

Research Article

The User Participation Incentive Mechanism of Mobile Crowdsensing Network Based on User Threshold

Hua Su , Qianqian Wu, Xuemei Sun, and Ning Zhang

School of Computer Science & Technology, Tiangong University, Tianjin 300387, China

Correspondence should be addressed to Hua Su; hua_207@126.com

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Mobile crowdsensing (MCS) network means completing large-scale and complex sensing tasks in virtue of the mobile devices of ordinary users. Therefore, sufficient user participation plays a basic role in MCS. On the basis of studying and analyzing the strategy of user participation incentive mechanism, this paper proposes the user threshold-based cognition incentive strategy against the shortcomings of existing incentive strategies, such as task processing efficiency and budget control. The user threshold and the budget of processing subtasks are set at the very beginning. The platform selects the user set with the lowest threshold, and the best user for processing tasks according to users' budget. The incentive cost of the corresponding users is calculated based on the user threshold at last. In conclusion, through the experiment validation and comparison with the existing user participation incentive mechanism, it was found that the user threshold-based incentive strategy is advantageous in improving the proportion of task completion and reducing the platform's budget cost.

1. Introduction

With the development of wireless communication and sensor technology, the communication functions of smart devices (smart phones, iPhone, Huawei, etc.), wearable devices (Google glasses, Apple watch, etc.), and vehicle electronic devices (GPS, OBD-II, etc.) are becoming more powerful than ever. All these smart devices, which are equipped with a variety of powerful built-in sensors, become an important information interface between users and the sensing environment and make it possible to design MCS. As a new cognitive method, MCS can accomplish many large-scale and complex sensing tasks by using various mobile terminal devices held by users through working with ordinary users and can be applied to many different fields through cooperating with users.

MCS system is composed of task publishers, MCS platform, and many users using mobile sensors. It enables ubiquitous mobile devices to collect and share local information through enhanced cognitive ability, so as to achieve a common goal [1]. In general, as a medium between ordinary users and task publishers, the cognitive

platform selects interested users to make paid cognition of tasks published by task publishers. A sensing task with reasonable budget is released to the crowdsourcing cognitive platform by a task publisher. Then, participants will be selected from the users who want to complete the sensing task. Upon receiving the cognition information provided by the recruited participants, the platform will reward them according to the cognition quality. For example, Chen et al. [2] used taxi and crowdsourcing platform for transporting the goods to be returned. Some startups have also been established and attracted millions of investments, such as Roadie; Cheng et al. [3] studied the application of crowdsourcing public transportation system in package distribution and proposed the adaptive limited delivery (ALD) method; Chen et al. [4] proposed to outsource the whole transportation task and described it as an integer linear programming issue which includes the maximum detour of drivers, capacity restriction, and options for passing packages between drivers, etc.

Incentive mechanism [5] aims to encourage users to participate in cognition activities and improve data

quality. Research on incentive mechanism of MCS network is gradually launched for the purpose of obtaining high-quality sensing data at a low cost. In view of various factors (sensor quality, noise, etc.), however, the sensing data quality contributed by a single user varies greatly. In [6], the individual quality determined by the cognition platform was included into the design of incentive mechanism, so as to maximize the benefits of MCS. In [7], a bid revision reverse auction (BRRA) was designed, in which participants were informed of the winning opportunities related to their bids and allowed to revise their bids repeatedly to find their most profitable bids. Restuccia et al. [8] proposed a participant selection method under the realistic situation that the task is effective in a limited time and the mobility of participants is uncertain. For example, when participants are vehicles, their movement tends to cover a specific area but they may not feel in time due to some unexpected reasons, such as traffic or severe weather conditions. Luo et al. [9] proposed a cross validation method where the data quality sensed by participants is evaluated by another group of people who are called validation population and the validation results are used for data improvement. In [10], a new multitask assignment plan, MTasker, was proposed, which uses the minimum cognitive quality threshold to achieve the optimal overall utility. The minimum perceptual quality threshold of a specific task is introduced to redefine the multitask assignment to assign each worker an appropriate set of tasks to maximize the effectiveness of the entire system. Liang et al. [11] studied the situation of spatial crowdsourcing under limited task probability coverage and budget, proposed a prediction model of workers' mobile behavior, and obtained the optimal solution of task allocation. In [12], a mathematical model of data quality evaluation was proposed, followed by a participant selection method of quality perception to improve data quality. Abououf et al. [13] assigned multiple staff to multiple tasks according to tasks and staff preferences so as to maximize their satisfaction and service quality and task completion confidence. Hui et al. [14] proposed two real auction mechanisms, i.e., OT-OFMCS and NOT-ONMCS, to select a group of optimal low-cost bid winning plans for the offline and online situation sensed by the mobile population, so as to maximize social welfare. Yui et al. [15] proposed a context cognitive C-MAB incentive mechanism to facilitate quality-based worker selection in MCS. It is an algorithm to evaluate the service quality and cost of employees through context (i.e., environment) and improve Thompson sampling worker selection (MTS-WS) to select workers by intensifying learning. In [16], the task allocation and path planning in MCS were studied with a view to maximizing the total task quality with limited user travel distance budget. The paper proposed a service computing framework for time constrained-task allocation in location-based crowdsensing systems. The proposed framework maximized the aggregated quality of information, reduced the budget and the response time to perform a task, and increased the average recommenders'

reputation and their payment [17]. The paper presented a comprehensive framework model that fully integrated human behavior factors for modeling task profile, worker arrival, and work ability and then introduced a service quality concept to indicate the expected service gain that a requester could enjoy when she had recruited an arrival worker by jointly taking into account work ability of workers as well as timeliness and reward of tasks [18]. The paper considered such a dynamic participant recruitment problem with heterogeneous sensing tasks which aimed to minimize the sensing cost while maintaining certain level of probabilistic coverage. Both offline and online algorithms were proposed to solve the challenging problem. Extensive simulations over a real-life mobile dataset confirmed the efficiency of the proposed algorithms [19].

The MCS network system still has some problems in user selection, task completion ratio, and budget cost, regardless of its broad application in many different fields. In this paper, a user threshold-based user incentive mechanism is proposed on the basis of system characteristic incentive mechanism. With the mechanism, the corresponding participation threshold and a budget for task cognition will be generated when the user receives a subtask and reported to the cognitive platform. Then, the cognitive platform selects the corresponding user set from all mobile users as participants according to a certain user selection method and calculates the reward that should be obtained when completing the subtask. The user finally decides whether to participate in the processing of the subtask in a specific way. The user threshold-based incentive mechanism can not only improve the task completion ratio but also reduce the user cost and save the total budget [20].

The structure of this paper is as follows: Part 1 introduces the mobile MCS network system; Part 2 expounds the threshold sensing model; Part 3 verifies the threshold-based cognition model and analyzes the results; and Part 4 is the summary of this paper.

2. MCS Network

The MCS network refers to the collaboration, either consciously or unconsciously, through the mobile Internet by taking the mobile devices of ordinary users as the basic cognitive units so as to distribute sensing tasks, collect sensing data, and finally complete large-scale and complex social sensing tasks. It mainly consists of three parts: sensing task, cognitive platform, and mobile users. To be specific, the sensing tasks are the total tasks held by task publishers who hope to collect data through users' participation and cooperation; cognitive platform, which is composed of multiple cloud cognitive servers, is the platform and medium for interaction between task publishers and mobile users [21]; mobile users are those who have mobile terminal devices in the region of interest and are willing to participate in task processing. They can collect data through various sensors embedded in the mobile device and connect with the cognitive platform through wireless network, so as to upload the sensing data to the server. As shown in Figure 1, in MCS

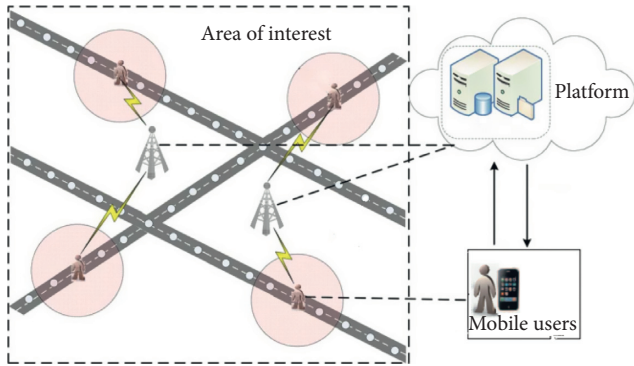


FIGURE 1: MCS network system.

network system, the cognitive platform publishes tasks in the region of interest and mobile users use various sensors in the mobile phone to sense tasks and submit them to the server, which pays the user remuneration.

2.1. Sensing Task. The task holder first determines a specific set of sensing tasks and then divides the group of tasks into several task subsets through the cognitive platform. In this paper, tasks are divided into task subsets of equal size and with no overlapping, which certainly simplifies the process of task allocation. The sensing task subset is published to the interested users in a certain area through the servers on the mobile platform and the selected mobile users execute the task subset and report to the server.

2.2. Cognitive Platform. The cognitive platform is composed of a group of servers located in the cloud. As a medium for task publishers and mobile users, it should, on the one hand, divide a certain sensing task into multiple sensing task subsets of equal size and with no overlapping and publish them to mobile users. On the other hand, it should take effective incentive mechanism to attract the participation of more users. The cognitive platform also needs to process and analyze the sensing data uploaded by mobile users and pays the corresponding rewards to cognitive users according to the incentive mechanism.

2.3. Mobile Users. Mobile users refer to a collection of users who hold mobile terminal devices in a region of interest and use various kinds of sensors embedded in the mobile devices, such as accelerometer, compass, gyroscope, GPS, microphone, and camera, to carry out the corresponding data sensing and connects server through various wireless networks, such as using mobile cellular network and short-range wireless communication, so as to upload the sensing data to the mobile platform and get paid.

3. Threshold Cognitive Model

MCS network mainly consists of three parts: user set U , task set T , and platform S . Task set T includes several subtasks, each of which is processed in turn (that is, before each subtask is processed, platform S will issue the subtask

processing request to the user). Each user will decide whether to accept the request to process the task and get the reward. This process is repeated until all tasks are processed or budget B is used up. Table 1 describes the symbols in the threshold cognitive model.

4. Task Type Classification

For any tasks to be processed, platform S first divides the task set T into several subtasks $k: k \in \{1, 2, 3, \dots, K\}$ and publishes these subtasks in a certain region. At the same time, the platform sets a utility value represented by u_k for each subtask in order to facilitate subtask evaluation. According to different task types, utility value u_k is divided into three different types; that is, utility is directly proportional to subtask size, the utility is directly proportional to the task completion ratio and the utility is inversely proportional to the task completion ratio.

4.1. The Utility is Directly Proportional to Subtask Size. The utility obtained by task publishers is directly proportional to the subtasks size to be executed. This task type only considers the subtask size, which means the larger the subtasks are, the higher the weight of the corresponding total sensing tasks is and the higher the utility value will be. The formula is shown as follows:

$$u_k = \frac{\lambda_k}{\lambda}. \quad (1)$$

For example, in the application of environmental monitoring, when the cognitive platform needs to monitor the environmental background noise in a region, the subtask size corresponds to the length of time when the mobile user provides noise monitoring. The longer the time, the larger the corresponding subtask size and the more the background noise information the server collects. In this paper, we only consider the case of equal size and with no overlapping so the utility value of each subtask is fixed. Considering that the subtask λ_k in this paper is equal in size and with no overlapping, it is a fixed value. The total task λ is fixed, so is the utility U_K of subtask.

4.2. The Utility is Directly Proportional to the Task Completion Ratio. The utility obtained by the task publisher is directly proportional to the overall sensing task progress, that is, the utility value of the subtask is directly proportional to the task progress. For this task type, consideration should be taken for the completion ratio of the total task at this stage. With the increase of the completion ratio of the total task, the utility value of the corresponding subtask will increase, as follows:

$$u_k = \frac{(\lambda(t) + \lambda_k)^\delta}{\lambda}, \quad (2)$$

where δ is a random variable in the range of $(0, 1)$. For example, in a video rendering application, if a subtask is not completed, the whole sensing task will fail. That is to say, with the execution of the task, the utility value of the

TABLE 1: Main symbols.

A_i	The i^{th} participant
N	Total number of participants
$N(t)$	The percentage of participants at time t
M_i	Number of subtasks completed by the i^{th} user
thres_i	Participation threshold for user i
C_i	Forecast effort for the i^{th} user
B	Budget for the i^{th} user
$B(t)$	Percentage of budget reserve at time t
U_i	The utility of the k^{th} subtask
I_k	The bid calculated by server for subtask k
λ	Total task size
λ_k	Size of each subtask
T	General tasks
K	Number of subtasks
$\lambda(t)$	Proportion of tasks completed at time t

remaining subtasks will gradually increase for the task publisher, which means the utility is directly proportional to the task progress.

4.3. The Utility is Inversely Proportional to the Task Completion Ratio. The utility obtained by the task publisher is inversely proportional to the overall sensing task progress; that is, the utility value of the subtask is inversely proportional to the task progress. For this task type, consideration shall be taken for the completion ratio of the total task at this stage. With the increase of the completion ratio of the total task, the utility value of the corresponding subtask will gradually decrease, as follows:

$$u_k = \frac{\lambda_k}{\lambda(t) + d}, \quad (3)$$

where d is a normal quantity in it. For example, in a target tracking application, the accuracy of target tracking will increase rapidly with the participation of the first mobile user A_1 , so the utility of the first subtask is the highest for task publishers. With the involvement of more users, the accuracy of target tracking will no longer increase, which means, with the execution of the task, the utility value of cognitive information provided by participating users decreases for task publishers; that is, the utility value is inversely proportional to task progress.

5. Users Effort and Incentive Strategy

After receiving the subtask, users in the task publishing area will generate the corresponding threshold thres_i and a predicted effort C for sensing the task, which will be reported to the cognitive platform. The platform selects a user set U which then is divided into $U_i: i \in \{1, 2, \dots, N\}$, and threshold thres_i of each subuser is confidential to other users. In this paper, where a subtask k is given, C_i is used to express the cost function; that is to say, the user's effort is affected by the size of the allocated subtask and is directly proportional to the subtask size, as shown in the following:

$$C_i = \alpha_i \lambda_k^{\beta_i}, \quad (4)$$

where α and β are two divisors in it.

According to the threshold cognitive incentive mechanism, the cognitive platform designs a threshold-based incentive mechanism in virtue of the residual $B(t)$ of the total budget, the utility value U_k of the subtask to be executed, and the threshold thres_i of the selected user. The formula used is shown as follows:

$$I_k = \frac{k}{\text{thres}_i} u_k B(t). \quad (5)$$

By selecting the appropriate parameter k , the incentive cost I_k of the server can be reduced and the budget reservation ratio can be increased.

6. User Participation Strategy

User A_i can decide whether to accept the processing request of the subtask finally according to the cost C_i required for processing subtask k and the reward I_k paid by platform S for k . In this paper, it is represented by the function P_i and the formula is shown as follows:

$$P_i = \begin{cases} 1, & \text{if } \frac{I_k}{C_i} > \text{thres}_i, \\ 0, & \text{otherwise.} \end{cases} \quad (6)$$

As shown in Algorithm 1, select the user with the lowest threshold in Line 4, apply formulas (1)–(3) to calculate the utility value of subtasks according to different task types in Line 5, and apply formulas (4) and (5) to calculate the user's effort and reward after processing subtasks in Lines 6–8. User accepts subtask requests according to the relationship of cost, reward, and threshold. This not only improves the user's participation rate and reduces effort but also speeds up subtask processing and reduces the total budget, as shown in Lines 9–12. Upon accepting the subtask, the user will compete for the next subtask, as shown in Lines 16–17.

7. Experimental Results and Analysis

7.1. Simulation Experiment Environment. In this paper, we set the total number of users $N=100$ and then divide the users into three groups according to their thresholds, i.e., high-threshold users, low-threshold users, and intermediate-threshold users. We also set the participation threshold thres_i for each user and the number of subtasks $K=1,000$ and the initial budget to $B=1,000$. The experiment is simulated in MATLAB R2014a.

7.2. Task Completion Proportion. The platform divides the task set into several subtasks and ensures that each subtask can be processed smoothly in turn. The goal of this paper is to finish the subtasks as soon as possible, which means, under the given budget limit, a higher task completion ratio can be achieved within a shorter time. Figure 2 shows the comparison chart between the two incentive mechanisms under the task type where the utility is directly proportional to subtask size. The x coordinate represents time while the y coordinate represents task completion ratio. In the simple

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Input: Tasks number  $K$ , set of users  $N$ , budget  $B$ 
Output: remaining budget  $B(t)$ , task percentage completed  $T(t)$ 
(1) initial the tasks and users, set credit values  $thres$ 
(2) while  $!k||B$ 
(3) for  $k = 1 : 1:K$ 
(4)  $Min\ thres_i \leftarrow$  find the user of the max credit value
(5)  $U_k \leftarrow$  calculate the utility of segment  $k$ 
(6)  $C_i \leftarrow$  calculate the cost of segment  $k$ 
(7)  $P_k \leftarrow$  calculate incentives for user
(8) According to  $C_i, P_k, thres$  to determine whether accept segment or not
(9) if accept segment
(10)  $N(t) \leftarrow$  calculate proportion of user participation
(11)  $B(t) \leftarrow B - P_k$ 
(12) else
(13) constant values
(14) end if
(15) end for
(16) calculate  $T(t)$ 
(17) Next loop
(18) end while
(19) return  $B(t), T(t)$ 
    
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ALGORITHM 1: Threshold cognition model.

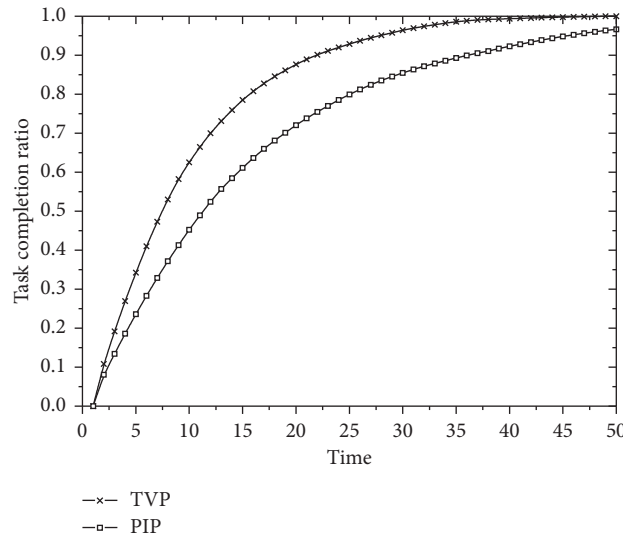


FIGURE 2: Task type where utility is directly proportional to subtask size.

participation mode, the threshold cognitive incentive mechanism (TVP) can complete the task faster and the completion speed of the participation cognition incentive mechanism (PIP) is relatively average at the beginning of task publishing. In this task type, both of the incentive mechanisms can better complete the tasks published by the server. By contrast, the threshold cognitive incentive mechanism (TVP) has a higher task completion ratio.

Figure 3 shows the comparison chart of the two incentive mechanisms under the task type where the utility is inversely proportional to task progress. The x coordinate represents time while y coordinate represents task completion ratio.

The threshold cognitive incentive mechanism (TVP) can complete tasks faster and the completion speed of participating in the cognitive incentive mechanism (PIP) is relatively average at the beginning of task publishing. In this task type, both of the two incentive mechanisms can better complete the tasks published by the server. By contrast, the threshold perception incentive mechanism (TVP) has a higher task completion ratio.

Figure 4 shows the comparison chart of the two incentive mechanisms in the task type where utility is directly proportional to task progress. The threshold cognitive incentive mechanism (TVP) can complete the task faster at the

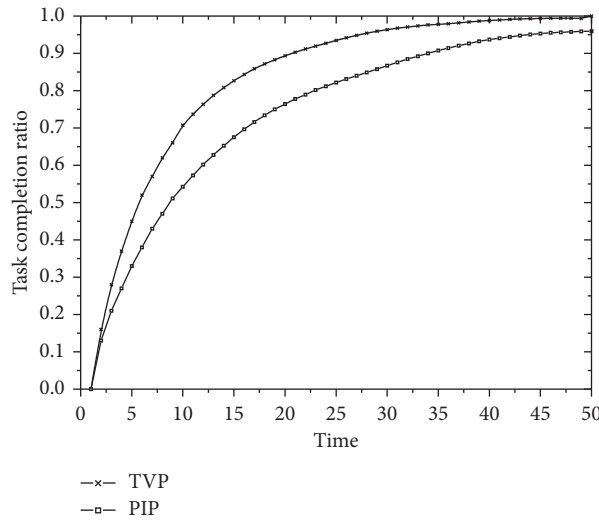


FIGURE 3: Task type where utility is inversely proportional to task progress.

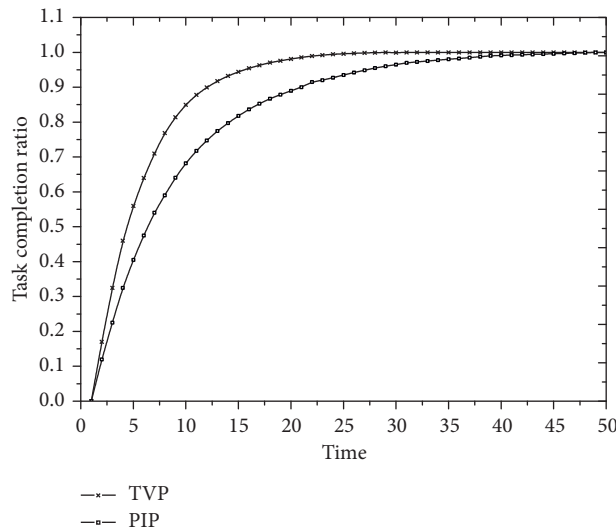


FIGURE 4: Task type where utility is directly proportional to task progress.

beginning of task publishing but both incentive mechanisms can complete the task published by the server in this task type well.

7.3. Budget Surplus Ratio. The platform pays the user according to the subtasks processed by them. One of the goals of this paper is to minimize the budget on the basis of ensuring smooth subtask treatment. Selecting users with high reputation to process subtasks can reduce the cost of processing subtasks C_i . Figure 5 shows the comparison chart of the two incentive mechanisms under the task type where utility is directly proportional to subtask size. The x coordinate represents time while the y coordinate represents budget reservation proportion. The chart represents the budget reserve ratio along with time. For the task type where utility is directly proportional to subtask size, both incentive

mechanisms perform well in the budget reservation proportion of the server, which can save the task publisher's budget dramatically.

Figure 6 shows the budget chart of the two incentive mechanisms under the task type where utility is inversely proportional to task progress. The x coordinate represents time while the y coordinate represents budget reservation proportion. This chart represents the budget reservation proportion along with time. The two incentive mechanisms spend budget at a faster speed at the beginning and then tend to be stable. By contrast, the budget reserve ratio of threshold cognitive incentive mechanism (TVP) is higher.

Figure 7 shows the budget comparison chart of the two incentive mechanisms under the task type with where utility is directly proportional to task progress. The x coordinate represents time while the y coordinate represents budget reservation proportion. This chart represents the budget

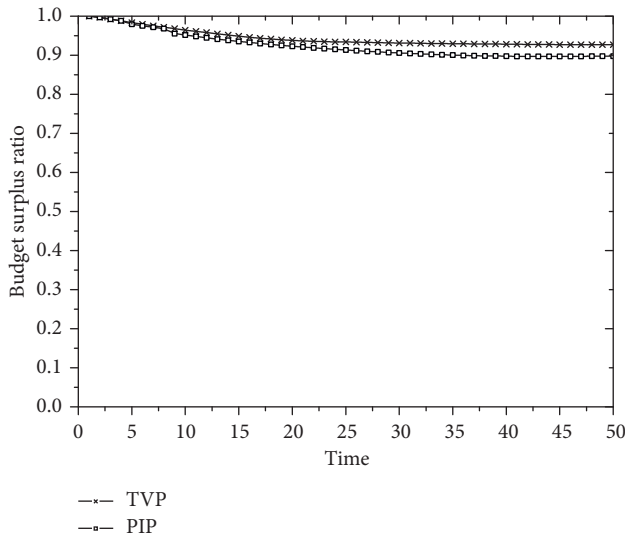


FIGURE 5: Task type where utility is directly proportional to subtask size.

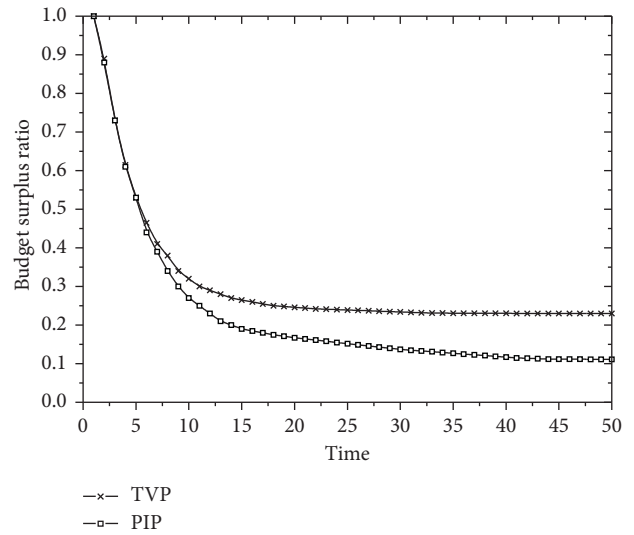


FIGURE 7: Task type where utility is directly proportional to task progress.

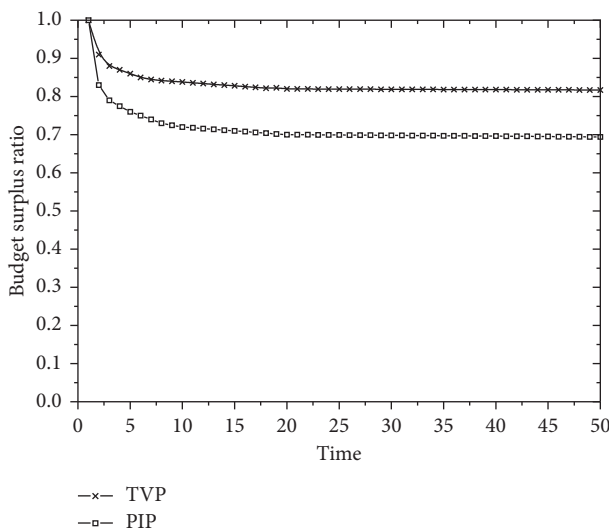


FIGURE 6: Task type where utility is inversely proportional to task progress.

reservation proportion along with time. In this type, both incentive mechanisms spend budget at a faster speed and the budget expenses are high because the server will allocate budget as much as possible to complete the reserved subtasks in order to finish all tasks.

8. Conclusion

This paper proposes the settings of the threshold of user participation based on the incentive mechanism of user participation cognition and selects the users with low threshold each time to process subtask set in turn. The utility value of subtask is affected by threshold, which further influences the platform’s payment mechanism for users. A new selection function is introduced to determine whether users

finally accept the processing request of subtask. Compared with the incentive mechanism of user participation awareness, this mechanism model is much advantageous in improving task completion speed and reducing budget.

General incentive mechanism methods, such as unequal division of subtasks and overlapping of processing time, will be taken into consideration in the future work on the basis of further improving the model. Other models can also be introduced at the same time to optimize model performance further.

Data Availability

The dataset supporting the conclusions of this article is included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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