Truthful Incentive Mechanism for Nondeterministic Crowdsensing with Vehicles

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Abstract—In this paper, we focus on the incentive mechanism design for a vehicle-based, nondeterministic crowdsensing system. In this crowdsensing system, vehicles move along their trajectories and perform corresponding sensing tasks with different probabilities. Each task may be performed by multiple vehicles jointly so as to ensure a high probability of success. Designing an incentive mechanism for such a crowdsensing system is challenging since it contains a non-trivial set cover problem. To solve this problem, we propose a truthful, reverse-auction-based incentive mechanism that includes an approximation algorithm to select winning bids with a nearly minimum social cost and a payment algorithm to determine payments for all participants. Moreover, we extend the problem to a more complex case in which the Quality of sensing Data (QoD) of each vehicle is taken into consideration. For this problem, we propose a QoD-aware incentive mechanism, which consists of a QoD-aware winning-bid selection algorithm and a QoD-aware payment determination algorithm. We prove that the proposed incentive mechanisms have truthfulness, individual rationality and computational efficiency. Moreover, we analyze the approximation ratios of the winning-bid selection algorithms. The simulations, based on a real vehicle trace, also demonstrate the significant performances of our incentive mechanisms.

Index Terms—Incentive mechanism, nondeterministic crowdsensing, quality of data, reverse auction, truthful

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1 INTRODUCTION

IN recent years, vehicles have been equipped with more and more components that can provide a better user experience such as wireless network interfaces, event data recorders, vehicular computers, etc. Vehicles that carry these components can be considered programmable and powerful mobile sensors which are able to communicate with the Internet and with each another. Furthermore, they move along roads day after day, and thus have the potential to collect data and permit the enabling of numerous novel applications such as traffic management [2], mobile advertising [3], [4], environment monitoring [5], [6], etc. All of these applications can be formalized as outsourcing location-based sensing tasks to mobile vehicles, which are also called *vehicle-based crowdsensing* [7], [8]. Roughly speaking, vehicle-based crowdsensing involves a platform that receives task requests from platform users and dispatches sensing tasks to mobile vehicles that are willing to serve.

Stimulating enough vehicles to participate in the crowdsensing is one of the most critical issues since it determines whether the crowdsensing can provide adequate sensing

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quality. While performing sensing tasks, participants may consume some resources, such as battery, storage, cpu, etc., and may even suffer threats to their privacy [9]–[11]. These factors could discourage them from participating in crowdsensing unless they receive sufficient rewards to compensate for the expenditures and the risks. Hence, an incentive mechanism that determines which participants should be recruited and how much reward should be paid to each of them is necessary. However, what makes the incentive mechanism design highly complicated is that a participant might strategically claim a higher cost than the real one to increase his/her payoff. Additionally, the mechanism also needs to minimize the social cost (i.e., the total sensing cost) and ensure the successful probability of performing tasks, which all contribute to the challenge.

In this paper, we focus on the incentive mechanism design for vehicle-based, nondeterministic crowdsensing. Consider a typical vehicle-based, nondeterministic crowdsensing system like [8], which consists of a platform, several platform users, and many mobile vehicles. The platform receives the sensing tasks associated with some Places of Interest (PoIs) from the platform users. The vehicles move along streets and can communicate with the platform via road-side infrastructures or cellular networks so that the platform can select vehicles to perform the sensing tasks. In general, these tasks are associated with different PoIs. Vehicles might be selected to perform a task only when they pass by the corresponding PoI, as illustrated in Fig. 1. Real vehicular trace analysis has shown that the mobile trajectory of each vehicle in real applications is nondeterministic [3], [8], [12]–[14]. Therefore, it is a probabilistic event that each vehicle will pass by a PoI and will perform the related task (i.e., *covers* this task). Due to this nondeterminacy, the platform user will require that the probability of each task being
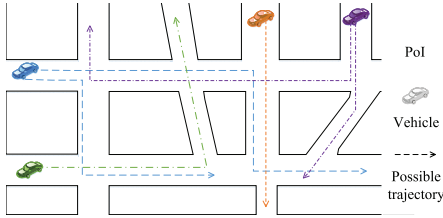
Fig. 1. An example of vehicle-based, nondeterministic crowdsensing: four vehicles move on their possible trajectories, pass by several PoIs, and collect sensing data during the time interval.

performed successfully is no less than a specified threshold to guarantee the total sensing quality of the crowdsensing. The platform, therefore, needs to stimulate enough vehicles to participate in the crowdsensing by using an incentive mechanism. This incentive mechanism should consider the truthfulness, individual rationality, computational efficiency, minimum social cost, and the constraints of vehicles' possible mobile trajectories simultaneously.

Currently, there have been many incentive mechanisms designed for crowdsensing/crowdsourcing [15]–[33]. In [15], Yang *et al.* design two incentive mechanisms, CCM and UCM, to maximize the utility of the crowdsourcer. They build the incentive mechanisms based on Stackelberg game and reverse auction, respectively. In [16], Zhao *et al.* propose an online incentive mechanism to maximize the utility of the crowdsourcer within a given budget. In [17], Wei *et al.* tend to stimulate both workers and crowdsourcers to participate in the dynamic mobile crowdsensing. They design a general incentive mechanism framework based on double auction to ensure the budget balance. In [24], Feng *et al.* design a social cost efficient incentive mechanism, TRAC, for the location-aware collaborative crowdsensing. In TRAC, each mobile user can perform a few location-related tasks and multiple users are stimulated to cooperatively perform a group of tasks. However, all of these incentive mechanisms only involve deterministic crowdsensing in which each user is assumed to perform a task either with a probability of 100% or with a zero probability. In contrast, we focus on the nondeterministic crowdsensing where tasks are performed by each vehicle/user with different probabilities from zero to 100%. Such a nondeterministic crowdsensing scenario is more consistent with the real world. Nevertheless, it will result in a non-integer set cover problem with non-linear constraints. The aforementioned incentive mechanisms for deterministic crowdsensing are not competent for this novel nondeterministic crowdsensing.

In this paper, we design a truthful, reverse-auction-based incentive mechanism to meet the requirements of our scenario. Since our mechanism uses a similar process for each platform user, we will only consider the scenario that consists of a single platform user. First, the platform receives the tasks, probability thresholds, and the time intervals from the platform user. It then sends them to the vehicles registered in the platform. After that, the vehicles reply with bids that contain the tasks on their possible trajectories and the corresponding costs. Next, the platform decides which bids should be selected to minimize the social cost, while ensuring that the joint probability of each task being successfully performed is no less than the given threshold. The platform also determines a payment for each bid in order to guarantee that each vehicle will report the real

costs (i.e. the truthfulness) and that the payoff of each bid is non-negative (i.e. the individual rationality). Finally, the platform will notify the vehicles of their winning bids, pay the vehicles after receiving sensing data from them, charge the platform user for the payments, and send the platform the sensing data. In summary, the incentive mechanism mainly consists of a winning-bid selection algorithm and a payment determination algorithm. Indeed, the designed incentive mechanism can be applied in many fields in real life, such as environment and noise monitoring [5], [6], crowd labeling [19], [34], social networks [35] and so on.

We highlight the main contributions as follows:

- We design a reverse-auction-based incentive mechanism for vehicle-based, nondeterministic crowdsensing. To the best of our knowledge, this is the first work on the crowdsensing incentive mechanism design that takes into consideration truthfulness, individual rationality, computational efficiency, social cost efficiency, and the nondeterministic crowdsensing scenario, where each task is performed with a joint probability, simultaneously.
- We prove that the winning-bid selection problem in our scenario is NP-hard since it leads to a nontrivial set cover problem with non-linear constraints. To solve the problem efficiently, we propose a nearly optimal winning-bid selection algorithm and analyze the approximation ratio.
- We propose an algorithm to determine the payments for the winning bids and theoretically prove that these payments can ensure the truthfulness and individual rationality of the mechanism.
- We extend the incentive mechanism design problem to a case where the Quality of Data (QoD) is taken into consideration. We propose a QoD-aware incentive mechanism consisting of a QoD-aware winning-bid selection algorithm and payment determination algorithm. We prove that the QoD-aware incentive mechanism is truthful and individually rational. Moreover, we analyze the approximation ratio of the QoD-aware winning-bid selection algorithm.
- We conduct extensive simulations on a real vehicle trace to demonstrate the significant performances of the proposed incentive mechanisms.

The rest of the paper is organized as follows. In Section 2, we introduce the system model and the problem. Then, we describe the detailed design of our mechanism and the related extension in Sections 3 and 4, respectively. The theoretical analysis and the evaluation of the incentive mechanisms are presented in Sections 5 and 6, respectively. After reviewing the related work in Section 7, we finally conclude the paper in Section 8.

2 SYSTEM MODEL AND PROBLEM

2.1 System Model

We consider a vehicle-based, nondeterministic crowdsensing system which consists of a platform, several platform users, and many vehicles. The platform accepts sensing requests from platform users who connect to the platform via Internet and negotiates with the vehicles either via cellular networks or road-side infrastructures [36]–[39], which

are left up to their preference. The platform will pay the rewards to vehicles after receiving data from them and will charge the platform users for the payments.

The system might contain several platform users. Since the sensing tasks for different platform users are distinct, the submitted bids are also separate. Here, the bid submitted by each vehicle indicates the cost of performing one platform user's sensing tasks, instead of the cost of performing all platform users' tasks on this trajectory. For the simplicity of descriptions, *we only consider one platform user, and we let the platform conduct the same operations for other platform users in the practical scenario.* The platform user wants to collect data (e.g., traffic congestion, noise pollution, air quality, etc.) from m PoIs which are distributed in different streets. Hence, it produces m PoI-related sensing tasks. These sensing tasks are denoted as a task set $\mathcal{S} = \{s_1, s_2, ..., s_m\}$ in which s_i is the i-th task ($1 \leq i \leq m$). Since the sensing data is time-sensitive, the platform user requires that the tasks are performed within a time interval $[t_1, t_2]$. The sensing data is meaningful only when the tasks are completed within the time interval $[t_1, t_2]$. Without Loss Of Generality (WLOG), we assume that $t_1 = 0$ and $t_2 = \mathcal{D}$. Since each task is performed with a probability in the nondeterministic crowdsensing, the platform user demands that the probability of each task in $\mathcal{S}$ being successfully performed be no less than a threshold η.

The vehicle-based, nondeterministic crowdsensing system also includes n mobile vehicles, denoted as $\mathcal{V} = \{v_1, v_2, ..., v_n\}$. These mobile vehicles move around different streets so that they might cover and perform the sensing tasks in $\mathcal{S}$. In general, the mobile behaviors of vehicles are uncertain. This characteristic has been captured by many real vehicular traces [3], [8], [12]–[14], [38]. Based on this observation, we assume that each vehicle has multiple possible trajectories and that each trajectory has a probability. More specifically, vehicle v_j has l_j possible trajectories. Each trajectory might cover a group of tasks. The tasks covered by vehicle v_j are denoted as $\{S_1^j, S_2^j, ..., S_{l_j}^j\}$ in which S_k^j is the set of tasks covered by the k-th trajectory ($1 \leq k \leq l_j$). Since the execution time of tasks is much smaller than the driving time of vehicles and each vehicle can obtain more extra income by performing more sensing tasks on a trajectory, each vehicle is always willing to perform all sensing tasks on its one driving trajectory. That is, the tasks in S_k^j, covered by the same trajectory, will be performed *as a whole* which means that either all of the tasks are performed or none of them are. Moreover, the probability of tasks in S_k^j being performed is the probability of the k-th trajectory, denoted by q_k^j. When a vehicle performs sensing tasks, it will consume battery, storage, cpu, and so on, which will result in a cost. The cost of v_j performing all tasks in S_k^j is denoted by c_k^j.

In the above system, the vehicles are deemed as common office workers. That is, the primary goal of the vehicles is to drive to their destinations, and the secondary goal is to perform some sensing tasks on their trajectories. All vehicles may submit bids for their possible trajectories. However, they select the trajectories according to the practical situation (e.g., traffic condition) at that time, instead of selecting the trajectories that maximize their benefits. Here,
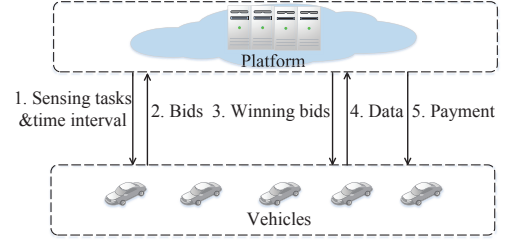

Fig. 2. The interactions between the platform and vehicles.

we assume that the platform can derive the value of q_k^j from v_j's historic movement records. This assumption is reasonable since the platform can trace the daily movements of the vehicles, and therefore, the platform can derive the trajectories and probabilities of vehicles. We also assume that the time it takes each vehicle to perform a task can be ignored since it is far less than that of the vehicle visiting a PoI in magnitudes. Here, we only consider the tasks that can be completed before $\mathcal{D}$. If a trajectory covers some extra tasks whose performing times are beyond $\mathcal{D}$, we will deem that these extra tasks cannot be performed by the corresponding vehicle.

2.2 Reverse-Auction-Based Incentive Mechanism

In the vehicle-based, nondeterministic crowdsensing system, the platform adopts a reverse-auction-based incentive mechanism to select participants and to determine the payments for them after receiving the request from the platform user. Since the tasks on a trajectory will be performed together, the mechanism is actually based on a reverse and combinatorial auction. The whole incentive mechanism mainly includes five rounds of interactions between platform and vehicles, as illustrated in Fig. 2:

1) The platform announces all PoI-related sensing tasks in $\mathcal{S}$ as well as $\mathcal{D}$ to the vehicles in $\mathcal{V}$ after receiving from the platform user.

2) Each vehicle v_j will reply to the platform with a set of bids, each of which is a tasks-bid pair $\beta_k^j = (S_k^j, b_k^j)$, in which S_k^j is the set of tasks covered by v_j's k-th trajectory and b_k^j is the cost claimed by v_j for performing all tasks in S_k^j. Here, the β_k^j is valid only when v_j moves along the k-th trajectory and performs the tasks in β_k^j (Note that, due to the nondeterminacy of v_j's mobile behaviors, it cannot guarantee that the claimed tasks in β_k^j will be performed indeed).

3) After receiving replies from all vehicles in $\mathcal{V}$, the platform selects a set of winning bids, denoted by Φ, from the received bids, denoted by Γ, to guarantee that all tasks in $\mathcal{S}$ are performed with a probability no less than a specified threshold η. A bid $\beta_k^j \in \Phi$ indicates that v_j will be selected to perform the tasks in S_k^j. After determining Φ, the platform will notify the vehicles of the corresponding winning bids. Also, the platform will determine the payment p_k^j for each bid β_k^j in Φ.

4) After receiving the winning bids, vehicle v_j will perform the tasks in each winning bid β_k^j until $\mathcal{D}$, when v_j moves along the k-th trajectory. Moreover, v_j will send the results back to the platform after it completes all tasks in S_k^j.

5) The platform will pay vehicle v_j with the money p_k^j for the bid β_k^j after receiving the results of S_k^j.

Note that the payment should be fair and the *payoff* of a bid β_k^j, which is defined as $p_k^j - c_k^j$, should be reasonable to attract more vehicles. However, the platform only knows the claimed cost b_k^j instead of the real cost c_k^j that v_j spends on performing S_k^j. In fact, c_k^j is known to nobody except v_j itself. v_j may strategically manipulate b_k^j to get a higher payoff. Such strategic manipulation might force the platform and the platform user to pay extra money. Thus, the whole mechanism needs to ensure that each vehicle will not manipulate its bids, i.e., the truthfulness.

2.3 Problem

In this subsection, we formalize the incentive mechanism design problem for the above vehicle-based, nondeterministic crowdsensing system. The mechanism design problem mainly consists of two subproblems: the winning-bid selection problem and the payment determination problem.

The optimization objective of the winning-bid selection problem is to minimize *social cost* which is defined as the sum of the winning bids' real costs. The metric of social cost indicates the total costs of the whole system performing sensing tasks, which is also widely concerned in other works [12], [24], [40]. Additionally, the winning-bid selection problem needs to meet the constraint that the joint probability of each task being successfully performed by the related vehicles is no less than the threshold η ($0 < \eta < 1$). For this constraint, we denote the joint probability of a task s_i being performed successfully as ρ_i^Φ and calculate it as follows:

$$\rho_i^\Phi = 1 - \prod_{\beta_k^j \in \Phi \wedge s_i \in S_k^j}(1 - q_k^j).$$

The Minimum-social-Cost winning-Bid Selection (MCBS) problem is formalized as follows:

$$\min \quad C(\Phi) = \sum_{\beta_k^j \in \Phi} c_k^j \qquad (1)$$

$$\text{s.t.} \quad \Phi \subseteq \Gamma, \qquad (2)$$

$$\rho_i^\Phi \geq \eta, \qquad 1 \leq i \leq m \qquad (3)$$

Here, (3) implies that the successful performing probability of each task is no less than the threshold. Additionally, we assume that there always exists at least one feasible solution for this problem. This assumption is reasonable since we can add more vehicles to $\mathcal{V}$ until the problem is solvable.

Second, the payment determination problem is to compute payments for winning bids. The payments should ensure that the vehicles are willing to participate in the crowdsensing and that they will not manipulate their claimed costs. Thus, the payment computation needs to make the whole incentive mechanism satisfy the following properties:

- **Individual Rationality**. Individual rationality indicates that each winner should be paid with a value no less than its real cost, which implies that each winner's payoff is not negative. Due to the non-negative payoff, each winner is willing to participate in the crowdsensing.

- **Truthfulness**. Truthfulness means that no bidder can improve his or her payoff by submitting different costs from the true values. According to Myerson's Theorem [41], *a mechanism is truthful if and only if:*

TABLE 1
Frequently used notations

Notations	Description
$\mathcal{S}, \mathcal{V}$	the sets of tasks and vehicles, respectively.
i, j, k	the indexes for tasks, vehicles and trajectories, respectively.
S_k^j	the set of tasks covered by v_j's k-th trajectory.
q_k^j	the probability of v_j's k-th trajectory.
c_k^j	the real cost that v_j spends on performing S_k^j.
b_k^j	the claimed cost (i.e., bid) for v_j on S_k^j.
β_k^j	the bid of v_j, containing S_k^j and b_k^j.
p_k^j	the payment for the bid β_k^j.
$\Gamma, \Gamma_{-\beta_k^j}$	the set of bids received by the platform, and the set of bids except β_k^j.
Φ, Φ'	the set of winning bids selected from Γ and $\Gamma_{-\beta_k^j}$, respectively.
ρ_i^Φ	the joint probability of s_i being successfully performed based on the winning bid set Φ.
η	the threshold of the joint probability.

the winner selection rule is monotone and each winner is paid with a critical value. The monotonicity indicates that if v_j wins the bid β_k^j when it claims a cost b_k^j for performing S_k^j, it will still win the bid when claiming a smaller cost $\hat{b}_k^j$ ($\leq b_k^j$). The critical value is the maximum bid value for a bid to win.

Additionally, the frequently used notations in this paper are summarized in Table 1.

3 DESIGN OF INCENTIVE MECHANISM

In this section, we propose a reverse-auction-based incentive mechanism consisting of solutions to the MCBS problem and the payment determination problem. We first analyze the NP-hardness of the MCBS problem, and then propose an approximation algorithm to resolve MCBS efficiently. Next, we propose another algorithm to compute the payments for all winning bids, which will induce the vehicles to report their costs truthfully.

3.1 NP-Hardness of MCBS

First, we analyze the complexity of the MCBS problem and derive the following theorem.

Theorem 1. The MCBS problem is NP-hard.

Proof: To prove the NP-hardness of the MCBS problem, we first prove that a special case of MCBS, where the probabilities of all trajectories are same (i.e., $q_k^j = \eta$ for $\forall j \in [1, n]$ and $k \in [1, l_j]$), is NP-hard. Since the constraint (3) can always be met, the special MCBS problem is actually to select a set of bids with least social cost to cover $\mathcal{S}$. Now, we introduce a well-known NP-hard problem, i.e., minimum weighted set cover (MWSC) problem. Given a set of elements $\mathcal{S} = \{s_1, \cdots, s_i, \cdots, s_m\}$ and the collection of some subsets $\Gamma = \{S^1, \cdots, S^j, \cdots, S^n\}$ in which $S^j \subseteq \mathcal{S}$ for $\forall j \in [1, n]$ and S^j has a weight c^j, find a least weight collection Φ of subsets from Γ such that Φ covers all elements in $\mathcal{S}$. By mapping S^j and c^j in MWSC to S_k^j and c_k^j in the special case of MCBS, respectively, we reduce the MWSC problem to the special MCBS problem in constant time. Obviously, the MWSC problem is actually equivalent to the special case of MCBS. Therefore, the special MCBS

problem is NP-hard. Further, the general MCBS problem is at least NP-hard and the theorem holds. ∎

Here, we emphasize that the MCBS problem is actually a non-trivial set cover problem. This is because the objective function of this problem is not an integer function. Furthermore, the constraint of this problem is a group of non-linear real functions. Owing to these two characteristics, the set cover approximation algorithms in [12], [15], [24], [42] cannot be utilized directly to solve the MCBS problem.

3.2 Winning-Bid Selection Algorithm

Since the MCBS problem is NP-hard, we propose a winning-bid selection approximation algorithm to solve it. Here, we first *assume that all vehicles report their costs truthfully, i.e.,* $b_k^j = c_k^j$. We will prove that this truthful assumption is reasonable and correct in the next section.

The approximation algorithm is based on a utility function and the marginal contributions of all bids in Γ. The *utility function* $U(\Phi)$ is the sum of the probabilities that all tasks in $\mathcal{S}$ are successfully performed with when selecting all bids in Φ, defined as follows:

$$U(\Phi) \triangleq \sum_{i=1}^{m} \min\{\rho_i^\Phi, \eta\}. \tag{4}$$

The *marginal contribution function* of a bid $\beta_k^j \in \Gamma - \Phi$ is the increased utility after adding β_k^j into Φ, defined as follows:

$$U_{\beta_k^j}(\Phi) \triangleq U(\Phi \cup \{\beta_k^j\}) - U(\Phi)$$

$$= \sum_{s_i \in S_k^j} (\min\{\rho_i^{\Phi \cup \{\beta_k^j\}}, \eta\} - \min\{\rho_i^\Phi, \eta\}). \tag{5}$$

The approximation algorithm mainly contains an iterative bid selection process. In each round of iteration, we greedily select the bid whose Marginal contribution Per Cost (MPC) is the maximal to expand the winning set until the utility of the whole winning set reaches the maximum value. The detailed algorithm is presented in Algorithm 1. At the beginning, the winning-bid set Φ is initialized as $\varnothing$ in Step 1. From Step 2 to Step 7, the greedy strategy, based on the utility function and the marginal contribution function, is adopted to select the winning bids in Step 3.

Here, we point out that although the basic formalism of our algorithm looks similar to the traditional set cover approximation algorithms (e.g., [15], [24]), our algorithm is intrinsically different from them. In general, the greedy criterion of the traditional algorithms is directly the value of the optimization objective defined in the problem. In contrast, our greedy criterion is the special utility function that we build for MCBS. This utility function not only contains the optimization objective of the MCBS problem, but also takes the non-linear constraint (3) into consideration. Furthermore, unlike existing algorithms that only deal with the integer set cover problems, our algorithm can solve the set cover problem with a real optimization objective function, such as MCBS.

The correctness of Algorithm 1 is supported by the following theorem.

Theorem 2. Algorithm 1 can always produce a feasible solution if MCBS is solvable.

Proof: If MCBS is solvable, selecting all bids in Γ will meet the constraints of MCBS. That is to say, Γ is at least a

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Algorithm 1 Winning-Bid Selection Algorithm

Input:　$\Gamma, m, \eta, \{q_k^j | S_k^j \in \Gamma\}$ before $\mathcal{D}$
Output: winning bid set Φ,　social cost $C(\Phi)$
1: $\Phi \leftarrow \varnothing, U(\Phi) \leftarrow 0, C(\Phi) \leftarrow 0$
2: **while** $U(\Phi) < m\eta$ **do**
3: 　　Select a bid β_k^j from $\Gamma - \Phi$ to maximize $\dfrac{U_{\beta_k^j}(\Phi)}{b_k^j}$
4: 　　$U(\Phi) \leftarrow U(\Phi) + U_{\beta_k^j}(\Phi)$
5: 　　$\Phi \leftarrow \Phi \cup \{\beta_k^j\}$
6: 　　$C(\Phi) \leftarrow C(\Phi) + b_k^j$
7: **return**　$\Phi, C(\Phi)$

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feasible solution, i.e., $\rho_i^\Gamma \geq \eta$ for $\forall s_i \in \mathcal{S}$, and $U(\Gamma) = m\eta$. Hence, Algorithm 1 will terminate for sure, either before or when all bids in Γ are added into Φ. When Algorithm 1 terminates, $U(\Phi) = m\eta$, indicating that $\min\{\rho_i^\Phi, \eta\} = \eta$ for $\forall s_i \in \mathcal{S}$. Then, $\rho_i^\Phi \geq \eta$ for $\forall s_i \in \mathcal{S}$, meeting the constraint (3). Therefore, Algorithm 1 produces a feasible solution for MCBS after it terminates, and the theorem holds. ∎

3.3 Payment Determination Algorithm

Besides the MCBS problem, the incentive mechanism also needs to solve the payment determination problem, i.e., it must decide how much to pay for each bid that is selected by Algorithm 1 while ensuring that the mechanism is truthful and individually rational.

To guarantee the truthfulness of the mechanism, the payment p_k^j for a winning bid β_k^j should depend on other bids in Γ instead of β_k^j itself. Therefore we first remove β_k^j from Γ to get a new bid set, denoted by $\Gamma_{-\beta_k^j}$. Based on $\Gamma_{-\beta_k^j}$, we re-select a new winning-bid set that is denoted by Φ'. Assume that in the q-th round of iteration of this new selection, Φ_q' is the winning set, and the winning bid $\beta_{k'}^{j'} \in \Phi_q'$. If β_k^j wants to win in the q-th round, the related cost must be no more than the value $b_{k'}^{j'} \cdot U_{\beta_k^j}(\Phi_{q-1}') / U_{\beta_{k'}^{j'}}(\Phi_{q-1}')$. Otherwise, the MPC of β_k^j will not be the maximal. We therefore determine p_k^j based on this critical value. To guarantee the individual rationality, the payment p_k^j must be no less than the real cost c_k^j. Hence, we set p_k^j as the maximum critical value:

$$p_k^j = \max\{\frac{U_{\beta_k^j}(\Phi_{q-1}')}{U_{\beta_{k'}^{j'}}(\Phi_{q-1}')} \cdot b_{k'}^{j'} | q = 1, 2, ...\}. \tag{6}$$

The detailed process is presented in Algorithm 2. The algorithm traverses all bids in Γ to decide the payment for each bid in Step 1. In Step 2, we initialize the payment p_k^j for β_k^j as 0 and the new winning set Φ' as $\varnothing$. If β_k^j is a winning bid in Step 3, we expand Φ' according to the greedy strategy that is also used in Algorithm 1, and we set the payment as the maximal critical value in Steps 4-9. Note that we use an equivalent expression instead of (6) in Step 8.

3.4 A Walk-Through Example

To better understand the two algorithms in our incentive mechanism, we use an example in Fig. 3 to show the processes of Algorithm 1 and Algorithm 2. In the example, $m = 4$, $\eta = 0.6$, $m\eta = 2.4$, $q_1^1 = 0.35$, $q_2^1 = 0.4$, $q_1^2 = 0.4$, $q_2^2 = 0.45$, $q_1^3 = 0.5$, and Γ is marked in Fig. 3. Algorithm 1 is conducted as follows:

Algorithm 2 Payment Determination Algorithm

Input: $\Gamma, \Phi, m, \eta, \{q_k^j | S_k^j \in \Gamma\}$ before $\mathcal{D}$

Output: the payment p_k^j for $\forall j \in [1, n]$ and $\forall k \in [1, l_j]$

1: **for all** $\beta_k^j \in \Gamma$ **do**
2:     $\Phi' \leftarrow \varnothing, p_k^j \leftarrow 0$
3:     **if** $\beta_k^j \in \Phi$ **then**
4:        **while** $U(\Phi') < m\eta$ **do**
5:           Select $\beta_{k'}^{j'}$ from $\Gamma_{-\beta_k^j} - \Phi'$ to maximize $\frac{U_{\beta_{k'}^{j'}}(\Phi')}{b_{k'}^{j'}}$
6:           $U(\Phi') \leftarrow U(\Phi') + U_{\beta_{k'}^{j'}}(\Phi')$
7:           $\Phi' \leftarrow \Phi' \cup \{\beta_{k'}^{j'}\}$
8:           $p_k^j \leftarrow \max\{p_k^j, \frac{U_{\beta_k^j}(\Phi')}{U_{\beta_{k'}^{j'}}(\Phi')} \cdot b_{k'}^{j'}\}$
9: **return** p_k^j for $\forall j \in [1, n]$ and $\forall k \in [1, l_j]$

- First round: $\Phi = \varnothing, U(\Phi) = 0, C(\Phi) = 0$.
- Second round: Due to $U(\Phi) = 0 < 2.4$, we compute $\frac{U_{\beta_1^1}(\Phi)}{b_1^1} = 0.26$, $\frac{U_{\beta_2^1}(\Phi)}{b_2^1} = 0.27$, $\frac{U_{\beta_1^2}(\Phi)}{b_1^2} = 0.4$, $\frac{U_{\beta_2^2}(\Phi)}{b_2^2} = 0.34$, $\frac{U_{\beta_1^3}(\Phi)}{b_1^3} = 0.5$. Since $\frac{U_{\beta_1^3}(\Phi)}{b_1^3}$ is the maximal, we update $\Phi = \{\beta_1^3\}, U(\Phi) = 1.5, C(\Phi) = 3$.
- Third round: Since $U(\Phi) = 1.5 < 2.4$, we continue to compute $\frac{U_{\beta_1^1}(\Phi)}{b_1^1} = 0.14$, $\frac{U_{\beta_2^1}(\Phi)}{b_2^1} = 0.07$, $\frac{U_{\beta_1^2}(\Phi)}{b_1^2} = 0.2$, $\frac{U_{\beta_2^2}(\Phi)}{b_2^2} = 0.16$. As $\frac{U_{\beta_2^2}(\Phi)}{b_1^2}$ is the maximal, we update $\Phi = \{\beta_1^3, \beta_1^2\}, U(\Phi) = 2.1, C(\Phi) = 6$.
- Fourth round: Owing to $U(\Phi) = 2.1 < 2.4$, we compute $\frac{U_{\beta_1^1}(\Phi)}{b_1^1} = 0.08$, $\frac{U_{\beta_2^1}(\Phi)}{b_2^1} = 0.03$, $\frac{U_{\beta_2^2}(\Phi)}{b_2^2} = 0.08$. WLOG, we select β_1^1 as the winner and update $\Phi = \{\beta_1^3, \beta_1^2, \beta_1^1\}, U(\Phi) = 2.4, C(\Phi) = 10$. Now $U(\Phi) = m\eta$ and Algorithm 1 terminates.

The above calculation shows that the set of winning bids is $\Phi = \{\beta_1^3, \beta_1^2, \beta_1^1\}$. Based on this result, Algorithm 2 is conducted as follows:

- First round: Since β_1^1 is a winning bid, $\Gamma_{-\beta_1^1} = \{\beta_2^1, \beta_1^2, \beta_2^2, \beta_1^3\}$. In the rounds of iteration from Step 4 to Step 9, the selected bids are $\beta_1^3, \beta_1^2, \beta_2^2$, in turn. Accordingly, $\frac{U_{\beta_1^1}(\varnothing)}{U_{\beta_1^3}(\varnothing)} \cdot b_1^3 = 2.1$, $\frac{U_{\beta_1^1}(\{\beta_1^3\})}{U_{\beta_1^2}(\{\beta_1^3\})} \cdot b_1^2 = 2.75$, $\frac{U_{\beta_1^1}(\{\beta_1^3, \beta_1^2\})}{U_{\beta_2^2}(\{\beta_1^3, \beta_1^2\})} \cdot b_2^2 = 4$. Hence, $p_1^1 = 4$.
- Second round: $p_2^1 = 0$, as $\beta_2^1 \notin \Phi$.
- Third round: Since $\beta_1^2 \in \Phi$, $\Gamma_{-\beta_1^2} = \{\beta_1^1, \beta_2^1, \beta_2^2, \beta_1^3\}$. In the computations of Steps 4-9, the selected bids are $\beta_1^3, \beta_2^2, \beta_1^1$, in turn. Then $\frac{U_{\beta_1^2}(\varnothing)}{U_{\beta_1^3}(\varnothing)} \cdot b_1^3 = 2.4$, $\frac{U_{\beta_1^2}(\{\beta_1^3\})}{U_{\beta_2^2}(\{\beta_1^3\})} \cdot b_2^2 = 3.69$, $\frac{U_{\beta_1^2}(\{\beta_1^3, \beta_2^2\})}{U_{\beta_1^1}(\{\beta_1^3, \beta_2^2\})} \cdot b_1^1 = 4$. Hence, $p_1^2 = 4$.
- Fourth round: As β_2^2 is not a winning bid, $p_2^2 = 0$.
- Fifth round: Since β_1^3 is a winning bid, $\Gamma_{-\beta_1^3} = \{\beta_1^1, \beta_2^1, \beta_1^2, \beta_2^2\}$. In the rounds of iteration from Step 4 to Step 9, the selected bids are $\beta_1^2, \beta_2^2, \beta_1^1$, in turn. Accordingly, $\frac{U_{\beta_1^3}(\varnothing)}{U_{\beta_1^2}(\varnothing)} \cdot b_1^2 = 3.75$, $\frac{U_{\beta_1^3}(\{\beta_1^2\})}{U_{\beta_2^2}(\{\beta_1^2\})} \cdot b_2^2 = 4.24$, $\frac{U_{\beta_1^3}(\{\beta_1^2, \beta_2^2\})}{U_{\beta_1^1}(\{\beta_1^2, \beta_2^2\})} \cdot b_1^1 = 3$. Hence, $p_1^3 = 4.24$.

We can find that the payment for each winning bid is no less than the related cost. Then v_1 and v_2 will perform the tasks successfully and will send the sensing data back to the platform. Hence, the platform only pays for β_1^1 and β_1^2 (as shown in Fig. 4). In this example, since v_3 does not perform the tasks and send data back, it gets nothing.
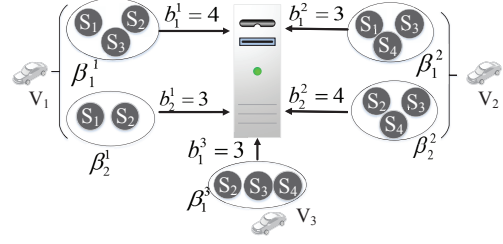

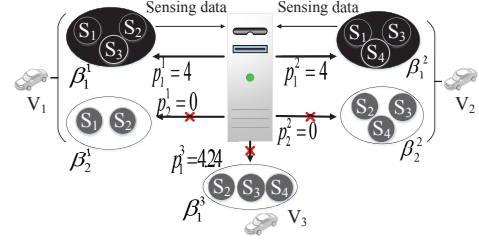Fig. 3. An example: v_1, v_2, v_3 send their bids to the platform.

Fig. 4. The result of the example: v_1 and v_2 perform their winning bids and get the payments after sending the sensing data back; v_3 gets nothing since it does not perform the tasks in the winning bid β_1^3.

4 QoD-AWARE INCENTIVE MECHANISM

In this section, we extend our problem to a case in which the Quality of Data (QoD) is taken into consideration. We first introduce the extended problem, where we integrate the constraint (3) and the QoD constraint. After that, we propose the QoD-aware incentive mechanism consisting of a winning-bid selection algorithm and a payment determination algorithm for the extended problem.

4.1 The Extended Problem

In addition to the successful probability, the QoD is also a major factor that needs to be considered in mechanism design, as pointed out by [20] [21]. The QoD indicates the usability of the sensing data. It might be affected by various factors including poor sensor quality, noise, lack of sensor calibration, and so forth. We consider a general class of crowdsensing applications in which the availability and preciseness of services significantly depend on the QoD, e.g., noise pollution monitoring and air quality monitoring. In these cases, the qualities of the sensing data collected by vehicles are different, and the platform user requires that the total quality of the received data for each task be no less than a threshold. More specifically, we assume that the platform not only requires that the probability of each task being successfully performed be no less than η, but also that the QoD for task s_i be no less than ξ_i. Additionally, just like [21], we assume that the QoD profile of the vehicles, denoted by $\mathcal{R} = \{r_1, r_2, ..., r_n\}$, is known to the platform since the platform maintains a historical record of vehicles' QoD profile $\mathcal{R}$. $\mathcal{R}$ can be calculated from the ground truth data or by utilizing algorithms such as those proposed in [20], [43]–[45]. Thus, the platform will receive a request including $\mathcal{S}, \eta, \{\xi_1, \xi_2, ..., \xi_m\}$ from the user.

Algorithm 3 QoD-Aware Winning-Bid Selection Algorithm

Input: $\Gamma, m, \eta, \mathcal{R}, \{\xi_1, \xi_2, ..., \xi_m\}, \{q_k^j | S_k^j \in \Gamma\}$ before $\mathcal{D}$
Output: winning bid set Φ, social cost $C(\Phi)$
1: $\Phi \leftarrow \varnothing, G(\Phi) \leftarrow 0, C(\Phi) \leftarrow 0$
2: **while** $G(\Phi) < m\eta + \sum_{i=1}^{m} \xi_i$ **do**
3:     Select a bid β_k^j from $\Gamma - \Phi$ to maximize $\frac{G_{\beta_k^j}(\Phi)}{b_k^j}$
4:     $G(\Phi) \leftarrow G(\Phi) + G_{\beta_k^j}(\Phi)$
5:     $\Phi \leftarrow \Phi \cup \{\beta_k^j\}$
6:     $C(\Phi) \leftarrow C(\Phi) + b_k^j$
7: **return** $\Phi, C(\Phi)$

To design a truthful incentive mechanism for this scenario, we need to solve both the winning-bid selection problem and the payment determination problem. In addition to the probability constraints, the winning-bid selection must also meet the QoD requirements. As vehicle $v_j \in \Phi$ performs each task in S_k^j with a probability of q_k^j, we can calculate the QoD expectation value μ_i^Φ of task s_i as follows:

$$\mu_i^\Phi = \sum_{\beta_k^j \in \Phi \wedge s_i \in S_k^j} (r_j q_k^j). \quad (7)$$

In fact, the definition of QoD expectation value μ_i^Φ is derived from the real-world example, e.g., crowd labeling [19], [34], where the sum of expectation values outputted by all winning vehicles denotes the final expected QoD. Then, we can formalize the QoD-MCBS problem as follows:

$$\min \quad C(\Phi) = \sum_{\beta_k^j \in \Phi} c_k^j \quad (8)$$

$$\text{s.t.} \quad \Phi \subseteq \Gamma \quad (9)$$

$$\rho_i^\Phi \geq \eta, \quad\quad\quad 1 \leq i \leq m \quad (10)$$

$$\mu_i^\Phi \geq \xi_i, \quad\quad\quad 1 \leq i \leq m \quad (11)$$

This QoD-MCBS problem can be simplified to MCBS when we let $r_j \geq \max\{\xi_1, \cdots, \xi_m\}$ for $\forall 1 \leq j \leq n$. Hence, QoD-MCBS is also NP-hard and an approximation algorithm is needed to solve this problem in polynomial time.

4.2 QoD-Aware Winning-Bid Selection Algorithm

To design an appropriate approximation algorithm, we first propose a QoD utility function and a QoD marginal contribution function. The QoD utility function $F(\Phi)$, which is the sum of the QoD for all tasks, is defined as follows:

$$F(\Phi) \triangleq \sum_{i=1}^{m} \min\{\mu_i^\Phi, \xi_i\}. \quad (12)$$

Based on $F(\Phi)$, the QoD marginal contribution of a bid $\beta_k^j \in \Gamma - \Phi$ is the increased QoD utility after adding β_k^j into Φ, defined as follows:

$$F_{\beta_k^j}(\Phi) \triangleq F(\Phi \cup \{\beta_k^j\}) - F(\Phi)$$
$$= \sum_{s_i \in S_k^j} (\min\{\mu_i^{\Phi \cup \{\beta_k^j\}}, \xi_i\} - \min\{\mu_i^\Phi, \xi_i\}). \quad (13)$$

To combine the constraints (10) and (11), we define the combination utility function $G(\Phi)$ as follows:

$$G(\Phi) = U(\Phi) + F(\Phi), \quad (14)$$

The corresponding combination marginal contribution is

$$G_{\beta_k^j}(\Phi) = U_{\beta_k^j}(\Phi) + F_{\beta_k^j}(\Phi). \quad (15)$$

Algorithm 4 QoD-aware Payment Determination Algorithm

Input: $\Gamma, \Phi, m, \eta, \mathcal{R}, \{\xi_1, \xi_2, ..., \xi_m\}, \{q_k^j | S_k^j \in \Gamma\}$ before $\mathcal{D}$
Output: the payment p_k^j for $\forall j \in [1, n]$ and $\forall k \in [1, l_j]$
1: **for all** $\beta_k^j \in \Gamma$ **do**
2:     $\Phi' \leftarrow \varnothing, p_k^j \leftarrow 0$
3:     **if** $\beta_k^j \in \Phi$ **then**
4:         **while** $G(\Phi') < m\eta + \sum_{i=1}^{m} \xi_i$ **do**
5:         Select $\beta_{k'}^{j'}$ from $\Gamma_{-\beta_k^j} - \Phi'$ to maximize $\frac{G_{\beta_{k'}^{j'}}(\Phi')}{b_{k'}^{j'}}$
6:         $G(\Phi') \leftarrow G(\Phi') + G_{\beta_{k'}^{j'}}(\Phi')$
7:         $\Phi' \leftarrow \Phi' \cup \{\beta_{k'}^{j'}\}$
8:         $p_k^j \leftarrow \max\{p_k^j, \frac{G_{\beta_k^j}(\Phi')}{G_{\beta_{k'}^{j'}}(\Phi')} \cdot b_{k'}^{j'}\}$
9: **return** p_k^j for $\forall j \in [1, n]$ and $\forall k \in [1, l_j]$

Based on the combination utility function and combination marginal contribution function, we propose the QoD-aware winning-bid selection algorithm in Algorithm 3. Similar to Algorithm 1, Algorithm 3 utilizes a greedy process in which the bid, whose combination MPC is the largest in each round of iteration, is added into the winning-bid set until the utility function achieves the maximum value $m\eta + \sum_{i=1}^{m} \xi_i$. We prove the correctness of Algorithm 3 in the following theorem.

Theorem 3. Algorithm 3 can always produce a feasible solution if QoD-MCBS is solvable.

Proof: Similar to Theorem 2, Γ is at least a feasible solution. Hence, Algorithm 3 will terminate for sure either before or after adding all bids in Γ into Φ. When it terminates, $G(\Phi) = U(\Phi) + F(\Phi) = m\eta + \sum_{i=1}^{m} \xi_i$. According to (4) and (12), $U(\Phi) \leq m\eta$ and $F(\Phi) \leq \sum_{i=1}^{m} \xi_i$. Hence, when Algorithm 3 terminates, $U(\Phi) = m\eta$ and $F(\Phi) = \sum_{i=1}^{m} \xi_i$, i.e. $\rho_i^\Phi \geq \eta$ and $\mu_i^\Phi \geq \xi_i$ for $\forall s_i \in \mathcal{S}$. The theorem holds. ∎

4.3 QoD-Aware Payment Determination Algorithm

To attract more vehicles and prevent them from manipulating the claimed costs, we need to decide a proper payment for each bid that is selected by Algorithm 3.

Actually, the idea of QoD-aware payment determination is similar to the basic payment determination in Section 3.3. We set the payment for each winning bid as the maximum critical value, i.e.,

$$p_k^j = \max\{\frac{G_{\beta_k^j}(\Phi'_{q-1})}{G_{\beta_{k'}^{j'}}(\Phi'_{q-1})} \cdot b_{k'}^{j'} | q = 1, 2, ...\}, \quad (16)$$

where the implications of the notations are the same as (6).

The detailed computation is presented in Algorithm 4. The algorithm first checks whether a bid β_k^j is winning in Step 3 and then recalculates the winning set when β_k^j is excluded from Γ from Steps 4-9. For the winning bids, the payments are the maximal critical values. For the losing bids, the payments are exactly 0.

5 MECHANISM ANALYSIS

In this section, we prove that both the basic and QoD-aware incentive mechanisms have the properties of truthfulness, individual rationality and computational efficiency. We also analyze the approximation ratios of Algorithm 1 and Algorithm 3. In each subsection, we first analyze the

property of the basic incentive mechanism and then analyze the QoD-aware incentive mechanism based on the related property of the basic incentive mechanism.

WLOG, we consider the q-th round of iteration in Algorithm 1. In this round, β_k^j is the winning bid and is added into the winning set Φ_q (a winning subset of Γ). Moreover, we also consider the q-th round of iteration for the payment computation of β_k^j in Algorithm 2 (See Steps 4-9), in which the winning set is denoted as Φ_q' (a winning subset of $\Gamma_{-\beta_k^j}$). Then, we prove the truthfulness and individual rationality properties as follows.

5.1 Truthfulness

To prove the truthfulness of the mechanisms, we first give a lemma on the winning set.

Lemma 1. $\Phi_t = \Phi_t'$, for $\forall t \in [0, q-1]$.

Proof: Note that Φ_t and Φ_t' are the winning sets selected from Γ and $\Gamma_{-\beta_k^j}$ respectively through the same greedy strategy. Since β_k^j is the winner of the q-th round, it must have not been selected as a winning bid before the q-th round. Therefore, although $\Gamma = \Gamma_{-\beta_k^j} \cup \{\beta_k^j\}$, the winning bids selected from Γ and $\Gamma_{-\beta_k^j}$ before the q-th round are the same. Hence, the lemma holds. ∎

Second, we prove that our mechanisms are bid-monotonic and payment-critical, which implies that the incentive mechanisms are truthful.

Lemma 2. Algorithm 1 is bid-monotonic.

Proof: Since β_k^j wins in the q-th round of iteration of Algorithm 1, the MPC of β_k^j, i.e., $U_{\beta_k^j}(\Phi_{q-1})/b_k^j$, is the maximal in this round, and it is no more than the MPC values of all bids in Φ_{q-1}. Assume that β_k^j reports a smaller cost $\hat{b}_k^j$ ($< b_k^j$). As $U_{\beta_k^j}(\Phi_{q-1})/b_k^j < U_{\beta_k^j}(\Phi_{q-1})/\hat{b}_k^j$, β_k^j still wins in or even before the q-th round according to the greedy selection rule in Algorithm 1. Lemma 2 holds. ∎

Lemma 3. The payments determined by Algorithm 2 for all winning bids are critical.

Proof: Assume that the winning bid β_k^j reports a cost $\hat{b}_k^j$ instead of b_k^j. To prove the criticality of the payment p_k^j, we need to prove that β_k^j will fail if $\hat{b}_k^j > p_k^j$, and that it will win if $\hat{b}_k^j \leq p_k^j$.

Case 1: $\hat{b}_k^j > p_k^j$. We consider the q-th round of iteration in Algorithm 1 and derive that

$$\frac{U_{\beta_k^j}(\Phi_{q-1})}{\hat{b}_k^j} = \frac{U_{\beta_k^j}(\Phi_{q-1}')}{\hat{b}_k^j} < \frac{U_{\beta_k^j}(\Phi_{q-1}')}{p_k^j} \leq \frac{U_{\beta_K^J}(\Phi_{q-1}')}{b_K^J}, \quad (17)$$

where β_K^J is a winning bid, so that $\Phi_q' = \Phi_{q-1}' \cup \{\beta_K^J\}$. In (17), the first equality depends on $\Phi_{q-1} = \Phi_{q-1}'$ in Lemma 1 and the last inequality depends on $p_k^j \geq b_K^J \cdot U_{\beta_k^j}(\Phi_{q-1}')/U_{\beta_K^J}(\Phi_{q-1}')$ according to (6). Hence, β_K^J is selected as the winner instead of β_k^j in the q-th round of iteration. Moreover, $\Phi_q = \Phi_{q-1} \cup \{\beta_K^J\} = \Phi_q'$. Repeating the above analysis, we can see that β_k^j will fail in all rounds of iteration of Algorithm 1.

Case 2: $\hat{b}_k^j \leq p_k^j$. WLOG, assume that Algorithm 1 runs when the input bid set is $\Gamma_{-\beta_k^j}$, which is exactly the process of computing the payment for β_k^j. According to (6), we

assume that $p_k^j = b_K^J \cdot U_{\beta_k^j}(\Phi_{q'-1})/U_{\beta_K^J}(\Phi_{q'-1})$, where β_K^J is the winner in the q'-th round of iteration of this process. Now, we run Algorithm 1 again with the input bid set Γ. We discuss two subcases of this new process: 1) β_k^j wins before the q'-th round; 2) β_k^j does not win before the q'-th round. In the q'-th round of iteration,

$$\frac{U_{\beta_k^j}(\Phi_{q'-1})}{\hat{b}_k^j} \geq \frac{U_{\beta_k^j}(\Phi_{q'-1})}{p_k^j} \geq \frac{U_{\beta_K^J}(\Phi_{q'-1})}{b_K^J}. \quad (18)$$

Therefore, β_k^j wins in this round. Synthesizing both subcases, β_k^j wins when $\hat{b}_k^j \leq p_k^j$.

In conclusion, the payments for all winning bids are critical, and the lemma holds. ∎

Theorem 4. Our basic incentive mechanism consisting of Algorithm 1 and Algorithm 2 is truthful.

Proof: According to Myerson's theorem [41], our incentive mechanism is truthful since the winning-bid selection rule is monotone (i.e., Lemma 2) and each winning bid is paid with a critical value (i.e., Lemma 3). ∎

Theorem 5. Our QoD-aware incentive mechanism consisting of Algorithm 3 and Algorithm 4 is truthful.

Proof: Despite of the utility function and the termination threshold, the winning-bid selection methods in Algorithm 1 and Algorithm 3 are the same. Hence, Algorithm 3 is also bid-monotonic according to Lemma 2. The payment determination criteria and methods are also the same in Algorithm 2 and Algorithm 4. Thus the payments determined by Algorithm 4 for all winning bids are also critical according to Lemma 3. Then, based on Myerson's theorem [41], our QoD-aware incentive mechanism is also truthful.∎

5.2 Individual Rationality

In this subsection, we prove the individual rationality of the incentive mechanisms and have the following theorems:

Theorem 6. Our basic incentive mechanism consisting of Algorithm 1 and Algorithm 2 is individually rational.

Proof: We assume that β_K^J wins in the q-th round of iteration of the inner loop (Steps 4-9) in Algorithm 2. Since β_k^j is the winner in the q-th round of Algorithm 1,

$$\frac{U_{\beta_K^J}(\Phi_{q-1})}{b_K^J} \leq \frac{U_{\beta_k^j}(\Phi_{q-1})}{b_k^j}. \quad (19)$$

According to (6) and Lemma 1,

$$b_k^j \leq \frac{U_{\beta_k^j}(\Phi_{q-1})}{U_{\beta_K^J}(\Phi_{q-1})} \cdot b_K^J = \frac{U_{\beta_k^j}(\Phi_{q-1}')}{U_{\beta_K^J}(\Phi_{q-1}')} \cdot b_K^J \leq p_k^j. \quad (20)$$

As each vehicle reports its real cost in the truthful incentive mechanism, we get $c_k^j = b_k^j$. Hence, $p_k^j \geq c_k^j$, indicating that the payoff of β_k^j is non-negative. The theorem holds. ∎

Theorem 7. Our QoD-aware incentive mechanism consisting of Algorithm 3 and Algorithm 4 is individually rational.

Proof: Since the payment for each winning bid determined by Algorithm 4 is the maximum critical value in (16), the QoD-aware incentive mechanism is also individually rational according to Theorem 6. The theorem holds. ∎

5.3 Computational Efficiency

We prove the computational efficiency of the two mechanisms in the following theorem.

Theorem 8. The basic and QoD-aware incentive mechanisms have a polynomial-time computational complexity.

Proof: 1) The basic incentive mechanism is composed of Algorithms 1 and 2. The computation overhead of Algorithm 1 is dominated by Step 3, which can be denoted by $O(|S_k^j||\Gamma|)$. Since Algorithm 1 loops at most $|\Gamma|$ times, its computational complexity is denoted by $O(|S_k^j||\Gamma|^2)$. Actually, since $|S_k^j|$ is much smaller than $|\Gamma|$, the computational complexity of Algorithm 1 can be deemed as $O(|\Gamma|^2)$ for simplicity. For Algorithm 2, since the outer loop (Step 1) runs $|\Gamma|$ times and the complexity of the inner loop (Steps 4-9) is $O(|\Gamma|^2)$, the complexity of Algorithm 2 is $O(|\Gamma|^3)$.

2) The QoD-aware incentive mechanism consists of Algorithms 3 and 4. The computational complexity of Algorithm 3 is the same as that of Algorithm 1, i.e., $O(|\Gamma|^2)$. Meanwhile, similar to Algorithm 2, the computational complexity of Algorithm 4 is denoted as $O(|\Gamma|^3)$.

Therefore, the theorem holds. ∎

5.4 Approximation Ratio Analysis

In this subsection, we first analyze the approximation ratio of Algorithm 1, followed by Algorithm 3.

5.4.1 Approximation Ratio of Algorithm 1

To figure out the approximation ratio of Algorithm 1, we first analyze the properties of the utility function $U(\Phi)$ and the optimization objective function $C(\Phi)$. For simplicity of description, we define two notations:
$$\pi(i|\Phi) \triangleq \prod_{\beta_k^j \in \Phi \wedge s_i \in S_k^j}(1 - q_k^j),$$
$$U(i|\Phi) \triangleq \min\{\rho_i^\Phi, \eta\}.$$
In addition, we consider two arbitrary bid sets, Φ_1 and Φ_2, $\Phi_1 \subseteq \Phi_2 \subseteq \Gamma$ and a bid $\beta_k^j \in (\Gamma - \Phi_2)$. Then, we have:

Lemma 4. $U(\Phi)$ is an increasing function.

Proof: According to the decreasing property of $\pi(i|\Phi)$, ρ_i^Φ is increasing. Therefore, $\rho_i^{\Phi_1} \leq \rho_i^{\Phi_2}$ and $U(i|\Phi_1) \leq U(i|\Phi_2)$ for $\forall s_i \in \mathcal{S}$. Then $U(\Phi_1) \leq U(\Phi_2)$ when $\Phi_1 \subseteq \Phi_2$, which implies that $U(\Phi)$ is increasing. ∎

Lemma 5. $U(\Phi)$ is submodular.

Proof: WLOG, we assume that for two arbitrary bid sets X and Y, $X \subseteq \Gamma$ and $Y \subseteq \Gamma$. For $\forall s_i \in \mathcal{S}$, we have the following conclusions:

1) $\pi(i|X \cup Y) \leq \pi(i|X), \pi(i|Y) \leq \pi(i|X \cap Y) \leq 1$;
2) $\rho_i^{X \cap Y} \leq \rho_i^X, \rho_i^Y \leq \rho_i^{X \cup Y} \leq 1$.

Based on these, we can get that:
$$\rho_i^X + \rho_i^Y - (\rho_i^{X \cup Y} + \rho_i^{X \cap Y})$$
$$= \pi(i|X \cup Y) + \pi(i|X \cap Y) - (\pi(i|X) + \pi(i|Y))$$
$$= \pi(i|X \cap Y)(1 - \pi(i|X - Y))(1 - \pi(i|Y - X)) \geq 0.$$
Hence,
$$\rho_i^X + \rho_i^Y \geq \rho_i^{X \cup Y} + \rho_i^{X \cap Y}. \qquad (21)$$

Now to prove that $U(\Phi)$ is submodular, we consider the relationships between $\rho_i^{X \cup Y}$, ρ_i^X, ρ_i^Y, $\rho_i^{X \cap Y}$, and η, which can be divided into the following four cases:

Case 1: $\rho_i^{X \cup Y} \leq \eta$. Then,
$$U(i|X) + U(i|Y) - U(i|X \cup Y) - U(i|X \cap Y)$$
$$= \rho_i^X + \rho_i^Y - (\rho_i^{X \cup Y} + \rho_i^{X \cap Y}) \geq 0.$$
Consequently,
$$U(i|X) + U(i|Y) \geq U(i|X \cup Y) + U(i|X \cap Y) \qquad (22)$$
when $\rho_i^{X \cup Y} \leq \eta$.

Case 2: $\rho_i^{X \cup Y} > \eta$ while $\rho_i^X, \rho_i^Y \leq \eta$. Then
$$U(i|X) + U(i|Y) - U(i|X \cup Y) - U(i|X \cap Y)$$
$$> \rho_i^X + \rho_i^Y - (\rho_i^{X \cup Y} + \rho_i^{X \cap Y}) \geq 0.$$
Hence, (22) also holds in this case.

Case 3: $\rho_i^X > \eta$ or $\rho_i^Y > \eta$ while $\rho_i^{X \cap Y} \leq \eta$. Consider ρ_i^X and ρ_i^Y:

1) If one of them is larger than η, (22) holds because both ρ_i^X and ρ_i^Y are no less than $\rho_i^{X \cap Y}$;
2) If they are both larger than η, (22) is still correct because $\rho_i^{X \cap Y} \leq \eta$.

Therefore, (22) is true in this case.

Case 4: $\rho_i^{X \cap Y} > \eta$. Now $U(i|X) + U(i|Y) - U(i|X \cup Y) - U(i|X \cap Y) = 0$, and (22) is valid.

In summary, (22) is valid in all cases. Hence, according to the above analysis and the fact that $U(\Phi) = \sum_{i=1}^m U(i|\Phi)$,
$$U(X) + U(Y) \geq U(X \cup Y) + U(X \cap Y),$$
which indicates that $U(\Phi)$ is submodular. ∎

Theorem 9. $U(\Phi)$ is a polymatriod function on 2^Γ.

Proof: We have that $U(\Phi) = 0$ when $\Phi = \varnothing$. According to Lemma 4 and Lemma 5, the theorem holds. ∎

Theorem 10. $C(\Phi)$ is a polymatroid function on 2^Γ.

Proof: According to $C(\Phi) = \sum_{\beta_k^j \in \Phi} c_k^j$, $C(\Phi)$ is an increasing function with $C(\varnothing) = 0$. As $C(\Phi_1 \cup \{\beta_k^j\}) - C(\Phi_1) = c_k^j \geq C(\Phi_2 \cup \{\beta_k^j\}) - C(\Phi_2)$, we have that $C(\Phi)$ is submodular. Therefore, $C(\Phi)$ is a polymatroid function on 2^Γ. ∎

Suppose ϕ is the winning bid set after Algorithm 1 terminates in the Q-th round of iteration. Let $\theta_1 = \min\{\frac{U_{\beta_q}(\Phi_{q-1})}{b_q}|q = 1, 2, 3, ...Q\}$, where β_q is the winning bid in the q-th round, $\theta_2 = \frac{C(\phi)}{m\eta}$, and $\theta = \max\{\frac{1}{\theta_1}, \theta_2\}$. Utilizing θ, we derive a new utility function, $U'(\Phi) = \theta U(\Phi)$, and the new marginal contribution of $\beta_k^j \notin \Phi$, $U'_{\beta_k^j}(\Phi) = \theta U_{\beta_k^j}(\Phi)$. Moreover, we derive the following theorems:

Theorem 11. $U'(\Phi)$ is a polymatroid function on 2^Γ.

Proof: According to Theorem 9 and the fact that θ is a constant, the theorem holds. ∎

Theorem 12. The MCBS problem can be equivalently reformalized as:
$$\min\{C(\Phi)|U'(\Phi) = U'(\Gamma), \Phi \subseteq \Gamma\} \qquad (23)$$

Proof: On one hand, the constraint (3) are met when $U(\Phi) = m\eta$ ($U'(\Phi) = \theta m\eta$) according to Theorem 2. On the other hand, for $\forall s_i \in \mathcal{S}$, $\min\{\rho_i^\Phi, \eta\} = \eta$, and $U'(\Phi) = \theta m\eta$, if $\rho_i^\Phi \geq \eta$, i.e., (3). That is to say, $U'(\Phi) = \theta m\eta$ is equivalent to the constraint (3), and we can replace (3) with $U'(\Phi) = \theta m\eta$. Since $U'(\Gamma) = \theta m\eta$, we can equivalently replace (3) with $U'(\Phi) = U'(\Gamma)$. The theorem holds. ∎

According to Theorems 10-12, the MCBS problem can be deemed as a minimum submodular cover with submodular cost problem [46]. Additionally, we can derive a new greedy algorithm that shares the same solution as Algorithm 1 by replacing $U(\Phi)$, $U_{\beta_k^j}(\Phi)$, and $m\eta$ in Algorithm 1 with $U'(\Phi)$, $U'_{\beta_k^j}(\Phi)$, and $\theta m\eta$, respectively. The derived algorithm also greedily selects the bid β_k^j, whose MPC, i.e., $U'_{\beta_k^j}(\Phi)/b_k^j$, is the maximal in each round of iteration. Then we can analyze the approximation ratio of the derived algorithm based on the theorem in [46]:

Theorem 13. If in each iteration of a greedy algorithm, the selected bid β_k^j always satisfies that $U'_{\beta_k^j}(\Phi)/b_k^j \geq 1$, then the greedy solution is a $(1 + \ln(\frac{U'(\Gamma)}{opt}))$-approximation, where U' is a polymatroid function on 2^Γ, opt is the cost of a minimum submodular cover, and $U'(\Phi) \geq opt$. ∎

Theorem 14. The derived algorithm achieves the $(1 + \ln\frac{\theta m\eta}{opt})$-approximation of the optimal social cost, where opt is the cost of the optimal solution to MCBS.

Proof: Note that $U'(\Gamma) = \theta U(\Gamma) = \theta m\eta$. Consequently, $U'(\Gamma) \geq m\eta\theta_2 = C(\phi) \geq opt$. Additionally, $U'_{\beta_k^j}(\Phi)/b_k^j \geq U_{\beta_k^j}(\Phi)/(\theta_1 \cdot b_k^j) \geq 1$ for $\forall \beta_k^j \in \Phi$ according to the definition of θ_1. Hence, the approximation ratio of the derived algorithm is $(1 + \ln\frac{\theta m\eta}{opt})$ based on Theorems 10-13. ∎

Theorem 15. Algorithm 1 achieves the $(1 + \ln\frac{\theta m\eta}{opt})$-approximation of the optimal social cost, where opt is the cost of the optimal solution to the MCBS problem.

Proof: Since the derived algorithm shares the same solution with Algorithm 1, Algorithm 1 approximates the optimal solution of MCBS within a factor of $(1 + \ln\frac{\theta m\eta}{opt})$ according to Theorem 14. ∎

5.4.2 Approximation Ratio of Algorithm 3

After getting the approximation ratio of Algorithm 1, we analyze Algorithm 3. We also define a notation:
$$F(i|\Phi) \triangleq \min\{\mu_i^\Phi, \xi_i\}.$$
Consider two arbitrary bid sets, Φ_1 and Φ_2, $\Phi_1 \subseteq \Phi_2 \subseteq \Gamma$, and a bid $\beta_k^j \in (\Gamma - \Phi_2)$. Then, we have:

Lemma 6. $F(\Phi)$ is an increasing function.

Proof: Considering the definition in (7), we get $\mu_i^{\Phi_1} \leq \mu_i^{\Phi_2}$ and $F(i|\Phi_1) \leq F(i|\Phi_2)$ for $\forall s_i \in \mathcal{S}$. Then, $F(\Phi_1) \leq F(\Phi_2)$ when $\Phi_1 \subseteq \Phi_2$, which implies that $F(\Phi)$ is increasing. ∎

Lemma 7. $F(\Phi)$ is a submodular function.

Proof: WLOG, we assume that for two arbitrary bid sets X and Y, $X \subseteq \Gamma$, and $Y \subseteq \Gamma$. For $\forall s_i \in \mathcal{S}$, we have the following conclusions:

1) $\mu_i^{X \cap Y} \leq \mu_i^X, \mu_i^Y \leq \mu_i^{X \cup Y}$;
2) $\mu_i^X + \mu_i^Y = \mu_i^{X \cup Y} + \mu_i^{X \cap Y}$.

Similar to the proof of Lemma 5, we have that $F(i|X) + F(i|Y) \geq F(i|X \cup Y) + F(i|X \cap Y)$ is valid in the following four cases:

1) $\mu_i^{X \cup Y} \leq \xi_i$;
2) $\mu_i^{X \cup Y} > \xi_i$ while $\mu_i^X, \mu_i^Y \leq \xi_i$;
3) $\mu_i^X > \xi_i$ or $\mu_i^Y > \xi_i$ while $\mu_i^{X \cap Y} \leq \xi_i$;
4) $\mu_i^{X \cap Y} > \xi_i$.

Hence, $F(X) + F(Y) \geq F(X \cup Y) + F(X \cap Y)$, and the theorem holds. ∎

Lemma 8. $G(\Phi)$ is a polymatroid function on 2^Γ.

Proof: Since both $F(\Phi)$ and $U(\Phi)$ are submodular based on Lemma 5 and Lemma 7, $G(\Phi)$ is submodular according to (14). Meanwhile, $G(\Phi)$ is also an increasing function because of the increasing property of $F(\Phi)$ and $U(\Phi)$. As $G(\varnothing) = 0$, the theorem holds. ∎

Suppose ϕ is the winning bid set after Algorithm 3 terminates in the Q-th round of iteration. Let $\alpha_1 = \min\{\frac{G_{\beta_q}(\Phi_{q-1})}{b_q} | q = 1, 2, 3, ... Q\}$, where β_q is the winning bid in the q-th round, $\alpha_2 = \frac{C(\phi)}{m\eta + \sum_{i=1}^m \xi_i}$, and $\alpha = \max\{\frac{1}{\alpha_1}, \alpha_2\}$. Utilizing α, we derive a new utility function, $G'(\Phi) = \alpha G(\Phi)$, and a new marginal contribution of $\beta_k^j \notin \Phi$, $G'_{\beta_k^j}(\Phi) = \alpha G_{\beta_k^j}(\Phi)$. Similar to the proofs in Section 5.4.1, we can have the following two theorems:

Theorem 16. $G'(\Phi)$ is a polymatroid function on 2^Γ.

Proof: According to Lemma 8 and the formula $G'(\Phi) = \alpha G(\Phi)$ in which α is a constant, the theorem holds. ∎

Theorem 17. The QoD-MCBS problem can be equivalently reformalized as:
$$\min\{C(\Phi)|G'(\Phi) = G'(\Gamma), \Phi \subseteq \Gamma\}.$$

Proof: The constraints (10) and (11) are simultaneously met when $U(\Phi) = m\eta$ and $F(\Phi) = \sum_{i=1}^m \xi_i$, that is, $G(\Phi) = m\eta + \sum_{i=1}^m \xi_i$ and $G'(\Phi) = \alpha(m\eta + \sum_{i=1}^m \xi_i)$. On the other hand, if $G'(\Phi) = \alpha(m\eta + \sum_{i=1}^m \xi_i)$, i.e., $U(\Phi) = m\eta$ and $F(\Phi) = \sum_{i=1}^m \xi_i$, for $\forall s_i \in \mathcal{S}$, we have $\rho_i^\Phi \geq \eta$ (10) and $\mu_i^\Phi \geq \xi_i$ (11). This indicates that $G'(\Phi) = \alpha(m\eta + \sum_{i=1}^m \xi_i)$ is equivalent to the constraints (10) and (11). Based on $G'(\Gamma) = \alpha(m\eta + \sum_{i=1}^m \xi_i)$, we can equivalently replace (10) and (11) with $G'(\Phi) = G'(\Gamma)$. The theorem holds. ∎

Based on Theorems 10, 16, and 17, QoD-MCBS can also be deemed a minimum submodular cover with submodular cost problem [46]. Similar to Section 5.4.1, when replacing $G(\Phi)$, $G_{\beta_k^j}(\Phi)$, and $m\eta + \sum_{i=1}^m \xi_i$ in Algorithm 3 with $G'(\Phi)$, $G'_{\beta_k^j}(\Phi)$, and $\alpha(m\eta + \sum_{i=1}^m \xi_i)$ respectively, we can get a new algorithm which shares the same solution with Algorithm 3 and has the approximation ratio of $(1 + \ln\frac{\alpha(m\eta + \sum_{i=1}^m \xi_i)}{opt})$ where opt is the cost of the optimal solution to the QoD-MCBS problem. Then, we have another theorem:

Theorem 18. Algorithm 3 achieves the $(1 + \ln\frac{\alpha(m\eta + \sum_{i=1}^m \xi_i)}{opt})$-approximation of the optimal social cost, where opt is the cost of the optimal solution to the QoD-MCBS problem.

Proof: Since the derived algorithm of Algorithm 3 shares the same solution to the QoD-MCBS problem, Algorithm 3 approximates the optimal solution of QoD-MCBS with a factor of $(1 + \ln\frac{\alpha(m\eta + \sum_{i=1}^m \xi_i)}{opt})$. The theorem holds. ∎

6 EVALUATION

We conduct extensive simulations to evaluate the performances of the proposed incentive mechanisms. The trace that we used, the simulation settings, the metrics and the results are presented as follows.
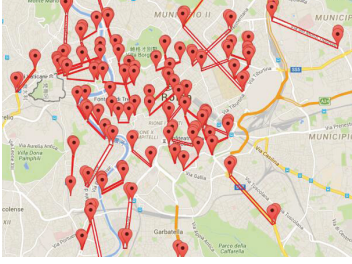
Fig. 5. The selected streets are noted by red marks on map of Rome.

6.1 The Trace and Settings

We adopt the widely-used trace in [14] which contains the GPS coordinates of approximately 320 taxi cabs collected over 30 days in Rome, Italy. All of the taxi cabs in the trace move along different streets in Rome day after day. In our simulations, we select 50 main streets from the trace, as illustrated in Fig. 5. In the selected streets, we randomly deploy {100, 200, 300, 400} sensing tasks. Furthermore, we choose 316 vehicles from the trace for our simulations by excluding those vehicles that visit the selected streets with low frequency.

In our simulations, we select 30 days' records of GPS coordinates for the chosen vehicles. We divide each day into two equal-length sensing periods, i.e., [0, 12] and [12, 24], and thus divide 30 days into 60 periods. Moreover, we let the sensing tasks be distributed in the same period and let the $\mathcal{D}$ of the tasks be set as 12 hours. The probability of each vehicle visiting a street (i.e. the probability of a trajectory) is estimated as follows. First, we determine whether a vehicle has visited a street in a sensing period by testing whether the coordinates of this vehicle located in the street during this period. Then, we count the number of sensing periods during which a vehicle has visited a street. This number divided by 60 is viewed as the average probability of the vehicle visiting the street. Additionally, the real costs of bids are generated based on three distributions, *i.e.*, uniform distribution (UNM), normal distribution (NORM) and exponential distribution (EXP). Each simulation is conducted with the three distributions. All simulations in this section are performed in JAVA on a Windows PC with a 3.2GHz Intel Core i5 CPU and 8GB memory.

6.2 The Evaluation Metrics, Methodology and Results

To evaluate the performance of our mechanisms, we use the following metrics: *number of winning bids, successful performing ratio, social cost, overpayment ratio, truthfulness, and individual rationality*. The Number of Winning Bids (NWB) measures the scale of crowdsensing. The Successful Performing Ratio (SPR) is the ratio of the number of the successfully performed crowdsensing tasks and the number of all tasks. The overpayment ratio is defined as:

$$\lambda = (P - C(\Phi))/C(\Phi),$$

where P is the total payment and $C(\Phi)$ is the total cost. It measures the cost paid by the platform user to induce the truthfulness of all vehicles. Truthfulness is the property ensuring that no bidder can improve his or her payoff by submitting a different cost from the real one. Individual rationality is the property which ensures that the payoff of each bid is non-negative.

TABLE 2
Default settings of major parameters

| Parameter name	Default value
Number of tasks m	100
Cost range $\mathcal{C}$	[10,20]
Threshold of successful performing probability η	0.6
Variance of NORM σ	10
Quality Range of tasks $\mathcal{Q}$	[0,0]
Quality Range of vehicles $\mathcal{R}$	[0,0]

The default settings of our simulations are shown in Table 2. We set the default QoD values $\mathcal{Q}$ and $\mathcal{R}$ as 0, which means that we conduct simulations for the basic incentive mechanism. The results are shown as follows.

Number of winning bids: We depict the evaluation on the NWB in Figs. 6, 10 and 16. We increase the number of tasks to verify the impact on the NWB, and the results show that the NWB will increase since we need more vehicles and bids to perform more tasks. Additionally, more bids are needed to meet constraint (3) when η increases, as shown in Fig. 16. However, when the average of the real cost increases, the NWB does not change much (see Fig. 10). This is because we have to keep the joint probability no less than η no matter how much it will cost. If $\mathcal{C}$ expands (i.e., the average cost increases), the MPCs of all bids will decrease, leading to results with fewer changes. We also find that the UNM needs the most bids and that the EXP needs the fewest.

Successful performing ratio: Fig. 7 plots the successful performing ratio when the number of tasks (i.e., m) changes from 100 to 400. With the increase of m, more bids will be selected, spontaneously leading to the increase of successful performing ratios. Fig. 11 and Fig. 17 plot the SPR when the cost range $\mathcal{C}$ and the threshold η increase, respectively. The SPR does not change much in Fig. 11, since the number of the winning bids changes little when $\mathcal{C}$ increases (see Fig. 10). The results in Fig. 17 show that the SPR is slightly larger than η. These results are reasonable, since the SPR is in the constraint (3). Additionally, the distribution of costs has little influence on the SPR based on the above figures. This is because we have guaranteed the successful performing probability of each task in the bid selection process.

Social cost: We verify the performance of the social cost by changing m, $\mathcal{C}$, and η, and present the results in Figs. 8, 12, and 18, respectively. These figures show that the social cost will increase if we increase m, $\mathcal{C}$, and η separately. This is because with the increase of m and η, the mechanism will select more bids to meet the constraint (3). If we increase the average cost (i.e., expand $\mathcal{C}$), the social cost will spontaneously increase. Additionally, the results in the three figures show that the social cost of UNM is larger than those of NORM and EXP. This is because the UNM produces greater costs than the others do. Since NORM produces more middle-range costs, the social cost of NORM is always less than that of the other two distributions.

Overpayment ratio: We depict the evaluation on overpayment ratio λ in Figs. 9, 13, and 19. The results show that λ is always less than 0.6, which means that the platform user does not have to pay much extra money to induce truthfulness. If we increase m and η in Fig. 9 and Fig. 19, λ will increase in accordance. This is because more
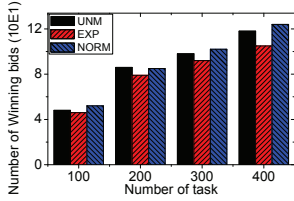
Fig. 6. NWB vs. m
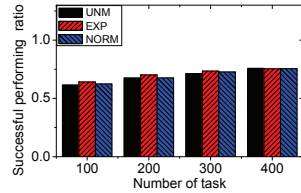
Fig. 7. SPR vs. m
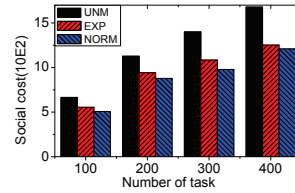
Fig. 8. Social cost vs. m
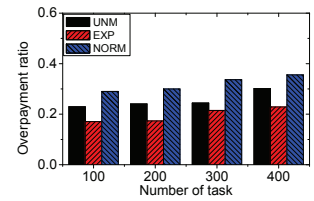
Fig. 9. Overpayment ratio vs. m
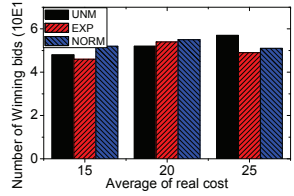
Fig. 10. NWB vs. $\mathcal{C}$
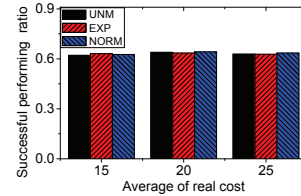
Fig. 11. SPR vs. $\mathcal{C}$
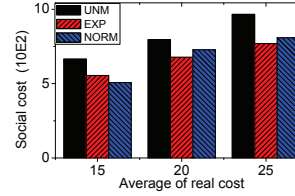
Fig. 12. Social cost vs. $\mathcal{C}$
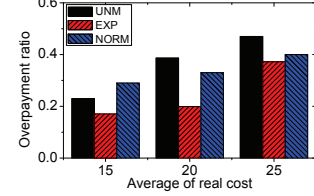
Fig. 13. Overpayment ratio vs. $\mathcal{C}$

vehicles and bids will be recruited and the increments of the payments are greater than those of the costs. We find that when $\mathcal{C}$ increases in Fig. 13, λ will also increase since the truthfulness guarantees that each payment is larger than the related cost and that the increments of the payments are larger than those of the costs.
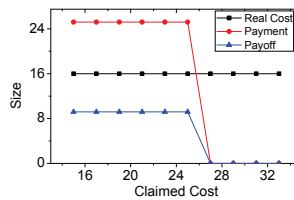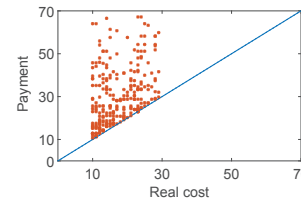

Fig. 14. Payoff of a bid

Fig. 15. Payments vs. costs

Truthfulness and individual rationality: To verify the truthfulness of our incentive mechanism, we randomly pick a winning bid, change its claimed cost, and recalculate the related payments as well as the payoffs. The results are illustrated in Fig. 14. The payment is 25.2, and the real cost is 16. Then, the payoff is 9.2. We find that the payoff remains unchanged if the claimed cost is no more than the payment. Moreover, when the claimed cost is larger than the critical value 25.2, the payoff becomes zero. We also verify the individual rationality by comparing the real EXP cost of each bid and the related payment, which is calculated when $m = 100$, $\eta = 0.6$, and $\mathcal{C} = [10, 30]$. Then we find that each payment is greater than the related cost (see Fig. 15).

We also conduct simulations under the condition that $\mathcal{Q}$ and $\mathcal{R}$ are not 0. More specifically, the range of $\mathcal{Q}$ is set as $\{[10, 15], [10, 20], [10, 25]\}$, the range of $\mathcal{R}$ is set as $[10, 20]$, and the other parameters are set as the default values. The results are shown in Figs. 20-23. Compared to the results of the basic mechanism in Figs. 6, 8, and 9 when $m = 100$, the results in Figs. 20, 22, and 23 show that more winning bids are needed, more social costs are spent, and higher overpayment ratios are produced since we have to meet the QoD constraint (11) besides the probability constraint. We also find that some SPRs in Fig. 21 are less than the related value of η, e.g., SPR of UNM is 0.51 when $\eta = 0.6$ and $\mathcal{Q} = [10, 15]$. This is because if the QoD constraints of some tasks are not met, we deem that these tasks are incomplete, even if they have been performed by a few vehicles.

7 RELATED WORK

There have been a few works [15]–[24], [28]–[33] on the incentive mechanism design for crowdsens-

ing/crowdsourcing, which can be divided into two categories: offline and online.

Offline incentive mechanism. In an offline scenario, the crowdsourcer/platform is aware of all users, and no users will come/leave during the process. In [15], Yang *et al.* proposed two types of mechanisms to maximize the utility of the corwdsourcer: CCM and UCM. They have shown that their mechanisms perform well by proving the unique Stackelberg Equilibrium of IMCC in CCM and giving the approximation ratio of IMCU in UCM. Feng *et al.* solve the problem of location-aware collaborative sensing in mobile crowdsourcing in [24] by proposing TRAC. They formulate WBDP as a linear set cover problem with minimum social cost and present an approximation algorithm that can approach the optimum solution within a factor of $1 + \ln(n)$. Zhang *et al.* [18] consider a scenario where a crowdsourcing job requires the collective effort of multiple participants. They propose incentive mechanisms for three models: SS-Model, SM-Model, and MM-Model. In [25], Luo *et al.* propose a different incentive mechanism based on *an all-pay auction* model, in which every bidder must pay for his bid regardless of whether he wins or losses the auction.

In addition, some works focus on the mechanism design for special problems, e.g., image labeling and noise sensing. In [19], Zhang *et al.* study the problem that how to stimulate workers to perform binary labeling tasks while maximizing the utility of the platform and meeting budget constraints. They profile the quality of the workers with Beta distribution functions and calculate them by Bayes' rule. In [20], [21], the authors incorporate the consideration of data quality into the design of incentive mechanism for noise sensing. Jin *et al.* [21] prefer to maximize social welfare while ensuring that the quality of each task is no less than a given threshold. Peng *et al.* [20] propose a mechanism to maximize the platform's profit. They estimate the quality of sensing data via the well-known expectation maximization algorithm and quantify the participants' contributions through information uncertainty reduction.

Online incentive mechanism. Different from the offline scenario, in an online scenario the statuses of users are dynamic. That is to say, the users and tasks come and leave randomly, and the crowdsourcer/platform only sees part of its users in one time interval. Considering this scenario, Zhao *et al.* [16] propose two online mechanisms, OMZ and OMG, that adopt a multiple-stage sampling ac-
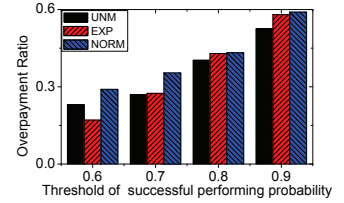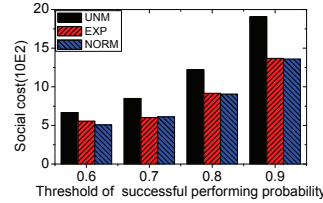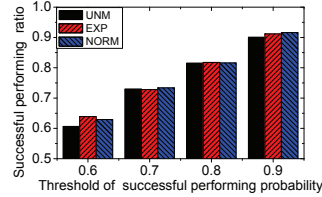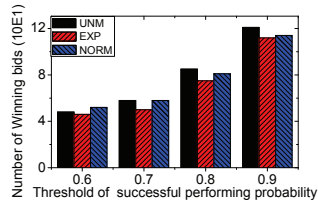
Fig. 16. NWB vs. η

Fig. 17. SPR vs. η

Fig. 18. Social cost vs. η

Fig. 19. Overpayment ratio vs. η

Fig. 20. NWB vs. $\mathcal{Q}$
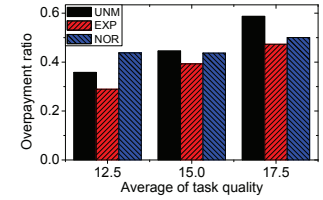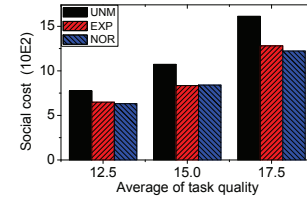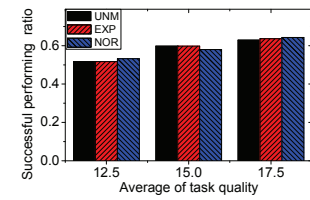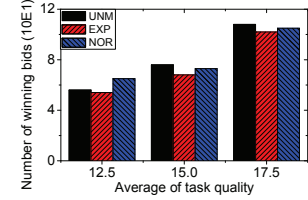

Fig. 21. SPR vs. $\mathcal{Q}$

Fig. 22. Social cost vs. $\mathcal{Q}$

Fig. 23. Overpayment ratio vs. $\mathcal{Q}$

ceptance process to maximize the value of the crowdsourcer without sacrificing utility. To satisfy the budget constraint, their mechanisms utilize the density threshold to filter out inapposite users. Moreover, both OMZ and OMG are competitive with the offline scenario. Zhang *et al.* [22] design three online, reverse-auction-based incentive mechanisms: TBA, TOIM, and TOIM-AD. TBA uses the first batch of bidders as a sample and makes decisions on the second batch of bidders. It is designed to pursue the maximization of the platform utility. TOIM is a truthful online mechanism which is highly competitive with the optimal solution in the zero arrival-departure model. TOIM-AD extends TOIM to the non-zero arrival-departure model. In [23], Zhu *et al.* first propose an offline mechanism where the platform knows the active time and the arrival time of each task at the beginning of the crowdsourcing. Based on this offline mechanism, they propose the online social welfare maximization mechanism which divides time into slots, finds the near-optimal solution, and decides the payments in each slot. The task allocation algorithm in the online mechanism achieves a constant competitive ratio of $\frac{1}{2}$. In [17], Wei *et al.* consider stimulating both service users and providers to participate in mobile crowdsourcing and model the interactions as an online double auction. They propose an expressive general framework that is suitable for different price schedules.

8 CONCLUSION

In this paper, we first design a truthful incentive mechanism for vehicle-based, nondeterministic crowdsensing, where the sensing tasks are performed with different probabilities and the probability of each task being successfully performed is no less than a threshold. After considering a more complex scenario where the platform has a requirement on the QoD, we also design a QoD-aware incentive mechanism. Through rigorous theoretical analysis, we prove that both incentive mechanisms have the properties of truthfulness, individual rationality, computational efficiency and social cost efficiency. Finally, we conduct lots of simulations on a real trace to verify the significant performances of our incentive mechanisms.

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