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A Budget Constraint Incentive Mechanism Based on Risk Preferences of Collaborators in Edge Computing

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Abstract: Mobile Edge Computing (MEC) is a new distributed computing method based on the mobile communication network. It can provide cloud services and an IT service environment for application developers and service providers at the edge of the network. Computation offloading is a crucial technology of edge computing. However, computation offloading will consume the resources of the edge devices, and therefore the edge devices will not offload computation unconditionally. In addition, the service quality of edge computing applications is related to the cooperation rate of edge devices. Therefore, it is essential to design an appropriate incentive mechanism to motivate edge devices to execute computation offloading. However, the current existing incentive mechanisms have two problems: Firstly, existing mechanisms do not account for probability distortions under uncertainty in collaborator utility valuation models. Secondly, the platform ignores the risk preferences of collaborators in multiple rounds of decision-making. To address these issues, we propose an incentive mechanism based on risk preference, IMRP. The IMRP considers the collaborator's probability distortion, introduces an uncertain utility bonus scheme, and builds a probability distortion model to influence the collaborator's willingness to offload tasks. The IMRP also considers the collaborator's risk preference and builds the collaborator's risk preference model to influence the collaborator's bidding decision. Simulation results show that our mechanism effectively improves the cooperation rate of edge devices and the utility of the requester.

Keywords: edge computing; computation offloading; probability distortion; risk preference

MSC: 37M10

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1. Introduction

In recent years, with the development of the Internet of Things, the application of the Internet of Things has put forward higher requirements on transmission bandwidth, delay, energy consumption, etc. In this case, due to the limited bandwidth, high time delay, and high energy consumption of the centralized processing mode of cloud computing, it is difficult to meet the high-performance requirements of users [1]. Therefore, Mobile Edge Computing is proposed as a new computing paradigm. Mobile Edge Computing incorporates servers into the aggregation nodes of the edge network [2] , such as cellular network base stations, Wi-Fi access points, and routers. This enables these aggregation nodes to have enhanced network, computing, and storage functionality. Computation offloading is a crucial technology in edge computing. It transfers computation-intensive tasks from resource-limited mobile users to nearby edge devices [3], reducing the transmission delay of applications. This enables users to obtain better Quality of Experience (QoE) and Quality of Service (QoS) [4]. Mobile users act as requester of offloading services, and edge devices serve as collaborators in delivering low-latency, high-performance computing services to terminal devices [5]. In recent years, various fields have adopted edge offloading technology to increase service quality. For example, in the field of robotics, edge computing is used for the manufacture of emotionally interactive intelligent robots [6] and the optimization of industrial robots [7]. In the field of surveillance and detection, edge computing is used in large video surveillance systems [8], vehicle driving behavior detection systems [9], and behavior-based identity recognition systems PreDriveID [10]. In the field of virtual reality, edge computing is used in Virtual Reality (VR) video processing frameworks, such as the Multi-User Virtual Reality (MUVR) framework [11] and the Furion framework [12].

The quality of edge computing applications depends greatly on the cooperation rate of collaborators. For a large-scale video surveillance system, greater participation in task offloading leads to more available computing resources and ultimately enhances the timeliness and accuracy of video surveillance services. However, during the process of assisted offloading, there are problems to consider. Firstly, offloading consumes the collaborator's computing resources, power, and storage space. Secondly, edge offloading sends task content to collaborators through the mobile communication network, resulting in a potential leak of confidential information. These two factors lead to edge devices not actively sharing computing resources. Therefore, it is crucial to develop appropriate incentive mechanisms based on diverse application requirements to stimulate collaborators to willingly offer computation offloading services.

Most of the current research on incentive mechanisms for computation offloading has two problems. Firstly, current mechanisms are mainly designed based on the expected utility model. Collaborators only consider the expected bonus of the current round. Current mechanisms do not consider the probability distortion of collaborators, nor do they consider the effect of past payoff on the collaborator's current expectation of bonus. The current incentive mechanisms increase payment to motivate collaborators to offload tasks, but this will cause the incentive effect to decline as the number of offloads increases under limited budget conditions. Secondly, most current incentive mechanisms are based on a single round of task offloading and do not consider the continuous influence of the collaborator's variable risk preference on their decisions, that is, they do not consider the correlation between successive decisions. Risk preference refers to an individual's attitude towards uncertainty, which can affect their expectations of uncertainty and the utility evaluation of the actual payoff. In this paper, risk preference is expressed as the deviation between the collaborator's expectation of the uncertainty bonus scheme and the actual bonus. The correlation between decisions means that collaborators' risk preferences will change with the payoff brought by collaborators' previous decisions and then influence collaborators' subsequent decisions. If the mechanism does not consider the impact of the payoff and risk preference of the past task offload on the subsequent task offloading, it will ignore the implicit cost of the decision sequence. Implicit cost refers to cost elements that are present in decisions but cannot be easily observed directly. In this paper, the implicit cost refers to the additional cost that the past benefit of the cooperator causes the requester to pay for the subsequent task offloading. If the implicit cost is ignored, the actual incentive effect will be lower than the theoretical incentive effect.

In order to address the above problems, we propose an incentive mechanism based on risk preference. Specifically, our contributions are summarized as follows:

- Propose a probabilistic bonus scheme for collaborators on the platform. Collaborators will be selected based on their bid and will have the opportunity to get a bonus by lowering their bid. The past bonus of the collaborators will affect the collaborators' expectations of the bonus, thus affecting the willingness to participate and the collaboration rate of the collaborators.
- Construct a risk preference factor model for the collaborators. The size of the bonus pool and each round of bonus payments affect the collaborators and the risk preference factor is dynamically updated. The collaborator's evaluation of the expected bonus is influenced by the risk preference factor. And this influences the collaborator's

evaluation of the extra bonus and the willingness to participate, thereby improving the collaborators' cooperation rate.

The rest of the paper is organized as follows. In Section 2, we briefly review related work. We introduce the system model of MEC and the proposed IMRP mechanism in Section 3. In Section 4, we perform and evaluate the effectiveness of the proposed mechanism through simulation experiments. Finally, we conclude this paper in Section 5.

2. Related Work

Currently, research on incentive mechanisms for computation offloading can be divided into two categories: monetary and non-monetary. Considering this classification, this section provides a summary of the current research. Table 1 classifies and summarises the literature on edge unloading incentive mechanisms in terms of incentive method, mechanism name, and purpose of research.

The dominant method used for computation offloading is the currency-based incentive mechanism that motivates collaborators to share computing and storage resources through monetary rewards [13]. Currency-based incentives can take various forms like game, auction, and contract mechanisms [14]. To promote interactivity and evenly distribute the workload from the centralized cloud, Ref. [15] proposes an incentive-compatible auction mechanism. Ref. [16] put forward a multi-round auction to address the efficiency and selfishness concerns in task offloading in vehicle fog computing systems. Ref. [17] introduced a double auction mechanism to examine the video caching issues in dense and diverse networks, in order to optimize social welfare. Ref. [18] described a Vickrey–Clarke–Groves (VCG)-based vehicle-to-vehicle (V2V) reverse auction mechanism to motivate selfish automobiles to share resources, shorten the duration of applications, and reduce the load on vehicles. Ref. [19] puts forth a reverse auction-based approach to motivate edge nodes in mobile social networks to offer caching services for the purpose of conserving urban energy. Ref. [20] investigates the task offloading problem in mobile edge computing for ultra-dense networks, utilizing game theory to reduce network delays and energy usage. In Ref. [21], a game theory technique is presented to minimize the execution costs of social groups in fog computing. Ref. [22] investigates data offloading within mobile edge computing and proposes a pricing strategy rooted in alliance games to optimize the effectiveness of each alliance. Ref. [23] proposes an incentive mechanism based on game theory, which serves to increase the utility provided by service providers and lower the energy consumption and task completion time of smart devices.

Table 1. Edge offloading incentive mechanism classification summary.

Incentive Method	Literature	Mechanism/Algorithm
Monetary rewards	[12]	Incentive-Compatible Auction Mechanism (ICAM)
Monetary rewards	[13]	Vehicular fog computing (VFC)-aware parking auction
Monetary rewards	[14]	Double Auction Mechanism Design for Video Caching
Monetary rewards	[15]	VCG-based reverse auction for computation offloading
Monetary rewards	[16]	Reverse auction game model with incentives for edge node
Monetary rewards	[17]	Software defined task offloading (SDTO) scheme
Social relationship	[18]	Socially aware dynamic computation offloading algorithm
Monetary rewards	[19]	Joint coalition-and-pricing based data offloading approach
Monetary rewards	[20]	Incentive-based optimal computation offloading scheme
Reputation mechanism	[22]	Reputation-based CSS incentive framework
Monetary rewards	[23]	Low-complexity heuristic algorithm
Monetary rewards	[24]	Virtual Bank with movement prediction (VBMP)
Mixed mechanism	[25]	Incentive mechanism that integrates rewards and reputation
Reputation mechanism	[26]	Reputation Framework for Vehicular Applications

Non-monetary mechanisms mainly include reputation and penalty mechanisms [24]. In Ref. [25], to study incentive problems in cooperative spectrum sensing (CSS) systems, a reputation-based indirect reciprocal game mechanism has been proposed. In Ref. [26], the joint problem of computation offloading and resource allocation is formulated as finding the optimal response using a mixed-integer non-linear function to maximize the offloading benefits of the users. Ref. [27] investigates terminal-to-terminal offloading methods and implements a virtual banking system with mobile forecasting to manage data offloading. In Ref. [28], an incentive mechanism combining auction and reputation is proposed to increase the offloading rate by rewarding the cooperative users and penalizing the selfish users. Ref. [29] introduced a novel reputation framework that provides caching incentives through an information-centric approach and routing incentives through a vehicle delay-tolerant approach, thereby improving data accessibility for mobile vehicles.

There are already a number of current incentive mechanisms that consider the budget constraint. According to Ref. [18], a V2V reverse auction mechanism based on VCG could be implemented. In addition, Ref. [21] suggests the use of game theory methods for the reduction of execution costs in edge computing. Ref. [30] proposes an iterative algorithm that uses subgradients to distribute the load and optimize the cost, which reduces the cost of offloading tasks and optimizes the budget constraint problem.

Currently, there are incentive mechanisms that consider the correlation between decision sequences. Ref. [31] uses game theory to incentivize participants to provide data for crowd sensing, and introduces a reputation model for participants that considers the experience between two participants. In each round, the reputation score of participants is dynamically updated by voting according to the participation results. The data trust of participants is evaluated by the reputation score, and the rewards in the form of badges are provided to participants according to the reputation score. Ref. [32] improves the traditional auction incentive mechanism by introducing a verification link and reducing interference from participant information on the platform. Additionally, this reference introduces a reputation model for participants. The reputation of participants is updated dynamically based on the quality of sensing data submitted in each round. This encourages participants to provide higher-quality data. Ref. [33] proposed an incentive mechanism based on reverse auction. This mechanism uses the user's previous completion of sensing tasks as the cumulative standard of their reputation value. The group of participants with the highest reputation value is then selected to complete the task, under the premise that the task publisher's budget is limited. Participants are rewarded based on the quality of perceptual data they submit, in order to motivate participants to submit high-quality data.

These budget-constrained incentive mechanisms only consider the perspective of a single round of task offloading. They do not consider the correlation between different rounds of task offloading and they do not consider the risk preferences of collaborators. A few incentive mechanisms that consider the correlation between different rounds of task offloading do so only through reputation, which is an exogenous factor prescribed by the incentive mechanism for collaborators. However, these incentive mechanisms do not consider the endogenous factor of collaborators, that is, the risk preference of collaborators. At the same time, some incentive mechanisms that consider relevance do not consider the budget constraint of the requester. Therefore, the actual incentive effect will be lower than the theoretical incentive effect.

In contrast to previous research, we jointly consider budget constraints and decision correlations and propose an Incentive Mechanism based on Risk Preferences, the IMRP.

3. Design and Analysis of the IMRP

Section 3.1 introduces the system model of the IMRP, including the physical model and logical model. Section 3.2 details the design and principle of the IMRP.

3.1. System Model

This section will further illustrate the physical model of the IMRP based on the physical background and construct the logical model of the IMRP.

3.1.1. Physical Model

As depicted in Figure 1, the Mobile Edge Computing (MEC) network consists of edge servers, mobile users, and a base station (BS). The edge server set is represented by I, the mobile user set by J, and the winner set by I^v. The edge server acts as a collaborator to assist in offloading tasks. Mobile users, acting as requesters, can offload tasks to collaborators. And the base station as a platform ensures the normal operation of task offloading. The following steps detail the process of offloading tasks: (1) The requester submits their offloading task request to the BS. (2) The BS broadcasts the requested information to the collaborator. (3) The collaborator provides a bid based on the bonus scheme and their own costs. (4) The BS determines the appropriate collaborator for the requester based on the quotation received, and the collaborator offloads the task, completes it, and returns the results. (5) The requester then pays the collaborator for their services.

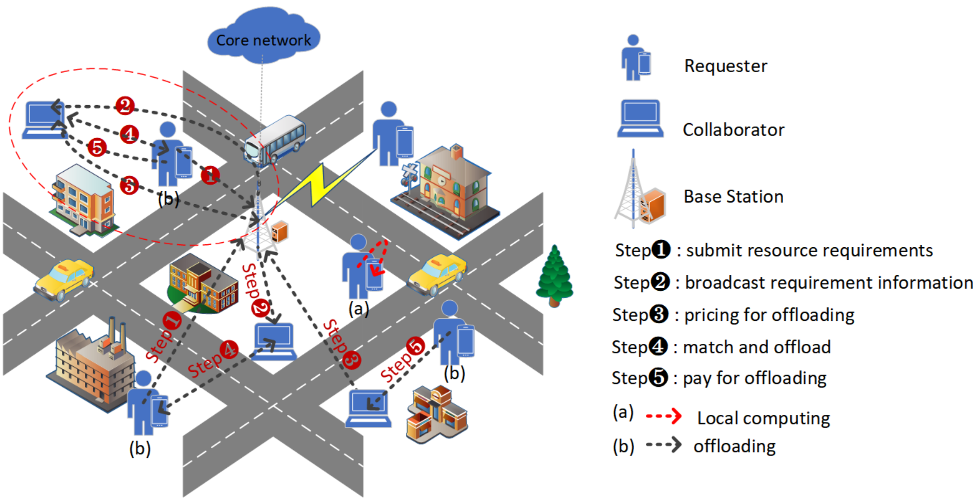

Figure 1. Physical model.

In computation offloading, mobile users offload tasks to the edge server for execution. At this juncture, the computation offloading delay is the total of the time taken to transmit the task and the time required for task execution at the edge server. The computation offloading delay can be expressed as Formula (1).

$$T_{i,j}^{off} = \frac{c_{\tau_j}}{f_i} + \frac{d_j}{R_{i,j}} \tag{1}$$

where c_{τ_j} represents the clock cycle necessary for task offloading. It is calculated through the formula $c_{\tau_j} = k_j \times d_j$, where d_j represents the size of the task that the jth requester needs to offload and k_j is the coefficient for CPU cycles. f_i represents the ith collaborator's clock frequency for task offloading. $R_{i,j}$ represents the transmission rate and can be expressed as Formula (2):

$$R_{i,j} = B_{i,j} \log\left(1 + \frac{p_{i,j} h_{i,j}^2}{\sigma^2}\right) \tag{2}$$

where $B_{i,j}$ represents the transmission bandwidth, and $p_{i,j}$ represents the mobile user's transmit power. $h_{i,j}$ represents the channel gain between the jth mobile user and the ith edge server. σ^2 represents background noise power. The task is offloaded from the mobile user to the edge server for execution. The energy consumption of the edge server can be expressed as Formula (3).

$$E_{i,j} = c_{\tau_j} \times \zeta_i^{PR} f_i^2 \tag{3}$$

where ζ_i^{PR} is the energy consumption factor of the collaborator. The cost of offloading tasks from collaborators can be expressed as Formula (4):

$$C_{i,j} = c_{\tau_j} \times \zeta_i^{PR} f_i^2 c_e \tag{4}$$

where c_e denotes the economic cost per unit of energy consumption.

The specific physical process of the IMRP is as follows:

(1) The platform designs a bonus scheme which is published to the requester and collaborator. The requester submits offloading requirements to the platform, including task size and maximum delay.
(2) The platform collects the requester's task set $\mathbb{T} = \{t_1, t_2, \ldots, t_n\}$ and broadcasts the requester's offloading requirement information.
(3) Collaborators decide whether to participate in task offloading based on their own willingness to participate. The collaborator submits a bid set $B_i = \{b_{i,1}, b_{i,2}, \ldots, b_{i,n}\}$ for the task to the platform based on its own offloading costs minus the expected bonus, otherwise, it will not be included in the range of candidates.
(4) The platform selects a collaborator based on the collaborator's bid $b_{i,j}$ and the delay of the offloaded task, and determines the selection factor $M_{i,j}^t \in \{0, 1\}$ based on the selection results. $M_{i,j}^t = 1$ means that the task of the jth requester is offloaded to the ith collaborator for execution, $M_{i,j}^t = 0$ means that the ith collaborator is not selected to offload the task.
(5) After the collaborator has completed the task and returned the result to the requester, the platform pays the collaborator a given payment $b_{i,j}$ and determines an extra bonus $Rw_{i,j}$ for the collaborator according to the bonus scheme.

3.1.2. Logical Model

The logical model of the IMRP is shown in Figure 2.

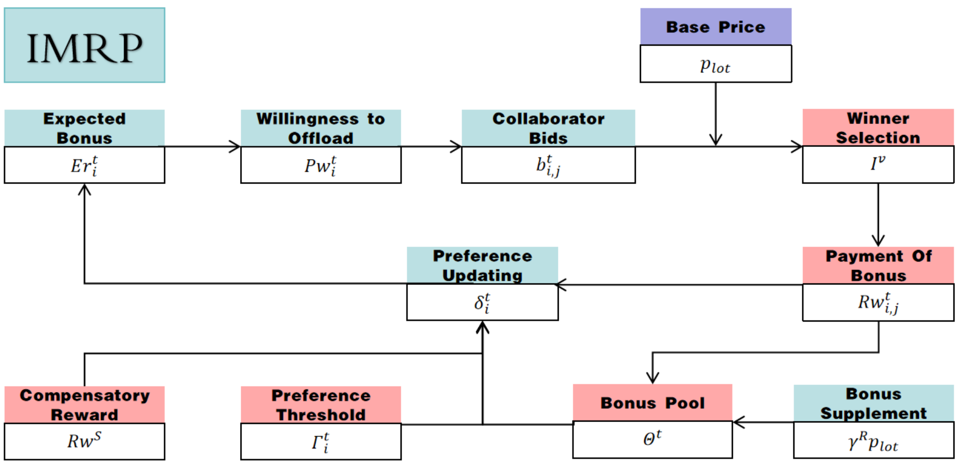

Figure 2. Design of logical framework for the IMRP.

After the platform publishes the bonus scheme, the collaborator calculates the expected bonus Er_i^t, and evaluates the willingness to participate in the offloading task. If they are willing to offload the task, they provide the platform with a bid $b_{i,j}^t$. The collaborator's expected bonus induces the collaborator to lower their bid to offload the task. If a collaborator's expected bonus Er_i^t is greater than the reference price p_{lot}, the collaborator's bid is adjusted and a collaborator is selected to offload the task. The reference price is given by the platform to avoid excessive reduction of the bid when the collaborator has a high expected bonus. After the collaborator completes the task, in addition to the given bid payment, the collaborator has the probability of receiving an extra bonus $Rw_{i,j}^t$. The extra bonus will increase the collaborator's risk preference, thus improving the collaborator's utility assessment for the probabilistic bonus. Meanwhile, the total bonus Θ^t is provided by the task requester, who has to pay an additional $\gamma^R p_{lot}$ per round as a maintenance fund. In this way, collaborators have a higher expectation of the bonus, so they are more willing to assist in task offloading. For collaborators who have performed task offloading multiple times without receiving extra bonus, the platform will directly issue compensatory payment Rw^s to maintain the collaborators' willingness to continue task offloading.

3.2. Incentives Mechanism Based on Risk Preference

3.2.1. Bids Based on Risk Preference

Collaborators will evaluate the expected bonus before making a decision to offload the task. Based on the current bonus scheme, bonus pool size, and bonus from the previous round, collaborators will evaluate the expected bonus in three main scenarios: (1) first-time task offloading or no extra bonus in the previous round and no one received first prize. (2) A small bonus was awarded in the previous round and no one received first prize. (3) A collaborator received first prize in the previous round. Next, we build models of collaborators' evaluation of expected bonuses in the three situations.

(1) First-time task offload or no extra bonus from the previous round.

In this case, the collaborators have not received any extra bonus, so the expected bonus is only related to the bonus scheme announced by the platform. Meanwhile, to reflect the heterogeneity of the collaborator's risk preference, each collaborator's initial degree of risk preference for extra bonus is different, a risk preference factor is introduced into the expected bonus, and the expected bonus evaluation model is expressed as Formula (5). Formula (5) is derived from Ref. [34]

$$Er_i^t = \sum_{\xi=1}^{k} \left(\psi_\xi^t\right)^{\delta_i^t} \varpi\left(p_\xi\right) \tag{5}$$

where ψ_ξ is the bonus size of each prize. And δ_{i}^t is the collaborator's risk preference factor during the tth round of offloading, and each collaborator will have an initial risk preference factor. The risk preference factor δ_i^t denotes the degree of deviation between the expected bonus and the actual bonus, and it will affect the utility of the collaborators. The risk preference factor will change dynamically with the size of the bonus pool, cumulative costs, and historical winnings. The details of setting the risk preference factor will be discussed in the next section. $\varpi\left(p_\xi\right)$ is the collaborator's probability distortion function of the probability of the collaborator winning each bonus. Because the collaborator's judgment of the objective probability is probabilistically distorted, we use it to reflect the collaborator's judgment of the winning probability. $\varpi\left(p_\xi\right)$ is modeled as Formula (6). Formula (6) is derived from Ref. [34]

$$\pi(p_\xi) = \frac{(p_\xi)^\gamma}{\left[(p_\xi)^\gamma + (1-(p_\xi))^{1-\gamma}\right]^{\frac{1}{\gamma}}}. \tag{6}$$

(2) A small bonus was awarded in the previous round and nobody was awarded first prize.

In the IMRP, the platform will broadcast to the collaborators who win the first prize. Collaborators have a self-interested bias towards other people winning the first prize. That is, other collaborators winning the first prize will increase the collaborators' expectation of the expected bonus. The utility evaluation therefore requires a discussion of whether someone in the group of collaborators has won the first prize.

Therefore, if no one in the group of collaborators received the first prize and the collaborators received the second or third prize in the previous round, the evaluation model of the expected bonus is established as Formula (7):

$$Er_i^t = \tau \sum_{\xi=1}^{k} \left(\psi_\xi^t\right)^{\delta_i^t} \varpi(p_\xi) + (1-\tau)\frac{\sum_{i\in I^v} Rw_{i,j}^{t-1}}{\sum M_{i,j}^{t-1}} \tag{7}$$

where $\sum_{i\in I^v} Rw_{i,j}^{t-1}$ is the ith collaborator's total bonus amount in the $(t-1)$th round, and $\sum M_{i,j}^{t-1}$ is the total number of tasks offloaded by the ith collaborator in the $(t-1)$th round.

(3) First prize awarded in the $(t-1)$th round.

If a first prize was awarded in the previous round, the first prize bonus in the previous round will affect the collaborator's estimate of the expected bonus, causing them to overestimate the expected bonus in this round. Therefore, in the IMRP mechanism, the expected bonus modeling in this case is as shown in Formula (8):

$$Er_i^t = \left(\psi_1^{t-1}\right)^{\delta_i^t} + \sum_{\xi=2}^{k} \left(\psi_\xi^t\right)^{\delta_i^t} \varpi(p_\xi). \tag{8}$$

After evaluating the expected bonus, the collaborator calculates the willingness value to offload and compares it with the willingness threshold to decide whether or not to offload. In the IMRP mechanism, the model for willingness to participate in offloading tasks is shown in Formula (9).

$$Pw_i^t = \tau^p \frac{\sum_r^{t-1}\sum_{i\in I^v} Rw_{i,j}^r}{\sum_r^{t-1}\sum_{i\in I^v} p_{lot}} + (1-\tau^p)\frac{Er_i^t}{p_{lot}} \tag{9}$$

where $\sum_r^{t-1}\sum_{i\in I^v} Rw_{i,j}^r$ denotes the sum of extra bonus received by the ith collaborator in the previous $(t-1)$ rounds of offloading tasks. And $\sum_r^{t-1}\sum_{i\in I^v} p_{lot}$ denotes the total cost paid by the ith collaborator to obtain extra bonus in the previous $(t-1)$ rounds of offloading tasks, τ^p is constant, $0 < \tau^p < 1$. The collaborator will participate in task offloading in the tth round and bid on the task when the willingness to participate in offloading task Pw_i^t is greater than or equal to the willingness threshold Pw_{th}^t. Er_i^t refers to the expected benefit of the extra bonus for the ith collaborator in the tth round.

In the IMRP, the willingness to participate is denoted by Pw_i^t. In the incentive mechanism without considering the reference price and probability distortion, the willingness to participate is denoted by $\overline{Pw_i^t}$. The relationship between Pw_i^t and $\overline{Pw_i^t}$ is illustrated by Theorem 1.

Theorem 1. *For the ith collaborator, if* $\psi_3^t \geq \sum_{\xi=1}^{k}\left(\psi_\xi^t\right)^{\delta_i^t} p_\xi$, *we can get* $Pw_i^t > \overline{Pw_i^t}$.

Proof of Theorem 1. In a payment scheme designed without a reference price and probability distortion, the ith collaborator's willingness to participate $\overline{Pw_i^t} = \tau\frac{\sum_r^{t-1}\sum_{i\in I^v} Rw_{i,j}^r}{\sum_r^{t-1}\sum_{i\in I^v} p_{lot}} + (1-\tau)\frac{\overline{Er_i^t}}{p_{lot}}$. The expected bonus of the ith collaborator in the tth round $\overline{Er_i^t}$ can be expressed as $\overline{Er_i^t} = \sum_{\xi=1}^{k}\left(\psi_\xi^t\right)^{\delta_i^t} p_\xi$.

(1) In the IMRP, when $\sum_{i\in I^v} Rw_{i,j}^{t-1} < \psi_3^t$,$\mathrm{Er}_i^t = \sum_{\xi=1}^{k}\left(\psi_\xi^t\right)^{\delta_i^t}\varpi(p_\xi)$, because $\varpi(p_\xi) > p_\xi$, we can get $Er_i^t > \overline{Er_i^t}$, and it means that $Pw_i^t > \overline{Pw_i^t}$.

(2) When $\sum_{i\in I^v} Rw_{i,j}^{t-1} \geq \psi_3^t$ and $\left|W_1^t\right| = 0$, $Er_i^t - \overline{Er_i^t} = \tau\sum_{\xi=1}^{k}\left(\psi_\xi^t\right)^{\delta_i^t}\varpi(p_\xi) + (1-\tau)\frac{\sum_{i\in I^v} Rw_{i,j}^{t-1}}{\sum M_{i,j}^{t-1}} - \sum_{\xi=1}^{k}\left(\psi_\xi^t\right)^{\delta_i^t} p_\xi$. Therefore, $Er_i^t - \overline{Er_i^t} \geq \tau\sum_{\xi=1}^{k}\left(\psi_\xi^t\right)^{\delta_i^t}\varpi(p_\xi) + (1-\tau)\psi_3^t -$

$\sum_{\xi=1}^{k}\left(\psi_{\xi}^{t}\right)^{\delta_i^t} p_{\xi}$. When $\psi_3^t > \sum_{\xi=1}^{k}\left(\psi_{\xi}^{t}\right)^{\delta_i^t}\varpi(p_{\xi})$, there is $\tau\sum_{\xi=1}^{k}\left(\psi_{\xi}^{t}\right)^{t}\varpi(p_{\xi}) + (1-\tau)\psi_3^t > \sum_{\xi=1}^{k}\left(\psi_{\xi}^{t}\right)^{\delta_i^t}\varpi(p_{\xi})$, $\sum_{\xi=1}^{k}\left(\psi_{\xi}^{t}\right)^{\delta_i^t}\varpi(p_{\xi}) > \sum_{\xi=1}^{k}\left(\psi_{\xi}^{t}\right)^{\delta_i^t} p_{\xi}$, then, $\tau\sum_{\xi=1}^{k}\left(\psi_{\xi}^{t}\right)^{\delta_i^t}\varpi(p_{\xi}) + (1-\tau)\psi_3^t - \sum_{\xi=1}^{k}\left(\psi_{\xi}^{t}\right)^{\delta_i^t} p_{\xi} > 0$, $Er_i^t - \overline{Er_i^t} > 0$. Therefore, $Pw_i^t > \overline{Pw_i^t}$ can be obtained.

When $\psi_3^t \le \sum_{\xi=1}^{k}\left(\psi_{\xi}^{t}\right)^{\delta_i^t}\varpi(p_{\xi})$, there is $Er_i^t - \overline{Er_i^t} \ge \tau\psi_3^t + (1-\tau)\psi_3^t - \sum_{\xi=1}^{k}\left(\psi_{\xi}^{t}\right)^{\delta_i^t} p_{\xi} = \psi_3^t - \sum_{\xi=1}^{k}\left(\psi_{\xi}^{t}\right)^{\delta_i^t} p_{\xi}$. Therefore, if $\psi_3^t \ge \sum_{\xi=1}^{k}\left(\psi_{\xi}^{t}\right)^{\delta_i^t} p_{\xi}$, we obtain that $Er_i^t > \overline{Er_i^t}$, $Pw_i^t > \overline{Pw_i^t}$.

(3) When $\left|W_1^t\right| > 0$, the total bonus will be drastically reduced. Therefore, $\psi_1^{t-1} \gg \psi_1^t$. We can get $Er_i^t > \overline{Er_i^t}$

In summary, when $\psi_3^t \ge \sum_{\xi=1}^{k}\left(\psi_{\xi}^{t}\right)^{\delta_i^t} p_{\xi}$, $Pw_i^t > \overline{Pw_i^t}$. Theorem 1 is proved. □

In the IMRP, if the willingness to participate value Pw_i^t is equal to or higher than the willingness threshold Pw_{th}, the ith collaborator bids on the task τ_j of the jth requester on the basis of the expected bonus Er_i^t, the reference price p_{lot} and the cost $C_{i,j}^t$ of offloading the task in the tth round. The ith collaborator's bid increases as the cost of offloading the task increases and decreases as the expected bonus increases. Formula (10) represents the bid of the ith collaborator for the jth requester's task τ_j.

$$b_{i,j}^t = \begin{cases} \varphi^b C_{i,j}^t - \left(\alpha^b p_{lot} + \beta Er_i^t\right) & Er_i^t > p_{lot}, Pw_i^t \ge \Gamma_{pw} \\ \varphi^b C_{i,j}^t - Er_i^t & Er_i^t \le p_{lot}, Pw_i^t \ge \Gamma_{pw} \\ 0 & \text{else} \end{cases} \tag{10}$$

To ensure that the collaborator's expected utility is positive, the value range for parameters φ^b and α^b in the bids must be determined. Therefore, Theorem 2 is given.

Theorem 2. *To ensure a collaborator's expected utility is positive, the collaborator's bid parameters should satisfy* $\frac{(\varphi^b-1)C_{i,j}^t}{p_{lot}-Er_i^t} < \alpha^b < 1$ *when* $Er_i^t > p_{lot}$*. And* $\varphi^b > 1$ *when* $Er_i^t < p_{lot}$.

Proof of Theorem 2. (1) When $Er_i^t > p_{lot}$, the collaborator's bid is influenced by the reference price, that is, $b_{i,j}^t = \varphi^b C_{i,j}^t - \left(\alpha^b p_{lot} + \beta Er_i^t\right)$. To ensure that the collaborator's expected utility $EUC_{i,j}^t = b_{i,j}^t + Er_i^t - C_{i,j}^t > 0$, substitute into $b_{i,j}^t$, we can obtain $\left(\varphi^b - 1\right)C_{i,j}^t - \alpha^b p_{lot} + (1-\beta)Er_i^t > 0$. And $\alpha + \beta = 1$, we can obtain $\left(\varphi^b - 1\right)C_{i,j}^t - \alpha^b\left(p_{lot} - Er_i^t\right) > 0$. Because $Er_i^t > p_{lot}$, we can obtain $\alpha^b > \frac{(\varphi^b-1)C_{i,j}^t}{p_{lot}-Er_i^t}$. In summary, we can obtain $\frac{(\varphi^b-1)C_{i,j}^t}{p_{lot}-\mathrm{Er}_i^t} < \alpha^b < 1$.

(2) When $Er_i^t \le p_{\mathrm{lot}}$, $b_{i,j}^t = \varphi^b C_{i,j}^t - Er_i^t$. To ensure that the collaborator's expected utility $EUC_{i,j}^t = b_{i,j}^t + Er_i^t - C_{i,j}^t > 0$, we substitute $b_{i,j}^t = \varphi^b C_{i,j}^t - Er_i^t$ into $EUC_{i,j}^t$. We can obtain $\varphi^b > 1$. Theorem 2 is proved. □

3.2.2. Utility Analysis of Collaborators

When the ith collaborator offloads the task of the jth requester, $p_{i,j}^t$ is the definite payment paid by the jth requester to the ith collaborator. In the IMRP, the utility of the ith collaborator in offloading the task τ_j of the jth requester can be expressed as Formula (11):

$$UC_{i,j}^t = \begin{cases} M_{i,j}^t \times \left(p_{i,j}^t + Rw_{i,j}^t - C_{i,j}^t\right)^{\delta_i^t} & i \in I^v \\ 0 & i \notin I^v \end{cases}, \tag{11}$$

where $M_{i,j}^t \in \{0,1\}$ represents the selection factor between collaborator and requester.

In the tth round, the ith collaborator's total utility for the offloading task is expressed as Formula (12):

$$UC_i^t = \sum_{j\in J} M_{i,j}^t \times \left(p_{i,j}^t + Rw_{i,j}^t - C_{i,j}^t\right)^{\delta_i^t}, \tag{12}$$

where δ_i^t represents the risk preference factor of the ith collaborator in the tth round. Collaborators are categorized into three groups based on risk preference types, where I_{risk} is the risk-seeking group, $I_{neutral}$ is the risk-neutral group, and $I_{aversion}$ is the risk-aversion group. Theorem 3 is applied to stipulate the value range of the risk preference factor for collaborators with diverse risk preference.

Theorem 3. *The risk preference factor δ_i^t of the ith collaborator who is risk-seeking, satisfies $\delta_i^t > 1$. δ_i^t of the ith collaborator who is risk-aversion, satisfies $0 < \delta_i^t < 1$. And δ_i^t of the ith collaborator who is risk-neutral, satisfies $\delta_i^t = 1$.*

Proof of Theorem 3. Calculate the first derivative of the collaborator's utility $UC_{i,j}^t$ with respect to payoff $\left(p_{i,j}^t + Rw_{i,j}^t\right)$ and we obtain $\frac{\partial UC_{i,j}^t}{\partial\left(p_{i,j}^t+Rw_{i,j}^t\right)} = \delta_i^t\left(p_{i,j}^t + Rw_{i,j}^t\right)^{\left(\delta_i^t-1\right)}$. Similarly, the second derivative of $UC_{i,j}^t$ with respect to $\left(p_{i,j}^t + Rw_{i,j}^t\right)$ gives $\frac{\partial^2 UC_{i,j}^t}{\partial\left(p_{i,j}^t+Rw_{i,j}^t\right)^2} = \delta_i^t\left(\delta_i^t - 1\right)\left(p_{i,j}^t + Rw_{i,j}^t\right)^{\left(\delta_i^t-2\right)}$. For $i \in I_{\text{risk}}$, $UC_{i,j}^t$ satisfies the condition $\frac{\partial UC_{i,j}^t}{\partial\left(p_{i,j}^t+Rw_{i,j}^t\right)} > 0$ and $\frac{\partial^2 UC_{i,j}^t}{\partial\left(p_{i,j}^t+Rw_{i,j}^t\right)^2} > 0$; For $i \in I_{\text{aversion}}$, $UC_{i,j}^t$ satisfies the condition $\frac{\partial UC_{i,j}^t}{\partial\left(p_{i,j}^t+Rw_{i,j}^t\right)} > 0$ and $\frac{\partial^2 UC_{i,j}^t}{\partial\left(p_{i,j}^t+Rw_{i,j}^t\right)^2} < 0$; For $i \in I_{\text{neutral}}$, $UC_{i,j}^t$ satisfies the condition $\frac{\partial UC_{i,j}^t}{\partial\left(p_{i,j}^t+Rw_{i,j}^t\right)} > 0$ and $\frac{\partial^2 UC_{i,j}^t}{\partial\left(p_{i,j}^t+Rw_{i,j}^t\right)^2} = 0$. That is, for collaborator $i \in I_{\text{risk}}$, risk preference factor satisfies $\delta_i^t > 1$. For collaborator $i \in I_{\text{aversion}}$, risk preference factor satisfies $0 < \delta_i^t < 1$. For collaborator $i \in I_{\text{neutral}}$, risk preference factor satisfies $\delta_i^t = 1$; Theorem 3 is proved. □

The collaborator's risk preference factor in the IMRP is related to the probability of winning, the size of the bonus pool, the current wealth value, and the winning situation in the previous round. When faced with a small probability of large bonuses, collaborators are risk-seeking. The previous bonus may increase the degree of the risk preference. And the previous loss will decrease the degree of the risk preference. That is, when the bonus pool is small, the collaborator is risk-averse; when the bonus pool is large, the collaborator is risk-seeking. Hence, if the bonus pool Θ^t is greater than the ith collaborator's preference transition threshold Γ_i^t, then the ith collaborator is risk-seeking. If the bonus pool is less than or equal to the ith collaborator's preference transition threshold, then the collaborator is risk-averse. If the bonus value in the previous round surpasses the reference price, the risk preference of the ith collaborator will rise and the value of δ_i^t will increase. When the bonus is lower than the reference price, the collaborator's risk preference will decrease and the δ_i^t value will go down. Because the risk preference is influenced by initial risk preference, historical gains, and bonus pool. In the IMRP, the risk preference factor is updated according to Formula (13).

$$\delta_i^{t+1} = e^{\left(\frac{\Theta^t-\Gamma_i^t}{\Gamma_i^t}\times\left(\delta_i^t+\frac{\sum_{j\in J}Rw_{i,j}^t+Rw^S}{\sum_{j\in J}p_{lot}}\right)\right)} \tag{13}$$

where δ_i^{t+1} is the risk preference factor of the ith collaborator in the $(t+1)$th round. Finally, $Rw_{i,j}^t$ denotes the actual bonus received.

The risk preference transition threshold is related to the current risk preference degree of the collaborator. The risk preference transition threshold decreases as the collaborator's risk preference increases. The relationship between risk preference transition threshold Γ_i^t and the ith collaborator's preference factor δ_i^t is expressed by Formula (14).

$$\Gamma_i^t = \frac{p_{\text{lot}}}{\sum_{\xi=1}^{2} \varpi(p_\xi) \gamma_\xi^{\delta_i^t}}^{(\delta_i^t)^{-1}} \tag{14}$$

3.2.3. The Selection of Winner

In the IMRP, the requester must provide the payment $p_{i,j}^t + \gamma^R p_{lot}$ to the platform after the collaborator has completed the task. The utility of the jth requester is expressed by Formula (15).

$$UR_{i,j}^t = V_j^t - \left(p_{i,j}^t + \gamma^R p_{lot}\right) \tag{15}$$

where V_j^t denotes the value of the requester's task. The total cost of the task to the jth requester is represented by $p_{i,j}^t + \gamma^R p_{lot}$. The definite payment received by the collaborator for offloading the task is represented by $p_{i,j}^t$, $p_{i,j}^t = b_{i,j}^t$, and $\gamma^R p_{lot}$ is added to the bonus pool by platform as extra bonus in the next round.

The utility of the ith collaborator's offloading task is expressed as Formula (16):

$$UC_{i,j}^t = p_{i,j}^t + Rw_{i,j}^t - C_{i,j}^t \tag{16}$$

Social welfare is defined as the total utilities of all requesters and collaborators. According to Formulas (15) and (16), social welfare can be expressed as $\sum_{i \in I^v} \sum_{j \in J} M_{i,j}^t \times \left(Rw_{i,j}^t - C_{i,j}^t + V_j^t - \gamma^R p_{lot}\right)$. To guarantee positive gain for the collaborator and utility for the requester, Theorem 4 is used to establish the parameter γ^R values range.

Theorem 4. *In the IMRP, to guarantee a positive utility $UR_{i,j}^t$ for the requester, γ^R has to satisfy $\gamma^R < \frac{V_j^t - C_{i,j}^t + Er_i^t}{p_{lot}}$.*

Proof of Theorem 4. (1) When $Er_i^t \le p_{lot}$, the bid of the collaborator $b_{i,j}^t = \varphi^b C_{i,j}^t - Er_i^t$. For the collaborator who offloads the task, platform gives a definite payoff $p_{i,j}^t = b_{i,j}^t = \varphi^b C_{i,j}^t - Er_i^t$. Substitute $p_{i,j}^t$ into Formula (15) and we can obtain $V_j^t - \gamma^R p_{lot} - \varphi^b C_{i,j}^t + Er_i^t > 0$, that is $\gamma^R < \frac{V_j^t - \varphi^b C_{i,j}^t + Er_i^t}{p_{lot}}$.

(2) When $Er_i^t > p_{lot}$, the ith collaborator's bid is $b_{i,j}^t = \varphi^b C_{i,j}^t - \left(\alpha^b p_{lot} + \beta Er_i^t\right)$. Substitute $p_{i,j}^t = b_{i,j}^t$ into $UR_{i,j}^t = V_j^t - \left(p_{i,j}^t + \gamma^R p_{lot}\right)$ and we can obtain $V_j^t - \gamma^R p_{lot} - \varphi^b C_{i,j}^t + \left(\alpha^b p_{lot} + \beta Er_i^t\right) > 0$. Therefore, γ^R should satisfy $\gamma^R < \frac{V_j^t - \varphi^b C_{i,j}^t + \left(\alpha^b p_{lot} + \beta Er_i^t\right)}{p_{lot}}$. Since Er_i^t is smaller than $\left(\alpha^b p_{lot} + \beta Er_i^t\right)$, we can conclude that $\frac{V_j^t - \varphi^b C_{i,j}^t + Er_i^t}{p_{lot}} - \frac{V_j^t - \varphi^b C_{i,j}^t + \left(\alpha^b p_{lot} + \beta Er_i^t\right)}{p_{\text{lot}}} < 0$. Therefore $\gamma^R < \frac{V_j^t - \varphi^b C_{i,j}^t + Er_i^t}{p_{lot}}$. Theorem 4 is proved. □

Theorem 4 proves that in the IMRP, if the value of γ^R is less than $\frac{V_j^t - \varphi^b C_{i,j}^t + Er_i^t}{p_{lot}}$, the requester's utility can be guaranteed to be positive.

In the IMRP, for the requester's task, B_j is the collaborators' bid set for the task τ_j. When $|B_j| = 1$, the requester's utility is positive and the delay of offloading the task is less than the maximum delay. That is, when $b_{i,j}^t < V_j^t - \gamma^R p_{lot}$, the jth requester selects the ith collaborator as the winner. When $|B_j| > 1$, the requester selects a collaborator as the winner. Select a collaborator based on the bid and delay, that is, under the condition that the maximum delay is met, the requester selects the collaborator with the lowest bid to offload the task.

When multiple requesters select the same collaborator simultaneously, the collaborator can only offload one task at a time. Therefore, the collaborator will select the task to offload first based on the task offer, task size, and expected bonus. Here, the payoff of the unit task is used to represent the priority $\Omega_{i,j}^t$ of the task chosen by the collaborator, who then selects the task with the highest task priority. Collaborators consider the compensation, extra bonus, and task size. Thus, the priority of the task is expressed by Formula (17):

$$\Omega_{i,j}^t = \frac{\delta^\Omega p_{i,j}^t + (1-\delta^\Omega) Er_i^t}{d_j^t} \tag{17}$$

where d_j^t denotes the size of the task of the jth requester.

In the IMRP, although the requester has to submit the total payment $b_{i,j}^t + \gamma^R p_{lot}$ to the platform, the utility of the requester is still improved compared to the mechanism without extra bonus. We define $UR_{i,j}^t$ as the utility of the jth requester in the IMRP, and $\overline{UR_{i,j}^t}$ as the utility of the requester when there is no extra bonus. To support this conclusion, we provide Theorem 5.

Theorem 5. *In the same application scenario, when* $Er_i^t > p_{lot}$, $UR_{i,j}^t > \overline{UR_{i,j}^t}$. *When* $Er_i^t \le p_{lot}$, *there is* $UR_{i,j}^t > \overline{UR_{i,j}^t}$ *only if* γ^R *satisfies* $\gamma^R < \frac{Er_i^t}{p_{lot}}$.

Proof of Theorem 5. (1) When no extra bonus is present, the collaborator has a bid of $\overline{b_{i,j}^t} = \varphi^b C_{i,j}^t$ and the requester's utility is $\overline{UR_{i,j}^t} = V_j^t - \varphi^b C_{i,j}^t$.

(2) In the IMRP, when $Er_i^t \le p_{lot}$, the collaborator's bid is $b_{i,j}^t = \varphi^b C_{i,j}^t - Er_i^t$ and the requester's utility is $UR_{i,j}^t = V_j^t - \varphi^b C_{i,j}^t + Er_i^t - \gamma^R p_{lot}$. Because $UR_{i,j}^t - \overline{UR_{i,j}^t} = V_j^t - \varphi^b C_{i,j}^t + Er_i^t - \left(V_j^t - \varphi^b C_{i,j}^t\right) - \gamma^R p_{lot} = Er_i^t - \gamma^R p_{lot}$, we can obtain $UR_{i,j}^t > \overline{UR_{i,j}^t}$ only if γ^R satisfies $\gamma^R < \frac{Er_i^t}{p_{lot}}$. When $Er_i^t > p_{lot}$, $b_{i,j}^t = \varphi^b C_{i,j}^t - \left(\alpha^b p_{lot} + \beta Er_i^t\right)$. Because $p_{i,j}^t = b_{i,j}^t$, the utility of the requester is $UR_{i,j}^t = V_j^t - \varphi^b C_{i,j}^t + \left(\alpha^b p_{lot} + \beta Er_i^t\right) - \gamma^R p_{lot}$. Since $Er_i^t > p_{lot}$, $\alpha^b + \beta = 1$, we can obtain $\left(\alpha^b p_{lot} + \beta Er_i^t\right) > p_{lot}$. Furthermore, $0 < \gamma^R < 1$, we can obtain $\gamma^R p_{lot} < p_{lot}$. Therefore, $UR_{i,j}^t - \overline{UR_{i,j}^t} = \left(\alpha^b p_{lot} + \beta Er_i^t\right) - \gamma^R p_{lot} > 0$. In summary, we can obtain $UR_{i,j}^t > \overline{UR_{i,j}^t}$. Theorem 5 is proved. □

Based on the selection of collaborator and requester above, we propose Algorithm 1 to specifically describe the winner selection process.

Algorithm 1 firstly selects the collaborator that maximizes the utility of the requester (lines 1–8). If multiple requesters selected the same collaborator to offload the task, the collaborator selects the requester's task with the highest task priority $\Omega_{i,j}^t$ (lines 9–21).

After completing the task, the collaborator returns the result to the requester, and platform calculates the collaborator's pay and bonus according to Algorithm 2.

We use Algorithm 2 to determine the payment and bonuses of the collaborators. For the collaborator who offloads the task, line 4 of the algorithm calculates the pay based on the collaborator's bid. Lines 5 to 13 of the algorithm calculate the extra bonus based on the collaborator's task number and the winning task number. Lines 16 of the algorithm indicate collaborators that have not offloaded tasks, their pay and bonus values are both zero. Line 19 of the algorithm is the calculation method for the total bonus in $(t+1)$th round.

Algorithm 1 Winner Selection Algorithm.

Input: Requester set J, Collaborator set I, Bid set B_j
Output: Selection factor $M_{i,j}^t$;

for $j = 1\ TO\ |J|$ **do**
  if $\left|B_j\right| == 1$ and $b_{i,j} < V_j^t - \gamma^R p_{lot}$ **then**
    $M_{i,j}^t = 1$
  else if $\left|B_j\right| > 1$ **then**
    $\mathbb{UR}_j^t \leftarrow UR_{i,j}^t = V_j^t - \left(b_{i,j}^t + \gamma^R p_{lot}\right)$
    Select the collaborator that maximizes the utility of the requester, $M_{i,j}^t = 1$
  end if
end for
for $j = 1\ TO\ |J|$ **do**
  for $i = 1\ TO\ |I|$ **do**
    if $\sum_{j=1}^{|J|} M_{i,j}^t > 1$ **then**
      $\Omega_{i,j}^t = \frac{\delta^\Omega p_{i,j}^t + \left(1-\delta^\Omega\right) Er_i^t}{d_j^t}$
      Select the task with the highest priority $\Omega_{i,j}^t$.
      The remaining requesters $M_{i,j}^t = 0$
    else if $\sum_{j=1}^{|J|} M_{i,j}^t == 1$ **then**
      if $UR_{i,j}^t < 0$ **then**
        $M_{i,j}^t = 0$
      end if
    end if
  end for
end for

Algorithm 2 Bonus payment algorithm.

Input: Collaborator set I, Winning task number Wt_w^t
Output: Payment $p_{i,j}^t$, Bonus $Rw_{i,j}^t$

for $i = 1\ TO\ |I|$ **do**
  Get the task number of the task offloaded by the collaborator $Tn_{i,j}^t$
  if $M_{i,j}^t == 1$ **then**
    $p_{i,j}^t = b_{i,j}^t$
    Caculate the count of same number $SN_{i,j}$ between $Tn_{i,j}^t$ and Wt_w^t
    if $SN_{i,j}{==}M-2$ **then**
      $Rw_{i,j}^t = \psi_3$,ψ_3 is a constant, $W_3^t \leftarrow$ the ith collaborator
    else if $SN_{i,j}{==}M-1$ **then**
      $Rw_{i,j}^t = \psi_2^t = \frac{\gamma_2(\Theta^t - |W_3^t|\psi_3)}{|W_2^t|}$,$W_2^t \leftarrow$ the ith collaborator
    else if $SN_{i,j}{==}M$ **then**
      $Rw_{i,j}^t = \psi_1^t = \frac{\gamma_1(\Theta^t - |W_3^t|\psi_3)}{|W_1^t|}$,$W_1^t \leftarrow$ the ith collaborator
    else
      $Rw_{i,j}^t = 0$
    end if
  else
    $p_{i,j}^t = 0$,$Rw_{i,j}^t = 0$
  end if
end for
$\Theta^{t+1} = \Theta^t - \sum_{\xi=1}^{k} \left|W_\xi^t\right| \psi_\xi^t + \sum_{i \in I^v} \sum_{j \in J} \gamma^R p_{lot} M_{i,j}^t$;

4. Simulations and Evaluations

In this section, we verify the IMRP through simulation experiments, and compare it with the Online Incentive Mechanism (OIM) [35] and the Profit Maximization Multi-Round Auction (PMMRA) mechanism [36] in terms of collaborator's bid, collaborator's cooperation rate, requester's utility, and social welfare. The OIM proposed in Ref. [35] is an online incentive mechanism for offloading Mobile Edge Computing tasks. This mechanism sets a low resource price at the beginning of the auction and gradually increases the resource price as resources are consumed, to motivate more collaborators to offload tasks and optimize resource allocation. The PMMRA mechanism considers a trusted third party as an auctioneer to host a sealed-bid auction and employs a performance–price ratio to determine the winner during the auction. The PMMRA mechanism is effective in ensuring the profits of resource providers and the benefits of mobile users. Since the incentive objectives are similar and they are newer research results, this paper uses OIM and PMMRA mechanisms as comparative papers.

This section is divided into two subsections. Section 4.1 presents the experimental parameters used. Sections 4.2 and 4.3 will analyze the results of the simulation experiment.

4.1. Experimental Environment Settings

First, in order to ensure the fairness of mechanism evaluation, we set the same experimental environment and parameter values for the IMRP, OIM, and PMMRA mechanisms. And since the experimental result data has a certain degree of randomness, we will repeat each experiment 500 times and take the average of the 500 experimental results as the data result. Table 2 lists the parameters used in the simulation and their settings.

Table 2. Experimental parameter settings.

Symbol and Description	Value
Bandwidth	40 MHZ
Transmission power	1.5 W
Background noise	−60 dBm
Task size	10–30 MB
Energy factor	10^{-26}
Unit Energy consumption	0.1
Mission value	0.1–10
Maximum task delay	5–15 s
Collaborator computing resources	2 GHZ
Collaborator risk preference	0.5–1.5

4.2. Mechanism Discussion

First, we discuss the impact of the bid coefficient, the reference coefficient and the bonus pool coefficient on the bids of collaborators.

According to Theorem 3, in order to guarantee a positive utility for the collaborator, φ^b should satisfy $\varphi^b > 1$ when $Er_i^t \le p_{lot}$. According to Theorem 4, to ensure the requester's utility is positive, γ^R should satisfy $\gamma^R < \frac{V_j^t - C_{i,j}^t + Er_i^t}{p_{lot}}$. Therefore, in this section, the discussion range for α^b is set to $[0.2, 0.8]$, the discussion range for φ^b is set to $[1.4, 2.0]$, and the discussion range for γ^R is set to $[0.2, 0.5]$.

Figure 3 shows the change in the average bid of the collaborators with the reference coefficient α^b, and the bid coefficient φ^b in the IMRP. It can be seen from Figure 3 that the average bid increases as the bid coefficient φ^b increases. As the reference coefficient α^b increases, the average bid also increases. In accordance with Formula (10), when $Er_i^t > p_{lot}$, as α^b increases, the proportion of p_{lot} in the bid increases, resulting in an increase in the average bid.

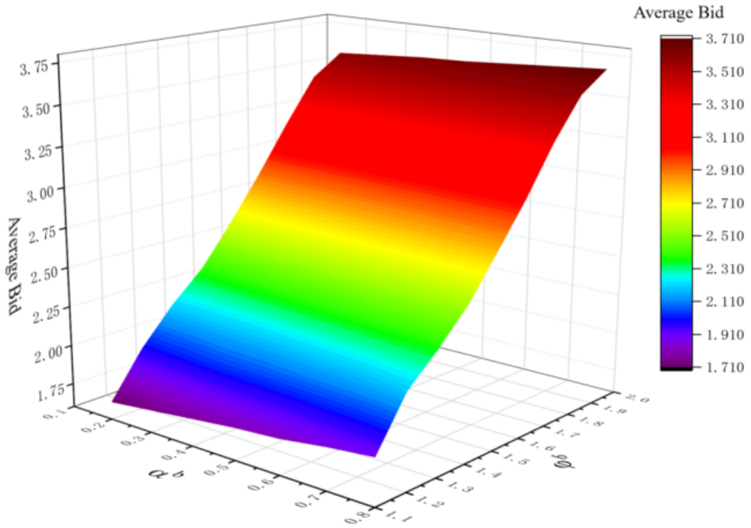

Figure 3. The change in the average bid of the collaborators with α^b and φ^b.

Figure 4 shows the impact of the bonus pool coefficient γ^R and the bid coefficient φ^b on the bid of the collaborator. As the prize pool coefficient increases, the average bid decreases. As the bonus pool coefficient increases, the bonus pool accumulates faster. The increase in the bonus pool increases the collaborator's expected value of the random bonus, causing the collaborator's bid for the task to decrease. However, as the bid coefficient increases, the average bid increases. And as both the bonus pool coefficient and the bid coefficient increase, the average bid tends to increase.

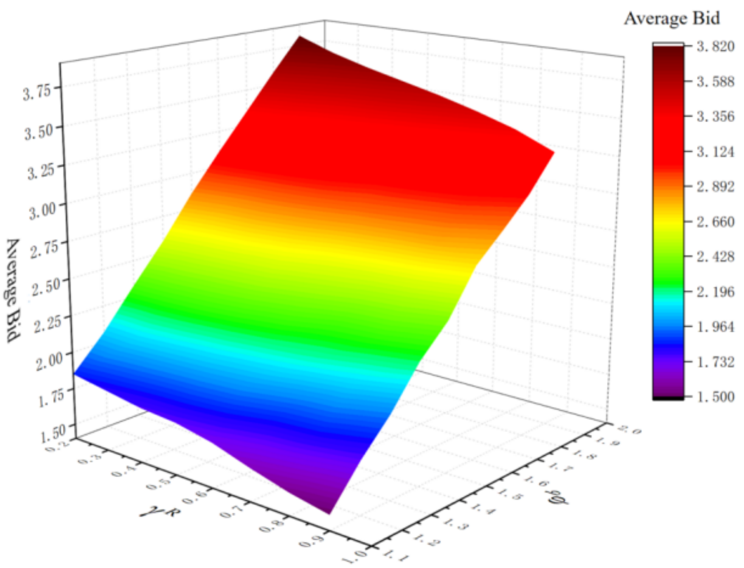

Figure 4. The change in the average bid of the collaborators with γ^R and φ^b.

Figure 5 shows the average bid of collaborators with different risk preferences in the IMRP as the rounds change. It is observed that $b_{i,j}^{\text{risk}} < b_{i,j}^{\text{neutral}} < b_{i,j}^{\text{aversion}}$. The bid of the risk-seeking collaborator is lower than that of the risk-neutral collaborator, and the bid of the risk-neutral collaborator is lower than that of the risk-averse collaborator.

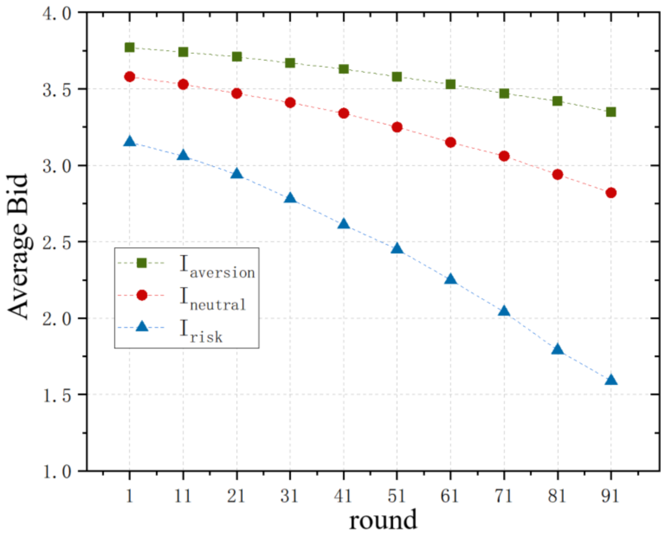

Figure 5. The average bid of collaborators with different risk preferences.

Figure 6 shows the willingness to participate of collaborators with different risk preferences. The diagram shows that the participation willingness values of the risk-averse collaborators are mostly lower than the participation willingness values of the risk-neutral collaborators, and the participation willingness values of the risk-neutral collaborators are lower than the participation willingness values of the risk-seeking collaborators. When a collaborator is risk-seeking, the bid for the task is lower than that of the risk-neutral and risk-averse collaborators, and the risk-seeking collaborator is more likely to sacrifice the established payoff in exchange for the opportunity to receive extra random bonuses.

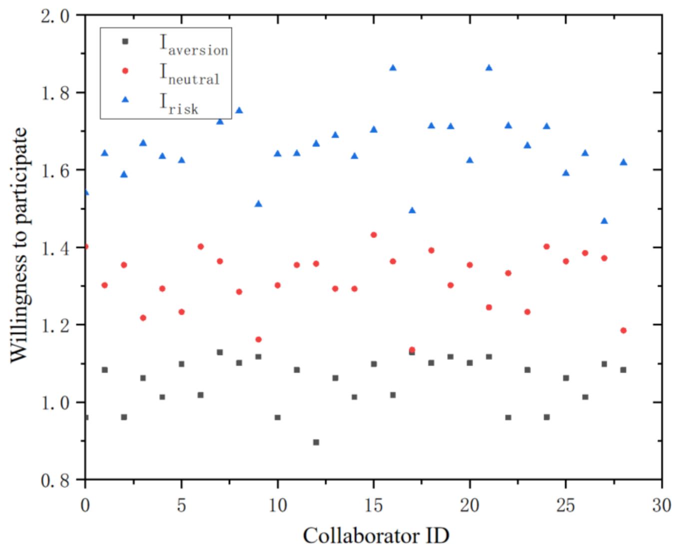

Figure 6. The willingness to participate of collaborators with different risk preferences.

4.3. Compare Results

This section compares the IMRP with the OIM and PMMRA mechanisms based on the parameter settings discussed previously.

Figure 7 shows the changes in the requesters' total utility under the three mechanisms as the number of requesters changes, when the number of collaborators is 30. It can be seen from Figure 7 that the total utility of the requesters under the three mechanisms increases as the number of requesters increases. And the total requester utility of the IMRP proposed in this paper is higher than that of the PMMRA and the OIM. Since the IMRP proposed in this paper has a random additional small probability large amount bonus, the collaborators lower their bids in exchange for the chance of winning, so the utility of the requester will be higher than the PMMRA mechanism and the OIM. On the other hand, as the number of requesters increases, so does the number of tasks, with a corresponding increase in the reward pool. An increase in the reward pool affects the expected reward for collaborators who offload tasks, allowing collaborators to offload tasks at a lower price.

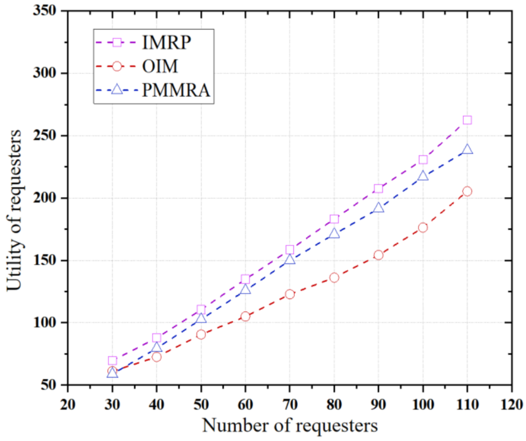

Figure 7. The changes in the requesters' total utility under the three mechanisms as the number of requesters changes.

Figure 8 shows the changes in the collaborators' total utility under the three mechanisms as the number of requesters changes, when the number of collaborators is 30. Figure 8 shows that as the number of requesters increases, the total utility of collaborators under the three mechanisms increases, and the utility of collaborators under the IMRP is always higher than that of collaborators under the OIM and the PMMRA mechanism. The average utility of collaborators offloading tasks decreases as the number of requesters increases in the IMRP due to the increase in requesters, the increase in the bonus pool, and the lower bid of collaborators for tasks. The OIM incentivizes collaborators to offload tasks through resource pricing, but the utility of collaborators is lower than that of the IMRP because resource pricing is low at the beginning. The PMMRA mechanism aims to increase the utility of the requester, which may result in lower utility for the collaborator. The IMRP uses random bonuses to motivate collaborators to offload tasks at a lower price. The random bonus improves the utility of the requester while also ensuring the utility of the collaborator.

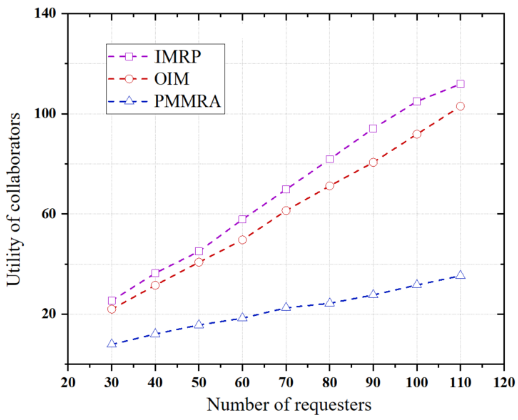

Figure 8. The changes in the collaborators' total utility under the three mechanisms as the number of requesters changes.

Figure 9 shows the changes in social welfare under the three mechanisms as the number of requesters changes, when the number of collaborators is 30. It is clear that social welfare increases with the number of requesters, because as the number of requesters increases, the number of tasks offloaded by the collaborators gradually increases, thereby increasing social welfare. The IMRP has better social welfare than the OIM and the PMMRA mechanism. The OIM reduces the rewards of collaborators through resource pricing, which improves the utility of the requester but lowers the social welfare. PMMRA mechanism aims to balance maximizing requester utility and minimizing delay, resulting in lower social welfare compared to the IMRP and OIM.

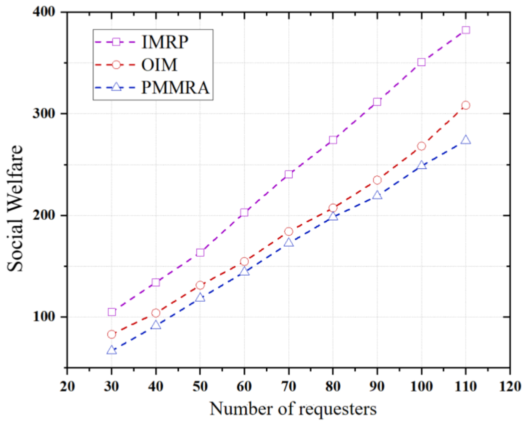

Figure 9. The changes in social welfare under the three mechanisms as the number of requesters changes.

Figure 10 shows the changes in social welfare under the three mechanisms as the number of collaborators increases, when the number of requesters is 75. Total social welfare increases as the number of collaborators increases and gradually stabilizes. When the number of collaborators is insufficient, some of the requester's tasks are not offloaded to collaborators. However, as the number of collaborators increases, the number of task offloads gradually increases, and social welfare also increases. When there are too many collaborators, the tasks of the requester are limited. The tasks of the requester are always offloaded by the most efficient collaborator, and social welfare tends to be stable. Thus, beyond a certain point, an increase in the number of collaborators does not lead to a corresponding increase in social welfare. Figure 6 shows that the social welfare under the IMRP is better than that under the OIM and PMMRA mechanisms.

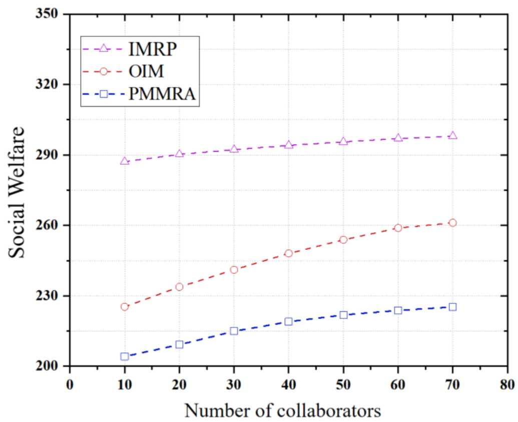

Figure 10. The changes in social welfare under the three mechanisms as the number of collaborators increases.

Figure 11 shows the changes in the total utility of requesters under the three mechanisms when the number of requesters is 75 and the number of collaborators changes. As shown in Figure 11, the total utility for the requester increases as the number of collaborators increases until the number of collaborators is so large that the requester's utility no longer increases. When the number of collaborators is too large, the requester's tasks become limited and are always offloaded by the most effective collaborator, so increasing the number of collaborators has no effect on the offloading task. Therefore, after the number of collaborators reaches saturation, increasing the number of collaborators will not affect the total utility of the requester.

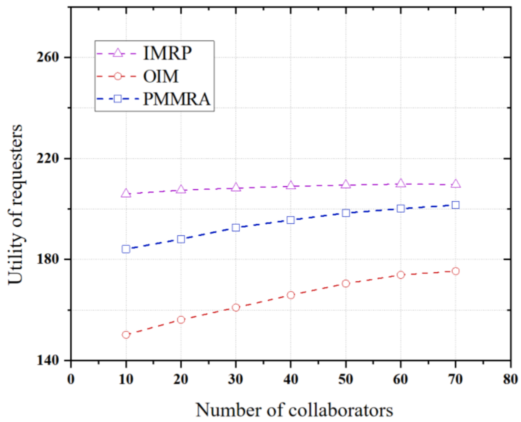

Figure 11. The changes in the total utility of requesters under the three mechanisms as the number of collaborators increases.

Figure 12 shows that the total utility of collaborators increases as the number of collaborators increases, up to a point where it stops increasing. Similar to Figure 11, once the number of collaborators reaches saturation, the requester consistently selects the most efficient collaborator to offload the task, so increasing the number of collaborators has no impact on the total utility of the collaborators. As the PMMRA mechanism has a low average collaborator utility, increasing the number of collaborators increases the collaborator utility less.

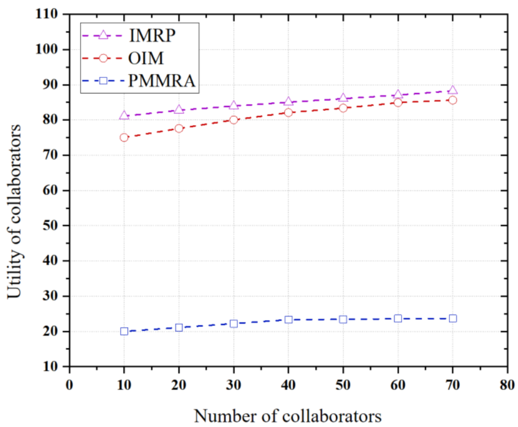

Figure 12. The changes in the total utility of collaborators under the three mechanisms as the number of collaborators increases.

Figure 13 shows the change in the number of task offloading as the number of collaborators increases, when the number of requesters is 75. When the number of collaborators is small, due to the small number of winners in each round of offloading tasks, the willingness of collaborators to participate is gradually decreased, so the number of offloaded tasks is small. However, the platform will issue compensatory payments to collaborators who have offloaded many times but without getting a bonus. Therefore, the number of tasks offloaded by the IMRP is higher than that of the OIM and PMMRA mechanisms. As the number of collaborators increases, the number of collaborators who receive bonuses and their willingness to participate increases, resulting in increased offloading. However, when the number of collaborators is large, the number of task offloadings no longer increases due to the limited tasks of the requester.

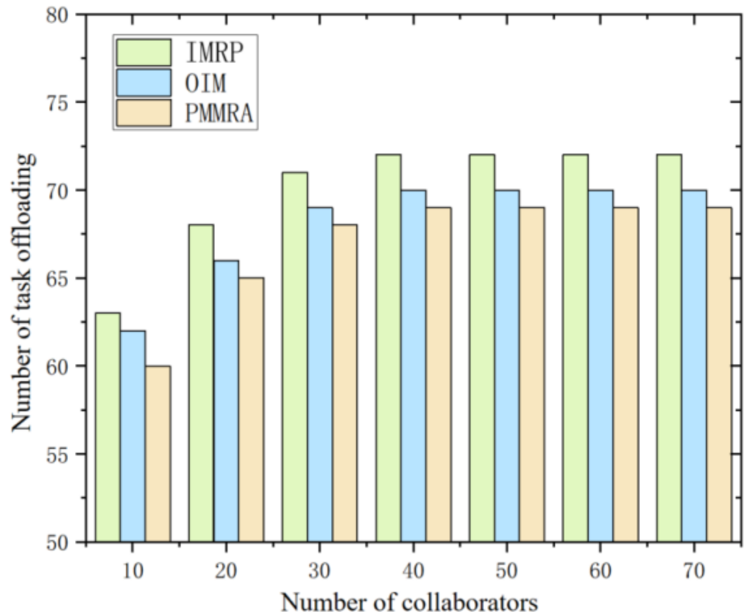

Figure 13. The change in the number of task offloading under the three mechanisms as the number of collaborators increases.

Figure 14 is a comparison diagram of the cooperation rate under different mechanisms. The diagram shows that the cooperation rate under the IMRP is lower than the OIM and PMMRA mechanism at the beginning, but significantly higher than the OIM and PMMRA mechanism. This is due to the small bonus pool at the beginning, which results in low attraction to collaborators. As task offloading progresses, the bonus pool gradually accumulates and becomes larger, which can effectively attract collaborators to offload the task. Therefore, the cooperation rate of the IMRP will be higher than that of the OIM and PMMRA mechanisms.

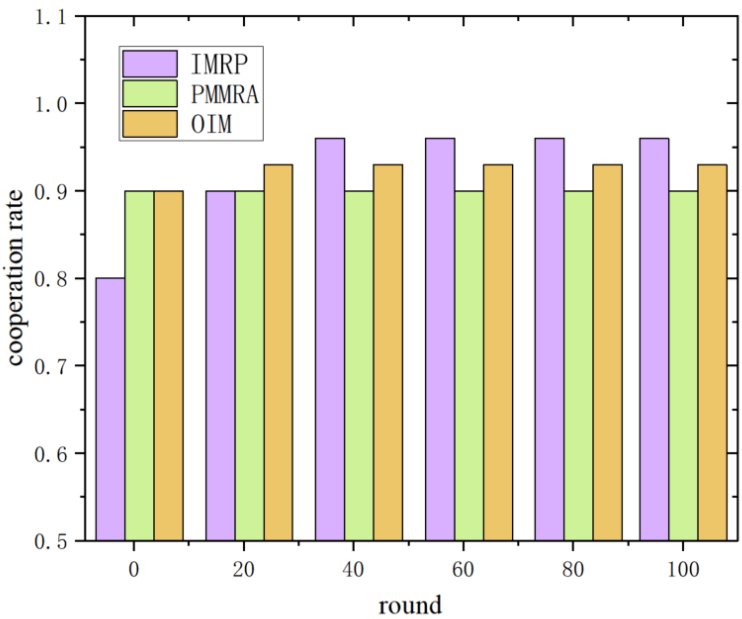

Figure 14. The cooperation rate under three different mechanisms.

5. Conclusions

Aiming at the problem of the low cooperation rate of collaborators in the MEC system, this paper designs the IMRP to improve the cooperation rate of collaborators under budget constraints. In the selection of the bonus scheme, the IMRP considers the probability distortion of collaborators. By introducing a probability distortion function into the collaborator utility evaluation model and a reference price into the bidding scheme, collaborators are induced to reduce the bid for task offloading. Meanwhile, the IMRP considers the risk preferences of the collaborators and the correlation of multi-round decisions. The risk preference factor is introduced to influence the collaborators' expectation of extra bonuses. In this way, the willingness of collaborators to participate in task offloading is improved, thereby increasing the collaboration rate of collaborators. Experimental results show that the IMRP can effectively improve the cooperation rate of collaborators under budget constraints.

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