Delay-Aware Incentive Mechanism for Crowdsourcing with Vehicles in Smart Cities

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***Abstract*—Vehicle-based crowdsourcing is becoming a powerful paradigm that can outsource intensive tasks in smart cities to vehicles by exploiting their on-board resources. In this paper, we focus on the problem of motivating vehicles to join the crowdsourcing system. Considering the various delay demands of tasks, we design a delay-aware incentive mechanism to efficiently and timely employ vehicles based on reverse auction, without acquiring their private trajectory information. To satisfy the diverse task delay demands, we enable each participating vehicle to estimate and report its own provisioned service quality, i.e., the estimated time of completion (ETC), for the tasks that it bids for. Then, the service provider, which hosts the crowdsourcing platform, determines the winning bids as well as the payments by jointly considering the ETCs and costs claimed by the participating vehicles. Due to the NP-hardness of the winning bid selection (WBS) problem, we develop an approximate algorithms for bid selection and payment determination, which can guarantee the truthfulness of participating vehicles. Simulation results demonstrate the effectiveness of our proposed incentive mechanism.**

I. Introduction

To realize the vision of smart cities, tremendous tasks including computing, communication and sensing (CCS) missions, are generated in urban area for various applications, such as environment monitoring, local information sharing, and statistic data analytics, etc. Although the traditional infrastructures, e.g., 4G/5G, mobile cloud computing, and sensor networks, have great potential in dealing with huge CCS demands, they can hardly survive through the ever-increasing data traffic and soaring smart city operations [1], [2]. To address this challenge, a promising idea is to exploit the idle onboard resources of vehicles to complement the traditional infrastructures [3]–[5]. As vehicles are becoming connected and autonomous, they are expected to be endowed with powerful CCS capabilities in the near future. Therefore, these onboard resources, if harvested and managed properly, can be utilized to provision CCS services in a smart-city environment without additional deployment cost, which can not only relieve the burden of our existing infrastructures, but also foster newly emerging smart-city applications.

A paradigm that outsources tasks to vehicles can be generalized as a vehicle-based crowdsourcing system. Although many works envision to employ vehicles for performing tasks [4]–[7], it is hardly to put this vision into practice without a viable incentive design. This is because vehicle owners are typically not willing to freely share their onboard resources in view of energy consumption in batteries, location privacy leakage and so on. However, designing an incentive mechanism for vehicle-based crowdsourcing is highly complicated. On the one hand, the participating vehicle may deliberately declare a cost higher than the real one for maximizing its payoff. Thus, an effective incentive mechanism should prevent the strategic behaviors of participating vehicles. On the other hand, it is hard to guarantee task delay in vehicle-based crowdsourcing owing to the dynamic mobility of vehicles, even though delay is typically the most demanding Quality-of-Service (QoS) requirement for supporting smart-city applications. To address this issue, we usually need the necessary information from participating vehicles, such as their trajectories, speed, and on-board resources, which however, sacrifices the privacy of vehicle owners and may discourage them from participating in. Thus, how to satisfy the delay demands of tasks while protecting the privacy of vehicles is extremely challenging in vehicle selection.

Incentive design for crowdsourcing with smartphones have been widely investigated in the existing literature [8], [9]. However, the high mobility distinguish vehicle-based crowdsourcing from crowdsourcing with smartphone. Some works such as [10], [11] investigated how to employ vehicles to achieve a large sensing coverage under limited budget. In [12], Gao et al. devised an auction-based incentive mechanism for vehicle-based sensing to minimize the total sensing cost of the service requester, assuming the trajectory probabilities can be estimated by recording the daily movement of each vehicle. However, this method may potentially sacrifice the privacy of participating drivers. Furthermore, above incentive mechanisms did not take the delay requirements into account.

In this paper, we design a delay-aware incentive mechanism for the vehicle-based crowdsourcing systems. Our main contributions are summarized as follows.

- We introduce a novel process for exchanging the necessary information between service provider and participating vehicles. Instead of asking vehicles to report their profiles (e.g., trajectories, on-board resources) to the service provider, we enable the vehicles to compute the ETCs for their bidding tasks by themselves, and report the ETCs to the service provider. This process can not only protect the privacy of vehicles, but provide a deterministic task delay for the service provider.
- In order to design the delay-aware incentive mechanism, we introduce the *task value function*, which quantifies the valuation of the service requester towards a task in terms

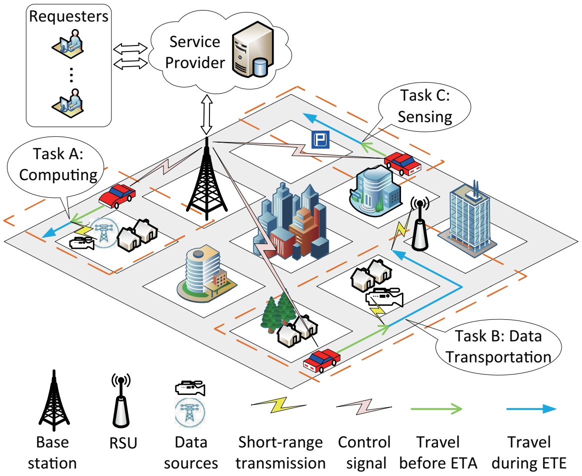

Fig. 1. Illustration of vehicle-based crowdsourcing system in a smart city. Task A, B and C are representative examples of CCS tasks.

of when it will be completed. Based on this, we develop an auction mechanism with the objective of maximizing the social welfare, which is defined as the difference between the total value of completed tasks and the social cost. The formulated winning bid selection (WB-S) problem appears to be a *non-monotone submodular maximization problem with a matroid constraint*, which is NP-hard, and has not been well studied in auction design as yet. Thus, we propose a novel approximation algorithm to solve it and determine the payment.

- We theoretically prove that our mechanism is truthful and computationally efficient. With extensive simulations, we demonstrate the effectiveness of our proposed incentive mechanism.

II. System Architecture

A. Basic Model

As illustrated in Fig. 1, a vehicle-based crowdsourcing system is composed of a service provider, some service requesters, and a huge number of participating vehicles in a smart city. For illustrative purpose, three representative CCS tasks are depicted in Fig. 1. Task A is a computing task where the vehicle is employed as edge computing server to provision computing services as illustrated in [3], [6]. Task B is a communication task where the data is being delivered to an intended place via store-carry-forward mechanism by exploiting vehicles' mobility as in [4]. Task C is a sensing task such as traffic monitoring, map updating, parking spot monitoring via employing vehicles' onboard sensors as illustrated in [5]. For each type of task, the service provider collects the task requests from the service requesters, and then publicizes the task to the vehicles in proper areas. Each task includes the necessary task description, which should specify the location and workload of the task. The interaction between a service requester and participating vehicles is modeled as single-round reverse auction, where the participating vehicles are the service sellers, the service requester is the service buyers, and the service provider acts as the auctioneer between these two sides. Each vehicles are allowed to submit multiple bids to the service provider, but at most win one bid (one set of tasks). To make the auction efficient, we assume that the maximum number of bids that one vehicle can submit is K. Let $I = \{1, 2, ..., |I|\}$ be the set of participating vehicles, $J = \{1, 2, ..., |J|\}$ be the set of released tasks, $J_{i,k}$ be the set of tasks in vehicle i's kth bid. Vehicle $i \in I$ has a cost $c_{i,k}$ for performing the tasks in $J_{i,k}$, which is privately known by itself. As a rational participant, vehicle i will not perform the the tasks in $J_{i,k}$ if the payment $p_{i,k}$ from the service requester is less than $c_{i,k}$. To assure its benefit, vehicle i should declare a reserve price $b_{i,k}$ for its kth bid, which is the claimed cost, to the service provider. Since vehicle i can strategically manipulate the reserve price $b_{i,k}$ in order to maximize its profit, $b_{i,k}$ is not necessarily equal to $c_{i,k}$. Except for the reverse price, vehicle i should also submit ETC for each task in its kth bid, i.e., $t^j_{i,k} \in \mathcal{T}_{i,k}$, where $\mathcal{T}_{i,k}$ is the set of ETCs for tasks in $J_{i,k}$. Consequently, the kth bid submitted by vehicle i can be described as a triplet $\beta_{i,k} = \{J_{i,k}, \mathcal{T}_{i,k}, b_{i,k}\}$, where $\beta_{i,k} \in B_i$. $B_i \in B$ is the bid set submitted by vehicle i, and B is the set of bids received by the service provider.

An example of the bidding process is shown in Fig. 2. Suppose the vehicle at A, denoted by vehicle i', has two preferred trajectories to its destination D, which are illustrated by blue solid arrow and green dash arrow. If vehicle i' submits two bids for tasks on these two trajectories respectively, the bid set of it is $B_{i'} = \{\beta_{i',1}, \beta_{i',2}\}$, where $\beta_{i',1} = \{\{1,4\}, \{t^1_{i',1}, t^4_{i',1}\}, b_{i',1}\}$, and $\beta_{i',2} = \{\{2,3,4\}, \{t^2_{i',2}, t^3_{i',2}, t^4_{i',2}\}, b_{i',2}\}$. Note that the tasks on different preferred trajectories, such as task 1 and 2, cannot be selected in the same bid. Here, we make a reasonable assumption that the auction results can potentially affect the trajectory selection of the vehicle owner under the premise that the destination will be not changed.

The ETC for a task can be calculated at the vehicle side based on the task description, i.e., the task location and workload, broadcasted by the service provider. Given a specified location, the intelligent navigation systems nowadays can already provide accurate estimated time of arrival (ETA) based on the real-time traffic conditions. Besides, through the workload information and vehicles' onboard capability, each vehicle can estimate the time of execution (ETE) for a task after arrival. The ETC is equal to summation of ETA and ETE.

B. Task Value Function

To aid the design of delay-aware incentive mechanism, we introduce a novel concept named task value function. Each task has a task value given by the service requester, which quantifies the valuation of requester towards this task, i.e., the maximum payment the requester is willing to pay. In general, the requester is willing to pay higher for a better service quality, which indicates that the task value actually decreases with delay. Based on above observations, we model the task value as a decreasing function of the delay. For illustrative purpose, we take the following task value functions

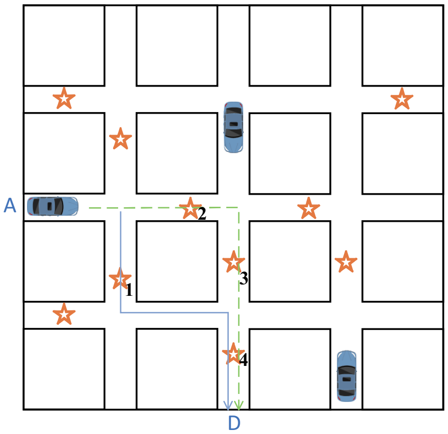

Fig. 2. An example of the bidding process. The blue cars represent the participating vehicles, and the stars represent the released tasks. A vehicle at A plans to travel to its destination D with two preferred trajectories, which are illustrated by blue solid arrow and green dash arrow respectively.

as a illustrative example, which is given by,

$$V(t_c) = \begin{cases} (a+K) - K(1+b)^t, & \text{if } t \leq T \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

with $K = \frac{a-c}{(1+b)^T - 1}$, where T is the task deadline, a represents the task value at $t = 0$, $b > 0$ sets the descent rate, and c represents the task value at $t = T$. In such case, the task value exponentially decreases with the delay. It is worth noticing that we do not impose any assumption on the form of task value function, and (1) is just an example. For practical implementation, the service requesters can choose the task value functions based on their preferences.

C. Mechanism Workflow

Our auction-based incentive mechanism is described as follows:

1) At the beginning, the service provider collects the task descriptions from the service requester, which should contain two components: *location*, and *workload*.
2) The service provider multicasts the task descriptions to the participating vehicles in the proper areas via base stations or roadside units (RSUs). After receiving the task descriptions, vehicle i determines one or several bids containing tasks on the its preferred trajectories, and estimates the ETC for each task in its bids. Then, it declares a set of bids $B_i = \{\beta_{i,1}, \beta_{i,2}, ...\beta_{i,k}\}$ to the service provider, where $k \leq K$.
3) After receiving all the bids, the service provider selects the set of winning bids and the corresponding payment based on the algorithms that we will introduce later. Notice that the criteria of vehicle selection not only relies on the reserve price, but also the ETC that each vehicle promises to provision. Then, the service provider notifies the winning vehicles to perform the task in their winning bids.
4) Once a winning vehicle performs the tasks in its winning bid on time, the service provider should rewards it by charging the service requester. For practical implementation, the service provider can set up an acceptable error ϵ so that if vehicle i completes the all tasks in its winning bids $\beta_{i,k}$ within $[t^j_{i,k} - \epsilon, t^j_{i,k} + \epsilon]$ for $t^j_{i,k} \in \mathcal{T}_{i,k}$, the service provider will reward vehicle i. Otherwise, the service requester will decline the payment to vehicle i.

D. Utilities of Service Requester and Vehicles

The utility of a service requester equals to the difference between the total value of the completed tasks and the payment to the winning vehicles, which is given by,

$$R(\boldsymbol{\omega}) = \sum_{j \in J} \gamma^j(\boldsymbol{\omega}) - \sum_{\beta_{i,k} \in \boldsymbol{\omega}} p_i, \quad (2)$$

and $\gamma^j(\boldsymbol{\omega})$ is defined by,

$$\gamma^j(\boldsymbol{\omega}) = \begin{cases} V^j\big(\min_{\beta_{i,k} \in \boldsymbol{\omega} \cap B^j} t^j_{i,k}\big), & \text{if } \boldsymbol{\omega} \cap B^j \neq \varnothing, \quad (3) \\ 0, & \text{otherwise}, \quad (4) \end{cases}$$

where $\boldsymbol{\omega}$ is the set of winning bids, $B^j \subseteq B$ is the set of bids containing task j, and $V^j(\cdot)$ is the task value function of task j. (3) implies that when more than one winning bid contains task j, the winner with the smallest ETC will actually perform this task for achieving the maximum task value.

The utility of vehicle $i \in I$ is,

$$v_i = \begin{cases} \sum_{\beta_{i,k} \in \boldsymbol{\omega} \cap B_i} (p_i - c_{i,k}), & \text{if } \boldsymbol{\omega} \cap B_i \neq \varnothing, \\ 0, & \text{otherwise}. \end{cases} \quad (5)$$

III. Auction Mechanism Design

Our auction mechanism consists of two steps, i.e., winning bid selection and payment determination.

A. Winning Bid Selection Algorithm

The social welfare is defined by the difference between the total value of completed tasks and the social cost. The optimization objective of the our bid selection problem is to maximize the the social welfare, and is formulated as follows,

$$\max_{\boldsymbol{\omega} \in B} V(\boldsymbol{\omega}) - \sum_{\beta_{i,k} \in \boldsymbol{\omega}} b_{i,k} \quad (6)$$

$$s.t. \quad |\boldsymbol{\omega} \cap B_i| \leq 1, \quad (7)$$

where $V(\boldsymbol{\omega}) = \sum_{j \in J} \gamma^j(\boldsymbol{\omega})$, which is the total value of tasks included in the winning bid set $\boldsymbol{\omega}$. The constraint (7) indicates that each vehicle at most win one bid. The objective function is non-monotone and submodular, and the proof is omitted here due to the space limitation. Moreover, there is a matroid constraint (7), which is the well-known partition matroid constraint [13]. Thus, the WBS problem appears to be a *non-monotone submodular maximization problem with a matroid constraint*, which is NP-hard [14]. Naturally, we need find an approximate method to resolve this problem. To guarantee the truthfulness, an approximation algorithm should not only obtain the results of the WBS problem, but can efficiently find the payment for ensuring the truthfulness. In [9], the authors design a truthful auction mechanism based

Algorithm 1 WBS Algorithm

Input: Set of tasks J , set B of all received bids, number of participating vehicles $|I|$.

Output: Set $\boldsymbol{\omega}$ of winning bids, and total social welfare U^*.

Initialize $\boldsymbol{\omega} = \varnothing$, and $U^* = 0$;
β_{i^*,k^*}= $\arg\max_{\beta_{i,k}\in B}(V_{\beta_{i,k}}(\boldsymbol{\omega}) - b_{i,k})$;
while $V_{\beta_{i^*,k^*}}(\boldsymbol{\omega}) - b_{i^*,k^*} > 0$ and $|\boldsymbol{\omega}| < |I|$ **do**
  $U^* = U^* + V_{\beta_{i^*,k^*}}(\boldsymbol{\omega}) - b_{i^*,k^*}$;
  $\boldsymbol{\omega} = \boldsymbol{\omega} \cup \{\beta_{i^*,k^*}\}$;
  $B = B\backslash\{\beta_{i^*,k^*}\}$;
  for all $\beta_{i^*,k} \in B$ **do**
    $B = B\backslash\{\beta_{i^*,k}\}$;
  end for
  β_{i^*,k^*}= $\arg\max_{\beta_{i,k}\in B}(V_{\beta_{i,k}}(\boldsymbol{\omega}) - b_{i,k})$;
end while

on greedy strategy. Unfortunately, since the bidder in [9] is allowed to only submit a single bid, their considered problem is an unconstrained non-monotone submodular maximization problem. Therefore, their approach cannot be used here.

In the following, we will develop a approximation algorithm to solve the WBS problem while guaranteeing the truthfulness. We first introduce the concept named marginal value of bid, which is the value of tasks that a new bid can contribute to the existing winning bid set. Given the existing winning bid set $\boldsymbol{\omega}$, the marginal value of the bid $\beta_{i,k}$ is defined by

$$V_{\beta_{i,k}}(\boldsymbol{\omega}) = V(\boldsymbol{\omega} \cup \{\beta_{i,k}\}) - V(\boldsymbol{\omega}). \tag{8}$$

The basic idea of our approximation algorithm is to greedily pick up the bid with the maximum marginal social welfare while satisfying the matroid constraint in each round. The marginal social welfare is defined as the contribution of social welfare to the existing winner set. Given an existing winning bid set $\boldsymbol{\omega}$, the marginal social welfare of $\beta_{i,k}$ is $V_{\beta_{i,k}}(\boldsymbol{\omega}) - b_{i,k}$. In each iteration, the bid with the maximum social marginal social welfare, denoted as β_{i^*,k^*}, is added to the set of winning bids $\boldsymbol{\omega}$ and removed from B. Besides, the bids that conflict with β_{i^*,k^*} are deleted from B. In nth iteration, we denote the set of winning bids as $\boldsymbol{\omega}^{(n)}$, the winning bid as $\beta^{(n)}$, and the reserve price as $b^{(n)}$. According to the submodularity of $V(\boldsymbol{\omega})$, we can obtain the following sorting:

$$\begin{aligned} V_{\beta^{(1)}}(\boldsymbol{\omega}^{(0)}) - b^{(1)} \geq V_{\beta^{(2)}}(\boldsymbol{\omega}^{(1)}) - b^{(2)} \geq ... \\ \geq V_{\beta^{(N)}}(\boldsymbol{\omega}^{(N-1)}) - b^{(N)} > 0, \end{aligned} \tag{9}$$

where $\boldsymbol{\omega}^{(0)} = \varnothing$, and N is the number of iterations. Naturally, N is the largest index such that $V_{\beta^{(N)}}(\boldsymbol{\omega}^{(N-1)}) - b^{(N)} > 0$. The approximation algorithm for WBS is summarized in Algorithm 1.

B. Payment Determination Algorithm

The payment to the vehicles should ensure that the optimal strategy for them is to truthfully report their cost. To this end, we should find the payment $p_{i,k}$ for winner $\beta_{i,k} \in \boldsymbol{\omega}$. As illustrated in Algorithm 2, given a winning bid $\beta_{i,k} \in \boldsymbol{\omega} \cap B_i$, the Payment Determination (PD) algorithm executes the WDB

Algorithm 2 PD Algorithm

Input: Set of tasks J, set of the winning bids $\boldsymbol{\omega}$, set of all received bids B, set of vehicle i's bids B_i, number of participating vehicles $|I|$.

Output: Payment p_i for vehicle $i \in I$.

for all $\beta_{i,k} \in \boldsymbol{\omega}$ **do**
  Initialize $\boldsymbol{\omega}_{-i} = \varnothing$, $p_i = 0$, $B_{-i} = B\backslash B_i$;
  β_{i^*,k^*}= $\arg\max_{\beta_{i,k}\in B_{-i}}(V_{\beta_{i,k}}(\boldsymbol{\omega}_{-i}) - b_{i,k})$;
  while $U_{\beta_{i^*,k^*}}(\boldsymbol{\omega}_{-i}) - b_{i^*,k^*} > 0$ and $|\boldsymbol{\omega}_{-i}| < |I| - 1$ **do**
    $\boldsymbol{\omega}_{-i} = \boldsymbol{\omega}_{-i} \cup \{\beta_{i^*,k^*}\}$;
    $B_{-i} = B_{-i}\backslash\{\beta_{i^*,k^*}\}$;
    $p_{i,k} = \max\big\{p_{i,k}, V_{\beta_{i,k}}(\boldsymbol{\omega}_{-i}) - (V_{\beta_{i^*,k^*}}(\boldsymbol{\omega}_{-i}) - b_{i^*,k^*})\big\}$;
    for all $\beta_{i^*,k} \in B_{-i}$ **do**
      $B_{-i} = B_{-i}\backslash\{\beta_{i^*,k}\}$;
    end for
    β_{i^*,k^*}= $\arg\max_{\beta_{i,k}\in B_{-i}}(V_{\beta_{i,k}}(\boldsymbol{\omega}) - b_{i,k})$;
  end while
  $p_i = \max\{p_{i,k}, V_{\beta_{i,k}}(\boldsymbol{\omega}_{-i})\}$;
end for

algorithm in the set B_{-i}, where $B_{-i} = B\backslash B_i$. In mth iteration, we denote the set of winning bids as $\boldsymbol{\omega}_{-i}^{(m)}$, the winning bid as $\beta_{-i}^{(m)}$, and the reserve price as $b_{-i}^{(m)}$. We calculate the maximum reserve price of $\beta_{i,k}$ so that $\beta_{i,k}$ instead of $\beta_{-i}^{(m)}$ is selected in nth iteration. This process is repeated for the first M iterations, where M is the largest index so that $V_{\beta_{-i}^{(M)}}(\boldsymbol{\omega}_{-i}^{(M-1)}) - b^{(M)} > 0$. In $(M+1)$th iteration, we can compute the maximum price $b^{(M+1)}$ such that $V_{\beta^{(M+1)}}(\boldsymbol{\omega}_{-i}^{(M)}) - b^{(M+1)} > 0$. Finally, the payment p_i is set as the maximum of these $M+1$ prices, which can be expressed by,

$$\begin{aligned} p_i = \max\Big\{ & V_{\beta_{i,k}}(\boldsymbol{\omega}_{-i}^{(M+1)}), \\ & \max_{1\leq m\leq M}\big\{V_{\beta_{i,k}}(\boldsymbol{\omega}_{-i}^{(m-1)}) - (V_{\beta_{-i}^{(m)}}(\boldsymbol{\omega}_{-i}^{(m-1)}) - b_{-i}^{(m)})\big\}\Big\}. \end{aligned} \tag{10}$$

C. Mechanism Analysis

In the following, we prove the desirable properties of our proposed incentive mechanism, including truthfulness, computational efficiency, individually rational and profitable.

Theorem 1: Vehicle $i \in I$ should truthfully report $B_i = \{\beta_{i,1}, \beta_{i,2}, ..., \beta_{i,k}\}$ for maximizing its utility.

Proof: For bid $\beta_{i,k} \in B_i$, vehicle i should submit a three-fold information, i.e., $J_{i,k}$, $\mathcal{T}_{i,k}$ and $b_{i,k}$, to the service provider. Clearly, $J_{i,k}$ and $\mathcal{T}_{i,k}$ should be truthfully reported, since the service provider can check whether and when the specified tasks are completed, and can directly decline the reward for vehicle i if it fails to complete the tasks on time. For vehicle i, we denote its winning bid by truthfully bidding as $\beta_{i,k^*} \in B_i$, its utility and received payment by truthfully bidding are v_i and p_i respectively. Similarly, we denote untruthful bid set as B_i', its winning bid by untruthfully bidding as $\beta_{i,k'} \in B_i'$, its utility and received payment by untruthfully bidding are v_i' and p_i'. We will prove that vehicle $i \in I$ should be truthful by showing $v_i \geq v_i'$ for all cases.

Case 1: The vehicle i loses with truthful bid set B_i, and also loses with untruthful bid set B_i'. In such case, we have $v_i' = v_i = 0$.

Case 2: The vehicle i loses with truthful bid set B_i, but wins with untruthful bid set B_i'. Losing the auction with truthful bid implies that $V_{\beta_{i,k}}(\boldsymbol{\omega}_{-i}^{(m-1)}) - c_{i,k} < V_{\beta^{(m)}}(\boldsymbol{\omega}_{-i}^{(m-1)}) - b^{(m)}$, and $V_{\beta_{i,k}}(\boldsymbol{\omega}_{-i}^{(M+1)}) < c_{i,k}$, for $1 \leq m \leq M$ and $\beta_{i,k} \in B_i$. According to (10), we can conclude that the payment $p_i' \leq c_{i,k}$, and thus $v_i' = p_i' - c_{i,k} \leq 0$. Therefore, $v_i \geq v_i'$ holds.

Case 3: The vehicle i wins with truthful bid set B_i, while losing with untruthful bid set B_i'. According to (10) and (5), it is easy to find that $v_i \geq 0$. Thus, we have $v_i \geq v_i'$.

Case 4: The vehicle i wins with truthful bid set B_i, and also with untruthful bid set B_i'. Besides, $\beta_{i,k'} = \beta_{i,k^*}$. According to (10), the payment will be not changed. Therefore, we have $v_i = v_i'$.

Case 5: The vehicle i wins with truthful bid set B_i, and also with untruthful bid set B_i'. Besides, $\beta_{i,k'} \neq \beta_{i,k^*}$. According to MDS algorithm, if the vehicle i winning with truthful bid β_{i,k^*} in m' iteration, we have

$$V_{\beta_{i,k^*}}(\boldsymbol{\omega}_{-i}^{(m'-1)}) - c_{i,k^*} \geq \max_{m' \leq m \leq M+1} \{V_{\beta_{i,k'}}(\boldsymbol{\omega}_{-i}^{(m-1)}) - c_{i,k'}\}, \tag{11}$$

which is due to the submodularity. Moreover, for iteration $m < m'$, we have

$$\max_{1 \leq m < m'} \{V_{\beta_{i,k'}}(\boldsymbol{\omega}_{-i}^{(m-1)}) - c_{i,k'} - (V_{\beta_{-i}^{(m)}}(\boldsymbol{\omega}_{-i}^{(m-1)}) - b_{-i}^{(m)})\} < 0. \tag{12}$$

In addition, since the item $(V_{\beta_{-i}^{(m)}}(\boldsymbol{\omega}_{-i}^{(m-1)}) - b_{-i}^{(m)})$ in (10) depends on the bids from other vehicles, they are equivalent for p_i and p_i'. Thus, based on (10)-(12), we can obtain that $p_i - c_{i,k} \geq p_i' - c_{i,k'}$, i.e., $v_i \geq v_i'$.

In sum, we have $v_i \geq v_i'$ for all cases, which means that being truthful is the optimal strategy for vehicles. The proof is complete. ■

Theorem 2: The proposed WBS and PD algorithms are computational efficient.

Proof: We should prove that our algorithms have polynomial-time computation complexity. For the WBS algorithm, finding the bid with maximum social welfare demands $\mathcal{O}(|I||J|K)$ time. Since the while-loop takes at most $K|J|$ times, the computational complexity of WBS algorithm can be denoted by $\mathcal{O}(|I|^2K^2|J|)$ time. Moreover, due to that K is typically much smaller than $|I|$ and $|J|$, the computational complexity can be simplified as $\mathcal{O}(|I|^2|J|)$. For the PD algorithm, a process similar to WBS algorithm is executed in each iteration of determining the payment to each winner. Since the maximum number of winners is I, the computational complexity of PD algorithm is $\mathcal{O}(|I|^3|J|)$. The proof is complete. ■

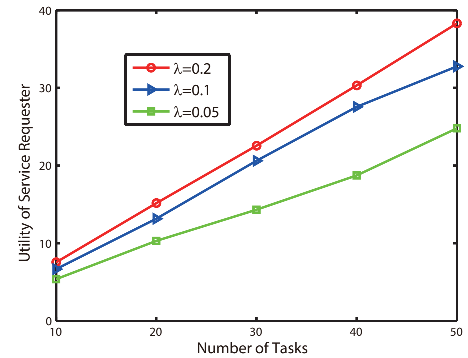

Fig. 3. The utility of service requester versus task deadline T and the arrival rate λ of vehicles.

Theorem 3: The proposed incentive mechanism is individually rational and profitable.

Proof: The proof is omitted due to space limitation. ■

IV. Performance Evaluation

In this section, we evaluate the performance of our proposed incentive mechanism. We consider the road network as in Fig. 2, which has 3 east-westward roads and 3 north-southward roads. The participating vehicles arrive at this road network at a random entrance according to poisson process with parameter λ, which is set as $0.05/s$, $0.1/s$ or $0.2/s$ in the simulations. The length of each road segment is set as 200 m, and each vehicle is assumed to move at a speed of 10 m/s. For each vehicle, its destination is randomly selected among the rest 11 entrances, and has at most 3 preferred trajectories with the shortest distance. To make the auction efficient, one vehicle is allowed to submit at most 3 bids, each of which corresponds to the tasks on one of its preferred trajectories. Due to the willingness of the vehicle owner, each task on his preferred trajectory only has a probability of 0.5 to be included in the corresponding bid. Without loss of generality, ETEs are assumed to follow uniform distribution over $[1, 10]$ seconds, and the cost $c_{i,k}$ is $c_0|J_{i,k}|$, where c_0 is assumed to follow uniform distribution over $[0.1, 0.5]$ [9]. We adopt (1) as the task value function, where $a = 1$, $c = 0.2$, $b = 0.05$ and $T = 300$, unless specified in the figures. An auction process starts at a random point of the timeline. It is worthy noting that the vehicles currently out of the road network can still participate in the auction and estimate ETCs for the tasks that they bid for. All of following simulations are obtained by averaging the results.

Fig. 3 illustrates the average utility of service requester by the number of tasks and the arrival rate of participating vehicles. It is not surprising to see that the utility of service requester increases with the number of released tasks, given the arrival rate of vehicles is fixed. This is because one vehicle is typically capable of performing multiple tasks on its preferred trajectory due to the spatial distribution of tasks. A higher arrival rate of vehicles also leads to higher utility of service requester. This matches our intuition as well because

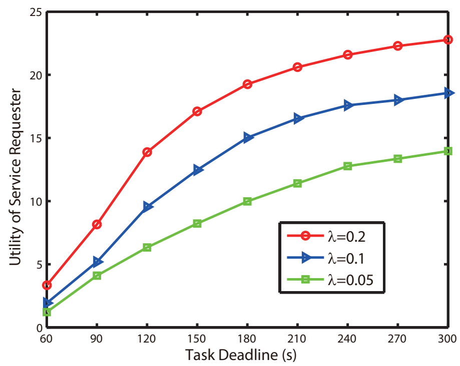

Fig. 4. The utility of service requester versus task deadline T and the arrival rate λ of vehicles, with $|J| = 30$.

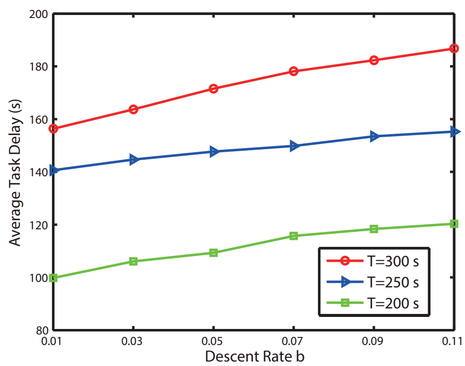

Fig. 5. The average task delay versus the descent rate b and task deadline T with $|J| = 30$ and $\lambda = 0.1/s$. With a given deadline T, a smaller b means that the task value is more sensitive to the delay within $[0, T]$.

there are more eligible vehicles to which the released tasks can be crowdsourced.

Fig. 4 evaluates the average utility of service requester by varying task deadline and arrival rate of vehicles. We observe that, the larger T is, the more utility that the service requester can gain in average. This is because a large amount of vehicles, including the vehicles relatively far away, are eligible to bid for the delay-tolerant task, thus providing more choices for bid selection and leading to a higher utility.

Fig. 5 illustrates the average task delay in terms of the task deadline and the descent rate of task value function. According to (1), a smaller T and b means that the task value is more sensitive to delay, and should be completed soon. For this reason, a smaller T and b leads to a reduced task delay. However, as a tradeoff, this change adversely affects the utility of service requester as observed from Fig. 4. Combining Fig. 4 and Fig. 5, we can conclude that our incentive mechanism can provide different service quality for the tasks with different delay demands.

V. CONCLUSIONS

In this paper, we have proposed a delay-aware incentive mechanism for vehicle-based crowdsourcing system. A truthful auction-based incentive mechanism has been proposed to employ vehicles relying on both the reserve prices and the provisioned service quality declared by vehicles. By allowing each participating vehicle to submit multiple bids, the formulated WBS problem appears to be a non-monotone submodular maximization problem with a matroid constraint, which is NP-hard. Thus, we proposed a novel approximation algorithm to solve the WBS problem while guaranteeing the truthfulness. Through extensive simulations, we validated the effectiveness of our proposed incentive mechanism.

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