Published in IEEE/ACM Transactions on Networking (2023), DOI: 10.1109/TNET.2023.3297258

PAM^{3}S: Progressive Two-Stage Auction-Based Multi-Platform Multi-User Mutual Selection Scheme in MCS

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***Abstract*— Mobile crowdsensing (MCS) has been applied in various fields to realize data sharing, where multiple platforms and multiple Mobile Users (MUs) have appeared recently. However, aiming at mutual selection, the existing works ignore making MUs' utilities with the limited resources and platforms' utilities while achieving the desired sensing data quality maximum as far as possible. Thus, they cannot motivate both MUs and platforms to participate. To address this problem, standing on both sides of MUs and platforms with conflicting interests, we propose a Progressive two-stage Auction-based Multi-platform Multi-user Mutual Selection scheme (PAM^{3}S). Specifically, in PAM^{3}S, we treat mutual selection as a two-stage auction and devise the auction models for MU and platform using forward and reverse auction ideas, presenting and maximizing the utilities from their respective perspectives. Then, based on the proposed progressive two-stage auction structure, we adopt 0-1 knapsack and Myerson's price theory to construct the first stage MU-oriented auction and the second stage platform-oriented auction, achieving devised models. Theoretical analysis shows that PAM^{3}S is economically robust. Extensive experiments on the real dataset demonstrate that PAM^{3}S respectively promotes platforms' and MUs' utilities by 76.23% and 10.74 times, compared with the existing works.**

***Index Terms*— Mobile crowdsensing, mutual selection, multi-platform multi-user, utility, auction.**

I. Introduction

With the popularity of smart mobile devices equipped with various sensors such as GPS, camera, and accelerometer, Mobile CrowdSensing (MCS) has become a new pattern of data collection and sharing. It promotes a sensing platform to recruit Mobile Users (MUs) to perform tasks for providing services, which can fully use a wide range of sensor resources without deploying specific infrastructures. Recently, more and more applications managed by different platforms have appeared. The heterogeneous MUs can join various platforms and submit their sensing data, such as real-time traffic monitoring data (Waze) [1], air quality monitoring data (U-Air) [2], and health management data (Runkeeper) [3]. It spawns the MCS market of multiple platforms and multiple MUs [4], [5], [6], as shown in Fig. 1. Different from the MCS scenario with a single platform, in this new scenario, each MU can choose several platforms to join to maximize his utility prospectively. Meanwhile, each platform tries to attract and recruit MUs to acquire sensing data to maximize its utility under a specific budget.

The smooth acquisition of sensing data for a platform relies on a certain number of MUs' participations. Meanwhile, MUs sacrifice their resources while performing tasks that are not beneficial to them [7], [8]. Thus, it is desired for the platform to provide compensation for MUs' loss, encouraging them to participate and complete sensing tasks. Currently, focusing on the multi-platform multi-user scenario, several works have been proposed to attract MUs to participate [5], [6], [9], [10], [11], [12], [13]. Nevertheless, the existing works still have the following problems.

Specifically, for MUs, the existing works make a MU select platforms with high declared payments [13] or considerable profits [5], [6], note that each MU may ignore his limited resources. These schemes cannot appropriately allocate MUs' resources for participating in tasks from multiple platforms. In particular, when a MU chooses several platforms with the highest declared payments, these platforms may consume up MU's limited resources, so the MU has no resources to join other platforms' tasks. Whereas, if the MU chooses platforms with relatively low declared payments while consuming the MU's fewer resources, he can select more platforms to join to get a higher utility because the MU can get profit from more platforms with the same resources. Therefore, these policies may make a MU get a low utility instead.

Moreover, for platforms, the existing works mainly focus on the competition among multiple platforms for attracting as many MUs as possible [5], [9], [10], [11] or reducing costs of recruiting MUs [13], while ignoring the quality of data MUs provide. These schemes cannot guarantee that platforms collect desired quality sensing data. Data gathered with low quality directly impacts the data value and further influences the sensing service quality. Therefore, the platforms may get

Manuscript received 6 November 2022; revised 12 April 2023 and 26 June 2023; accepted 15 July 2023; approved by IEEE/ACM Transactions on Networking Editor S. Magnusson. This work was supported in part by the National Natural Science Foundation of China under Grant 62125205 and in part by the Key Research and Development Program of Shaanxi under Grant 2023KXJ-190. *(Corresponding author: Xinghua Li.)*

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Digital Object Identifier 10.1109/TNET.2023.3297258

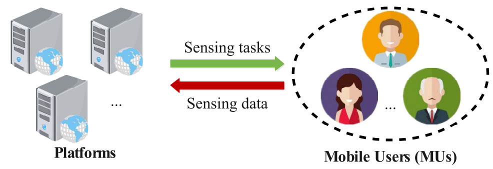


Fig. 1. **A simple example of multiple platforms and multiple MUs.** Each sensing platform is responsible for broadcasting tasks and recruiting MUs. Then, the recruited MUs submit the collected sensing data to the platform. After processing the received data, the platform obtains the sensing results to provide further services.

low utilities and even negative ones. Overall, the existing works cannot maximize MUs' and platforms' utilities as much as possible, failing to promote both to participate in the multi-platform multi-user scenario.

To address the aforementioned issues, we propose a **P**rogressive two-stage **A**uction-based **M**ulti-platform **M**ulti-user **M**utual **S**election scheme (PAM^{3}S) in MCS. Unlike traditional mechanisms used in the existing works, we innovatively devise the two-stage auction for this selection. The contributions of this paper are summarized as follows:

- We regard mutual selection in the multi-platform multi-user scenario as a two-stage auction and establish the auction models respectively for MU and platform. The selection of inclined platforms by MU and recruitment of MUs by the platform are progressively modeled as the forward MU auction and reverse platform auction. Meanwhile, we consider the limited resources of MUs and the quality of sensing data gathered by platforms and redesign the utility of MU and the platform. The established models guide MU and the platform to obtain satisfactory utilities.
- We implement the proposed two-stage model. We design the first stage MU-oriented auction by adopting the ideas of 0-1 knapsack and Myerson's price theory, where each resource-constrained MU selects the inclined platforms and computes the asking prices for these platforms. Based on this auction, we progressively give the second stage platform-oriented auction. Each platform determines the final recruited MUs and the payments employing Myerson's price theory.
- Theoretical analysis shows that PAM^{3}S achieves design goals, including individually rational, truthful, and budget balanced. Extensive experiments on the real dataset indicate that the utilities of platforms and MUs respectively increase 76.23% and 10.74 times on average compared with the existing works. Moreover, the platform's sensing data quality and the MU's resource utilization are improved by 35.00% and 2.20 times, respectively.

The rest of this paper is organized as follows. In section II, we review the existing works. Section III gives the system model, assumptions, design goals, and preliminaries. The detailed scheme, including our auction models and corresponding constructions, is demonstrated in section IV. Section V and section VI present the theoretical analysis and performance evaluation, respectively. Finally, we give the conclusion and future work in section VII.

II. Related Work

This section reviews the existing works for the multi-platform multi-user scenario. We give the comparison of the existing works and PAM^{3}S in TABLE I.

TABLE I
Comparison of the Existing Works and PAM^{3}S

Works	TM	MMP	SDQ	AMRA	NP
[9]	Non-cooperative game	✗	✗	✗	Single
[10]	Non-cooperative game & Evolutionary game	✗	✗	✗	Multiple
[11]	Non-cooperative game	✗	✗	✗	Multiple
[12]	Non-cooperative game	✗	✗	✗	Multiple
[5]	Stackelberg game	✗	✗	✗	Single
[6]	Stackelberg game	✗	✗	✗	Multiple
CPAS- [13]	One-stage auction	✗	✗	✗	Single
VPAS- [13]	One-stage auction	✗	✗	✓	Multiple
[4]	-	✗	✓	✗	Multiple
PAM^{3}S	Two-stage auction	✓	✓	✓	Multiple

Note: **TM**: Theoretical method; **MMP**: Maximizing MUs' utilities under resources constraints and platforms' utilities with certain sensing data quality as far as possible; **SDQ**: Sensing data quality; **AMRA**: Appropriate MUs' resources allocation; **NP**: Number of platforms each MU joins; -: none consideration.

Unlike the MU recruitment works in the single platform scenario [14], [15], [16], [17], Peng et al. [9] first paid attention to the multi-platform multi-user scenario. They pointed out that MUs could migrate among multiple platforms to seek more utilities. The proposed scheme makes each platform decide its bid independently by regarding the bidding competition among multiple platforms as a non-cooperative game. Later, Peng et al. [10] further treated the migration of MUs as an evolutionary game. They demonstrated that both platforms and MUs could reach game equilibrium. Because the works above only take platforms' current profits into account, Peng et al. [11] extended the devised non-cooperative game to a repeated game, enabling each platform to optimize the long-term profits. Following the idea of regarding the bidding competition among multiple platforms as a non-cooperative game, Chakeri and Jaimes [12] discussed two cases where each platform fixed the bid in advance and set the bid dynamically. However, most of the works above just explore the competition among multiple platforms. Aiming this problem, Li et al. [5] regarded the sensing data sharing between multiple platforms as many-to-many bargaining in addition to formalizing the platforms' competition as a two-stage Stackelberg game. Nie et al. [6] enabled the approving profits for platforms and MUs by formulating the interactions between them as a multi-leader multi-follower Stackelberg game with social influence of MUs. The collusive reward strategies are also discussed under the cooperation of platforms. Focusing on a set of task owners and MUs, Cai et al. [13] proposed several distributed auctions for selection, including the Cost-Preferred Auction Scheme (CPAS), the Valuation-Preferred Auction Scheme (VPAS), and so on. Their proposed auctions fit the sensing task diversity. Unlike the works above, Ni et al. [4] concerned the privacy issues under MU recruitment, where the decentralized trust management proposed allows MUs to join different platforms.

However, the existing works supporting multi-platform multi-user scenarios focus on attracting MUs mainly. They do not appropriately allocate the resources of MUs to maximize their utilities as far as possible under resource constraints. Meanwhile, they also fail to maximize platforms' utilities as much as possible with high-quality sensing data. Thus,

TABLE II
MAINLY USED NOTATIONS

Notations	Descriptions
$\mathcal{P} = \{P_1, P_2, \cdots, P_n\}$	Multiple platforms
$\mathcal{M} = \{M_1, M_2, \cdots, M_m\}$	Multiple MUs
b_i	Bid of P_i
ε_i	Sensing quality threshold of P_i
z_i	Desired resources of P_i
l_i	Number of recruited MUs of P_i
$a_{j,i}$	Asking price of M_j for P_i
$c_{j,i}$	Cost per unit resource consume by M_j joining P_i
Z_j	Possessing resources of M_j
$p_{i,j}$	Paid payment of P_i for M_j
$\mathcal{W}_{j,\mathcal{P}}$	Winning platform set that M_j intends to join
$\mathcal{W}_{i,\mathcal{M}}$	Winning MU set that P_i aims to recruit
$\mathcal{U}_{P_i}$	Utility of P_i
$\mathcal{U}_{M_j}$	Utility of M_j

the existing works cannot obtain appropriate results, reducing MCS practicability.

III. Problem Formulations and Preliminaries

This section first presents the system model and assumptions. Then, it gives detailed design goals and preliminaries. Prior to further description, it demonstrates the mainly used notations in TABLE II.

A. System Model and Assumptions

We are concerned about the multi-platform multi-user scenario, where several platforms and large amounts of MUs exist. The system model is shown in Fig. 2. Let $\mathcal{P} = \{P_1, P_2, \cdots, P_n\}$ be the platform set and $\mathcal{M} = \{M_1, M_2, \cdots, M_m\}$ be the MU set, where $n, m \geq 2$. The functions of entities are shown below.

Platforms: When recruiting MUs, each platform P_i publishes its recruitment information, where $1 \leq i \leq n$ (*step 1*). Receiving multiple participation intentions from MUs, P_i determines the final recruited MUs (*step 4*), informs them of the results, and allocates the sensing tasks (*step 5*). Furthermore, P_i pays the payments to the recruited MUs after receiving the sensing data (*step 7*). Since the accurate evaluation of a MU relies on long-term tracking, P_i evaluates the sensing situation of each recruited MU according to the received sensing data [18].

MUs: Certain MU M_j first decides the inclined platforms and computes the asking prices after receiving the recruitment information, where $1 \leq j \leq m$ (*step 2*). Then, M_j sends the relevant asking prices to each inclined platform (*step 3*). If M_j is selected by platform P_i, he joins P_i, performs the sensing task, and submits the sensing data (*step 6*). The payment compensates the cost of M_j for performing the task.

In our system, PAM^{3}S makes some assumptions for platforms and MUs as follows:

- **Assumption 1:** Each platform P_i declares the bid representing the upper bound of payment to be paid for the recruited MU. P_i can claim a higher bid than the real one to attract more MUs and a lower bid for fewer payments. However, P_i will not lie about the other items in the recruitment information since P_i cannot improve its utility by declaring fake ones.

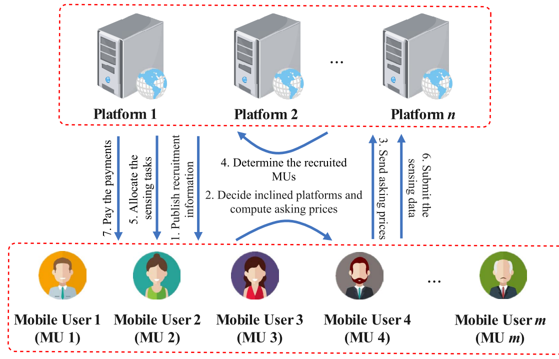


Fig. 2. System model.

- **Assumption 2:** For MU M_j, the existing works have pointed out that the platform can evaluate and select appropriate MUs for high-quality sensing results [18], [19], [20], where the evaluations are usually based on the long-term observation of MUs' submitted data. Multiple platforms can also maintain the MUs' evaluations cooperatively [4]. We assume the MU's evaluation can be stored and shared among multiple platforms, which is similar to that banks share consumers' credit information to filter undependable ones and can be realized by technology such as blockchain. Thus, M_j cannot forge his sensing evaluations. Once M_j joins a platform that requires more resource consumption than he owned, he will submit insufficient sensing data. This behavior reduces his evaluation and influences his subsequent participation in turn. Thus, M_j will not allocate the resources to the platforms beyond his reach. Nevertheless, M_j may declare a fake asking price representing his lower bound of the acceptable payment for realizing the higher utility.
- **Assumption 3:** Similar to the general assumption in the existing works [21], [22], we assume that the platforms' bidding strategies are only constrained by the budgets, but not other factors such as the strategies of MUs. Under this assumption, both platforms and MUs independently respond best from their respective perspectives to maximize the utilities in the auctions.

B. Design Goals

This subsection gives the design goals. Unlike traditional mechanisms such as Vickrey-Clarke-Groves (VCG), which is efficient and aims to realize the socially optimal solution, the original goal of PAM^{3}S is to maximize the utilities of both MUs and platforms as far as possible. PAM^{3}S regards mutual selection as an auction. It also desires economic robustness (i.e., individual rationality, truthfulness, and budget balance). The design goals are established as follows.

- **Conditional utility maximization:** It is natural for each platform to reduce its payments for a high utility, and for each MU, less payment means a lower utility, which has conflict. Based on this fact, when M_j determines the inclined platforms, he requires the maximum utility $\mathcal{U}_{M_j} \in \mathbb{R}$ under the limited resources as far as possible. Furthermore, on the premise that MUs are willing to join, P_i also expects a high utility $\mathcal{U}_{P_i} \in \mathbb{R}$, which should be as maximum as possible.
- **Individual rationality:** The utilities of each platform and each MU should be no less than zero in PAM^{3}S, implying $\mathcal{U}_{P_i} \geq 0$ and $\mathcal{U}_{M_j} \geq 0$, for $\forall P_i \in \mathcal{P}, M_j \in \mathcal{M}$.

- **Truthfulness:** Each platform and each MU should declare the bid and asking prices truthfully. Specifically, for P_i, it requires $\mathcal{U}_{P_i} \geq \mathcal{U}'_{P_i}$, where $\mathcal{U}_{P_i}$ is the utility brought by P_i's real bid, and $\mathcal{U}'_{P_i} \in \mathbb{R}$ is not. Meanwhile, for M_j, we have $\mathcal{U}'_{M_j} \leq \mathcal{U}_{M_j}$, where $\mathcal{U}_{M_j}$ is the utility under the real asking price and $\mathcal{U}'_{M_j} \in \mathbb{R}$ is the utility under the forged price.
- **Budget balance:** Each platform must have enough payments to pay the final recruited MUs, avoiding financial deficits.

C. Preliminaries

This subsection introduces some related background knowledge, including 0-1 knapsack and Myerson's price theory.

1) 0-1 Knapsack: Suppose there are t different items $\gamma_1, \gamma_2, \cdots, \gamma_t$ and a knapsack with volume $\mathcal{K} \in \mathbb{Z}$. Each item γ_s has a volume μ_s and a price e_s, where $1 \leq s \leq t$, $\mu_s \in \mathbb{Z}$, $e_s \in \mathbb{R}$. Then 0-1 knapsack aims to select several items forming the set $\mathcal{B}$ to be put in the knapsack for maximizing the knapsack's total prices. Under the volume restraint $\mathcal{K}$, the selection of $\mathcal{B}$ is shown by Eq. 1:

$$\max \sum_{s=1}^{t} e_s g_s, \quad \text{s.t.} \quad \sum_{s=1}^{t} \mu_s g_s \leq \mathcal{K},$$
$$g_s = \begin{cases} 1, & \text{if } \gamma_s \in \mathcal{B}, \\ 0, & \text{if } \gamma_s \notin \mathcal{B}. \end{cases} \tag{1}$$

Note that it is necessary to explore the various states before and after putting γ_s in $\mathcal{B}$. How to select $\mathcal{B}$ is an NP-hard problem.

2) Myerson's Price Theory: Myerson's price theory [23] has proved that an auction satisfies truthfulness if it satisfies the following properties:

- **Monotonicity.** It means once a buyer (seller) wins the auction by bidding (asking) a value, then he can still win the auction by bidding (asking) the higher (lower) value.
- **Critical payment.** For a buyer (seller), the critical payment is the lower (upper) bound of bidding (asking). Once a winning buyer (seller) bids (asks) less (higher) than this value, he fails the auction. Each winner is desired to be paid with the critical payment.

The theory is adopted as an effective way to realize the truthfulness of the auction.

IV. Scheme Design: PAM^{3}S

In the multi-platform multi-user scenario, since the lack of care for MUs' resource constraints and platforms' acquired sensing data quality, the existing works cannot maximize utilities of MUs and platforms as far as possible. As two sides of the auctions, there is a contradiction between platforms and MUs, making maximizing their utilities simultaneously impossible. Both platforms and MUs make their own decisions of collaborators according to facing contexts, which differs from the double auction, where buyers and sellers seek a specific price to reach a deal. Note that the key for platforms to earn profits is that MUs are willing to join and perform tasks. Meanwhile, MUs may also refuse to join once they are selected by unintended platforms, causing the recruitment's failure. Thus, we regard mutual selection as a two-stage auction. We first establish the forward and reverse auction models for MU and platform, respectively. Then, we present corresponding implementations on the models.

A. Our Auction Models for MU and Platform

In this subsection, we first establish the forward MU model, which gives the specific utilities of MU and further considers the necessary processes to maximize the utilities. Then, we present the reverse platform model for the platform similarly. Both models are the guidelines for the implementation later.

1) Forward MU model. Take certain MU $M_j \in \mathcal{M}$ into account first. M_j is expected to maximize his utility with the same resources, which requires high payments and acceptable costs to allocate the resources appropriately. We have the following analysis.

• *Sensing cost:* Under the limited resources, PAM^{3}S enables each MU to decide whether to join a platform or not according to the cost. The cost of joining a platform derives from collecting sensing data mainly. Meanwhile, Guo et al. [24] pointed out that MUs' sensing data usually contains their sensitive information, such as locations and ambient sounds. The potential privacy risk also impacts the cost. Restuccia et al. [25] further pointed out that MUs had significant control over the sensing process. The lack of expertise when joining a new platform may bring more costs than joining the platforms that MUs are familiar with. For joining the platform P_i, let the cost per unit resource of M_j be $c_{j,i} \in \mathbb{R}^+$, and $z_i \in \mathbb{Z}$ be the units of consumed resources that P_i requires, which measures how much work of the objective data amount M_j needs to sense. Then, M_j's total cost of joining P_i is $c_{j,i}z_i$. Certain MU has distinct costs for the different platforms with various demands. And different MUs have different sensing costs for a platform, even under the same resource requirement and sensing quality. The cost is the private information that only M_j can learn.

• *Asking price:* Certain MU realizes the higher utility if he receives more payments. Let an asking price be the lower bound of the payment that MU aims to get from a platform. Instead of taking sensing costs as asking prices in the existing works, a MU has precisely calculated asking prices for different inclined platforms in our scenario to guarantee his high utility. The asking price that M_j declares for P_i is $a_{j,i} \in \mathbb{R}^+$. Then, MU can be motivated to join the platform by only receiving enough payment to compensate for his cost. Thus, the asking price should be no less than the cost as Eq. 2,

$$a_{j,i} \geq c_{j,i}z_i. \tag{2}$$

The MUs' asking prices to the several platforms impact the received payments, further influencing the utility.

Through joining platforms, M_j obtains the payments relating to his asking prices to compensate for the costs. Concretely, if M_j joins P_i and allocates the resources, we can mark that $y_{j,i} = 1$. Otherwise, we have $y_{j,i} = 0$. M_j receives payment $p_{i,j} \in \mathbb{R}^+$ from P_i once joining, which is shown later. Then, M_j's utility $\mathcal{U}_{M_j}$ can be defined as the result that his total received payments minus the whole costs, meaning $\sum_{P_i \in \mathcal{P}} (p_{i,j} - c_{j,i}z_i y_{j,i})$. Moreover, the forward auction of M_j is:

$$\begin{aligned} \max \quad & \mathcal{U}_{M_j} = \sum_{P_i \in \mathcal{P}} (p_{i,j} - c_{j,i}z_i y_{j,i}) \\ \text{s.t.} \quad & y_{j,i} \in \{0, 1\}, i = 1, 2, \cdots, n, \\ & \sum_{P_i \in \mathcal{P}} z_i \leq Z_j, \end{aligned} \tag{3}$$

where $Z_j \in \mathbb{Z}$ denotes M_j's total units of resources, and $\sum_{P_i \in \mathcal{P}} z_i \leq Z_j$ implies that the sum of allocated resources should not exceed M_j owns.

To achieve Eq. 3, M_j determines which platforms to join and what asking prices to declare. This procedure mainly consists of three processes, namely preliminary screening, winning platform determination, and asking price determination. Specifically, M_j first conducts the preliminary screening to filter out the inappropriate platforms, such as those with high costs or low bids that are given later. M_j obtains $\mathcal{P}_j$ after receiving the recruitment information published by $\mathcal{P}$, $\mathcal{P}_j \subseteq \mathcal{P}$. Then, by the idea of the forward auction, M_j chooses the platforms to join through winning platform determination, which analyzes his expected realized utilities. M_j can learn which platforms make him maximize the utility with the same resources. Overall, M_j has $\vec{y_j} = (y_{j,1}, y_{j,2}, \cdots, y_{j,n})$ to denote whether to join $\mathcal{P} = \{P_1, P_2, \cdots, P_n\}$. If $y_{j,i} = 1$, we mark P_i as a winner for M_j. Let $\mathcal{W}_{j,\mathcal{P}}$ be the winner set of M_j, then we have

$$\begin{cases} y_{j,i} = 1, & \text{if } P_i \in \mathcal{W}_{j,\mathcal{P}}, \\ y_{j,i} = 0, & \text{if } P_i \notin \mathcal{W}_{j,\mathcal{P}}. \end{cases} \tag{4}$$

We mark the platforms in $\mathcal{W}_{j,\mathcal{P}}$ as $\mathcal{W}_{j,\mathcal{P}} = \{P'_1, P'_2, \cdots, P'_{|\mathcal{W}_{j,\mathcal{P}}|}\}$. After obtaining $\mathcal{W}_{j,\mathcal{P}}$, M_j calculates the corresponding asking prices for the inclined platforms via asking price determination, which is denoted as $\vec{a_j} = (a_{j,1'}, a_{j,2'}, \cdots, a_{j,|\mathcal{W}_{j,\mathcal{P}}|'})$. M_j receives the final payments after joining the platforms and submitting the collected sensing data.

2) Reverse platform model. We then consider the certain platform $P_i \in \mathcal{P}$. P_i expects to recruit several satisfactory MUs with affordable payments to maximize its utility. The following requirements are demanded.

- *Sensing data quality:* High-quality sensing data guarantees excellent sensing services. Ni et al. [4] and Bhattacharjee et al. [26] pointed out that the quality of sensing data depends on the recruited MUs, which is relatively subjective. A MU may deliberately submit incorrect or forged data to break the MCS system while consuming the platform's required resources. The platform can evaluate the MU's reliability in various ways, such as calculating the similarity between the MU's submitted sensing data and the final sensing result. We assume that multiple platforms share evaluations of MUs, which is out of our scope. To ensure the sensing data quality, each platform in PAM^{3}S sets different thresholds under kinds of sensing tasks. The threshold restricts the lower bound of the evaluations that the recruited MUs should meet, guaranteeing the platform recruiting satisfactory MUs. In a real case, the platform that targets traffic monitoring generally has a higher threshold than the platform that targets noisy management. Moreover, the different platforms may have different thresholds even undertaking the same task. The platforms determine the specific thresholds depending on their demands. PAM^{3}S lets MUs' evaluations within the interval $[0, 100]$, where 0 represents no sensing quality guaranteed, 100 means the highest quality, and 50 is neutral. Let $\varepsilon_i \in \mathbb{R}$ be the threshold of P_i set for the current sensing task, $\varepsilon_i \in [0, 100]$.
- *Published bid:* Under the budget limitation, each platform aims to recruit several MUs to achieve the sensing service, in which the budget is the highest profit the platform can make. Obviously, a platform is unwilling to provide the services once it cannot earn any profits. Thus, each platform has the bid as the upper bound of the payment it is willing to pay for a recruited MU. Suppose P_i aims to recruit l_i MUs. As mentioned above, P_i sets ε_i to guarantee the sensing data quality, implying all recruited MUs should realize the quality higher than the platform set. Then, P_i declares the bid b_i for attracting desired MUs, where $b_i \in \mathbb{R}^+$ and $b_i l_i$ should be equal to the budget.

For certain MU M_j, if P_i recruits M_j, we have $x_{i,j} = 1$. Otherwise, we have $x_{i,j} = 0$. P_i pays the payment $p_{i,j}$ to M_j. The utility $\mathcal{U}_{P_i}$ of P_i can be defined as the profits brought by all recruited MUs minus the paid payments, that is $\sum_{M_j \in \mathcal{M}} (b_i x_{i,j} - p_{i,j})$. Furthermore, P_i's reverse auction can be obtained as:

$$\begin{aligned} \max \quad & \mathcal{U}_{P_i} = \sum_{M_j \in \mathcal{M}} (b_i x_{i,j} - p_{i,j}) \\ \text{s.t.} \quad & x_{i,j} \in \{0, 1\}, j = 1, 2, \cdots, m, \\ & \sum_{M_j \in \mathcal{M}} x_{i,j} = l_i, \\ & \forall x_{i,j} = 1, \ \tilde{e}_j \geq \varepsilon_i, \end{aligned} \tag{5}$$

where $\tilde{e}_j \in \mathbb{R}$ is the sensing evaluation of M_j for collecting data, $\tilde{e}_j \in [0, 100]$. In this Eq, $\sum_{M_j \in \mathcal{M}} x_{i,j} = l_i$ requires P_i to recruit l_i MUs, and $\forall x_{i,j} = 1, \ \tilde{e}_j \geq \varepsilon_i$ denotes that each recruited MU should have the evaluation, which is no less what P_i desires.

P_i aims to achieve Eq 5. It first publishes the recruitment information to attract MUs and then performs the processes of winning MU determination and payment determination according to the reverse auction concept. Specifically, P_i's recruitment information is $(b_i, \varepsilon_i, z_i)$, where $z_i \in \mathbb{Z}$ means the required resources of P_i to indicate the objective amount of data a recruited MU needs to sense. Let $\mathcal{M}_i$ be the set of the MUs intending to join P_i, $\mathcal{M}_i \subseteq \mathcal{M}$. After obtaining $\mathcal{M}_i$, P_i decides which MUs to recruit to maximize its utility through winning MU determination. P_i has $\vec{x_i} = (x_{i,1}, x_{i,2}, \cdots, x_{i,m})$ on $\mathcal{M} = \{M_1, M_2, \cdots, M_m\}$, where $x_{i,j}$ is default to be 0 once $M_j \notin \mathcal{M}_i$. If $x_{i,j} = 1$, we mark M_j as the winner of P_i. Otherwise, M_j is not the winner of P_i. Let P_i's winner set be $\mathcal{W}_{i,\mathcal{M}}$, then we have

$$\begin{cases} x_{i,j} = 1, & \text{if } M_j \in \mathcal{W}_{i,\mathcal{M}}, \\ x_{i,j} = 0, & \text{if } M_j \notin \mathcal{W}_{i,\mathcal{M}}, \end{cases} \tag{6}$$

and $\sum_{j=1}^{m} x_{i,j} = |\mathcal{W}_{i,\mathcal{M}}| = l_i$. Later, P_i calculates the final payments for the MUs in $\mathcal{W}_{i,\mathcal{M}}$ through payment determination, which further ensures the maximum utility. Thus, P_i also outputs the corresponding payments $\vec{p_i} = (p_{i,1'}, p_{i,2'}, \cdots, p_{i,|\mathcal{W}_{i,\mathcal{M}}|'})$ for the set $\mathcal{W}_{i,\mathcal{M}}$. Note that $p_{i,j} = 0$ if $x_{i,j} = 0$. Otherwise, $p_{i,j} > 0$.

B. Concrete Implementations of Auction Models

The detailed implementations of PAM^{3}S are shown in Fig. 3. To prevent the case that MU rejects to join after the platform selects him, PAM^{3}S first implements the first stage MU-oriented auction, where MU acts as the auctioneer. Then, the second stage platform-oriented auction is carried by the platform as the auctioneer progressively.

Specifically, in the first stage MU-oriented auction, certain MU chooses the platforms to join. The MU's asking prices for inclined platforms are further calculated. Since the resources of the MU are limited, how to allocate resources appropriately

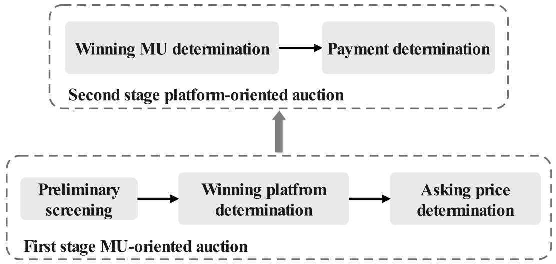


Fig. 3. Concrete implementation of auction models.

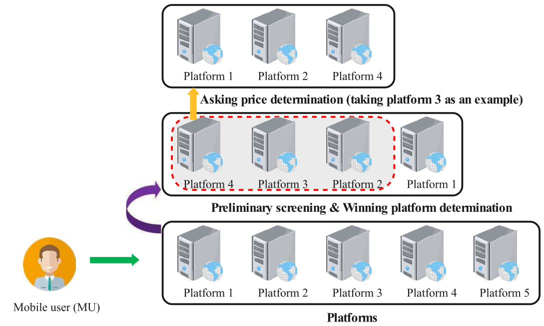


Fig. 4. Main operations of the first stage MU-oriented auction.

to multiple platforms to realize maximum utility is NP-hard, where the 0-1 knapsack problem is adopted. Moreover, while calculating an asking price by adopting Myerson's price theory, the process of determining the critical payment of the target platform through critical neighbors is complex, and specific recruitment results of inclined platforms cannot be learned before the platforms perform auctions. Thus, the relevant asking price is devised especially from the view of resources, which can be further simplified in the implementation. Based on the above, the second stage platform-oriented auction enables the platform to select the final recruited MUs on MUs' willingness to participate by taking sensing quality into account, in which Myerson's price theory is also employed.

1) First Stage MU-Oriented Auction: Under the guidance of the forward MU model, the first stage MU-oriented auction is shown as follows.

Step1: Publish information by platforms. Each $P_i \in \mathcal{P}$ publishes its recruitment information $(b_i, \varepsilon_i, z_i)$ to all MUs $\mathcal{M} = \{M_1, M_2, \cdots, M_m\}$ at the beginning of the auction.

Step2: Filter platforms and auction. Each $M_j \in \mathcal{M}$ selects the platforms to form the initial platform set $\mathcal{P}_j$ by taking the platforms' required sensing quality, resources, and bids into account. Later, M_j performs the auction based on $\mathcal{P}_j$ to obtain the winner set $\mathcal{W}_{j,\mathcal{P}} \subseteq \mathcal{P}_j$ through winning platform determination. Meanwhile, M_j also calculates the asking prices to the platforms in $\mathcal{W}_{j,\mathcal{P}}$ via asking price determination.

Step3: Announce auction results by MUs. The MU like M_j sends the calculated asking prices to all platforms in $\mathcal{W}_{j,\mathcal{P}}$ after completing the auction of the first stage.

Next, we present the main operations involved in ***Step2***, which are mentioned in the forward MU model. As shown in Fig. 4, the MU receives the published recruitment information from five platforms. By screening platforms preliminarily to filter out the unsuitable ones (platform 5), the winning platforms are determined based on the remaining platforms, as shown in the red dotted box. After obtaining the winning platform set, the MU computes the asking price for each platform by removing the target one from the initial platform set in turn.

Preliminary screening. Certain MU M_j selects which platforms are intended to join initially. For P_i, M_j does not join P_i, meaning $y_{j,i} = 0$ under the following cases:

- The sensing evaluation of M_j does not reach the quality threshold of P_i, indicating $\tilde{e}_j < \varepsilon_i$;
- The resources owned by M_j do not meet P_i's requirements, meaning $Z_j < z_i$;
- The joining cost of M_j cannot be made up by P_i's declared compensation, implying $b_i \leq c_{j,i} z_i$.

Otherwise, M_j regards P_i as the inclined platform temporarily and sets $y_{j,i} = 1$. M_j obtains $\mathcal{P}_j = \{P_i \in \mathcal{P} | y_{j,i} = 1\} = \{\tilde{P}_1, \tilde{P}_2, \cdots\}$ at this time.

Winning platform determination. Based on $\mathcal{P}_j$, M_j further determines which of them to join can maximize $\mathcal{U}_{M_j}$. The utility M_j gets after joining P_i is expected to be $(b_i - c_{j,i} z_i)$. M_j has total resources Z_j. Suppose Z_j is the knapsack volume. We can treat the resources required by each platform in $\mathcal{P}_j$ as the item's volume and treat the utility that the platform brings to M_j as the item price. Then, the problem of maximizing $\mathcal{U}_{M_j}$ within Z_j is equivalent to selecting items under a certain knapsack volume to make the prices of the loaded items reach the highest. Therefore, the problem of M_j to determine the winning platform set $\mathcal{W}_{j,\mathcal{P}} \subseteq \mathcal{P}_j$ can be viewed as the 0-1 knapsack problem. Since the 0-1 knapsack problem has been well-known as an NP-hard problem, winning platform determination is also NP-hard.

PAM^{3}S adopts dynamic programming to determine the winning platform set. Whenever MU decides to join a platform, this decision affects the overall outputs. `Algorithm 1` gives the specific process. In the inputs, $\vec{b} = (b_{\tilde{1}}, b_{\tilde{2}}, \cdots, b_{|\tilde{\mathcal{P}}_j|})$ and $\vec{z} = (z_{\tilde{1}}, z_{\tilde{2}}, \cdots, z_{|\tilde{\mathcal{P}}_j|})$ denote the bids and the required resources of the platforms in $\mathcal{P}_j$, respectively. Meanwhile, the sensing costs per unit resource for M_j to join $\mathcal{P}_j$'s involved platforms are $\vec{c_j} = (c_{j,\tilde{1}}, c_{j,\tilde{2}}, \cdots, c_{j,|\tilde{\mathcal{P}}_j|})$. Based on these, the expected utilities that each platform in $\mathcal{P}_j$ brings to M_j form the utility set $\{(b_{\tilde{1}} - c_{j,\tilde{1}} z_{\tilde{1}}), (b_{\tilde{2}} - c_{j,\tilde{2}} z_{\tilde{2}}), \cdots, (b_{|\tilde{\mathcal{P}}_j|} - c_{j,|\tilde{\mathcal{P}}_j|} z_{|\tilde{\mathcal{P}}_j|})\}$. Denote $\mathcal{U}[p,q]$ as the utility that M_j gets after consideration p platforms and q units resources, where $0 \leq p \leq |\mathcal{P}_j|$ and $0 \leq q \leq Z_j$. While executing the algorithm, the winning platform set $\mathcal{W}_{j,\mathcal{P}}$ is initially (line 1). Through lines 3-10, `Algorithm 1` calculates the maximum utility of M_j as expected. In particular, M_j decides whether to join $\tilde{P}_p \in \mathcal{P}_j$ if his current resources meet $\tilde{P}_p$'s demands (line 9) and rejects joining $\tilde{P}_p$ directly if his resources are less than $z_{\tilde{p}}$ (lines 5-7). After obtaining the maximum utility, lines 12-16 trace back to which platforms M_j intends to join. If M_j's utility remains unchanged regardless of taking a certain platform into account or not, M_j does not join this platform. Otherwise, this platform is added in $\mathcal{W}_{j,\mathcal{P}}$. `Algorithm 1` returns $\mathcal{W}_{j,\mathcal{P}} = \{P'_1, P'_2, \cdots, P'_{|\mathcal{W}_{j,\mathcal{P}}|}\}$, and $\{P'_1, P'_2, \cdots, P'_{|\mathcal{W}_{j,\mathcal{P}}|}\} \subseteq \{\tilde{P}_1, \tilde{P}_2, \cdots\}$.

Asking price determination. M_j calculates the asking prices preparing to declare for each platform in $\mathcal{W}_{j,\mathcal{P}}$. At this time, PAM^{3}S utilizes the critical payment proposed by Myerson's price theory. `Algorithm 2` gives the specific process.

Take the calculation of $a_{j,k'}$ for $P'_k \subseteq \mathcal{W}_{j,\mathcal{P}}$ as an example, $1 \leq k \leq |\mathcal{W}_{j,\mathcal{P}}|$. M_j first removes P'_k from $\mathcal{P}_j$, and

Algorithm 1 Winning platform selection

Input: $\mathcal{P}_j$, sequences $\vec{b}=(b_{\tilde{1}}, b_{\tilde{2}}, \cdots, b_{|\tilde{\mathcal{P}}_j|})$,
$\vec{z}=(z_{\tilde{1}}, z_{\tilde{2}}, \cdots, z_{|\tilde{\mathcal{P}}_j|})$,
$\vec{c_j}=(c_{j,\tilde{1}}, c_{j,\tilde{2}}, \cdots, c_{j,|\tilde{\mathcal{P}}_j|})$, and Z_j

Output: $\mathcal{W}_{j,\mathcal{P}}$

Set $\mathcal{W}_{j,\mathcal{P}} \leftarrow \varnothing$, $\mathcal{U}[0,q] \leftarrow 0$, $\mathcal{U}[p,0] \leftarrow 0$, $p, q \in \mathbb{Z}$, $0 \leq p \leq |\mathcal{P}_j|$, $0 \leq q \leq Z_j$;
// *Calculating M_j's maximum utility*
for $p \leftarrow 1$ *to* $|\mathcal{P}_j|$ **do**
  for $q \leftarrow 1$ *to* Z_j **do**
    if $q < z_{\tilde{p}}$ **then**
      // *$z_{\tilde{p}}$ is the resources required by the p-th platform $\tilde{P}_p$ in $\mathcal{P}_j$*
      $\mathcal{U}[p,q] \leftarrow \mathcal{U}[p-1,q]$;
    else
      $\mathcal{U}[p,q] \leftarrow max(\mathcal{U}[p-1,q], \mathcal{U}[p-1, q-z_{\tilde{p}}] + (b_{\tilde{p}} - c_{j,\tilde{p}} z_{\tilde{p}}))$;
      // *M_j is going to join $\tilde{P}_p$ if the utility increases*
// *Searching the platforms achieving the maximum utility*
for $p \leftarrow |\mathcal{P}_j|$ *to* 1 **do**
  if $q - z_{\tilde{p}} \geq 0$ & $\mathcal{U}[p,q] == \mathcal{U}[p-1, q-z_{\tilde{p}}] + (b_{\tilde{p}} - c_{j,\tilde{p}} z_{\tilde{p}})$ **then**
    // *The utility that $\tilde{P}_p$ brings to M_j is involved in the maximum utility*
    $\mathcal{W}_{j,\mathcal{P}} \leftarrow \mathcal{W}_{j,\mathcal{P}} \cup \tilde{P}_p$;
    $q \leftarrow q - z_{\tilde{p}}$;
return $\mathcal{W}_{j,\mathcal{P}}$;

re-performs `Algorithm 1` to get the new winner set $\mathcal{W}'_{j,\mathcal{P}}$. Then, the platforms that replace P'_k appearing in $\mathcal{W}'_{j,\mathcal{P}}$ can be regarded as the critical neighbors of P'_k intuitively. However, since the different platforms have different requirements, under the resource constraints of M_j, $\mathcal{W}'_{j,\mathcal{P}}$ may be totally different with $\mathcal{W}_{j,\mathcal{P}}$. The number of platforms replacing P'_k may be one or more, and the other inclined platforms of M_j may differ. We therewith regard the platforms newly appearing in $\mathcal{W}'_{j,\mathcal{P}}$ as P'_k's critical neighbors. The critical neighbors not only bring utility change related to P'_k but also bring change related to other platforms. Instead of focusing on which critical neighbor replace which platforms in $\mathcal{W}_{j,\mathcal{P}}$ and computing the relevant changed utilities, we calculate the asking price from the view of the resources. The critical neighbors cause changes in resource allocation. Let $d_{j,k'} \in \mathbb{R}$ be the absolute value of the result that utilities realized under the resources whose allocation is changed minus utilities realized under the same resources in $\mathcal{W}_{j,\mathcal{P}}$ before. M_j obtains $d_{j,k'}$, and calculates the asking price as $a_{j,k'} = b_{k'} - d_{j,k'}$, where $b_{k'}$ is P'_k's bid. The specific recruitment results of inclined platforms can only be learned after the platforms perform auctions. $a_{j,k'}$ gives how much utility P'_k should bring to M_j at least for its required resources while the resources allocated to other platforms in $\mathcal{W}_{j,\mathcal{P}}$ bring expected utilities, which is the critical payment of P'_k. With respect to resource utilization, $d_{j,k'}$ is coincidentally equal to utilities realized by $\mathcal{W}_{j,\mathcal{P}}$ minus utilities realized by $\mathcal{W}'_{j,\mathcal{P}}$, which can simplify the above process. Thus, `Algorithm 2` utilizes this property to calculate $d_{j,k'}$. Moreover, if there is no critical neighbor for P'_k, PAM^{3}S has $a_{j,k'} = c_{j,k'} z_{k'}$, which equals M_j's costs for joining P'_k.

Algorithm 2 Asking price decision

Input: $\mathcal{P}_j$, $\mathcal{W}_{j,\mathcal{P}}$

Output: $\vec{a_j} = (a_{j,1'}, a_{j,2'}, \cdots, a_{j,|\mathcal{W}_{j,\mathcal{P}}|'})$

for $k \leftarrow 1$ *to* $|\mathcal{W}_{j,\mathcal{P}}|$ **do**
  Executing **Algorithm 1** for $\mathcal{P}_j \setminus P'_k$ and get $\mathcal{W}'_{j,\mathcal{P}}$;
  if $\mathcal{W}'_{j,\mathcal{P}} \subseteq \mathcal{W}_{j,\mathcal{P}}$ **then**
    // *No critical neighbor exists for P'_k*
    $a_{j,k'} = c_{j,k'} z_{k'}$;
  else
    // *Critical neighbor exists for P'_k*
    Set $\mathcal{U}_k \leftarrow 0$, $\mathcal{U}_{-k} \leftarrow 0$;
    for $v \leftarrow 1$ *to* $|\mathcal{W}_{j,\mathcal{P}}|$ **do**
      $\mathcal{U}_k = \mathcal{U}_k + (b_{v'} - c_{j,v'} z_{v'})$;
    for $v \leftarrow 1$ *to* $|\mathcal{W}'_{j,\mathcal{P}}|$ **do**
      $\mathcal{U}_{-k} = \mathcal{U}_{-k} + (b_{v'} - c_{j,v'} z_{v'})$;
    $d_{j,k'} = \mathcal{U}_k - \mathcal{U}_{-k}$; // *Calculating the utility difference based on critical neighbors*
    $a_{j,k'} = b_{k'} - d_{j,k'}$;
  Adding $a_{j,k'}$ to $\vec{a_j}$;
return $\vec{a_j} = (a_{j,1'}, a_{j,2'}, \cdots, a_{j,|\mathcal{W}_{j,\mathcal{P}}|'})$;

Up to now, M_j obtains $\mathcal{W}_{j,\mathcal{P}}$ and calculates the asking prices for each involved platform. The prices are sent to the corresponding inclined platforms for the second stage auction.

2) Second Stage Platform-Oriented Auction: According to the reverse platform model, the progressive second stage platform-oriented auction is based on the first stage auction as follows.

Step4: Check MUs and auction. P_i checks if the MUs in $\mathcal{M}_i$ have sensing evaluations higher than the sensing quality threshold after receiving the relevant asking prices. For example, P_i desires $\tilde{e}_j \geq \varepsilon_i$ for M_j. Then, as shown in the reverse platform model, P_i performs winning MU determination to obtain the final recruited MU set $\mathcal{W}_{i,\mathcal{M}}$. Furthermore, it performs payment determination to compute the paid payment for each recruited MU.

Step5: Announce auction results by platforms. P_i announces the auction results to the corresponding MUs.

Next, PAM^{3}S presents winning MU determination and payment determination in ***Step4***, which are similar to Fig. 4.

Winning MU determination. Let $\mathcal{M}_i$ be $\{\tilde{M}_1, \tilde{M}_2, \cdots\}$, and the corresponding asking prices be $(a_{\tilde{1},i}, a_{\tilde{2},i}, \cdots)$. P_i sorts the MUs in $\mathcal{M}_i$ with sensing evaluations higher than the threshold by non-decreasing order based on the received asking prices. Suppose all MUs in $\mathcal{M}_i$ have the evaluations higher than ε_i and they have been sorted well, implying $a_{\tilde{1},i} \leq a_{\tilde{2},i} \leq \cdots$. P_i always expects to minimize the total paid payments. Thus, the first l_i MUs form the winning MU set $\mathcal{W}_{i,\mathcal{M}}$ naturally, which is marked as $\mathcal{W}_{i,\mathcal{M}} = \{M'_1, M'_2, \cdots, M'_{|\mathcal{W}_{i,\mathcal{M}}|}\}$. The detailed operations are shown in lines 2-5 of `Algorithm 3`.

Algorithm 3 Winning MU selection and Payment decision

Input: $\mathcal{M}_i = \{\tilde{M}_1, \tilde{M}_2, \cdots\}$, $(a_{\tilde{1},i}, a_{\tilde{2},i}, \cdots)$
Output: $\mathcal{W}_{i,\mathcal{M}}$, $\vec{p_i} = (p_{i,1'}, p_{i,2'}, \cdots, p_{i,|\mathcal{W}_{i,\mathcal{M}}|'})$
1 // *Obtaining the winning MU set* $\mathcal{W}_{i,\mathcal{M}}$
2 Set $\mathcal{W}_{i,\mathcal{M}} \leftarrow \varnothing$;
3 Sorting MUs in $\mathcal{M}_i$ with non-decreasing order according to asking prices; // *Assuming* $a_{\tilde{1},i} \leq a_{\tilde{2},i} \leq \cdots$
4 **for** $v \leftarrow 1$ *to* l_i **do**
5 $\quad$ $\mathcal{W}_{i,\mathcal{M}} \leftarrow \mathcal{W}_{i,\mathcal{M}} \cup \tilde{M}_v$;
6 // *Calculating payments for MUs in* $\mathcal{W}_{i,\mathcal{M}}$
7 **for** $o \leftarrow 1$ *to* $|\mathcal{W}_{i,\mathcal{M}}|$ **do**
8 $\quad$ Executing lines 2-5 for $\mathcal{M}_i \setminus M'_o$ and get $\mathcal{W}'_{i,\mathcal{M}}$;
9 $\quad$ $p_{i,o'} = a_{l'_i,i}$; // $a_{l'_i,i}$ *is the* l_i*-th MU's asking price in* $\mathcal{W}'_{i,\mathcal{M}}$
10 $\quad$ Adding $p_{i,o'}$ to $\vec{p_i}$;
11 return $\mathcal{W}_{i,\mathcal{M}}$, $\vec{p_i} = (p_{i,1'}, p_{i,2'}, \cdots, p_{i,|\mathcal{W}_{i,\mathcal{M}}|'})$;

Payment determination. P_i calculates the payment for each MU in $\mathcal{W}_{i,\mathcal{M}}$. It also adopts the critical payment in Myerson's price theory. Lines 7-10 of `Algorithm 3` present the process. When P_i calculates the payment $p_{i,o'}$ for $M'_o \in \mathcal{W}_{i,\mathcal{M}}$, it first removes M'_o from $\mathcal{M}_i$, and re-performs lines 2-5 of `Algorithm 3`, $1 \leq o \leq |\mathcal{W}_{i,\mathcal{M}}|$. The MU who replaces M'_o in the new winning MU set $\mathcal{W}'_{i,\mathcal{M}}$ is M'_o's critical neighbor. The corresponding asking price is the critical payment. Then P_i pays M'_o with the critical payment $p_{i,o'}$. It has been pointed out that the global smartphone market is growing rapidly [27], and large amounts of smartphone users can naturally become potential MUs [14]. The existing works have supposed there are sufficient MUs in MCS [28], [29]. We also suppose $|\mathcal{M}_i| \geq (l_i + 1)$ to guarantee that PAM^{3}S is truthful, indicating that P_i can always recruit the desired number of MUs and collect satisfactory sensing data. It implies that each recruited MU has a critical neighbor that will replace him to win in the platform's performed auction once the MU does not participate while determining the critical payment.

So far, PAM^{3}S completes mutual selection in the multi-platform multi-user scenario.

C. Discussion

The proposed progressive two-stage auction enables each MU and each platform to make the best determination according to their present objective conditions. During this process, unlike the traditional auction where the participant's utility is straightforward, the MU's utility after the first stage auction is uncertain until platforms complete auctions. Thus, based on the platforms' bids, the MU seeks his maximum utility as expected. The untruthful bids of platforms damage the utilities of MUs. Meanwhile, the untruthful asking prices of MUs are a disadvantage to platforms' utilities. We make platforms, and MUs keep truthful. They will not change bids and asking prices once determined. The bid of a platform will not be affected by MUs strategies. Nevertheless, the following limitations occur.

Limitations. Except for the bids, PAM^{3}S does not address the problem that platforms misreport the other items in recruitment information as described in **Assumption 1**, which is on the basis that PAM^{3}S focuses on utility. The misreporting of the other items can mislead MUs into participating and further break the system. The existing works [30] indicated that a subset of misreport patterns is usually considered for practical auction designs. We will think about this limitation in the future. Moreover, PAM^{3}S supposes there are always sufficient MUs for the platforms to select from. Once the MUs are insufficient, an available way for the platform to make the recruitment successful is reducing the number of recruited MUs to raise the bid more competitively. The insufficient MUs make it difficult for the platform to obtain satisfactory sensing data and provide corresponding services, while MUs may ask maliciously due to lack of competition, damaging the platform. Other more effective methods to solve the case of insufficient MUs will be considered in the future, which are out of our scope.

Owning the characteristic design intention and specific operations, PAM^{3}S differs from traditional mechanisms. Specifically, unlike VCG, which concerns socially optimal and match MUs to the platform with the highest bid, PAM^{3}S provides specific winner selection and asking price/payment decision to maximize both MUs' and platforms' utilities as far as possible. PAM^{3}S also realizes budget balance, as proved later, which is not generally established in VCG. Moreover, PAM^{3}S's mutual selection is different from the classical double auction. It does not require MUs to submit their prices while platforms submit their bids simultaneously. PAM^{3}S makes a MU determine which platforms to join and calculates asking prices for the inclined platforms. Unlike the double auction that aims to choose a price to clear the market, PAM^{3}S allows MUs and platforms to make deals based on specific calculated prices. Thus, PAM^{3}S, rather than a double auction, is suitable for the multi-platform multi-user scenario.

V. Theoretical Analysis

This section mainly analyzes PAM^{3}S from the property, performance bound, computational complexity, and communication overhead.

A. Property

PAM^{3}S's property is indicated from the perspective of design goals.

Theorem 1: *PAM^{3}S enables conditional utility maximization.*

Proof: PAM^{3}S performs the first-stage MU auction and the second-stage platform auction. We prove that this two-stage auction can furthest maximize MUs' and platforms' utilities.

We first show that PAM^{3}S can make a platform maximize its utility.

After receiving $\mathcal{M}_i$, P_i determines the winning MU set $\mathcal{W}_{i,\mathcal{M}}$. Utilizing proof by contradiction, it is supposed that there exists the MU set $\mathcal{W}'_{i,\mathcal{M}}$, which can maximize P_i's utility rather than $\mathcal{W}_{i,\mathcal{M}}$. We can learn that there has a MU M''_o, $M''_o \in \mathcal{W}'_{i,\mathcal{M}}$, and $M''_o \notin \mathcal{W}_{i,\mathcal{M}}$. At this time, the utility P_i gets from M''_o is:

$$b_i - p_{i,o''}, \tag{7}$$

where $p_{i,o''}$ is the payment P_i pays for M''_o. $p_{i,o''}$ is M''_o's critical payment, which equals the asking price of M''_o's critical neighbor. Since P_i prioritizes MUs with low asking prices after checking, we have $a_{o'',i} \leq p_{i,o''}$, $a_{o'',i}$ is M''_o's asking price for P_i. However, since $M''_o \notin \mathcal{W}_{i,\mathcal{M}}$, we can learn that the critical payment of any MU in $\mathcal{W}_{i,\mathcal{M}}$ is no more than $a_{o'',i}$, meaning that P_i gets less utility from M''_o than any MU in $\mathcal{W}_{i,\mathcal{M}}$. Thus, PAM^{3}S can maximize the platform's utility.

We then show that PAM^{3}S can also maximize a MU's utility. Since the MU's utility after the first stage auction is uncertain, we separately prove that PAM^{3}S makes a MU determine the winning platform set and calculate relevant asking prices appropriately to maximize the utility as expected.

1) After receiving recruitment information and performing preliminary screening, `Algorithm 1` enables MU M_j to determine the winning platform set $\mathcal{W}_{j,\mathcal{P}}$ that realizes the maximum expected utility.

For $\tilde{P}_p$, which is the *p-th* considered platform in $\mathcal{P}_j$, when M_j determines whether select $\tilde{P}_p$ or not to get more utility under q units resources, we have $\mathcal{U}[p,q] \leftarrow max(\mathcal{U}[p-1,q], \mathcal{U}[p-1,q-z_{\tilde{p}}]+(b_{\tilde{p}}-c_{j,\tilde{p}}z_{\tilde{p}}))$ by dynamic programming. It means that $\mathcal{U}[p,q]$ depends on $\mathcal{U}[p-1,q]$ or $\mathcal{U}[p-1,q-z_{\tilde{p}}]+(b_{\tilde{p}}-c_{j,\tilde{p}}z_{\tilde{p}})$ merely. We have regarded the winning platform selection as the 0-1 knapsack problem with optimal substructures. Both $\mathcal{U}[p-1,q]$ and $\mathcal{U}[p-1,q-z_{\tilde{p}}]+(b_{\tilde{p}}-c_{j,\tilde{p}}z_{\tilde{p}})$ have been obtained with the optimal solution. Thus, $\mathcal{U}[p,q]$ is also optimal. After considering all platforms in $\mathcal{P}_j$ under total resources iteratively, the corresponding platforms that M_j intending to join can realize the maximum expected utility.

2) The asking prices calculated in `Algorithm 2` enable the MU to seek utilities from the platforms in $\mathcal{W}_{j,\mathcal{P}}$ as expected.

For $P'_k \in \mathcal{W}_{j,\mathcal{P}}$, M_j calculates the asking price $a_{j,k'}$. We have $a_{j,k'} = c_{j,k'}z_{k'}$ or $a_{j,k'} = b_{k'} - d_{j,k'}$. Since $d_{j,k'}$ is calculated by the idea of critical payment from the view of resources, we can see that $d_{j,k'}$ is equal to the utility that P'_k brings to M_j at most and no less than 0. Then, $c_{j,k'}z_{k'} \leq a_{j,k'} \leq b_{k'}$, meaning that $a_{j,k'}$ is available for M_j to seek expected utility from P'_k though P'_k will perform the auction later. Moreover, the asking prices can constrain platforms to bid truthfully, as given in proving the truthfulness of PAM^{3}S. Thus, the asking prices can further guarantee $\mathcal{W}_{j,\mathcal{P}}$ is exactly the winning platform set for M_j. Overall, PAM^{3}S enables a MU to maximize his utility though the recruitment result is uncertain. ***Theorem 1*** is proved. □

Theorem 2: *PAM^{3}S is individually rational for platforms and MUs.*

Proof: For certain platform P_i, if it does not recruit MU M_j, then $x_{i,j} = 0$, and $p_{i,j} = 0$. We have

$$b_i x_{i,j} - p_{i,j} = 0,\ x_{i,j} = 0. \tag{8}$$

Otherwise, $x_{i,j} = 1$. The asking price of M_j is $a_{j,i} = b_i - d_{j,i}$ or $a_{j,i} = c_{j,i}z_i$, satisfying $a_{j,i} \leq b_i$. According to lines 7-10 of `Algorithm 3`, the payment $p_{i,j}$ of M_j satisfies

$$p_{i,j} \leq b_i, \tag{9}$$

which means

$$b_i x_{i,j} - p_{i,j} \geq 0,\ x_{i,j} = 1. \tag{10}$$

Thus, we can conclude that

$$\mathcal{U}_{P_i} = \sum_{M_j \in \mathcal{M}} (b_i x_{i,j} - p_{i,j}) \geq 0, \tag{11}$$

indicating that P_i meets the individual rationality.

For certain MU M_j, if he does not join platform P_i, then $y_{j,i} = 0$, $p_{i,j} = 0$, which means that

$$p_{i,j} - c_{j,i}z_i y_{j,i} = 0,\ y_{j,i} = 0. \tag{12}$$

Otherwise, $y_{j,i} = 1$. M_j receives the payment $p_{i,j}$ paid by P_i, where $p_{i,j} \geq a_{j,i}$. Because M_j's asking price is $a_{j,i} = c_{j,i}z_i$ or $a_{j,i} = b_i - d_{j,i} \geq c_{j,i}z_i$, we have

$$p_{i,j} - c_{j,i}z_i y_{j,i} \geq 0,\ y_{j,i} = 1. \tag{13}$$

As a result,

$$\mathcal{U}_{M_j} = \sum_{P_i \in \mathcal{P}} (p_{i,j} - c_{j,i}z_i y_{j,i}) \geq 0, \tag{14}$$

the individual rationality of MU is satisfied.

Therefore, ***Theorem 2*** is proved. □

Lemma 1: *If a platform wins the auction with the bid b, it also wins the auction when bidding $b' > b$.*

Proof: Let certain MU realize the maximum utility $\mathcal{U}_M^{(max)} \in \mathbb{R}$ as expected after performing winning platform determination. If a winning platform rises its bid from b to b', the new maximum utility $\tilde{\mathcal{U}}_M^{(max)} \in \mathbb{R}$ for the MU intuitively to be

$$\tilde{\mathcal{U}}_M^{(max)} = \mathcal{U}_M^{(max)} + b' - b. \tag{15}$$

However, suppose the platform loses the auction with b' through the proof by contradiction. Then, $\tilde{\mathcal{U}}_M^{(max)}$ does not involve the utility deriving from this platform. We have

$$\tilde{\mathcal{U}}_M^{(max)} > \mathcal{U}_M^{(max)} + b' - b \Rightarrow\ \mathcal{U}_M^{(max)} < \tilde{\mathcal{U}}_M^{(max)} - b' + b. \tag{16}$$

Eq. 16 means that $\mathcal{U}_M^{(max)}$ is not the MU's maximum utility when the platform bids b, which brings the conflict with the proposition. Thus, ***Lemma 1*** is proved. □

Lemma 2: *If a MU wins the auction with the asking price a, he also wins the auction when asking $a' < a$.*

Proof: In the auction, the platform selects several MUs with the lowest asking prices to recruit. The MU with $a' < a$ must win the auction if he wins the auction with a. Therefore, ***Lemma 2*** is proved. □

Theorem 3: *PAM^{3}S satisfies truthfulness as given in subsection III-B.*

Proof: We first prove that PAM^{3}S ensures the truthfulness of platforms, which always bid as the budget constraints. Then, we prove the truthfulness of MUs, which also declare the calculated asking prices. All proofs are based on ***Lemma 1*** and ***Lemma 2***. We take the auctions between P_i and M_j as an example.

Suppose P_i has the real bid b_i, and the fake bid is b'_i. We have the following cases.

Case 1: If $b'_i > b_i$ or $b'_i < b_i$, P_i always loses the auction regardless of b'_i and b_i. In this case, the utility that P_i realizes from M_j is 0.

Case 2: If $b'_i > b_i$, P_i wins the auction with both b'_i and b_i. At this point, P_i's bid increases by $(b'_i - b_i)$. However, the asking price $a'_{j,i}$ of M_j under b'_i is unchanged if no critical neighbor of P_i exists, which equals to $c_{j,i}z_i$, that is $a'_{j,i} = a_{j,i}$. If there exists critical neighbor of P_i, the calculated $d'_{j,i}$ also increases by $(b'_i - b_i)$, then we have

$$\begin{aligned} a'_{j,i} &= b'_i - d'_{j,i} \\ &= b_i + (b'_i - b_i) - (d_{j,i} + (b'_i - b_i)) \\ &= b_i - d_{j,i} = a_{j,i}. \end{aligned} \tag{17}$$

Therefore, P_i cannot realize a higher utility by bidding b'_i.

Case 3: If $b'_i < b_i$, P_i wins the auction with both b'_i and b_i. The bid of P_i decreases by $(b_i - b'_i)$, we have $a'_{j,i} = c_{j,i}z_i = a_{j,i}$ if no critical neighbor of P_i exists. Otherwise, if P_i has critical neighbors, due to the fact that the calculated $d'_{j,i}$ also decreases by $(b_i - b'_i)$, we have

$$\begin{aligned} a'_{j,i} &= b'_i - d'_{j,i} \\ &= b_i - (b_i - b'_i) - (d_{j,i} - (b_i - b'_i)) \\ &= b_i - d_{j,i} = a_{j,i}. \end{aligned} \tag{18}$$

P_i also cannot realize a higher utility by bidding b'_i.

Case 4: If $b'_i > b_i$, P_i loses the auction with b_i, and wins with b'_i. When P_i wins the auction, if there is no critical neighbor, we have

$$b'_i > c_{j,i}z_i \geq b_i. \tag{19}$$

At this point, M_j asks $a_{j,i} = c_{j,i}z_i$. The payment that P_i pays to M_j satisfies $p_{i,j} \geq a_{j,i}$ if P_i recruits M_j. Thus, the utility that P_i gets from M_j is nonpositive. If there exists the critical neighbor, suppose the maximum utility that M_j realizes as expected is $\mathcal{U}_{M_j}^{(max)} \in \mathbb{R}$ when P_i bids b_i, and $\tilde{\mathcal{U}}_{M_j}^{(max)} \in \mathbb{R}$ when P_i bids b'_i. To make P_i win the auction with b'_i, it requires

$$(b'_i - b_i) \geq (\tilde{\mathcal{U}}_{M_j}^{(max)} - \mathcal{U}_{M_j}^{(max)}). \tag{20}$$

Meanwhile, the asking price of M_j is

$$a_{j,i} = b_i + (b'_i - b_i) - (\tilde{\mathcal{U}}_{M_j}^{(max)} - \mathcal{U}_{M_j}^{(max)}) \geq b_i. \tag{21}$$

P_i cannot get the positive utility from M_j because of $p_{i,j} \geq a_{j,i}$. Thus, it is disabled for P_i to get a higher utility than 0 by bidding b'_i.

Case 5: If $b'_i < b_i$, P_i loses the auction with b'_i, and wins with b_i. This case means that P_i can get the utility from M_j no less than 0 with b_i. Nevertheless, P_i's utility is 0 when bidding b'_i. Therefore, P_i still cannot realize a higher utility by bidding b'_i.

The discussions above show that if M_j asks $a_{j,i}$ as ruled, P_i cannot realize a higher utility by bidding falsely. However, M_j may ask for more or less than $a_{j,i}$ out of considering improving utility, as shown below.

Suppose M_j asks $a'_{j,i}$, where $c_{j,i}z_i \leq a'_{j,i} \leq a_{j,i}$. Because P_i learns that M_j may decrease the asking price to $c_{j,i}z_i$ at most, it could bid falsely in the auction to win and decide whether to recruit M_j later. This situation leads that *Case 4* mentioned above cannot be avoided. However, the fake bid of P_i is unfavorable for M_j to determine which platforms to join to maximize M_j's utility. The first stage MU-oriented auction is meaningless. Thus, M_j will not asking $a'_{j,i} \leq a_{j,i}$.

We also focus on the case in which M_j asks $a'_{j,i} > a_{j,i}$. The increase of M_j's asking price has no impact on the bid of P_i. Under this condition, we have the following cases:

- No matter M_j asks $a'_{j,i}$ or $a_{j,i}$, he always wins the auction. The payment for M_j remains the critical payment, which is unchanged. Thus, M_j cannot realize a higher utility by asking $a'_{j,i}$.
- M_j wins the auction when asking $a_{j,i}$, and loses when asking $a'_{j,i}$. With $a_{j,i}$, we have

$$p_{i,j} - c_{j,i}z_i y_{j,i} \geq 0, \tag{22}$$

  meaning $a_{j,i}$ brings the nonnegative utility for M_j. Since $a'_{j,i}$ makes M_j's utility be 0, M_j also cannot get a higher utility by asking $a'_{j,i}$.

To sum up, M_j cannot realize a higher utility by increasing or decreasing $a_{j,i}$. The truthfulness of MUs is established. On this premise, PAM^{3}S also ensures the truthfulness of platforms. Thus, ***Theorem 3*** is proved. □

Theorem 4: *PAM^{3}S ensures budget balance shown in subsection III-B.*

Proof: Considering P_i, it has the bid b_i. Meanwhile, $a_{j,i} \leq b_i$ for M_j in the auction. If M_j wins the auction, P_i's final paid payment $p_{i,j}$ is the critical payment of M_j, which is the asking price of M_j's critical neighbor and still does not exceed b_i. Thus, we have

$$b_i x_{i,j} - p_{i,j} \geq 0, \ x_{i,j} = 1. \tag{23}$$

Otherwise, if M_j loses the auction, we have

$$b_i x_{i,j} - p_{i,j} = 0, \ x_{i,j} = 0. \tag{24}$$

Eq. 25 always holds to achieve budget balance,

$$\sum_{M_j \in \mathcal{M}} (b_i x_{i,j} - p_{i,j}) \geq 0. \tag{25}$$

Therefore, ***Theorem 4*** is proved. □

B. Performance Bound

We further analyze the performance bound of PAM^{3}S from the view of the platform and the MU, respectively. Before a detailed description, we define the following two cases in which the utilities obtained by MUs or platforms can be viewed as values that bound the best utilities under the specific contexts since there are natural conflicts between MUs and platforms' utilities.

Platform_optimal: A platform determines the winning MU set and recruits the corresponding MUs in the set without making MUs perform a first-stage auction, meaning the platform can choose from a broader range of MUs.

MU_optimal: Each MU determines the winning platform set and is recruited by all inclined platforms.

In *Platform_optimal*, a MU will regard sensing costs as asking prices for the corresponding platforms since the MU does not perform the first stage auction to maximize the utility. As for *MU_optimal*, a platform can suffer because the number of recruited MUs does not align with its expectations, and the paid payments exceed its budget. The platform also cannot calculate the appropriate payments for MUs since each MU does not have critical neighbors. Therefore, we rule that each platform recruits all MUs selecting it and pays the MUs with its bid to guarantee the best utility of MUs, which is not feasible in reality.

Take MU M_j and platform P_i as an example during analysis. Let $Pr_{k',j}$ be the probability that P'_k recruits M_j, $P'_k \in \mathcal{W}_{j,\mathcal{P}}$, $Pr_{k',j} \in \mathbb{R}$, and $0 \leq Pr_{k',j} \leq 1$. $a_{l',i}$ is the asking price of the critical neighbor determined by P_i under the second stage platform-oriented auction. And we assume $a_{opt,i}$ is the asking price of the critical neighbor P_i determines under *Platform_optimal*. The relationship between $b_{k'}$ and $p_{k',j}$ is described by the function f_1, and the relationship between $a_{l',i}$ and $a_{opt,i}$ is described by the function f_2. We have $b_{k'} = f_1(p_{k',j})$ and $a_{opt,i} = f_2(a_{l',i})$.

Theorem 5: *For a MU M_j and a platform P_i, we have $\mathcal{U}_{M_j} \geq \min(Pr_{k',j}(1 - \frac{p_{k',j}}{c_{j,k'}z_{k'}}))\mathcal{U}_{M_j}^{(max)}$ and $\mathcal{U}_{P_i} \geq (1 - \frac{a_{l',i}}{b_i})\mathcal{U}_{P_i}^{(max)}$, respectively, where $\mathcal{U}_{M_j}$, $\mathcal{U}_{P_i}$ are M_j's and P_i's utilities in PAM^{3}S, and $\mathcal{U}_{M_j}^{(max)}$, $\mathcal{U}_{P_i}^{(max)}$ represent* *their optimal utilities realized under MU_optimal and Platform_optimal.*

Proof: We first discuss the performance bound from the view of the MU. Specifically, under *MU_optimal*, since M_j is recruited by each platform he is inclined to and is paid with the platform's bid, we can learn that $\mathcal{U}_{M_j}^{(max)} = \sum_{P'_k \in \mathcal{W}_{j,\mathcal{P}}} (b_{k'} - c_{j,k'} z_{k'})$, where $c_{j,k'} z_{k'}$ is the total costs for M_j to join P'_k.

As for $\mathcal{U}_{M_j}$, at this time, on the one hand, M_j may not be recruited by the inclined platform P'_k, where the probability of recruitment is $Pr_{k',j}$. On the other hand, M_j's received payment $p_{k',j}$ is no more than $b_{k'}$. Therefore, we have $\mathcal{U}_{M_j} = \sum_{P'_k \in \mathcal{W}_{j,\mathcal{P}}} Pr_{k',j}(p_{k',j} - c_{j,k'} z_{k'})$.

In extreme cases, if $\mathcal{U}_{M_j}^{(max)} = 0$, there must be $\mathcal{U}_{M_j} = 0$, meaning $\mathcal{U}_{M_j}^{(max)} = \mathcal{U}_{M_j}$. Otherwise, we can learn that

$$\begin{aligned}
\frac{\mathcal{U}_{M_j}}{\mathcal{U}_{M_j}^{(max)}} &= \frac{\sum_{P'_k \in \mathcal{W}_{j,\mathcal{P}}} Pr_{k',j}(p_{k',j} - c_{j,k'} z_{k'})}{\sum_{P'_k \in \mathcal{W}_{j,\mathcal{P}}} (b_{k'} - c_{j,k'} z_{k'})} \\
&\geq \min(\frac{Pr_{k',j}(p_{k',j} - c_{j,k'} z_{k'})}{b_{k'} - c_{j,k'} z_{k'}}) \\
&= \min(\frac{Pr_{k',j}(p_{k',j} - c_{j,k'} z_{k'})}{f_1(p_{k',j}) - c_{j,k'} z_{k'}}) \\
&= \min(Pr_{k',j}(1 - \frac{p_{k',j} - f_1(p_{k',j})}{c_{j,k'} z_{k'} - f_1(p_{k',j})})). \qquad (26)
\end{aligned}$$

Since $0 < c_{j,k'} z_{k'} \leq p_{k',j}$, $c_{j,k'} z_{k'} < f_1(p_{k',j})$, and $p_{k',j} \leq f_1(p_{k',j})$ establish, we have $\frac{p_{k',j} - f_1(p_{k',j})}{c_{j,k'} z_{k'} - f_1(p_{k',j})} \leq \frac{p_{k',j}}{c_{j,k'} z_{k'}}$. Therefore,

$$\begin{aligned}
\frac{\mathcal{U}_{M_j}}{\mathcal{U}_{M_j}^{(max)}} &\geq \min(Pr_{k',j}(1 - \frac{p_{k',j} - f_1(p_{k',j})}{c_{j,k'} z_{k'} - f_1(p_{k',j})})) \\
&\geq \min(Pr_{k',j}(1 - \frac{p_{k',j}}{c_{j,k'} z_{k'}})). \qquad (27)
\end{aligned}$$

We also analyze the platform's performance bound. P_i will recruit l_i MUs with the lowest asking prices $a_{opt,i}$ of the determined critical neighbor under *Platform_optimal*. Then $\mathcal{U}_{P_i}^{(max)} = \sum_{M_j \in \mathcal{M}} (b_i x_{i,j} - p_{i,j}) = l_i(b_i - a_{opt,i})$, where $\forall x_{i,j} = 1$, $p_{i,j} = a_{opt,i}$.

The payment that equals to $a_{l',i}$ and paid in PAM^{3}S is no less than $a_{opt,i}$, which is the main difference between $\mathcal{U}_{P_i}$ and $\mathcal{U}_{P_i}^{(max)}$. It can be seen that $\mathcal{U}_{P_i} = \sum_{M_j \in \mathcal{M}} (b_i x_{i,j} - p_{i,j}) = l_i(b_i - a_{l',i})$, $\forall x_{i,j} = 1$, $p_{i,j} = a_{l',i}$ at this time.

Similarly, $\mathcal{U}_{P_i}^{(max)} = \mathcal{U}_{P_i} = 0$ if $\mathcal{U}_{P_i}^{(max)} = 0$ in extreme cases. Otherwise, we have

$$\begin{aligned}
\frac{\mathcal{U}_{P_i}}{\mathcal{U}_{P_i}^{(max)}} &= \frac{l_i(b_i - a_{l',i})}{l_i(b_i - a_{opt,i})} \\
&= \frac{b_i - a_{l',i}}{b_i - f_2(a_{l',i})} \\
&= 1 - \frac{a_{l',i} - f_2(a_{l',i})}{b_i - f_2(a_{l',i})}. \qquad (28)
\end{aligned}$$

Due to the fact $0 < a_{l',i} \leq b_i$, meaning $0 < \frac{a_{l',i}}{b_i} \leq 1$, $\frac{a_{l',i} - f_2(a_{l',i})}{b_i - f_2(a_{l',i})} \leq \frac{a_{l',i}}{b_i}$. Thus,

$$\frac{\mathcal{U}_{P_i}}{\mathcal{U}_{P_i}^{(max)}} \geq 1 - \frac{a_{l',i}}{b_i}. \qquad (29)$$

□

C. Computational Complexity

This subsection gives the computational complexities of the proposed algorithms (`Algorithm 1`-`Algorithm 3`) as follows.

Consider the first stage MU-oriented auction. In `Algorithm 1`, the dynamic programming is utilized first by M_j with Z_j on $|\mathcal{P}_j|$ platforms. The required computational complexity is $O(|\mathcal{P}_j| Z_j)$. Then, M_j traces back to $|\mathcal{P}_j|$ platforms to determine the inclined ones with the complexity $O(|\mathcal{P}_j|)$. Let the maximum resources among m MUs be Z, and a MU intends to join n platforms at most. The upper bound computational complexity of `Algorithm 1` is $O(nZ)$.

As for `Algorithm 2`, to calculate the asking prices, M_j first removes each platform like P'_k in $\mathcal{W}_{j,\mathcal{P}}$ from $\mathcal{P}_j$ and re-performs `Algorithm 1`. The corresponding computational complexity is $O((|\mathcal{P}_j| - 1) Z_j)$. Later, M_j gets $d_{j,k'}$ by counting of utilities before and after removing P'_k with the complexity $O(|\mathcal{W}_{j,\mathcal{P}}|)$ if $|\mathcal{W}_{j,\mathcal{P}}| \geq |\mathcal{W}'_{j,\mathcal{P}}|$, and with the complexity $O(|\mathcal{W}'_{j,\mathcal{P}}|)$ otherwise. The asking price $a_{j,k'}$ can be calculated within the constant complexity $O(1)$. Supposing there are $|\mathcal{W}_{\mathcal{P}}|$ winning platforms at most, `Algorithm 2` has the computational complexity of $O(|\mathcal{W}_{\mathcal{P}}|(n-1)Z)$, $|\mathcal{W}_{\mathcal{P}}| \leq |\mathcal{P}_j| \leq n$.

We can get the computational complexities of `Algorithm 3` through a similar analysis. Let there be at most m MUs intending to join a platform, and the maximum number of recruited MU is l. `Algorithm 3` has the complexity $O(m^2) + O(l) + O(l(m-1)^2)$, in which $O(m^2)$ is the computational complexity of sorting m MUs with non-decreasing order according to their asking prices.

D. Communication Overhead

PAM^{3}S has the limited communication overhead as follows.

In the first stage MU-oriented auction, P_i publishes $(b_i, \varepsilon_i, z_i)$ to m MUs. M_j sends the calculated asking prices to the n' platforms intending to join, where $n' \in \mathbb{Z}$, $0 \leq n' \leq n$. At this time, it requires a message for P_i and n' messages for M_j to transmit. Numbers can represent both the messages of the recruitment information and the asking prices. Then, after receiving the asking prices from m' MUs, P_i checks these MUs and performs winning MU determination and payment determination, where $m' \in \mathbb{Z}$, $0 \leq m' \leq m$. These processes have no message to transmit. Later, the auction results are sent by P_i to m' MUs, which need m' messages to transmit. Since the single number can represent whether MU is recruited or not, P_i transmits m' numbers.

Take 10 platforms and 500 MUs as an example, meaning $n = 10$, and $m = 500$. Suppose $n' = n$ and $m' = m$, which are the largest values that n' and m' can reach. We have 1.96 KB for P_i and 0.04 KB for M_j to transmit while a number owns 32 bits, which is consistent with the practice. The communication overheads are limited. Furthermore, with the development of 5G technology, the bandwidth and communication capabilities for platforms and MUs will be improved. PAM^{3}S's communication overhead is negligible.

VI. Performance Evaluation

This section discusses the performance of PAM^{3}S through extensive experiments. We first give the experimental setup. Then, detailed discussions are provided.

TABLE III
THE PARAMETERS' VALUES

Parameters	Values
b_i	$[15,30]$ *(default)*, $[5,20]$, $[25,40]$
z_i	$[5,15]$
ε_i	70 *(default)*, 65, 75
Percentage of unreliable MUs	30% *(default)*, 40%
MUs' costs fluctuation	20% *(default)*, 30%

Note: Unless otherwise specified, the parameters have the default values.

A. Experimental Setup

Experimental environment: The experiments are programmed with Java language, and the experimental environment is Apple M1, 16GB RAM. The Operating System is macOS Big Sur.

Dataset and parameters setup: The experiments are built on the real data set Urban Data [31], widely applied in the MCS research [32]. We adopt the taxi GPS data, consisting of taxi id, latitude, longitude, occupancy status, etc. The taxis are viewed as MUs. The limited resources that each MU owns are obtained by counting the number of times that the taxi is not occupied. Because of the large amount of GPS data, we select 380 active taxis for the experiments, meaning $m = 380$. Meanwhile, suppose there are 7 platforms in the system, $n = 7$. Each platform aims to recruit 30 MUs. According to the existing works, the values above are just set as an example. Since each platform targets different applications and has various sensing tasks, the same MU has different costs for different platforms. Similar to the existing works [33], we regard the distance between the MU and the platform's sensing task as the required total cost under demanded resources.[1] The locations of sensing tasks are generated randomly within the area determined by the minimum and maximum latitudes and longitudes of all MUs. Besides distance, the MU's cost is influenced by other factors. Thus, the cost above also fluctuates. The values of parameters are set in TABLE III. To capture MUs' various sensing evaluations, we set some MUs unreliable, which with low evaluations. The sensing evaluations for these MUs are within $[20, 50]$, while the evaluations for the others are within $[50, 100]$.

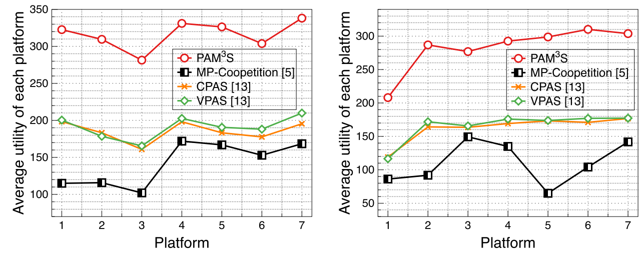
Comparison indexes: We compare PAM^{3}S's performance with the existing works [5], [13]. In particular, we are mainly concerned with the platforms' competition in MP-Coopetition [5]. And we consider Cai et al. [13] proposed CPAS and VPAS. Both of them are the latest works based on the auction. The indexes include the utilities of platforms and MUs, platforms' achieved sensing quality and earned profits, MUs' resource utilization, as well as execution time delay are compared.

B. Utilities

This subsection first evaluates platforms' and MUs' utilities, then pays attention to the optimality gap.

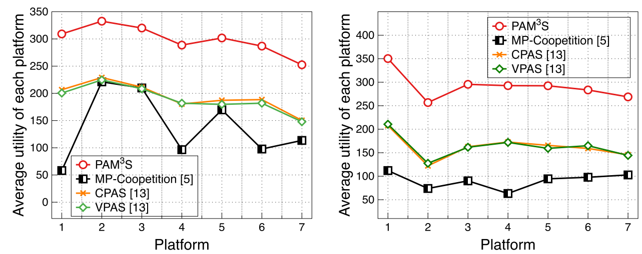
• **Utility of platform:** The utility of a platform depends on the earned profits and the paid payments. In particular, the earned profits are mainly determined by the recruited MUs' achieved sensing quality. And the payments are related to the platforms' bids. Thus, each platform's utility is discussed from the sensing quality and bids.

[1]Here, we just take an example for making the distance as the total cost, which is easy to calculate on the dataset and can be others.



(a) $\varepsilon_i = 65$. (b) $\varepsilon_i = 75$.

Fig. 5. **Average utility of each platform under different sensing quality thresholds.** *PAM^{3}S enables the highest utilities regardless of the thresholds.*



(a) 30% unreliable MUs. (b) 40% unreliable MUs.

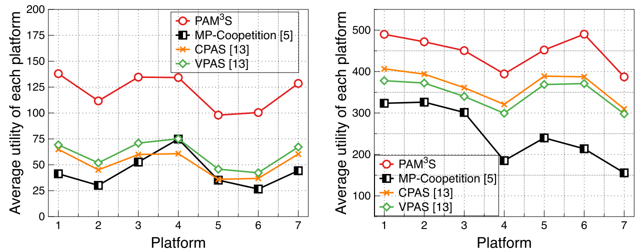
Fig. 6. **Average utility of each platform under different distributions of MUs' sensing evaluations.** *PAM^{3}S makes each platform's average utility better than the existing works.*

In PAM^{3}S, the sensing quality is influenced by the sensing quality thresholds and the distributions of MUs' sensing situations reflected by the sensing evaluations. Fig. 5(a) and Fig. 5(b) give the average utility of each platform under different thresholds in 100 experiments. Since more platforms can recruit satisfied MUs when their thresholds are 65, the average utilities are higher than when their thresholds are 75. For example, the average utilities of PAM^{3}S, MP-Coopetition, CPAS, and VPAS are 322.65, 115.00, 198.33, and 200.41 for platform 1 when the thresholds are 65; when the thresholds equal to 75, platform 1's average utilities correspond to 208.03, 86.16, 118.96, and 116.62, respectively.

Since all recruited MUs in PAM^{3}S have the sensing evaluations as each platform desires, the brought profits are high, as shown in Fig. 12 and Fig. 14. Meanwhile, PAM^{3}S lets a MU join multiple platforms. Each platform can recruit appropriate MUs, which avoids the limited successful recruitment to reduce average utility. Therefore, PAM^{3}S enables the highest utilities regardless of the thresholds. Additionally, a MU in MP-Coopetition is only allowed to join one platform. Unlike the other works, where each platform will not continue to recruit MUs once its requirement is satisfied, most of the MUs in MP-Coopetition may join a few platforms. It causes MP-Coopetition's different curve patterns, which may have larger fluctuation than others, as shown in Fig. 5(b) and other figures.

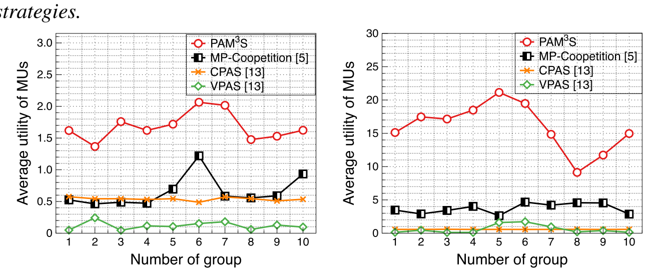
Fig. 6(a) and Fig. 6(b) show each platform's average utility under different distributions of MUs' sensing evaluations in 100 experiments. By taking platform 5 as an example, the average utilities of PAM^{3}S, MP-Coopetition, CPAS, and VPAS are 301.75, 169.70, 187.28, and 179.79, when the percentage of unreliable MUs that with low evaluations is 30%; when the percentage is 40%, the corresponding utilities are 292.46, 94.44, 165.67, and 159.28, respectively.

Because PAM^{3}S enables each platform to recruit MUs with sensing evaluations as its threshold set, meaning high sensing quality, PAM^{3}S earns high profits. Meanwhile, the recruitment of MUs with low sensing evaluations causes low profits for the platform of the existing works. Thus, PAM^{3}S always makes



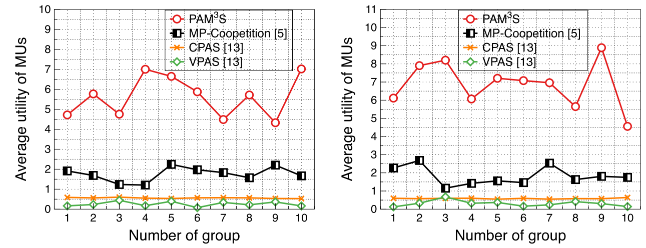
(a) $b_i \in [5, 20]$. (b) $b_i \in [25, 40]$.

Fig. 7. **Average utility of each platform under different bidding scopes.** *PAM^{3}S ensures the utility of each platform is good no matter the bidding strategies.*



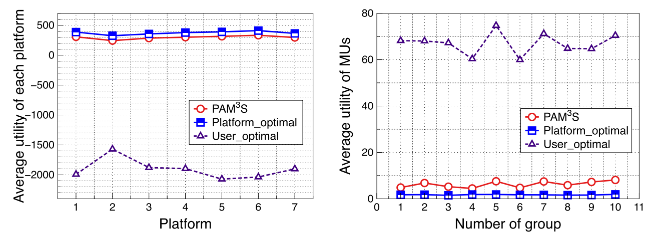
(a) $b_i \in [5, 20]$. (b) $b_i \in [25, 40]$.

Fig. 8. **Recruited MUs' average utilities under different bidding scopes of platforms.** *The average utilities of MUs in PAM^{3}S are higher than the existing works in general.*



(a) 20% costs fluctuation. (b) 30% costs fluctuation.

Fig. 9. **Recruited MUs' average utilities under different costs.** *PAM^{3}S ensures high utilities of final recruited MUs no matter the fluctuation of costs.*



(a) Platforms' utilities. (b) MUs' utilities.

Fig. 10. **The average utilities of platforms and recruited MUs of PAM^{3}S, *Platform_optimal*, and *MU_optimal* that reflect the optimality gap.** *The optimality gap of PAM^{3}S is acceptable from the perspectives of platforms' and MUs' utilities.*

each platform's utility better than the existing works regardless of the percentage of unreliable MUs.

In addition, Fig. 7(a) and Fig. 7(b) give each platform's average utility under different bidding scopes. Taking platform 4 as an example, in Fig. 7(a), the average utilities of PAM^{3}S, MP-Coopetition, CPAS, and VPAS are 134.22, 74.83, 60.78, and 75.13, respectively, while 394.33, 185.06, 320.77, and 299.41 in Fig. 7(b).

The increase in the bid makes the platform recruit the desired MUs with a greater probability, which reduces the auction's failure. Therefore, the average utility for each platform rises. Overall, PAM^{3}S ensures the platform's preferable utility no matter the bidding strategies.

• **Utility of MU:** Certain MU's utility relies on the received payments and the costs of joining platforms. Because a MU's final received payments are influenced by the bids of each platform he joins, we mainly focus on platforms' bids and MUs' costs. This section divides 100 experiments into ten groups equally. The final recruited MUs' average utility under each experiment is calculated first, then the result of every group is observed.

Fig. 8(a) and Fig. 8(b) show the average utilities of the recruited MUs under various platforms' bidding scopes. When $b_i \in [5, 20]$, the average results on MUs' utilities of several groups for PAM^{3}S, MP-Coopetition, CPAS, and VPAS are 1.68, 0.65, 0.54, and 0.12, respectively. And the corresponding utilities are 15.95, 3.73, 0.57, and 0.58 while $b_i \in [25, 40]$.

PAM^{3}S enables a MU to join multiple platforms under specific resources. Under this condition, thanks to utility-based winning platform determination, careful asking price determination, and payment determination, the average utilities of recruited MUs in PAM^{3}S are higher than the existing works. Moreover, for PAM^{3}S, once a MU joins the platform with a higher bid, he can obtain a higher payment. Therefore, the average utilities in Fig. 8(b) are higher than in Fig. 8(a).

Apart from the costs of MUs having 20% fluctuation as default, we also discuss the average utilities of the recruited MUs while their costs fluctuate by 30%. The results are shown in Fig. 9(a) and Fig. 9(b), respectively.

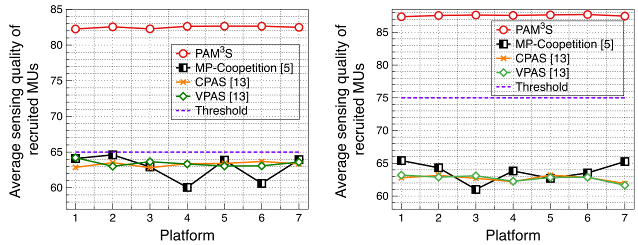
The change in costs brings the variation of MUs' asking prices, which further impacts the received payments. However, as the results of payments minus costs, the utilities of the recruited MUs are not significantly influenced. PAM^{3}S ensures the high utilities of recruited MUs no matter the costs' fluctuation. Compared with the existing works, PAM^{3}S increases 10.74 times of MUs' utilities on average under the default parameters.

• **Optimality gap:** We discuss the optimality gap of PAM^{3}S based on the utilities by comparing with *Platform_optimal* and *MU_optimal*. Note that our scenario has multiple platforms which face the same MUs. We make multiple platforms recruit MUs in random order in *Platform_optimal* to avoid the situation where MUs are selected by several platforms simultaneously but do not have enough resources to cooperate. A MU will not participate in the subsequent recruitment once resources are exhausted.

Fig. 10(a) and Fig. 10(b) give the realized utilities of platforms and MUs reflecting the optimality gap, respectively.

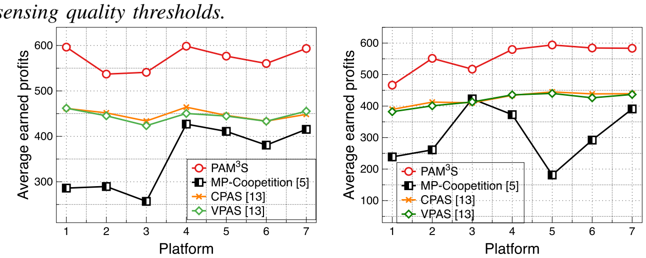
In Fig. 10(a), the platforms' utilities in *Platform_optimal* are higher than PAM^{3}S. Moreover, the utilities of platforms in *MU_optimal* are the lowest. We can see that in *MU_optimal*, platforms even obtain negative utilities because too many MUs are needed to be paid. PAM^{3}S's progressive auction considers the platforms' utilities in the second stage, making the results relatively considerable, which are a little lower than the utilities in *Platform_optimal* and higher than those in *MU_optimal*. Overall, the optimality gap of PAM^{3}S is limited in the experiments from the perspective of platforms' utilities by comparing with *Platform_optimal*.

Moreover, in Fig. 10(b), the utilities of recruited MUs in *MU_optimal* are the highest but do not feasible in practice. Since *Platform_optimal* does not think about MUs' utilities, which does not allow each MU to allocate his resources well to seek more utility, the utilities of recruited MUs are low. Similarly, PAM^{3}S's progressive auction considers the MUs' utilities in the first stage, leading to the results well.



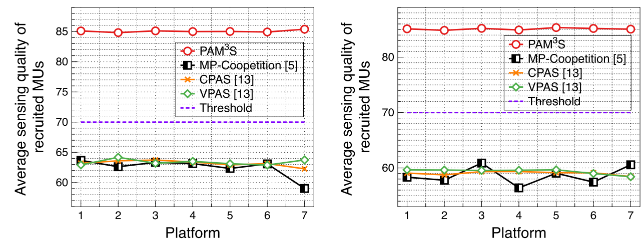
(a) $\varepsilon_i = 65$. (b) $\varepsilon_i = 75$.

Fig. 11. **Average sensing quality of each platform for recruited MUs under different thresholds.** *PAM^{3}S ensures the recruited MUs satisfy the sensing quality thresholds.*



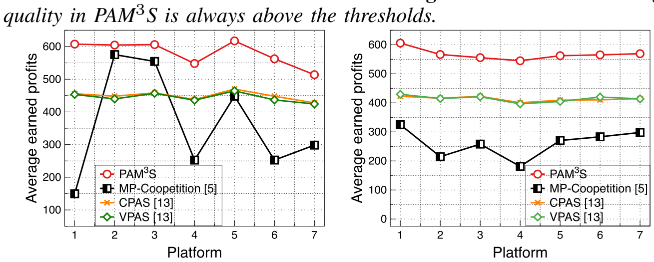
(a) $\varepsilon_i = 65$. (b) $\varepsilon_i = 75$.

Fig. 12. **Average earned profits of each platform under different thresholds.** *The platform's earned profits in PAM^{3}S are the highest compared to existing works.*



(a) 30% unreliable MUs. (a) 40% unreliable MUs.

Fig. 13. **Average sensing quality of each platform for the recruited MUs under different distributions of MU's sensing evaluations.** *The average quality in PAM^{3}S is always above the thresholds.*



(a) 30% unreliable MUs. (b) 40% unreliable MUs.

Fig. 14. **Average earned profits of each platform under different distributions of MUs' sensing evaluations.** *PAM^{3}S's profits are the highest with various MUs' evaluation distributions.*

The optimality gap of PAM^{3}S is also acceptable from the perspective of MUs' utilities by comparing with *MU_optimal*.

C. Sensing Quality and Earned Profits

First, this subsection observes each platform's average sensing quality of the recruited MUs, measured by MUs' sensing evaluations. Then, the specifically earned profits are discussed. When computing the average quality of MUs under 100 experiments, the situation where the platform does not recruit any MU is not considered.

Fig. 11(a) and Fig. 11(b) give each platform's average sensing quality of recruited MUs under different thresholds. Because the threshold set by each platform in Fig. 11(b) is higher than that in Fig. 11(a), the final recruited MUs in Fig. 11(b) have more excellent sensing evaluations in PAM^{3}S, which makes the higher average sensing quality. Meanwhile, ensuring the sensing quality is above the thresholds in the existing works is difficult.

PAM^{3}S enables each recruited MU to meet the threshold. For MP-Coopetition, CPAS, and VPAS, the platform does not consider MUs' sensing evaluations. Thus, the average sensing quality of each platform is the highest in PAM^{3}S compared with the existing works.

For the earned profits, let the profits brought by the sensing data derived from the MU with a lower sensing evaluation than the threshold be the profits achieved by the MU with expected evaluation times the proportion of the low evaluation in the threshold. The profits achieved by the MU with expected evaluation exactly mean the platform's bid. Each platform's average earned profits under different thresholds are shown in Fig. 12. Specifically, when the thresholds are 65, the average earned profits for platform 4 of 100 experiments are 598.50, 426.92, 464.22, and 450.32 for PAM^{3}S, MP-Coopetition, CPAS, and VPAS; the relevant profits are 579.60, 372.74, 434.16 and 435.57 when the thresholds are 75.

On the one hand, the sensing data derived from the MU with the evaluation lower than the threshold brings a low profit to the existing works. On the other hand, PAM^{3}S enables a MU to join multiple platforms, making more platforms recruit satisfied MUs to earn high profits. Thus, the platform's earned profits in PAM^{3}S are the highest compared to existing works.

Fig. 13(a) and Fig. 13(b) present the average sensing quality of each platform for the recruited MUs under different MUs' sensing evaluation distributions. Regardless of the distributions, since PAM^{3}S ensures all the recruited MUs have evaluations no less than platforms' demand, the average quality is always above the thresholds, as solid red lines show. For MP-Coopetition, CPAS, and VPAS, the platform does not consider MUs' sensing evaluations. Therefore, the corresponding average quality cannot reach the thresholds. Compared with 30% unreliable MUs, each platform is more likely to recruit unreliable MUs when the percentage is 40%. Thus, the existing works' average sensing quality in Fig. 13(b) is lower than in Fig. 13(a).

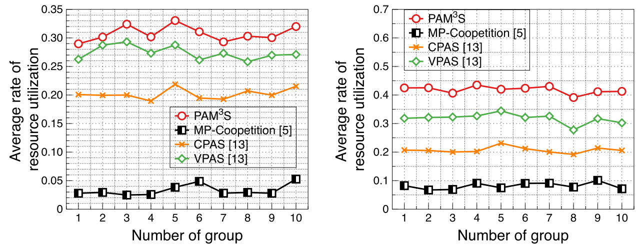
Fig. 14 gives each platform's average earned profits under different distributions of MUs' sensing evaluations. As the results show, the earned profits under 30% unreliable MUs are generally higher than that under 40% for the existing works. Similarly, the platform's profits are the highest in PAM^{3}S.

D. Resource Utilization of MUs

This section evaluates the resource utilization of MUs. Specifically, M_j's utilization rate of resources is defined as Z'_j/Z_j, where Z'_j is the allocated units of resources, and Z_j is M_j's total units of resources. We also divide 100 experiments into ten groups. The average resource utilization rate of the recruited MUs is calculated for each group based on the average value of each experiment.

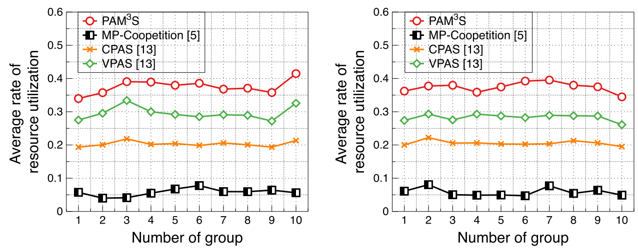
We discuss the resource utilization of the recruited MUs under different platforms' bidding scopes and MUs' costs. Both of them impact whether a MU joins a platform. The results are shown in Fig. 15 and Fig. 16, respectively.

Since there are 7 platforms in the system, and each of them aims to recruit 30 MUs, the platform with a high bid and little costs determined by 380 MUs will have enough choices. Moreover, the platform fails to recruit MUs once the number of MUs is less than required. The recruited



(a) $b_i \in [5, 20]$. (b) $b_i \in [25, 40]$.

Fig. 15. **Resource utilization of the recruited MUs under different bidding scopes of platforms.** *PAM^{3}S can always guarantee the MUs' high resource utilization under different platforms' bids.*



(a) 20% costs fluctuation. (b) 30% costs fluctuation.

Fig. 16. **Resource utilization of the recruited MUs under different costs.** *The recruited MUs' average resource utilization rates of PAM^{3}S are high regardless of the costs.*

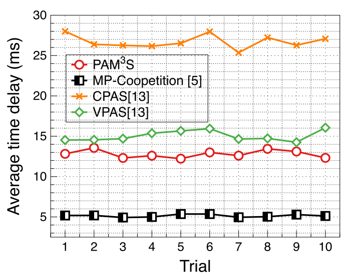


Fig. 17. **Average execution time delay.** *The time delay of PAM^{3}S is limited.*

MUs' average resource utilization rate is not generally high. However, PAM^{3}S can still guarantee relatively high results. Similar to PAM^{3}S, since VPAS enables MUs to join multiple platforms, the average resource utilization rates of recruited MUs are also high. As for MP-Coopetition and CPAS, each MU only joins one platform. Thus, the resource utilization rates of these two works are low. In general, compared with the situation where $b_i \in [5, 20]$, the relevant rates are higher when $b_i \in [25, 40]$. There is no significant impact of cost fluctuation on the results.

E. Execution Time Delay

Last, we discuss the execution time delay of PAM^{3}S and the existing works. The results are shown in Fig. 17, where we treat every 100 experiments as a trial for calculating the average time delay. The PAM^{3}S's time delay is limited to about 12.80 ms.

Because CPAS requires multiple iterations of the auction until a termination condition is met, its required time delay is the highest. For VPAS, since the auction just needed to run once, the relevant average time delay reduces. Although PAM^{3}S executes the auction with two progressive stages, the adoption of effective methods like dynamic programming while solving 0-1 knapsack makes its average time delay close to VPAS and even smaller. The average time delay of MP-Coopetition is the least since only simple arithmetical operations are desired.

VII. Conclusion and Future Work

The existing works fail to maximize the utilities of platforms and MUs as far as possible in the multi-platform multi-user scenario, which impedes MCS development. Aiming at this problem, we propose PAM^{3}S, a progressive two-stage auction-based multi-platform multi-user mutual selection scheme. Specifically, we develop the forward and reverse auction models to maximize the utilities of MUs and platforms. Later, on account of the forward MU model, the first stage MU-oriented auction is constructed, based on which the second stage platform-oriented auction is further constructed under the guidance of the reverse platform model. This progressive two-stage auction completes mutual selection well. Theoretical analysis shows that PAM^{3}S meets design goals. Extensive experiments on the real dataset indicate PAM^{3}S is effective.

In the future, to address the limitations and enable the selection in the multi-platform multi-user scenario to be better, we will establish more detailed auction models to cope with more complex situations, such as platforms misreporting other items rather than bids in recruitment information and the number of MUs is not enough in MCS.

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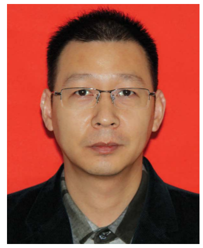

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