DPIM: Dynamic Pricing Incentive Mechanism for Mobile Crowd Sensing

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Abstract. As an emerging paradigm for collecting sensory data, Mobile Crowd Sensing (MCS) technology has found widespread application. The successful application of MCS technology relies not only on the active participation of participants but also on the continuous demand for sensing task from data requestors. However, existing researchers predominantly focus on designing participant incentive mechanisms to attract participant to engage in the sensing activities, while the incentive mechanisms for data requestors are rarely addressed. To address the gap, we conceptualize the interactions between data requestors and participants as a queueing process. Building upon utility theory, we propose Dynamic Pricing Incentive Mechanism (DPIM) that dynamically offers optimal incentive guidance to the sensing platform. Moreover, we devise two distinct utility optimization modes for data requestors: one for maximizing their utility and the other for achieving utility equilibrium. These modes are tailored to meet the distinct utility requirement of the sensing platform and data requestors. Through simulations and theoretical analysis, we demonstrate that DPIM effectively provides incentives for the sensing platform across different utility modes.

Keywords: Mobile Crowd Sensing (MCS) · Queueing theory · Utility theory · Incentive mechanism · Utility equilibrium mode

1 Introduction

With the rapid development of advanced technologies, such as artificial intelligence, humans require a large amount of data to make informed decisions. However, driven by the demand for sensory data, traditional Internet of Things (IoT) technology has exhibited deficiencies in sensing coverage, real-time performance, data types, and so on [1]. Fortunately, diverse intelligent mobile devices embedded with powerful sensors are becoming increasingly popular, such as smartphones, smart bracelets, and drones. Additionally, these devices are equipped with multiple powerful sensors, such as global position system receivers, cameras, and microphones, which can be used as the sensing units [2]. Consequently, Mobile Crowd Sensing (MCS) emerges as an appealing paradigm that empowers human to collaboratively monitor a diverse range of human activities and

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environment [3]. Leveraging the improved context of human awareness, MCS boasts numerous advantages, including flexible and cost-effective deployment, multi-source heterogeneity of sensory data, wide coverage, and high scalability [4]. Presently, MCS technology has found successfully applications in various fields, including smart agriculture [5,6], environmental monitoring [7,8], traffic monitoring [9,10] etc.

The successful application of MCS technology cannot be achieved without incentive mechanisms for both data requestors and participants. To attract data requestors to publish more sensing tasks in MCS system and stimulate participant to engage in the sensing activities, it is crucial to design incentive mechanisms that reduce data requestor payment for releasing the sensing tasks while increasing participant rewards for implementing and uploading sensory data. Nowadays, numerous incentive mechanisms have been studied and can be categorized into entertainment points incentive mechanism, monetary incentive mechanism, and trust and reputation incentive mechanism. Among these, the monetary incentive mechanism is assumed to be the most direct and effective one [11].

One of the most popular monetary incentive mechanisms is based on the auction model. Wang *et al.* designed the participant incentive mechanism based on reverse auction, in which sensing platform selects participants according to task budget and participant bids [12]. Wang *et al.* proposed a double auction scheme with personalized privacy incentive, in which participants provide their bids that involves both participant resource consumption and privacy cost [13]. Ng *et al.* introduced an all-pay auction to attract the edge devices to participate in the coded computation tasks, wherein all edge devices submit their bids, and the cloud server maximize its utility by determining rewards for the winners [14]. It can be observed that the incentive mechanisms [12–14] solely consider the participant incentive within constraints like data requestor budgets, sensory data quality requirements, while the incentives for data requestors are not addressed.

Additionally, some incentive mechanisms are based on the two-sides MCS system, wherein data requestors directly provide rewards to participants. Gao *et al.* formulated the interactions between data requestors and participants as a two-stage Stackelberg differential game model, considering the average behavior of participants to solve the dynamic sensing task pricing problem [15]. Liu *et al.* adopted a model-free reinforcement learning based pricing approach to optimize pricing policy to achieve the lower payments and robustness requirement across varying quality levels [16]. Han *et al.* proposed a novel ex-ante posted pricing mechanism to jointly determine an appropriate posted price and a set of candidate participants, aiming to minimize the total expected cost of paying the participants [17]. It is evident that the incentive mechanisms [15–17] provide participant rewards and are constrained by the sensing tasks budget from data requestors, while not addressing the incentive requirements of data requestors.

Some studies also leverage utility theory to design incentive mechanisms. Ma *et al.* proposed transforming the dual objectives of minimizing the payment and maximizing the task coverage ratio into a comprehensive utility function for joint optimization [18]. Yucel *et al.* addressed the task assignment problem, aiming to simultaneously maximize the system utility and participants satisfaction [19]. Liu *et al.* introduced the concepts of capital deposit and intertemporal choice from behavioral economics, devising an addiction incentive mechanism that influences the participant utility and demand function [20]. Sarker *et al.* developed a workload allocation policy that strikes a reasonable tradeoff between participant utility and sensing platform profit [21]. Obviously, the incentive mechanisms mentioned above primarily consider sensing platform utility or participant utility, while utility requirements from data requestors have not received sufficient attention in the researches [18–21].

It is undeniable that the successful application of MCS technology is inseparable from the continuous demand for sensory data by data requestors. Without such demands, sensing activities would not have occurred, and the widespread application of MCS technology would not have been possible. Therefore, it is crucial to design a reasonable incentive mechanism to encourage data requestor to publish sensory data demands, referred to as the sensing task in MCS system. To the best of our knowledge, this work represents the first research endeavor that seeks to address the data requestor incentive issue in MCS by leveraging queueing theory and utility theory. The main contributions of the paper can be summarized as follows:

- Abstract MCS system as a queuing system, and model the utilities of data requestors, participants, and the sensing platform based on utility theory.
- Propose the Dynamic Pricing Incentive Mechanism (DPIM) that provides incentive guidance for the sensing platform, with the existence of a feasible optimal incentive solution being proved.
- Introduce the data requestor utility maximization mode and data requestor utility equilibrium mode to cater to the distinct utility requirements of the sensing platform and data requestors.
- Conduct simulations and analysis to demonstrate the effectiveness of the proposed incentive mechanism.

The remainder of this paper is organized as follows. In Sect. 2, we present the system model and problem formulation. Then, in Sect. 3 we introduce the design of proposed incentive mechanism. Section 4 carries on the experimental results and related analysis and the conclusion is given in Sect. 5.

2 Preliminary and Problem Formulation

In the MCS system, sensing activities are initiated by data requestors and proceed only when data requestors accept the sensing task pricing offered by the sensing platform. Consequently, if the pricing surpasses the expectations of data requestors, they may decline to publish the sensing tasks, causing an immediate halt in sensing activities. As a result, designing an effective incentive mechanism to encourage data requestors to publish sensing tasks in the MCS system holds immense significance.

2.1 Model Introduction

The MCS system under study comprises a sensing platform, data requestors, and participants. The interactions between data requestors and participants can be conceptualized as a continuous-time queueing process with $t \geq 0$. This process monitors the number of data requestors and participants within the system. We assume that the arrival process for data requestors and participants respectively follows Poisson distribution with rates λ and μ. New participants join the queue at a rate of μ^a, while participants already in the system exit the MCS system with a probability $q_e \geq 0$. The queueing process for data requestors and participants is depicted in Fig. 1.

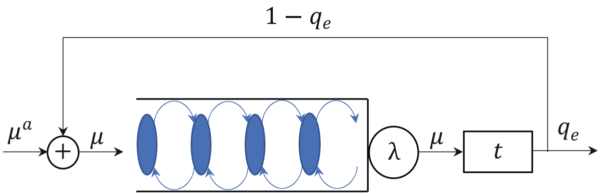

Fig. 1. Data requestor and participant queueing process

For data requestor, we assume that their expected pricing for a sensing task is independent of the distribution F_U, where U signifies the expected pricing for publishing a sensing task. If the pricing $P > 0$ offered by the sensing platform is lower than the data requestor's expected pricing, that is, $U \geq P$, the sensing task will be published. If not, data requestor will forego publishing the sensing task.

For participant, we assume that the expected reward for a sensing task is independent of the distribution F_W, where W represents the participant's expected reward for accepting sensing task. If the reward $p > 0$ provided by sensing platform exceeds the participant expected reward, that is, $p \geq W$, the participant will accept the sensing task. Otherwise, the participant will decline it. Additionally, participants can decide whether to remain in MCS system after completing a sensing task.

For sensing platform, to achieve the optimal incentive, we propose DPIM in which sensing platform dynamically offers reward p to participants and provides pricing $q_c p$ to data requestors, with q_c being the pricing coefficient. Consequently, the revenue of sensing platform becomes $(q_c - 1)p$. Considering that the sensing platform also has profit requirements, therefore, $q_c - 1 \geq 0$.

For ease of reference, Table 1 presents a compilation of the major variables utilized in the paper.

Table 1. Parameter setting for simulation.

Variables	Descriptions
p	Participant reward
P	Data requestor pricing
q_c	Data requestor pricing coefficient
λ_0	Data requestor initial arrival rate
λ_r	Data requestor real arrival rate
$\hat{\lambda}$	Data requestor effective arrival rate
μ^a	New participant arrival rate
μ_0	Participant initial arrival rate
μ_r	Participant real arrival rate
q_e	Participant departure rate
F_U	Data requestor expected pricing distribution
F_W	Participant expected reward distribution
U	Data requestor expected pricing
W	Participant expected reward
u_r	Data requestor utility
u_p	Sensing platform utility
u_w	Participant utility
T_c	Sensing platform cost for sensing activity
P_W	Participant cost for executing sensing tasks

2.2 Utility Model Definition

Since the number of completed sensing tasks in a steady-state condition is determined by the successful matching rate between data requestors and participants, the effective data requestor arrival rate can be denoted as $\hat{\lambda}$, Therefore, the utilities of the data requestor, participant, and sensing platform can be formulated as follows.

The data requestor's utility is the difference between the value of sensory data and the payment made to the sensing platform. Thus, the data requestor utility model u_r can be formulated as follows:

$$u_r = \hat{\lambda} \frac{1}{\bar{F}_U(q_c p)} \int_{q_c p}^{\infty} (U - q_c p) f_U(U) dU \tag{1}$$

The participant's utility is the difference between the reward provided by sensing platform and the actual cost incurred by the participant while performing the sensing tasks. Hence, the participant utility model u_w can be represented as follows:

$$u_w = \hat{\lambda} \left[\frac{1}{F_W(p)} \int_{0}^{p} (p - W) f_W(W) dW - P_W \right] \tag{2}$$

Among it, P_W represents the actual cost paid by participant for collecting the sensory data.

The sensing platform's utility is the difference between the expense paid by data requestor, the operation loss of the sensing platform, and the participant reward. Thus, the sensing platform utility model u_p can be represented as follows:

$$u_p = \hat{\lambda}\big[(q_c - 1)p - T_c\big] \tag{3}$$

Among it, T_c signifies the operational loss incurred by the sensing platform in managing the sensing activities.

Based on the utility models described above, we propose DPIM which provides the optimal data requestor pricing $q_c p$ and participant reward p to achieve different utility requirements under various utility modes.

3 Design of DPIM

The data requestor initial arrival process signifies the potential sensing task requests within the MCS system, and we assume it follows Poisson distribution with rate λ_0. Consequently, the data requestor real arrival rate λ_r, which reflects the effective rate of released sensing tasks, can be expressed as follows [22]:

$$\lambda_r = \lambda_0 \bar{F}_U(q_c p) = \lambda_0 \big[1 - F_U(q_c p)\big] \tag{4}$$

Assuming the participant initial arrival process to the available-participants queue follows a Poisson distribution with rate μ_0, and when the queueing process is in a steady-state, we obtain,

$$\mu^a = \mu_r q_e = \mu_0 F_W(p) \tag{5}$$

Among it, μ_r indicates the rate of participants who accept the sensing tasks.

With the MCS system parameters remaining constant, it is evident that p and q_c are the only two variables in the equations. In the MCS system, since the successful matching amount between data requestors and participants in steady-state is determined by the real arrival rate of data requestors or participants, the real and effective data requestor arrival rate $\hat{\lambda}(q_c, q)$ can be redefined as follows:

$$\hat{\lambda}(q_c, q) = \min\left\{ \lambda_0 \bar{F}_U(q_c p), \frac{\mu_0}{q_e} F_W(p) \right\} \tag{6}$$

The existing incentive mechanisms typically aim to maximize sensing platform utility. However, the sensing platform utility maximization mode solely considers the utility requirement of the sensing platform, disregarding the utility requirement of the data requestor. Thus, we introduce the data requestor maximization mode and data requestor utility equilibrium mode.

3.1 Data Requestor Utility Maximization Mode

Based on the definition of data requestor utility model, data requestor utility maximization mode under DPIM can be formulated as follows:

$$\begin{aligned} \max\ u_r &= \hat{\lambda}(q_c, p)\left[\frac{1}{\bar{F}_U(q_c p)}\int_{q_c p}^{\infty}(U - q_c p) f_U(U)dU\right] \\ s.t.\ &(q_c - 1)p - T_c \geq 0 \\ &\frac{1}{F_W(p)}\int_0^p (p - W) f_W(W)dW - P_W \geq 0 \\ &\hat{\lambda}(q_c, p) = \min\left\{\lambda_0 \bar{F}_U(q_c p), \frac{\mu_0}{q_e} F_W(p)\right\} \end{aligned} \tag{7}$$

Model (7) is employed to determine the optimal incentive for data requestors and participants under DPIM. If a solution for the model does not exist, it loses its role in providing incentive guidance. Therefore, proving the existence of an optimal incentive is necessary.

Theorem 1. *Given* $(\lambda_0, \mu_0) \in R_+^2$*,* $q_c \in [1, M_1]$*,* $p \in [M_2, M_3]$*, and continuous distribution* F_U*,*F_W*, where* M_1*,* M_2 *and* M_3 *are all finite real value, the optimal participant reward* p *and pricing coefficient* q_c *that maximize data requestor utility must exist.*

Proof. The proof process can be divided into two steps. First, define a closed interval, and then prove that the model is continuous on the closed interval, thereby demonstrating the existence of a feasible solution for the model within the closed interval.

Step 1: Since the participant reward p and pricing coefficient q_c are the only two variables in the model, and considering $q_c \in [1, M_1]$ and $p \in [M_2, M_3]$, it is evident that the model exists within the closed interval.

Step 2: Prove the continuity of model (7). By the definition of continuity, let the function $y = f(x)$ be defined in the neighborhood of any point x_0 in the model interval. If $\lim\limits_{\Delta x \to 0} \Delta y = \lim\limits_{\Delta x \to 0} \left[f(x_0 + \Delta x) - f(x_0)\right] = 0$, then $y = f(x)$ is continuous at point x_0, indicating the model's continuity within the interval. Let q_{c1} and p_1 be any points in the domain, and assume their increment are respectively Δq_{c1} and Δp_1. Therefore,

$$\begin{aligned}\lim_{\substack{\Delta q_{c1}\to 0\\ \Delta p_1\to 0}} \Delta y &= \lim_{\substack{\Delta q_{c1}\to 0\\ \Delta p_1\to 0}} \left[f(q_{c1}+\Delta q_{c1}, p_1+\Delta p_1) - f(q_{c1}, p_1)\right]\\
&= \lim_{\substack{\Delta q_{c1}\to 0\\ \Delta p_1\to 0}} \Bigg(min\left\{\lambda_0 \bar{F}_U(q_{c1}+\Delta q_{c1})(p_1+\Delta p_1), \frac{\mu_0}{q_e} F_W(p_1+\Delta p_1)\right\}\\
&\left\{\frac{1}{\bar{F}_U\left((q_{c1}+\Delta q_{c1})(p_1+\Delta p_1)\right)} \int_{(q_{c1}+\Delta q_{c1})(p_1+\Delta p_1)}^{\infty} \left(U-\left(q_{c1}+\Delta q_{c1}\right)\right.\right.\\
&\left.(p_1+\Delta p_1)\right) f_U(U)dU + \frac{1}{F_W(p_1+\Delta p_1)} \int_0^{p_1+\Delta p_1} (p_1+\Delta p_1-W) f_W(W)dW\\
&\left.-P_W + \left[(q_{c1}+\Delta q_{c1}-1)(p_1+\Delta p_1)-T_c\right]\right\} - min\left\{\lambda_0 \bar{F}_U(q_{c1}p_1), \frac{\mu_0}{q_e} F_W(p_1)\right\}\\
&\left\{\frac{1}{\bar{F}_U(q_{c1}p_1)} \int_{q_{c1}p_1}^{\infty} (U-q_{c1}p_1) f_U(U)dU + \frac{1}{F_W(p_1)} \int_0^{p_1} (p_1-W) f_W(W)dW\right.\\
&\left.\left.-P_W + \left[(q_{c1}-1)p_1 - T_c\right]\right\}\right)\end{aligned}$$

Since $1 \leq q_c \leq M_1$, $M_2 \leq p \leq M_3$, and both F_U and F_W are continuous distributions, we have $\bar{F}_U(q_c p) \geq 0$ and $F_W(p) \geq 0$. Therefore, $\lim_{\substack{\Delta q_{c1}\to 0\\ \Delta p_1\to 0}} \Delta y = 0$.

It can be concluded that model (7) is continuous within the closed interval, confirming the existence of a feasible solution. In other words, the model must have a solution within the defined domain to maximize data requestor utility.

3.2 Sensing Platform Utility Maximization Mode

As per the definition of the sensing platform utility model, the sensing platform utility maximization mode under DPIM can be expressed as follows:

$$\begin{aligned}&\max\ u_p = \hat{\lambda}(q_c, p)\left[(q_c-1)p - T_c\right]\\
&s.t. (q_c-1)p - T_c \geq 0\\
&\frac{1}{F_W(p)} \int_0^p (p-W) f_W(W)dW - P_W \geq 0\\
&\hat{\lambda}(q_c, p) = \min\left\{\lambda_0 \bar{F}_U(q_c p), \frac{\mu_0}{q_e} F_W(p)\right\}\end{aligned} \quad (8)$$

Model (8) is utilized to determine the optimal incentive under DPIM. If a solution of the model does not exist, then it loses its function of providing incentive guidance for the sensing platform. Therefore, it is imperative to prove the existence of the optimal incentive under sensing platform utility maximization mode. Since the proof process is akin to Theorem 1, we will not reiterate it here.

3.3 Data Requestor Utility Equilibrium Mode

The data requestor utility equilibrium mode pertains to the utility equilibrium between the sensing platform and data requestors. This equilibrium can be expressed as follows:

$$u_p - u_r = 0 \quad (9)$$

Substituting equations (1) and (3) into equation (9), we obtain,

$$\frac{1}{\bar{F}_U(q_c p)}\int_{q_c p}^{\infty}(U-q_c p)f_U(U)dU-\left[(q_c-1)p-T_c\right]=0 \tag{10}$$

Taking Eq. (10) as the additional nonlinear equality constraint for model (8), the data requestor utility equilibrium model can be formulated as follows:

$$\begin{aligned}
&\max\ u_p=\hat{\lambda}(q_c,p)[(q_c-1)p-T_c]\\
&s.t.(q_c-1)p-T_c\geq 0\\
&\frac{1}{F_W(p)}\int_0^p(p-W)f_W(W)dW-P_W\geq 0\\
&\hat{\lambda}(q_c,p)=\min\left\{\lambda_0\bar{F}_U(q_c p),\frac{\mu_0}{q_e}F_W(p)\right\}\\
&\frac{1}{\bar{F}_U(q_c p)}\int_{q_c p}^{\infty}(U-q_c p)f_U(U)dU-\left[(q_c-1)p-T_c\right]=0
\end{aligned} \tag{11}$$

Model (11) is employed to determine the optimal incentives for data requestors and participants under DPIM. It is imperative to prove the existence of the optimal incentive solution. Based on the proof of the existence of feasible solutions for the sensing platform utility maximization mode, it can be deduced that a feasible solution must exist for the data requestor utility equilibrium mode as well. Thus, we will not repeat the proof process.

4 Experiments

To demonstrate the effectiveness and performance of DPIM, simulations and analysis are carried out under various utility modes.

4.1 Parameter Setting

Simulations involve altering fundamental parameters of the MCS system, such as the data requestor and participant initial arrival rates, data requestor expected

Table 2. Parameter setting for simulation.

Simulation parameters	Value	Unit
Data requestor initial arrival rate	5000	
Participant initial arrival rate	1000	
Participant leave rate	0.8	
Data requestor expected pricing	$N(50, 10)$	RMB
Participant expected reward	$N(35, 5)$	RMB
Participant cost	5	RMB
Sensing platform cost	0.15	

pricing, and participant expected reward, while keeping other parameters constant. The performance of the proposed incentive mechanism, data requestor utility, and sensing platform utility are thoroughly analyzed. The initial parameter setting for the simulations are presented in Table 2. For clarity, we abbreviate the term 'sensing platform utility maximum mode' as 'PUM', 'data requestor utility equilibrium mode' as 'DRUE', and 'data requestor utility maximum mode' as 'DRUM'.

4.2 Simulation and Analysis

Impact of Data Requestor Initial Arrival Rate. The participation of data requestor in sensing activities directly influences the sensing task demand within MCS system, thereby significantly impacting the incentive mechanism. In the simulation, the data requestor initial arrival rate is varied between 1000 and 6000. The simulation results are depicted in Figs. 2 and 3.

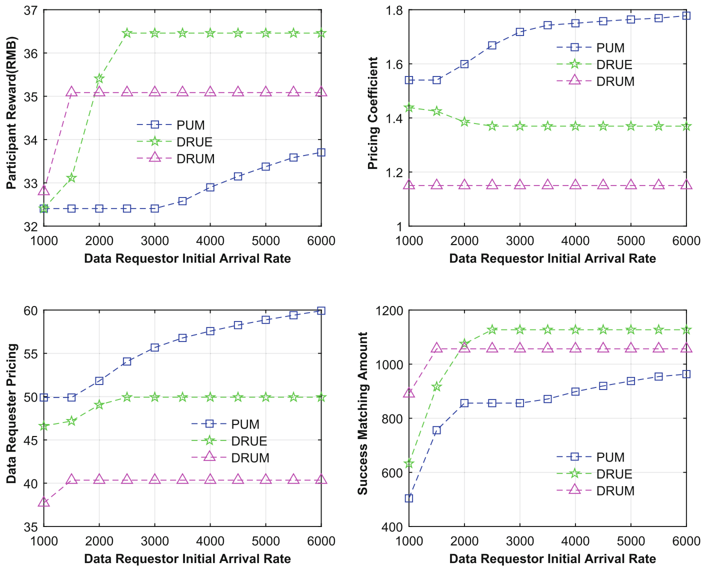

Fig. 2. Data requestor initial arrival rate impacts on incentives

In Fig. 2, the increase of data requestor initial arrival rate corresponds to an upward trend in participant reward, data requestor pricing and successful matching amount under each utility mode. Given the constant participant initial arrival rate, once the number of sensing tasks surpasses the maximum participant supply, the augmentation of participant reward no longer bring more participants, leading to a stabilization of the incentive. In practice, as participant

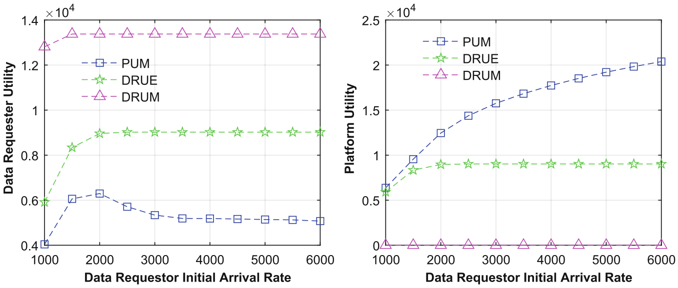

Fig. 3. Data requestor initial arrival rate impacts on utilities

reward increases, it is highly likely that more participants will engage in sensing activities, causing participant supply to expand and the successful matching count to increase.

Figure 3 illustrates the influence of the data requestor initial arrival rate on the utilities of both the sensing platform and data requestors. Evidently, as the data requestor initial rate remains low, both data requestor and sensing platform utilities rise. It can be deduced from the incentive analysis that with a substantial increase in the data requestor initial rate, both the incentive and successful matching count stabilize. Consequently, the utilities of the sensing platform and data requestor also stabilize.

Impact of Participant Initial Arrival Rate. The participation of participants in sensing activities directly affects the participant supply within the MCS system, which also exerts a significant influence on the incentive mechanism. In the simulation, the participant initial arrival rate is varied between 200 and 6200. The simulation results are shown as Figs. 4 and 5.

In Fig. 4, it can be observed that with an increase in the participant initial arrival rate, the participant reward, pricing coefficient, and data requestor pricing display a downward trend, while the count of successfully matched sensing tasks exhibits an upward trend. Given the fixed data requestor initial arrival rate, when the number of participants exceeds the maximum sensing task demand, the reduction in data requestor pricing does not result in more sensing tasks being performed. Consequently, the incentive eventually stabilizes. In practice, as data requestor pricing decreases, it is certain that more sensing tasks will be released, leading to an increase in the successful matching count of sensing tasks.

Figure 5 illustrates the impact of the participant initial arrival rate on the utilities of both the sensing platform and data requestors. Clearly, when the data requestor initial rate is low, both data requestor and sensing platform utilities increase. As revealed by the incentive mechanism analysis, when the data requestor initial rate becomes sufficiently high, the utilities of both data requestors and the sensing platform stabilize.

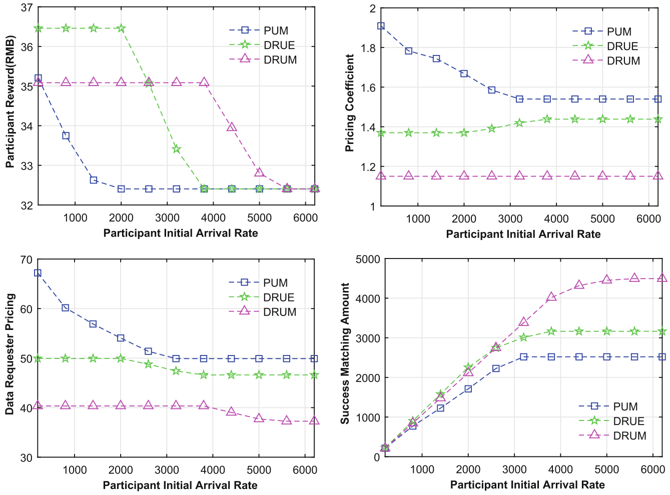

Fig. 4. Participant initial arrival rate impacts on incentives

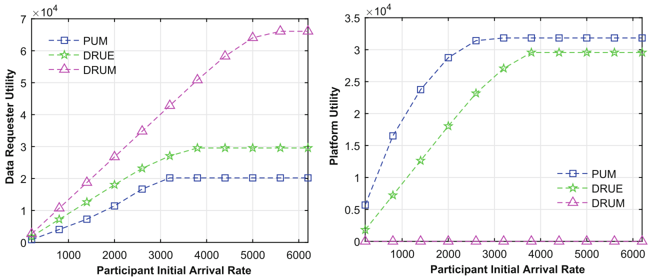

Fig. 5. Participant initial arrival rate impacts on utilities

Impact of Data Requestor Expected Pricing. The data requestor expected pricing is a significant factor influencing the incentive mechanism. In the simulation, the data requestor expected pricing is adjusted between 50 and 100. The simulation results are presented in Figs. 6 and 7.

In Fig. 6, it can be observed that an increase in the data requestor expected pricing leads to an upward trend in both participant reward and the pricing coefficient. This trend arises from the fact that higher data requestor expected pricing stimulates more sensing task demands within the MCS system. Consequently, the sensing platform enhances the participant reward to attract more participants to meet the heightened sensing task demands. Simultaneously, the platform mitigates the increased sensing task demand by elevating data requestor pricing.

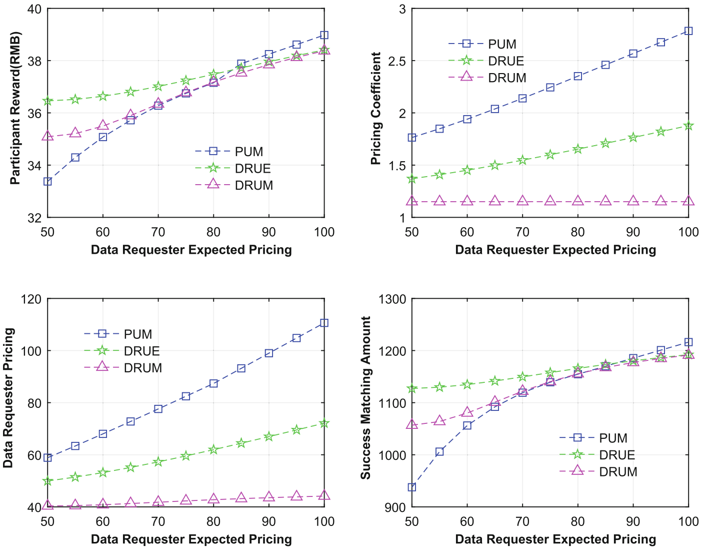

Fig. 6. Data requestor expected pricing impacts on incentives

Figure 7 reveals that an increase in data requestor expected pricing results in an upward trend for both the sensing platform and data requestor utilities. In the context of the sensing platform utility maximization mode, an increase in data requestor expected pricing has limited impact on data requestor utility. Conversely, within the data requestor utility equilibrium mode, the rise in data requestor expected pricing minimally affects sensing platform utility.

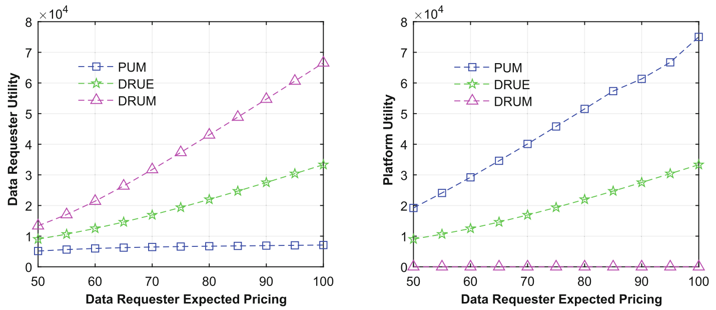

Fig. 7. Data requestor expected pricing impacts on utilities

Impact of Participant Expected Reward. The participant expected reward constitutes another significant factor influencing the incentive mechanism. In the simulation, the participant expected reward is varied between 10 and 30. The simulation results are displayed in Figs. 8 and 9.

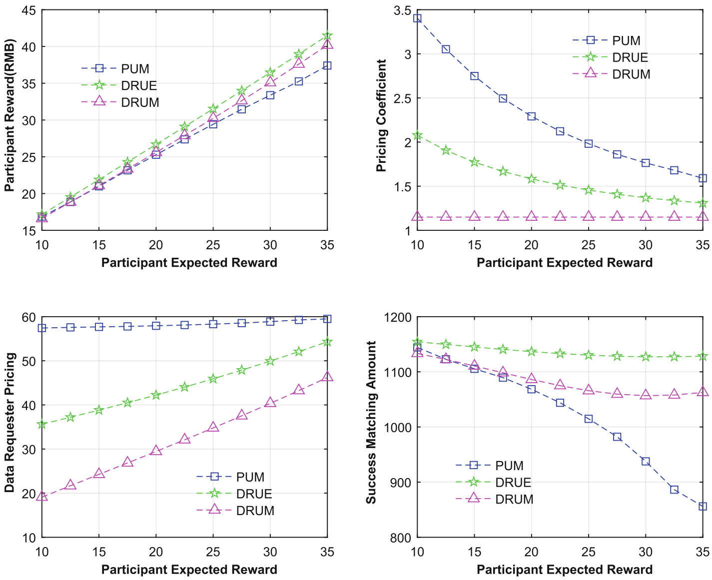

Fig. 8. Participant expected reward impacts on incentive mechanism

Figure 8 demonstrates that an increase in the participant expected reward corresponds to an upward trend in the participant reward. This alignment with intuition stems from the fact that the sensing platform needs to enhance the participant reward to attract more participants. Simultaneously, data requestor pricing increases, even though the pricing coefficient exhibits a downward trend. The count of successfully matched tasks exhibits a negative correlation with the participant expected reward. According to economic theory, the rise in participant expected reward unavoidably reduces both the sensing task demand and the participant supply.

Figure 9 illustrates that both sensing platform and data requestor utilities decline with an increase in the participant expected reward. This result is anticipated from the analysis of the incentive mechanism. Furthermore, within the sensing platform utility maximization mode, the increase in participant expected reward has a minimal impact on data requestor utility. In contrast, under the data requestor utility equilibrium mode, the increase in participant expected reward has a slight impact on sensing platform utility.

Furthermore, it is evident that both the pricing coefficient and data requestor pricing are consistently the lowest under the data requestor utility equilibrium

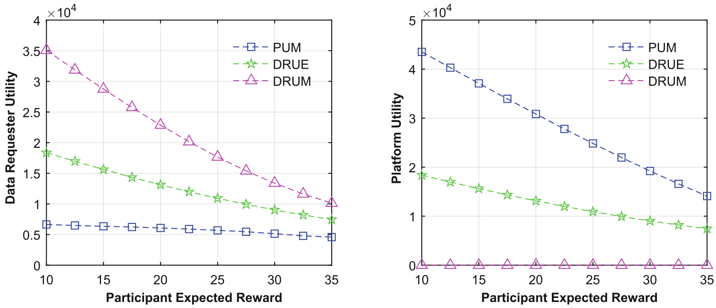

Fig. 9. Participant expected reward impacts on utilities

mode, and the highest under the sensing platform utility maximization mode. Moreover, the data requestor utility mode consistently maximizes data requestor utility, while the sensing platform utility mode maximizes the sensing platform. To achieve a balance between data requestor and sensing platform utilities, the sensing platform can dynamically adjust the incentive based on different utility modes and real-time parameters of the MCS system, such as data requestor expected pricing, and the participant and data requestor arrival rates.

5 Conclusion

In this paper, to design the incentive mechanism for data requestors, we first abstract the interaction between data requestors and participants in sensing activities as a queueing process and introduce DPIM based on utility theory. Then, to satisfy the data requestor's utility requirements, we have designed both the data requestor utility maximization mode and the data requestor utility equilibrium mode, each accompanied by a proof of the existence of a feasible solution. Finally, simulation results demonstrate that the sensing platform can effectively manage the demand for sensing tasks and the supply of participants through the incentive mechanism. Moreover, the utility of both data requestors and the sensing platform can be satisfied in their respective utility modes.

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