(\sum_{z=1}^N e^{-time_z}\right)^2} - b \end{cases} \quad (26)$$

Assume that  $R_{w_{quality_i}} = 0$ ,  $R_{w_{time_i}} = 0$ , it can be seen from the above equation is not stationary points in the range  $\begin{cases} quality_0 \leq quality_i \leq 1 \\ time_0 \leq time_i \leq t \end{cases}$ . Thus, the maximum value of payoff must be obtained at the boundary. That is,

- i)  $\begin{cases} quality_i = quality_0 \\ time_i = t, \end{cases}$
- ii)  $\begin{cases} quality_i = quality_0 \\ time_i = time_0 \end{cases}$
- iii)  $\begin{cases} quality_i = 1 \\ time_i = time_0, \end{cases}$
- iv)  $\begin{cases} quality_i = 1 \\ time_i = t \end{cases}$

Then the payoff of worker  $i$  can be represented,

$$\begin{aligned} R_{w_i}^1 &= x_i + \frac{quality_0}{A_1 + quality_0} * Q - \frac{e^{-time_0}}{A_2 + e^{-time_0}} * T - time_0 * b \\ R_{w_i}^2 &= x_i + \frac{quality_0}{A_1 + quality_0} * Q - \frac{e^{-t}}{A_2 + e^{-t}} * T - time_0 * b \\ R_{w_i}^3 &= x_i + \frac{1}{A_1 + 1} * Q - \frac{e^{-t}}{A_2 + e^{-t}} * T - t * b \\ R_{w_i}^4 &= x_i + \frac{1}{A_1 + 1} * Q - \frac{e^{-time_0}}{A_2 + e^{-time_0}} * T - t * b \end{aligned} \quad (27)$$

where  $A_1 = \sum_{z=1}^{N \neq i} quality_z$ ,  $A_2 = \sum_{z=1}^{N \neq i} e^{-time_z}$ .  $\frac{quality_0}{A_1 + quality_0} < \frac{1}{A_1 + 1}$ ,  $\frac{e^{-t}}{A_2 + e^{-t}} < \frac{e^{-time_0}}{A_2 + e^{-time_0}}$ , therefore,

$$\begin{cases} R_{w_i}^1 = \min\{R_{w_i}^1, R_{w_i}^2, R_{w_i}^3, R_{w_i}^4\} \\ R_{w_i}^3 = \max\{R_{w_i}^1, R_{w_i}^2, R_{w_i}^3, R_{w_i}^4\}. \end{cases}$$

Finally, the optimal strategy of worker  $i$  is  $\begin{cases} quality_i = 1 \\ time_i = t \end{cases}$ , and the optimal payoff is  $R_{w_i}^3$ .

Similar to case i), we can obtain the optimal strategy of similar to worker  $i$  for case ii), iii), iv). Similarly, we can obtain the optimal strategy of the crowdsourcing platform.

$$s_u(q_{max}, q'_u(o)) = \frac{\min_{u=2}^{n-1} \left\{ \min_{o=2}^{m-1} \{ |q'_u(m-1) - q'_u(o)| \} \right\} + \rho \max_{u=2}^{n-1} \left\{ \max_{o=2}^{m-1} \{ |q_{max} - q'_u(o)| \} \right\}}{|q'_u(m-1) - q'_u(o)| + \rho \max_{u=2}^{n-1} \left\{ \max_{o=2}^{m-1} \{ |q_{max} - q'_u(o)| \} \right\}} \quad (16)$$



TABLE III  
SETTING OF PARAMETERS

<b>Parameter</b>	$\eta$	$\beta$	$\delta$	$\varpi$	$\omega$	$Q$	$T$	$\alpha$	$U$
<b>Value</b>	1000	1000	1.5	-7	1	150	50	0.05	1.5
<b>Parameter</b>	$c_p$	$R$	$\vartheta$	$quality_0$			$time_0$		
<b>Value</b>	0.5	5	0.2	0.3	0.5	0.7	5	7	9

## VI. SIMULATION RESULTS

### A. Experiment Setting

This article uses *Netlogo* simulation platform to verify the above proposals. Parameters in the following experiments are set in Table III, and the meaning of the parameters in this table has been described in the above sections.

To verify the feasibility of using cooperation promotion solution (*CP*), we first simulate and analyze the changing trend of requester's payment and the variation trend of quality of service. Secondly, we compare the accuracy of *cos-evaluation* algorithm (*CE*) with *Markov-GM* model [41], *ARMA* model, and then we compare the requester's payoff in *CP*, *ALLD*, *ALLC*, *CToD*, and *TFT*. To check the validity of quality of service improvement solution (*QI*), we use Facebook social network [42] and auction dataset [43] to simulate the interaction process between the platform and workers. We first simulate and analyze the impact of quality of service threshold and completion time threshold on worker and platform's payoff, and determine their respective values. Secondly, to validate the accuracy of *grey interval estimation* model (*GIE*), we compare *QI* separately with normal distribution interval estimation model and exponential distribution interval estimation model. Thirdly, we also analyze the worker's payoff trend under the influence of two constraint conditions: quality of service level and task completion time. And finally we compare *QI* with the data of quality of service and platform's cost indicators in *NQA* [15], *EMA* [30] and *SZD* [44].

### B. Verification of Cooperation Promotion Solution

1) *Changing Trend of Requester's Payment*: Fig. 2 shows the changing trend of requester's payment to the crowdsourcing platform in two different payment modes. If the requester's reputation is lower than the threshold value, the requester's payment decreases when his reputation increases. If the crowdsourcing platform makes the payment according to the worker's quality of service, payment decreases when the quality of service level decreases. By comparing these two different payment modes, we can see that the highest value of the payment according to quality of service is lower than the lowest value of the payment made according to the reputation, which means that requester with high reputation can enjoy quality service at a relatively low cost. In this payment mode, the requester will try to increase his reputation to lower cost, and then the requester will actively adopt cooperative action in the interaction process.

2) *Variation Trend of Quality of Service*: In order to evaluate the workers' quality of service ( $Q$ ) more accurately and scientifically, we use the fuzzy logic rules [45] by introducing three factors that affecting the quality of service, i.e., workers' reputation ( $R$ ), task size ( $T$ ), and task complexity ( $C$ ). Besides, to show the effectiveness of this method more clearly, we assume the task size is 0.3, the variation trend of quality of service level is shown in Fig. 3. We can see that  $R$  has a

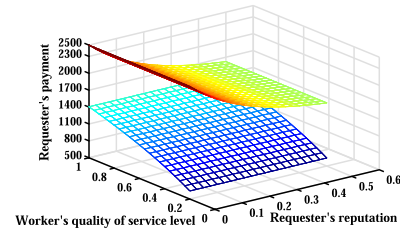


Fig. 2. Requester's payment trend.

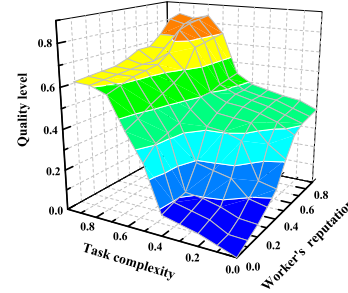


Fig. 3. Quality of service variation trend.

TABLE IV  
COMPARISON OF PREDICTION RESULTS AND ERRORS

Period	Value	Markov-GM		ARMA		CE	
		value	error	value	error	value	error
1	833.6	833.6	0	833.6	0	833.6	0
2	758.4	804.2	6.039	790.3	4.2062	772.8	1.8987
3	579.6	651.8	12.4569	601	3.6922	564.3	2.6398
4	905.4	866.8	4.2633	863.2	4.6609	910.1	0.5191
5	877.8	909.5	3.6113	853.1	2.8138	891.8	1.5949
6	646.2	695.4	7.6137	685.6	6.0972	663.1	2.6153
7	824.5	761.8	7.6046	786.3	4.6331	818.4	0.7398
8	896.3	864.5	3.5479	878.6	1.9748	887.3	1.0041
ME			5.642		3.5098		1.3765
9	859.1	802.6	6.5766	835.4	2.7587	868.4	1.0825
10	707.9	759.8	7.3154	742.8	4.9301	718.8	1.5398
ME			6.9541		3.8444		1.3111

significant influence than  $C$ . From the trend in the curvature of this graph, apparently, when the  $R$  is more than 0.4, the worker's quality of service level increases rapidly with the increasing value of  $R$ .

3) *Accuracy of the Cos-evaluation Algorithm (CE)*: As shown in Table IV, we use the data of the first 8 periods as the original prediction sequence and compare the *CE* separately with the *ARMA* model [29] and the improved *Markov-GM* model [33]. The comparison of prediction results and errors of each method are shown in Table IV. As shown in this table, the mean error (*ME*) [46] in *CE* is 1.3111%, which is much smaller than that in *Markov-GM*. And the *ME* in *ARMA* is 3.8444%, which is about 3 times larger than that in *CE*. Therefore, it is clear that the prediction accuracy of *CE* is significantly better than that of the other two methods.

4) *Comparison of the Requester's Payoff*: Fig. 4 compares the requester's payoff in five solutions, *ALLC* refers to the requester always plays cooperation strategy, *ALLD* refers to the requesters always plays defection strategy, *CToD* refers to the requester plays the strategy of previous rounds, and *TFT* means that if the opponent cooperates, the player will cooperate, otherwise, the player will betray. Fig. 4(a) compares

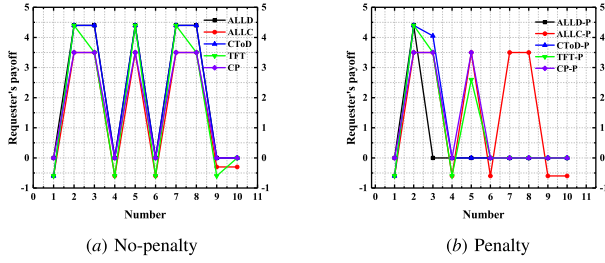


Fig. 4. Comparison of requester payoff.

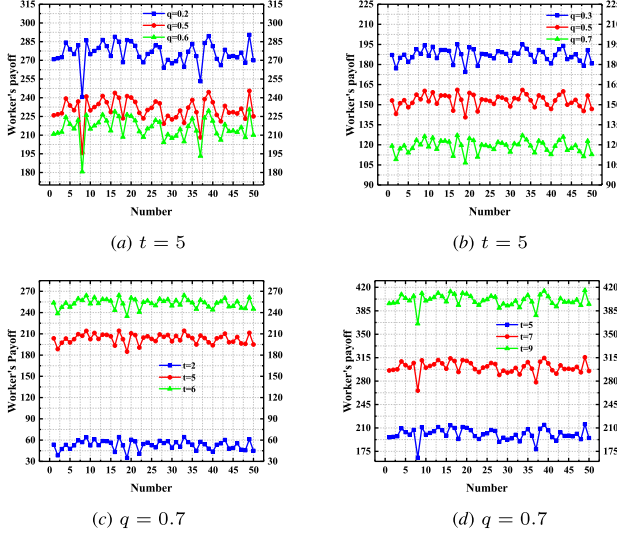


Fig. 5. Worker's payoff.

the requester's payoff in five solutions with no penalty policy. From this figure, we can see that the requester obtains the highest accumulative payoff in *ALLD* solution. This is because the crowdsourcing platform does not adopt any penalty strategy, the short-sighted requester can take the betrayal strategy to maximize his payoff. Fig. 4(b) compares the requester's payoff in five solutions with penalty policy, the requester obtains the highest accumulative payoff in *ALLC* solution, this is because the requester's cost increases with the increasing number of betraying times. Once the requester's betrayal time more than 2 (the platform can accept the maximum value of requester's betrayal time), the crowdsourcing platform will no longer perform tasks for it and blacklist this short-sighted requester. Therefore, if and only if the requester plays the cooperation strategy can promote sustainable development between the requester and the crowdsourcing platform in *CP* solution.

### C. Verification of Quality of Service Improvement Solution

1) *The Impact of Quality of Service Level Threshold and Completion Time Threshold on the Payoff of Workers and Platforms:* Fig. 5 and Fig. 6 compare the trends of worker's and platform's payoff. We assume that the reward of the platform to complete tasks is 300, and the cost of recruiting workers is 200. We set the completion time threshold  $t \in [1 - 10]$  and the quality of service threshold  $q \in [0, 1]$  respectively to stimulate experiments for analyzing the impact of quality of service threshold and completion time threshold on the payoff of workers and platforms. Due to the limitation of space, we just show the results of  $q = 0.2, 0.3, 0.5, 0.6, 0.7$  and

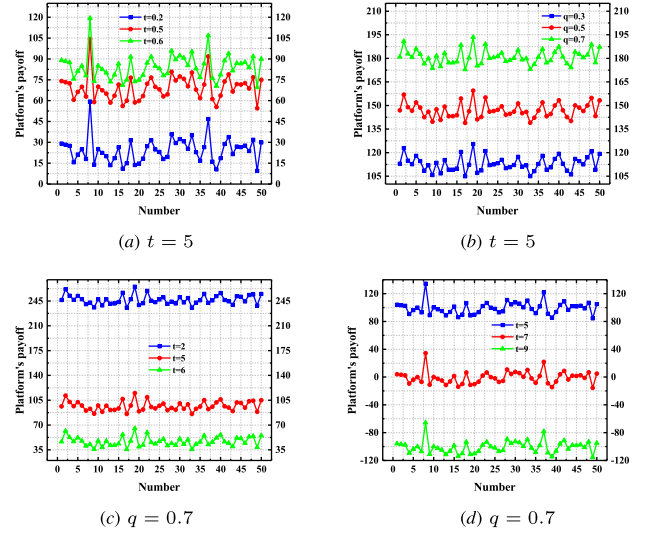


Fig. 6. Platform's payoff.

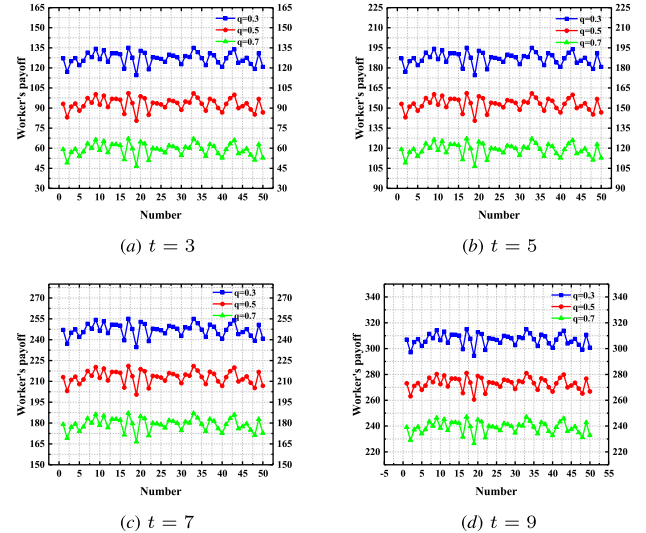


Fig. 7. Worker's payoff.

$t = 5, q = 0.7$  and  $t = 2, 5, 6, 7, 9$ . As shown in Fig. 5, if the completion time threshold is fixed, the workers' payoff decreases with the increasing number of the quality of service threshold; otherwise, if the quality of service threshold is fixed, the workers' payoff increases with the increasing number of the completion time threshold. From Fig. 6, it can be seen that if the completion time threshold is fixed, the platform's payoff increases with the increasing number of the quality of service threshold; otherwise, the platform's payoff decreases with the increasing number of the completion time threshold.

2) *Determining the Quality of Service Threshold and Completion Time Threshold:* From Fig. 7, we can see that when the values of the completion time threshold  $t$  and quality of service threshold  $q$  correspond to the following conditions  $t = 3, q = 0.3, 0.5, 0.7, t = 5, q = 0.3, 0.5, 0.7$  and  $t = 7, q = 0.7$ , the workers' payoffs are lower than 200 which do not exceed the cost of the platform to recruit workers.

The comparison of platforms' extra payoff is shown in Fig. 8. The platform's extra payoff refers to the difference between the expected rewards paid to the workers and the actual rewards paid to the workers. As shown in this figure, under the following conditions, i.e., the completion time

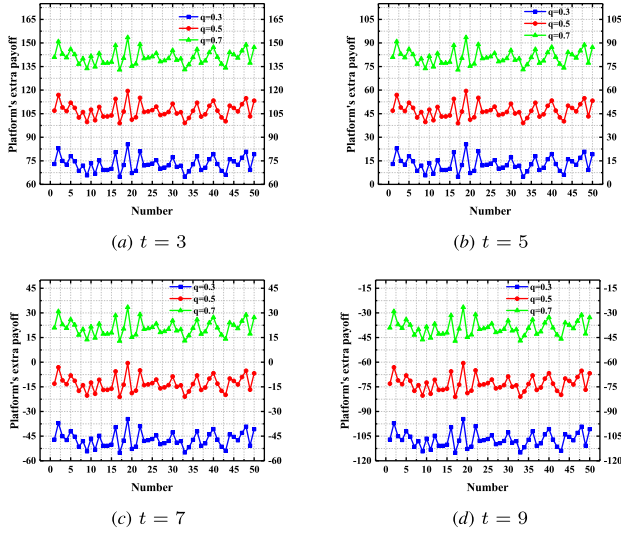


Fig. 8. Platform's extra payoff.

TABLE V  
COMPARISON OF NORMAL DISTRIBUTION MODEL AND GIE

Estimated value $\mu$	Normal distribution interval	Interval length	GIE	Interval length
20	[19.301,20.863]	1.562	[19.582,20.0241]	0.4421
21	[20.0260,21.6005]	1.5745	[21.0863,21.2405]	0.1542
22	[20.8166,22.3583]	1.5417	[21.2603,22.3371]	1.0741
23	[22.5748,24.1338]	1.5742	[22.7608,23.7247]	0.9639
24	[23.5596,25.1292]	1.5696	[23.6477,24.4903]	0.8426
25	[24.8420,26.3673]	1.5253	[24.8069,25.1197]	0.3128
26	[24.2007,25.7691]	1.5684	[25.6841,26.7023]	1.0182
27	[26.8900,28.4276]	1.5376	[25.8393,27.3870]	1.5477
28	[27.2457,28.7891]	1.5434	[27.9802,28.9823]	1.0021
29	[28.1099,29.6779]	1.568	[28.7655,29.0514]	0.2948
30	[28.3361,29.9175]	1.5814	[29.9749,30.0577]	0.0828

threshold and quality of service threshold are set  $t = 3$ ,  $q = 0.3, 0.5, 0.7$ ,  $t = 5$ ,  $q = 0.3, 0.5, 0.7$  and  $t = 7$ ,  $q = 0.7$ , the platform's extra payoffs are larger than 0. In particular, if the above two thresholds are too low or too high, it is difficult to guarantee that the worker's quality of service is up to standard and the tasks are completed within the specified time. According to the experimental results, we can obtain the quality of service threshold and the completion time threshold are  $q = 0.7$ ,  $t = 5$ .

### 3) Accuracy of Grey Interval Estimation Model (GIE):

From Table V and Table VI, if we compare interval range of all three models, the grey interval in this article not only contains the estimated values  $\mu$  and  $\lambda$ , but also has small errors; if we compare estimated interval length among three models, grey estimated interval length is apparently shorter than the mean value estimated interval length of normal distribution and exponential distribution. In conclusion, our new model performs better than the rest two models as the grey interval is short-length and more accurate.

### 4) Validity of Auction-screening Method (AS):

Fig. 9 demonstrates the worker's quotation distribution in history. Interval A refers to worker's rational cost interval by using grey interval estimation model (GIE). \* refers to cost forecasting result after using the cost-evaluation algorithm (CE). To lower the cost for platform, we reduce the interval

TABLE VI  
COMPARISON OF EXPONENTIAL DISTRIBUTION MODEL AND GIE

Estimated value $\lambda$	Exponential distribution interval	Interval length	GIE	Interval length
0.1	[0.0929,0.1005]	0.0076	[0.0958,0.1004]	0.0046
0.2	[0.1986,0.2148]	0.0162	[0.1987,0.2012]	0.0025
0.3	[0.2886,0.3121]	0.0235	[0.2990,0.3094]	0.0104
0.4	[0.3855,0.4170]	0.0315	[0.3995,0.4001]	0.0006
0.5	[0.4567,0.4940]	0.0373	[0.4793,0.4997]	0.0204
0.6	[0.5687,0.6151]	0.0464	[0.5932,0.6016]	0.0084
0.7	[0.6635,0.7176]	0.0541	[0.6996,0.7084]	0.0088
0.8	[0.7488,0.8099]	0.0611	[0.7729,0.8216]	0.0487
0.9	[0.8651,0.9357]	0.0706	[0.8935,0.9033]	0.0098
1	[0.9806,1.0606]	0.08	[0.9986,1.0183]	0.0197
1.1	[1.0552,1.1413]	0.0861	[1.0804,1.1268]	0.0464

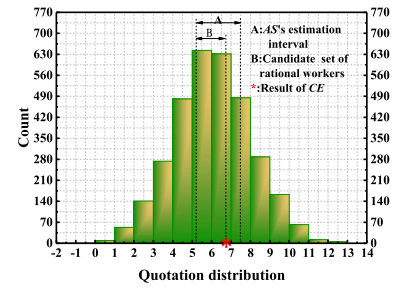


Fig. 9. Worker's quotation distribution.

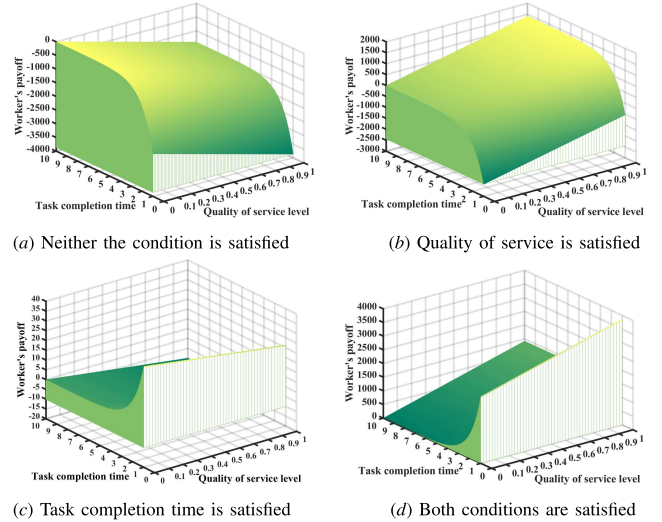


Fig. 10. Worker's utility trend.

A to interval B at the point of cost forecasting result. Interval B refers to the quotation interval when the platform is hiring worker (candidate worker's set which consists of workers who give rational quotation within this interval). This article uses AS and CE to predict the worker's rational quotation interval more accurately and to further complete the task of screening proper worker candidate.

### 5) Effectiveness of Reward Distribution Method:

Fig. 10 shows the worker's payoff changing trend influenced by the two conditions of workers' quality of service level and task completion time. As shown in Fig. 10(a), we can see that if two conditions are not met, even if the crowdsourcing platform pays the same amount of the worker's quotation at

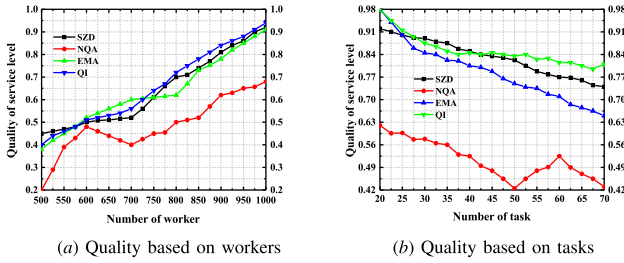


Fig. 11. Comparison of quality of service level.

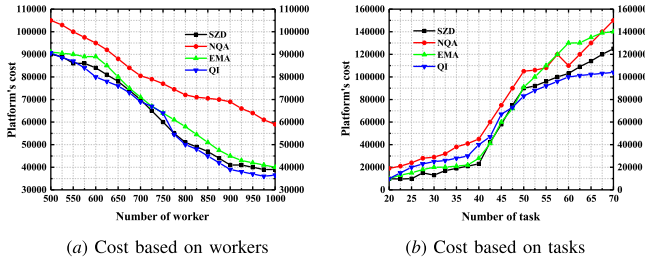


Fig. 12. Comparison of platform's cost.

the very beginning, the worker will have to pay penalty for not meeting the needs and will have a negative payoff. From Fig. 10(b) and Fig. 10(c), we can see that if a worker meets the need of one constraint condition, his payoff will decrease due to the penalty that he has to pay to the crowdsourcing platform for not meeting the other condition. This mechanism can effectively prevent workers from meeting only one condition for higher rewards. Fig. 10(d) demonstrates that the worker will have the highest payoff if two conditions are both met. The reward distribution method can propel the worker to complete tasks in time with good quality.

6) *Comparison of Quality of Service Level*: Referring to the two variables: number of workers and number of tasks, Fig. 11 shows the comparison of quality of service in four solutions. Fig. 11(a) shows how the number of workers can influence quality of service level. As the number of workers increases, the overall quality level keeps increasing in all four solutions. In *QI*, the quality of service level is low at the very beginning due to the rapid increasing of the number of workers, as some workers do not balance the quality of service and task completion time well. But after the number of workers reaches 725, the quality of service level keeps increasing and has an even better effect than other solutions. Fig. 11(b) demonstrates how the number of tasks can influence workers' quality of service level. In general, the quality of service level drops when the number of tasks increases. But because we use the reward distribution method in this article, workers will try to improve their quality of service in order to earn the highest award (or in order to avoid paying penalty). Therefore, the quality of service level in general has not been deeply affected.

7) *Comparison of Platform's Cost*: Fig. 12 demonstrates the comparison of platforms' cost under the four models. As shown in Fig. 12(a), we can see that as the number of workers increases, the cost of crowdsourcing platform keeps decreasing in all four solutions. But our proposed solution has a better effect than the other three. The reason is that as the number of workers increases, the crowdsourcing platform will have more options. Fig. 12(b) shows how the number of tasks can influence the cost of crowdsourcing platform.

As the number of tasks increases, the cost of crowdsourcing platform increases in all four solutions. After the number of tasks reaches 48 in *QI*, the cost of crowdsourcing platform does not increase sharply like others and stays lower than other solutions. This is because the payment to workers is divided into two parts in *EMA* and *SZD*: worker's quotation and extra reward, which work together with our proposed *QI*. If the worker's quality of service and task completion time cannot meet the need of the crowdsourcing platform, worker's final payoff is surely to become lower than the worker's quotation at the very beginning. The reduced part of the payment to those workers can be used to pay to other high quality workers as extra reward. Therefore, the cost of crowdsourcing platform is relatively low in this case.

## VII. CONCLUSION

Crowdsourcing system can be applied in many different fields, especially in business domain. Most of the multinational corporations. The proposed scheme in this article is used to solve the existing two problems in this system. The *cooperation promotion solution (CP)* can encourage both the requester and the crowdsourcing platform to actively choose the cooperative strategy to maximize their payoff, and the *quality of service improvement solution (QI)* can obtain a reasonable candidate set of rational workers and effectively promote workers to complete tasks with high quality and in time. The effectiveness of the proposed proposals is verified by detailed simulation experiments.

In future researches, we will continue to pay attention to the platform's cost prediction model and further improve the accuracy of prediction results.

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