ASC: Actuation System for City-wide Crowdsensing With Ride-sharing Vehicular Platform

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ABSTRACT

Vehicular mobile crowdsensing (MCS) enables a lot of smart city applications, such as smart transportation, environmental monitoring etc. Taxis provide a good platform for MCS due to their long operational time and city-scale coverage. However, taxis, as a non-dedicated sensing platform, does not guarantee high sensing coverage quality (large and balanced). This paper presents *ASC*, a system that actuates vehicular taxis fleets for optimal sensing coverage quality while matching ride requests with taxis. We propose a near-optimal algorithm that integrates 1) a mobility prediction model that guides the selection of taxis to actuate and 2) a ride request prediction model to help match ride request with taxis, lower incentive cost and improve taxi drivers' motivation. Extensive simulation and real-world experiments in a testbed with 230 actuated taxis show that our *ASC* can achieve up to 40% improvement in sensing coverage quality improvement and up to 20% better ride request matching rate than baselines approaches. In addition, to achieve a similar level of sensing coverage quality, our *ASC* only requires 10% of the baseline budget.

KEYWORDS

Smart City, Mobile Crowdsensing, Actuation System, Ride-sharing

1 INTRODUCTION

The rapid growth of mobile devices with powerful sensing units has promoted the development of mobile crowdsensing (MCS), in which spatially distributed participants collectively sense and share data [1–3]. The extracted information from shared data can be used to measure, map, analyze, or estimate any processes of interest, which enlightens a lot of smart city applications, such as traffic conditions, air pollution, noise level, etc [4–6].

Vehicle fleets are an important platform for MCS due to their high mobility and large range. Especially, traditional taxis and new forms of taxis (Uber, Lyft and Didi) operate throughout the city with long operational time. These fleets enable large scale sensing data with high spatiotemporal coverage and make a lot of urban sensing applications feasible [7, 8].

Sensing coverage quality, which considers both amount and balance of data collection, is one of the key performance indices (KPI) of the MCS system that influence the quality of the information collection [9]. Good quality data collection requires both large and balanced coverage in the spatial and temporal domain [10]. Large coverage ensures sufficient information is collected, while balanced coverage ensures informative data collection.

As non-dedicated sensing platforms, MCS systems using taxis do not guarantee good sensing coverage quality even with large numbers of taxis. This is because most taxis gather around busy areas, like central business districts (CBDs), while little data are collected in other areas [11]. A lot of past work has been done to improve the sensing coverage quality. Auction-based or game-theoretical mechanisms have been proposed to actuate MCS participants [12–15]. These approaches require the participants to select and bid the task. These approaches rely on a large number of rational participants and incorporate all their preferences. As a result, they are particularly sensitive to driver participation and attention. Furthermore, they do not incorporate the future mobility of the unselected vehicles on the overall sensing coverage quality, which brings a lot of uncertainty on the effectiveness of the sensing coverage quality after actuation.

It is difficult to optimize sensing coverage quality in a vehicular MCS with a limited budget due to **two major challenges: high uncertainty on actuation effectiveness, and conflicting goals between the vehicle fleet and MCS platform.**

- *High uncertainty on actuation effectiveness:* With limited budget, only small percent of the whole vehicle fleet can be actuated and the future mobility of the rest vehicles are not considered. As a result, the effectiveness of actuation is highly uncertain.
- *Conflicting goals:* As a non-dedicated sensing platform, taxis make individual optimal decisions on looking for new ride requests (customers), which makes them gather in the busy areas with more ride requests. This leads to much fewer taxis showing up and less data being collected at the rest parts of the city. As a result, simply actuating taxis with a monetary incentive causes high actuation cost and low motivation [16].

This paper answers the question: how can we efficiently actuate non-dedicated sensing platforms (ride-based vehicles) to achieve optimal sensing coverage quality with limited budget? We present *ASC*, a system that actuates vehicular taxi fleets for optimal sensing coverage quality through incorporation of matching ride requests with taxis. *ASC* determines routes for all the available taxis through two main steps. 1) The system first adopts a mobility prediction model to forecast the near-future taxi destinations. The prediction guides the system to decide which taxis to select for actuation to achieve maximum sensing coverage quality improvement. The system intends to spend budget on taxis, which are predicted to head for busy areas (instead of those heading for sparse areas), and actuates them to sparse areas. As a result, actuating one taxi brings more sensing quality improvement. 2) *ASC* includes a ride request prediction model to predict near-future ride requests across the city. Based on this prediction, the system chooses routes to actuate taxis,

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which aims to improve the overall sensing coverage quality and match the ride requests with the taxis. This not only lowers the cost of actuation but also improves the motivation for the driver [16]. Utilizing these two key steps, the system sends the actuated routes and corresponding monetary incentives to the selected taxis.

The main contributions of this paper are:

- A system that simultaneously optimizes the sensing coverage quality while matching ride requests for the taxi fleets.
- Formulate the collaborative task and propose a near-optimal algorithm, which integrates 1) a mobility prediction model and 2) a ride request prediction model to lower incentive cost and improve taxi drivers' motivation.
- Evaluate the system with real city-scale deployment and history trajectory data in the city of Beijing, China.

The remainder of the paper is organized as follows: Section 2 presents problem definition. Section 3 introduces our system overview, key parts in the system, as well as the key algorithm. Section 4 discusses the experiments for system evaluation. Section 5 concludes the paper respectively.

2 PROBLEM DEFINITION

In this section, we discuss the problem of optimizing sensing coverage quality in vehicular MCS. Our actuation system is not dependent on the particular applications and can be used for any type of high-level vehicular MCS tasks. The preliminary definition is firstly given. Then we describe the goal of our system. Finally, we formulate the problem of optimizing sensing coverage quality.

According to spatial and temporal resolution setup (d_s and d_t), the system discretizes the focus rectangle area into n_x by n_y congruent *grids* (x_i, y_j) and *time slices* t_k. The longitude, latitude and time index is represented with x_i, y_j and t_k respectively. It is noticed that according to the average taxi speed, we set d_s and d_t so that a taxi covers at most d_s within d_t.

2.1 Key Definitions

Worker: Denoting taxis fleet as C, each worker $c \in C$ represents a taxi carrying sensors for different applications. The worker runs inside the map of target city and keep collecting data during the trajectory. The spatial coordinate of c at time t is denoted as (x_t^c, y_t^c) and obtained by global positioning system(GPS).

Actuation period: The actuation period $T = nd_t$ denotes time length for the selected taxis to finish the actuation route. For simplicity but without loss of generality, we set $T = 5d_t$ in this paper. The changing of n does not change the problem and solution.

Actuation Task: An actuation task for a worker c refers to a route that we ask the worker to cover within an actuation period T. The route consists of a sequence of coordinates for each d_t during the actuation period and expressed as

$$\left\{(x^c{}_\tau, y^c{}_\tau), (x^c{}_{\tau+d_t}, y^c{}_{\tau+d_t}), ..., (x^c{}_{\tau+T}, y^c{}_{\tau+T})\right\},$$

where $(x^c{}_\tau, y^c{}_\tau)$ is the original location of the taxi c when the actuation task starts at time τ.

Actuation Availability: At the beginning of each actuation period T, each worker c reports its actuation availability. An available worker means there is no passenger on the taxi and the driver is willing to follow the assigned trajectory with the given monetary incentive. A worker is called an "actuated worker" when it accepts an actuation task, and a "non-actuated worker" otherwise.

Budget & Monetary Incentive: The budget R is the total amount of money available to actuate workers during each actuation period. When a worker c is assigned an actuation task, a monetary incentive $B(c)$ is also allocated. The total monetary incentives do not exceed the given budget R.

Sensing Coverage: The sensing coverage A refers to the set of data points collected by all workers during one actuation period T, including both "actuated" and "non-actuated" workers.

2.2 Actuation Objective

The objective of actuation is to achieve optimal sensing coverage quality (large and balanced) by actuating part of the vehicle fleets with given limited budget. We define the sensing coverage quality $\phi(A)$ as a combination of the total amount of sensed data and the balance level of the sensed data distribution over the covered area. The balance level represents how uniformly the sensed data are distributed in both the temporal and spatial domains. We quantify this using the entropy of the sensed data distribution. Thus, the overall sensing coverage quality is obtained by the weighted sum of the total amount of sensed data and the entropy of their distribution.

Eq. 1 shows mathematical formulation of $\phi(A)$, where $E(A)$ is entropy of data distribution (data balance), and $Q(A)$ is the number of data points [10]. $\alpha \in (0, 1)$ is tuned to be large when balancing the data distribution is the main focus of the actuation task, and small when the main focus is collecting a large amount of data.

$$\phi(A) = \alpha E(A) + (1 - \alpha)\log Q(A). \tag{1}$$

2.3 Problem Formulation

To optimize the sensing coverage quality $\phi(A)$ with limited budget R, the system needs to 1) select the "correct" taxis to actuate that efficiently utilizes the budget and 2) plan the actuation task routes for each selected taxi. Therefore, we give the mathematical formulation of the actuation problem at time t as:

$$\max_{I(c_i), \left\{(x_c^t, y_c^t), \ldots, (x_c^{t+T}, y_c^{t+T})\right\}} \phi(A) \tag{2}$$

$$s.t.\ 0 \le x_{c_i}^\tau \le n_x d_s, \mathrm{t} \le \tau \le t + T, \mathrm{i} = 1, \ldots |C| \tag{3}$$

$$0 \le y_{c_i}^\tau \le n_y d_s, \mathrm{t} \le \tau \le t + T, \mathrm{i} = 1, \ldots |C| \tag{4}$$

$$|x_{c_i}^\tau - x_{c_i}^{\tau-d_t}| \le d_s, \mathrm{t} \le \tau \le t + T, \mathrm{i} = 1, \ldots |C| \tag{5}$$

$$|y_{c_i}^\tau - y_{c_i}^{\tau-d_t}| \le d_s, \mathrm{t} \le \tau \le t + T, \mathrm{i} = 1, \ldots |C| \tag{6}$$

$$\sum_{i=1}^{|C|} B(c_i) \cdot I(c_i) \le R \tag{7}$$

$I(c_i) = 1$ represents worker c_i is selected for actuation and 0 vice versa. Eq. (3) and (4) constrains that the system only consider workers' mobility within the focus area. The Eq. (5) and (6) constrains that each worker covers at most d_s within d_t. The Eq. (7) constrains that total monetary incentives do not exceed the given budget R.

In our system, at the beginning of each actuation period T, taxis automatically report their information including: taxi id, current location, and actuation availability for the coming actuation period. It is noticed that in our system only the taxis without passengers are available for actuation. In addition, drivers can always set their availability to false if they are not willing to join. Based on the reported information, tasks and monetary incentives are calculated and assigned to selected available taxis. We assume taxis follow the actuation task routes until the end of the the actuation period if they accept them.

3 SYSTEM DESIGN

This section introduces how we design the actuation system to optimize sensing coverage quality to address the two major challenges. We first discuss how the system integrates the mobility prediction model and the ride request prediction model in Section 3.1. We then introduce the design of our monetary incentives in Sections 3.2. Finally, the multi-incentive algorithm is described in Section 3.3.

3.1 System Overview

To optimize sensing coverage quality, we design our actuation system based on two key observations: **1) The cost of actuating one taxi depends on whether the system can match a taxi with a ride request at the destination.** If the system matches the taxi with a ride request, the taxi driver is willing to accept a lower monetary incentive since they can earn money from the new rides [16]. **2) The sensing coverage quality after actuation depends on selecting which taxis to actuate.** We do not have to actuate taxis that plan to head for sparse areas, as changing their trajectories would not significantly improve the sensing coverage quality. On the other hand, changing the trajectories of those that plan to head for busy areas and actuating them towards sparse areas improves sensing coverage quality more.

Therefore, we integrate two prediction models into our system. The mobility prediction model forecasts the mobility of taxis, which offers guidance for the system to wisely select which taxis to actuate. To be specific, the system selects taxis heading for dense areas and actuates them to sparse areas, which leads to higher sensing coverage quality improvement with actuated taxi. The ride prediction model forecasts the coming ride requests over the city. When taxis are matched with ride requests, taxi drivers are willing to accept a lower incentive. As a result, the cost of actuating a taxi is lowered and more taxis can be actuated for better sensing coverage quality with the same budget.

Figure 1 shows how we design the system to integrate the two prediction models for actuation. Taxis report their real-time trajectory data and whether they are available for actuation to *ASC*. Unavailability can occur for two reasons: customers already riding in taxis, or drivers' unwillingness to be actuated. *ASC* calculates 1) which taxis to be actuated, 2) where they will be actuated, and 3) how much monetary incentive they are paid, and potential ride request at the actuation destination. The results are sent back to the taxis, thus actuating them to achieve sensing coverage quality optimization.

The *Pre-Processing* module discretizes the focus rectangle area of the city and the time with the given spatial and temporal resolution (d_s and d_t). It is noticed that according to the average taxi speed, we set d_s and d_t so that a taxi covers at most d_s within d_t.

The *Vehicle Mobility Prediction* module, which is trained by each taxi's history trajectory data, predicts taxi mobility. The prediction

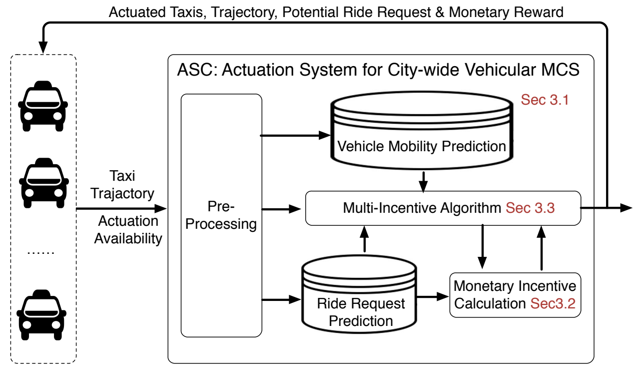

Figure 1: The figure shows the architecture of system.

output is fed to the *Multi-Incentive Algorithm* module to guide the system to wisely select the taxis to actuate, which improves the effectiveness of the actuation. **It is noticed that *ASC* allows different mobility prediction models. For simplicity but without loss of generality, this paper adopts a Markov based mobility prediction model.**.

The *Ride Request Prediction* module predicts ride requests over the city, whose results are sent to the *Multi-Incentive Algorithm* module. Based on this prediction, the *Multi-Incentive Algorithm* module selects routes for actuated taxis. The *Ride Request Prediction* module uses historical ride request data, which can be derived from taxi occupancy data, to train the ride request model. The system framework allows for different ride request prediction models. For simplicity but without loss of generality, this paper adopts a graph-based ride request prediction model [17].

The *Monetary Incentive Calculation* module calculates the incentive based on the selected routes from the *Multi-Incentive Algorithm* module and the prediction from the *Ride Request Prediction* module. The results are sent back to the *Multi-Incentive Algorithm* module for further optimization.

The *Multi-Incentive Algorithm* module selects the taxis to be actuated and designs trajectories for those taxis by collaboratively considering 1) taxi mobility predictions from the *Vehicle Mobility Prediction* module, 2) ride request predictions from the *Ride Request Prediction* and 3) monetary incentive from the *Monetary Reward Calculation* module. The details will be discussed in Section 3.3.

3.2 Monetary Incentive

The key idea of our monetary incentive design is to include the probability of getting a ride request in the destination planned for the actuated taxi. This can decrease the monetary cost for actuating taxis by utilizing the underlying incentives of providing taxis a higher chance to get passengers at the destination of assigned task. In this way, we could actuate more taxis and better utilize the budget to improve the sensing coverage quality.

The difference between taxis' distribution and the ride request distribution makes it possible to provide taxi a higher chance to get passengers in sparse sensed area. Therefore, if we could actuate the vehicles to the sparsely sensed areas with greater ride request probabilities, the cost for actuating taxis would be decreased and quality of sensing coverage will be improved. Meanwhile the utilities of the taxis are ensured, and overall transportation efficiency is

ALGORITHM 1: Multi-Incentive Algorithm for Taxis and Trajectory Selection.

Input: Current location x_0, Budget R, Taxis availability, Ride request model *Request*, Mobility prediction model P
Output: Actuated taxis ID, planned trajectory and monetary incentive for actuated taxis
Initialize:
  Select taxis and trajectory randomly until the budget is full
  Output the initial feasible solution S based on actuated taxis and P for non-actuated taxis
while ϕ *converges* **do**
  Select the grid with maximum taxis passing through
  Take out the set of taxis S_{tmp} which pass through the maximum grid
  Compute and rank the contribution of trajectories of taxis belonging to S_{tmp}
  Select the taxi with minimum contribution and update its trajectory with monetary incentive defined by *Request*
  Keep updating the trajectory until the budget constraint R is satisfied
  Update S and calculate the updated sensing quality ϕ
Return $S^\star = S$

improved. Therefore we design the monetary incentive $B(c)$ offered to taxi c as follows

$$B(c) = \max(r_{max} - r_u \cdot Request(x_c^T, y_c^T, T), r_{min}), \qquad (8)$$

where r_{min} and r_{max} are minimum and maximum monetary incentive to actuate one taxi respectively. This definition is based on the following reasons. First, maximum incentive r_{max} should equal maximum cost that the taxi incurs by following our route. Thus, we can find r_{max} from the gas, time cost and passenger count of driving during the actuation period. We can offer lower incentives, however, if taxis encounter ride requests while following our trajectories: taxis could then earn additional money from serving these requests, which lowers their net cost from following our route. The $Request(i, j, t)$ represents the predicted ride request distribution in location of (i, j) at the t time interval, which is estimated using the ride request prediction model in [17]. r_u is the unit monetary incentive for one ride request. Moreover, even with a high possibility to get new ride request, each taxi still needs a minimum monetary incentive to motivate, which is r_{min}.

3.3 Multi-Incentive Taxis and Trajectory Selection Algorithm

To solve the NP-hard optimization problem in Eq.(2) – (7), we propose a fast, near-optimal heuristic-based algorithm to find an approximate solution. The core idea of our algorithm is to 1) find the time and locations with many taxis passing through, and 2) dispatch these taxis to different trajectories with very few taxis passing through. This is because actuating the taxis in a sparse area does not solve the problem of most taxis gathering in dense areas. The idea of the proposed algorithm is based on the Complementary Constructive Procedure (CCP). We first initialize a feasible solution S under the constraints, which is easy to implement by selecting taxis until the budget is full. Then we keep updating the solution to improve the objective function, which is the sensing quality. As Algorithm 1 shows, in the initialized feasible solution, we can find the corresponding time and location pair that contains maximum data points. We can also find the set S_{tmp} of taxis that pass through the location at the respective time. A key step is then that for taxis belonging to the set S_{tmp}, the expectation of the current trajectories is computed based on the current data point distribution. In this way, we can have an overall idea about which taxis passing through the maximum grid contribute the least to the overall data distribution balance level. Then we traverse this list of taxis from least to most contribution one to select taxis to dispatch to a new trajectory or not actuate. Similarly, we firstly compute the expectation value of each prospective trajectory, including random run without actuation, on the current data distribution. Then the algorithm traverses the prospective trajectories according to descending expectation value until the sensing coverage quality is improved. Finally, the solution is updated based on the selected trajectory and taxi. With multiple iterations, the solution keeps updating until the estimate of sensing coverage quality converges.

4 EVALUATION

In this section, we evaluate our system's ability to achieve optimizing sensing coverage quality. In addition, we also verify the ability to match ride requests with taxis, which is an essential actuation motivation for taxis. We first introduce how we design a simulation based on real historical taxi trajectory data and real experiments on a taxi testbed for evaluation in Section 4.1. Then, we present and analyze the simulation and experiment results in Sections 4.2 and 4.3 respectively.

4.1 Evaluation Setup

We evaluate our system on a taxi testbed as well as a simulation based on real historical taxi trajectory data in the center area of Beijing. The evaluation area occupies a size of $15km$ by $15km$ and we set the α value as 0.5. The major setup parameters of the evaluations are listed below.

Real Taxi Testbed Experiment Setup: To test our system in a realistic setting, we recruited taxis to run in the city of Beijing. We evaluate our system at different time period of a day, which are 0:00am, 6:00am, 12:00pm and 6:00pm. In addition, we also evaluate the system at 9:00am since it is a peak time in a day. We run the taxis on routes calculated by our system. For each route, a researcher hailed a taxi. The researcher suggested routes for the driver based on our system outputs. The drivers are free to modify routes. During the whole process, an Android App named GPS Logger was used to collect real-time GPS taxi data. In total we collected traces from 230 actuated taxis over a period of 14 days. The experiment was approved under the university IRB *STUDY2017_00000342*.

Historical Trajectory Data Description: We use the Beijing taxi trajectory dataset in November of 2015 to conduct simulations based on real historical taxi trajectory data. The dataset is formatted as: taxi id, time stamp, longitude, latitude, occupancy flag. The occupancy flag represents whether the taxi is occupied by customers. The temporal and spatial resolutions are 60 seconds and 1 meter respectively. We extract the ride requests in the city according to the

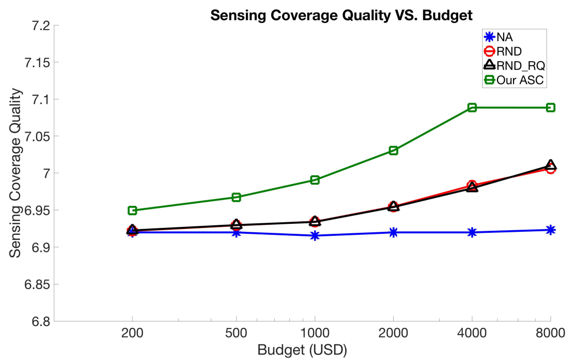

Figure 2: This figure shows the sensing coverage quality with different budget. Our *ASC* shows up to 40% more improvement than *RND* and *RND_RQ*. To achieve similar sensing coverage quality, our *ASC* needs 200 USD while *RND* and *RND_RQ* need 2000 USD.

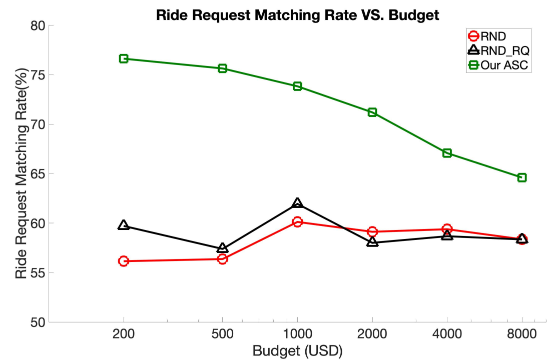

Figure 3: This figure shows ride request matching rate with different budget. Our *ASC* consistently shows up to 20% matching rate than *RND* and *RND_RQ*.

occupancy flag transformations. A ride request is obtained when a taxi's occupancy flag is turned to occupied.

General System Setup: Every actuation period, we randomly select 500 active taxis as the total vehicle fleet. We take temporal and spatial resolution as 2 minutes and 1 km since the average taxi speed in Beijing is 30km/h and 2 minutes can cover 1 km, which is one grid. The incentive in our system is given in units of US dollars (USD). We adopt $r_u = 2(USD)$, $r_{min} = 2(USD)$ and $r_{max} = 20(USD)$, since 2 USD is the flag-down fare of Beijing Taxi and 20 USD is enough to cover the cost for one trajectory ($\sim 10km$) in one incentive period under the bad traffic condition. We take the first 3 weeks' data to train mobility prediction and ride request prediction and the rest days of the month to test the system. We evaluate our system at different time period of a day, which are 0:00am, 6:00am, 12:00pm and 6:00pm. In addition, we also evaluate the system at 9:00am since it is a peak time in a day. In the taxi testbed, the actuated taxis run on real roads as described earlier. In the simulated experimentation, we assume the actuated taxis follow the planned trajectories in an average velocity and finish the tasks before the end of one incentive period.

Performance Metric: We adopt value of sensing coverage quality (SCQ) ϕ, which is the objective of our problem as shown in Eq 1, as our performance metric. High value of ϕ means better sensing coverage quality.

Baselines: We adopt different baselines to validate different parts of our system on improving sensing coverage quality. These parts include mobility prediction model, ride request prediction model and our core algorithm.

- *No Actuation (NA)*: This method does nothing to actuate taxis or match ride requests. All the taxis just follow their original trajectories. By comparing this method with our *ASC* system, we can check the performance improvement of our entire system.
- *Random Actuation (RND)*: This method randomly selects taxis and routes within the given budget. RND always offers the maximum monetary incentive. By comparing this method with our *ASC* system, we can check the performance improvement brought from the two prediction models.
- *Random Actuation with Ride Request Prediction (RND_RQ)*: This method also randomly select taxis and actuation routes within the given budget. At the same time, *RND_RQ* tries to match ride requests with taxis. As a results, the cost to actuate one taxi will be lower than *Random Actuation (RND)*. By comparing this method with *RND*, we can check the improvement from the ride request model. By comparing this method with our *ASC*, we can check the improvement from the mobility prediction model.

4.2 Simulation Performance

In order to evaluate how budget affects the sensing coverage quality with our *ASC* and baselines, we plot the sensing coverage quality in Figure 2. First, for *ASC*, *RND* and *RND_RQ*, sensing coverage quality improves with increasing budget. Higher budgets allow for more actuated taxis, leading to better sensing coverage quality. Second, our *ASC* always shows an advantage over the three baselines. Especially when budget is 4000 USD, our *ASC* achieves 61% improvement while *RND* and *RND_RQ* only give 22% and 20% improvement over *NA* respectively. The 40% advantage of our *ASC* comes from two parts. The ride request prediction model helps our *ASC* lower the incentive cost by matching the ride request with taxis. In addition, the mobility prediction model guides our *ASC* to select taxis which bring more sensing coverage quality improvement. Third, our *ASC* arrives at saturation point at 4000 USD while other baselines still keep increasing even at 8000 USD. This shows that with the help of two prediction models, our *ASC* has much higher efficiency on sensing quality coverage improvement. To be specific, to achieve similar sensing coverage quality, our *ASC* need 200 USD while *RND* and *RND_RQ* needs 2000, which is 10× of our expense. Finally, although *RND_RQ* can lower incentive cost by matching more ride requests and thus actuating more taxis, it still does not exceed the sensing coverage quality of *RND*. This shows that even with more actuated taxis, randomly selecting taxis to actuate does not bring sensing coverage quality improvement. The similar trend of *RND* and *RND_RQ* validates the effect of our mobility prediction model.

To evaluate how budget affects the ride request matching of different methods, we plot ride request matching rate in Figure 3. First, a large budget does not necessarily ensure large ride request

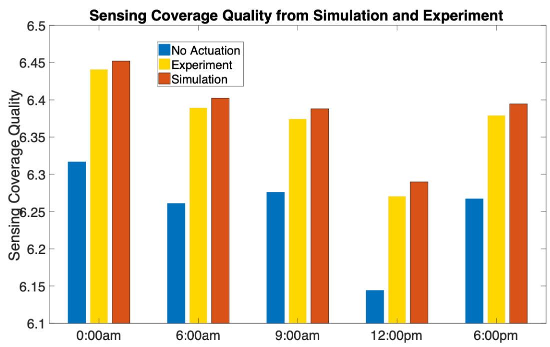

Figure 4: The figure shows sensing coverage quality from real experiment, simulation and non-actuation.

matching rate, which is different from sensing coverage quality. This is because the first priority of our *ASC* is to improve sensing coverage quality. To ensure sensing coverage quality improvement, *ASC* will sacrifice ride request matching rate. Second, for different budgets, our *ASC* has up to 20% larger ride request matching rate and than *RND* and *RND_RQ*. This shows that even though our *ASC* sacrifices ride request matching rate to guarantee sensing coverage quality improvement, it still keeps a higher matching rate than other methods.

4.3 Experiment Results

To check the performance of our system in real operational condition, we conducted experiments on a taxi based testbed at 5 representative time periods mentioned in Section 4.1. Our experimental evaluation accounts for real-time traffic patterns, which the simulation does not. We compare the *ASC* experiment results with *ASC* simulation results to illustrate that our system is practical. In addition, we include the non-actuation results as a baseline.

Figure 4 shows the sensing coverage quality from real experiment, physical feature based simulation and non-actuation. At all representative times, sensing coverage quality values from experiment are similar to simulated values, which shows that physical feature based simulation can be used to analyze system operation in the real world. It is noticed that sensing coverage quality values from experiment are a little bit lower than that from simulation. This is because simulation results are theoretically near-optimal while real experiment involve practical factors that prevent it from achieving simulation results. These factors include traffic jams, temporary road closure, lack of direct routes to follow the designed trajectories, etc. In addition, both simulation and experiment sensing coverage quality show advantages over non actuation results. This proves that our system improves sensing coverage quality in both simulation and experiment.

5 CONCLUSION

This paper presents *ASC*, a system that actuates vehicular taxis fleets for optimal sensing coverage quality through incorporation of matching ride requests with taxis. We propose a near-optimal algorithm that integrates 1) a mobility prediction model that guides the selection of taxis to actuate and 2) a ride request prediction model to help match ride requests with taxis, lower incentive cost and improve taxi drivers' motivation. Extensive simulation and experiments on taxi testbed show that our *ASC* achieves up to 40% more sensing coverage quality improvement and up to 20% more ride request matching rate than baselines. Additionally, our *ASC* achieves similar sensing coverage quality as baseline algorithms with only 10% of the budget requirement. The proposed algorithm can be extended to drone-based MCS platform in the future [18, 19].

REFERENCES

[1] Charith Perera, Arkady Zaslavsky, Peter Christen, and Dimitrios Georgakopoulos. Sensing as a service model for smart cities supported by internet of things. *Transactions on Emerging Telecommunications Technologies*, 25(1):81–93, 2014.

[2] Yu Liu, Xinlei Chen, Yong Niu, Bo Ai, Yong Li, and Depeng Jin. Mobility-aware transmission scheduling scheme for millimeter-wave cells. *IEEE Transactions on Wireless Communications*, 17(9):5991–6004, 2018.

[3] Xinlei Chen, Yulei Zhao, and Yong Li. Qoe-aware wireless video communications for emotion-aware intelligent systems: A multi-layered collaboration approach. *Information Fusion*, 47:1–9, 2019.

[4] Robert Ighodaro Ogie. Adopting incentive mechanisms for large-scale participation in mobile crowdsensing: from literature review to a conceptual framework. *Human-centric Computing and Information Sciences*, 6(1):24, 2016.

[5] Xinlei Chen, Yulei Zhao, Yong Li, Xu Chen, Ning Ge, and Sheng Chen. Social security aided d2d communications: Performance bound and implementation mechanism. *IEEE Journal on Selected Areas in Communications*, 2018.

[6] Jie Feng, Xinlei Chen, Rundong Gao, Ming Zeng, and Yong Li. Deeptp: An end-to-end neural network for mobile cellular traffic prediction. *IEEE Network*, 32(6):108–115, 2018.

[7] Xinlei Chen, Xiangxiang Xu, Xinyu Liu, Hae Young Noh, Lin Zhang, and Pei Zhang. Hap: Fine-grained dynamic air pollution map reconstruction by hybrid adaptive particle filter. In *Proceedings of the 14th ACM Conference on Embedded Network Sensor Systems CD-ROM*, pages 336–337. ACM, 2016.

[8] Xinlei Chen, Xiangxiang Xu, Xinyu Liu, Shijia Pan, Jiayou He, Hae Young Noh, Lin Zhang, and Pei Zhang. Pga: Physics guided and adaptive approach for mobile fine-grained air pollution estimation. In *Proceedings of the 2018 ACM International Joint Conference and 2018 International Symposium on Pervasive and Ubiquitous Computing and Wearable Computers*, pages 1321–1330. ACM, 2018.

[9] Osamu Masutani. A sensing coverage analysis of a route control method for vehicular crowd sensing. In *Pervasive Computing and Communication Workshops, 2015 IEEE International Conference on*, pages 396–401. IEEE, 2015.

[10] Shenggong Ji, Yu Zheng, and Tianrui Li. Urban sensing based on human mobility. In *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, pages 1040–1051. ACM, 2016.

[11] Raghu K Ganti, Fan Ye, and Hui Lei. Mobile crowdsensing: current state and future challenges. *IEEE Communications Magazine*, 49(11), 2011.

[12] Dejun Yang, Guoliang Xue, Xi Fang, and Jian Tang. Incentive mechanisms for crowdsensing: crowdsourcing with smartphones. *IEEE/ACM Transactions on Networking*, 24(3):1732–1744, 2016.

[13] Dong Zhao, Xiang-Yang Li, and Huadong Ma. How to crowdsource tasks truthfully without sacrificing utility: Online incentive mechanisms with budget constraint. In *INFOCOM, 2014 Proceedings IEEE*, pages 1213–1221. IEEE, 2014.

[14] Lingjie Duan, Takeshi Kubo, Kohei Sugiyama, Jianwei Huang, Teruyuki Hasegawa, and Jean Walrand. Incentive mechanisms for smartphone collaboration in data acquisition and distributed computing. In *INFOCOM, 2012 Proceedings IEEE*, pages 1701–1709. IEEE, 2012.

[15] Dejun Yang, Guoliang Xue, Xi Fang, and Jian Tang. Crowdsourcing to smartphones: Incentive mechanism design for mobile phone sensing. In *Proceedings of the 18th annual international conference on Mobile computing and networking*, pages 173–184. ACM, 2012.

[16] Xinglin Zhang, Zheng Yang, Wei Sun, Yunhao Liu, Shaohua Tang, Kai Xing, and Xufei Mao. Incentives for mobile crowd sensing: A survey. *IEEE Communications Surveys & Tutorials*, 18(1):54–67, 2016.

[17] Abhinav Jauhri, Brian Foo, Jerome Berclaz, Chih Chi Hu, Radek Grzeszczuk, Vasu Parameswaran, and John Paul Shen. Space-time graph modeling of ride requests based on real-world data. *arXiv preprint arXiv:1701.06635*, 2017.

[18] Xinlei Chen, Aveek Purohit, Carlos Ruiz Dominguez, Stefano Carpin, and Pei Zhang. Drunkwalk: Collaborative and adaptive planning for navigation of micro-aerial sensor swarms. In *Proceedings of the 13th ACM Conference on Embedded Networked Sensor Systems*, pages 295–308. ACM, 2015.

[19] Xinlei Chen, Aveek Purohit, Shijia Pan, Carlos Ruiz, Jun Han, Zheng Sun, Frank Mokaya, Patric Tague, and Pei Zhang. Design experiences in minimalistic flying sensor node platform through sensorfly. *ACM Transactions on Sensor Networks (TOSN)*, 13(4):33, 2017.