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QUEST: Quality-informed Multi-agent Dispatching System for Optimal Mobile Crowdsensing

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***Abstract*—We address the challenges in achieving optimal Quality of Information (QoI) for non-dedicated vehicular Mobile Crowdsensing (MCS) systems, by utilizing vehicles not originally designed for sensing purposes to provide real-time data while moving around the city. These challenges include the coupled sensing coverage and sensing reliability, as well as the uncertainty and time-varying vehicle status. To tackle these issues, we propose *QUEST*, a QUality-informed multi-agEnt diSpaTching system, that ensures high sensing coverage and sensing reliability in non-dedicated vehicular MCS. *QUEST* optimizes QoI by introducing a novel metric called ASQ (aggregated sensing quality), which considers both sensing coverage and sensing reliability jointly. Additionally, we design a mutual-aided truth discovery dispatching method to estimate sensing reliability and improve ASQ under uncertain vehicle statuses. Real-world data from our deployed MCS system in a metropolis is used for evaluation, demonstrating that *QUEST* achieves up to 26% higher ASQ improvement, leading to a reduction of reconstruction map errors by 32-65% for different reconstruction algorithms.**

***Index Terms*—Internet of Things; Mobile sensing and applications; Mobile Crowdsensing; Data Quality**

I. Introduction

Mobile crowd sensing (MCS) has become a promising paradigm for collecting large amounts of spatio-temporal data [1]. It takes advantage of the mobility of mobile devices carried by crowds to gather information from multiple sources, allowing extensive coverage. Non-dedicated vehicular sensing platforms, such as taxis, delivery drones [2], [3], and ride-sharing vehicles like Uber and Lyft, can collect data while moving in the cities, and thus provide cost-effective and easily maintainable solutions for MCS. By utilizing the collective sensing capabilities of these non-dedicated vehicles, MCS enables people to benefit from a wide range of applications that improve human life and decision-making processes, including public infrastructure [4], traffic [5], and public policy [6].

One of the main problems in non-dedicated vehicular MCS is to ensuring optimal quality of information (QoI), which depends on both *sensing coverage* and *sensing reliability*. Sensing coverage refers to the spatial and temporal extent of data collection, while sensing reliability refers to the accuracy and consistency of sensors' measurements. However, as non-dedicated vehicles are primarily used for transportation, they tend to crowd in busy areas, leading to low sensing coverage elsewhere [7]. Additionally, lacking constant calibration, sensors on non-dedicated vehicles can lead to variations and uncertainties in their readings, affecting sensing reliability. Moreover, these two aspects often conflict. Specifically, increasing sensors in a region may improve sensing coverage, but introduce noise and inconsistency among readings, reducing sensing reliability. On the other hand, relying solely on high-quality sensors for data collection could improve sensing reliability, but lead to insufficient coverage, resulting in data gaps and limited spatial information. This trade-off between sensing coverage and sensing reliability makes it difficult to strike a balance, especially with uncertain and varying sensing reliability, increasing the challenges in achieving high-quality data collection.

Existing solutions have put great effort into improving the QoI of the non-dedicated vehicular MCS systems, which can be classified into the following two categories. *1. Improving sensing coverage through vehicle dispatch*, including various dispatch strategies such as game theory, dynamic programming [8], and reinforcement learning [9]. However, these approaches often overlook ensuring sensing reliability, resulting in potentially unreliable data and misleading information. *2. Ensuring sensing reliability of individual sensors*, such as using external references [10], or machine learning interpolation [11], to improve sensing reliability of low-cost sensors. Despite their effectiveness in certain scenarios, these approaches often assume the availability of specific types of sensors or external references for calibration, making their application limited or prohibitively expensive [12] for many real-world scenarios.

The challenges of ensuring QoI in non-dedicated vehicular MCS systems can be summarized as follows. *The first challenge is the inherent trade-off between sensing coverage and sensing reliability*. As described above, balancing these two aspects is significant due to their conflicting optimization relationship.. *The second challenge lies in the difficulty of accurately estimating individual sensors' sensing reliability*.

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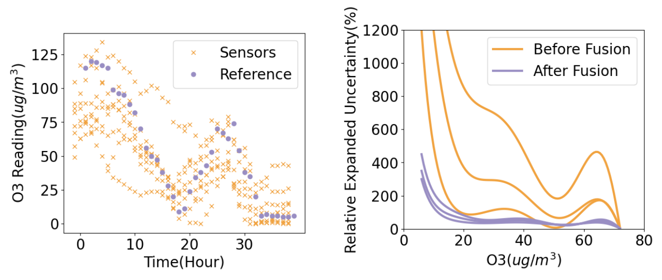


(a)Deviations and variations of low cost sensors by time.

(b)Data fusions for improving sensing reliability, reproduced from [13].

Fig. 1: Motivations for *QUEST*

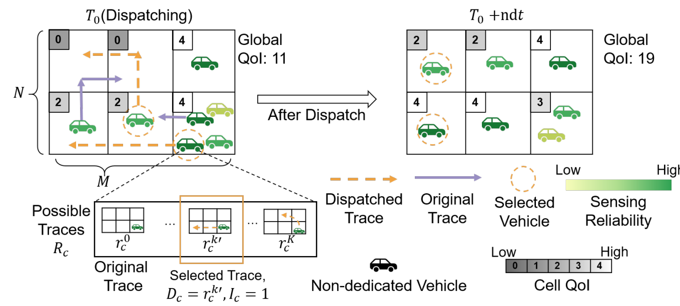


Fig. 2: This figure illustrates how dispatching non-dedicated vehicular MCS in uneven sensing reliability setups can improve QoI by making the coverage optimal.

The constant mobility and varying locations of the sensors, coupled with factors like sensor drifting, introduce significant challenges in determining the accuracy and consistency of their readings. Therefore, optimizing both sensing coverage and sensing reliability becomes complex and dynamic, hindering QoI improvement in such scenarios.

To address these challenges, we propose *QUEST*, a QUality-informed multi-agEnt diSpaTch system to perform dynamic sensing reliability assurance and coverage-driven dispatch during non-dedicated vehicular MCS tasks. First, we introduce a novel metric, aggregated sensing quality (ASQ), balancing sensing coverage and sensing reliability considerations. Based on the insight that sensing reliability of multiple inferior sensors can be compensated by quantities [13], ASQ aggregates the readings of multiple inferior sensors, providing a measure comparable to a superior sensor. This enables optimal trade-off by utilizing vast inferior sensor data. Second, we design a mutually assisted dispatch framework, inspired by the core concepts of truth discovery. In this framework, dispatch decisions are influenced by inferenced sensing reliability, which is derived from readings of multiple sensor sources. Dispatch also improves sensing reliability inference through careful trajectory overlap selection. This ensures adaptive, optimized data collection for high-quality information gathering. To evaluate the performance of our framework, we have deployed a MCS system, involving 29 taxis over two months, to collect fine-grained air pollution data. The result showcases the effectiveness and potential of the *QUEST* in achieving optimal QoI in non-dedicated vehicular MCS scenarios.

To summarize, we make the following contributions.

1) To the best of our knowledge, we are the first to formalize and address a comprehensive dispatch problem for non-dedicated vehicular MCS, with the corresponding metrics, ASQ, to jointly ensure both high sensing coverage and sensing reliability.
2) We design a mutually assisted dispatch framework to improve both sensing reliability inference and ASQ in real time.
3) We evaluate the performance of our proposed solution using real-world data collected by a MCS system deployed at a metropolis.

The remainder of this paper is organized as follows. Formulation of the coupled problem of sensing coverage with sensing reliability in §II. We then present the algorithm details in §III and evaluate the performance in §IV. Then we present the related work in §VI. Finally, we discuss the generalizability and limitation of our work in §V and conclude in §VII.

II. System model & Definition

We consider a non-dedicated vehicular MCS system that faces the challenge of uneven sensing coverage and sensing reliability. To address this issue, we present case studies (§II-A), illustrate the system model and parameters of the dispatch system (§II-B), and explain how we model sensing reliability and sensing coverage as two significant components of vehicular sensing performance (§II-C) to ultimately improve QoI.

A. Motivation Case Studies

In non-dedicated vehicular MCS, the accurate sensing of O_3 levels is of critical importance for assessing air quality and understanding potential health risks. However, commonly deployed low-cost O_3 sensors may exhibit significant deviations from ground-truth measurements, as illustrated in Fig. 1(a). These deviations can hindering the ability to make informed decisions based on the sensed information. Moreover, the lack of constant calibration for sensors mounted on non-dedicated vehicles introduces uncertainties in the reliability of their measurements, further complicating the data collection process.

We explore the potential of data fusion techniques to enhance sensing reliability *by compensating the quality of inferior sensors with quantity*. As demonstrated in previous research [13], data fusion can play a pivotal role in reducing the relative expanded uncertainty of multiple sensors that exhibit significant deviations from each other(Fig. 1(b)). By adopting data fusion approaches, we can capitalize on the collective sensing capabilities of multiple non-dedicated sensors. This allows us to harness their potential, covering a broader geographical area and obtaining a more accurate representation of the environment.

TABLE I: Major Notations

Symbol	Descriptions of Notations
$t \in \{1, \dots, T\}$	tth time slots to collect the data
T	time slot numbers in one dispatch period
(x, y)	grid coordinates, where $x \in \{1, \dots, M\}, y \in \{1, \dots, N\}$
$c \in \{1, \dots, C\}$	the cth vehicle in all C vehicles
I_c	whether vehicle agent c. is dispatched
r_c	the r_cth trajectory of $c, r_c \in \{0, \dots, R_c\}$
R_c	all possible trajectories for vehicle agent c.
$D_c^{r_c^k}$	the seleted trajectory of the vehicle agent c, a $M \times N \times T$ tensor, also noted as $D_c^{r_c}$, denoting selection of the r_cth trace for c.
B	the budget for the dispatching system
$w_c \in \{1, \dots, \mathcal{W}\}$	the estimated sensing reliability for sensor c
β	balance factor
$m_c^{(x,y,t)}$	the reading of sensor c at a given spatial-temporal grid (x, y, t)
$m_{(*)}^{(x,y,t)}$	the aggregated result at a given spatial-temporal grid (x, y, t)
$b_c \in \{1, \dots, \mathcal{B}\}$	the constant bias for sensor c

B. System Models

The proposed dispatching system aims to improve the Quality of Information (QoI) by ensuring optimal sensing coverage while addressing the sensing reliability issue. To achieve this, the platform selects routes for taxis and allocates a paid incentive budget to drivers (as shown in Fig. 2) to expand the sensing coverage of taxis in the system. Although many current dispatching systems have overlooked sensing reliability, it is one of our main contributions to the field. We consider an optimized spatial-temporal distribution with even sensing coverage and sensing reliability as the optimal solution, as it provides representative insights for various applications [14], [8]. The basic notations used in this paper are summarized in Table I.

To efficiently capture and analyze the geographical area of interest, we utilize a discrete spatial-temporal map represented by a grid $M \times N$. Each cell on the grid is denoted by its coordinates (x, y), where x ranges from $x \in 1, \dots, M$ and y ranges from $1, \dots, N$, representing longitude and latitude, respectively. The time dimension is discretized into time slots of duration dt minutes, denoted by t ranging from $1, \dots, T$.

Within the grid map, we have C vehicles unevenly distributed. Vehicles are all equipped with sensors, enabling automatic data collection at each time slot t. Each vehicle, denoted as vehicle $c = 1, \dots, C$, has a set of possible traces, denoted as $\mathcal{R}_c$. $\mathcal{R}_c$ includes K different traces, represented by the 3D tensor $\mathbf{r}_c^k \in R^{M \times N \times T}$, indicating vehicle's presence within the grid map $M \times N$ over sensing period T. Specifically, $\mathbf{r}_c^k$ provides spatial occupancy information of the vehicle in each time slot. We use $\mathbf{D}_c$ to represent the selected trace for vehicle c from the set of possible traces.

The proposed dispatch operation revolves around selecting the optimal trace from the trace sets $r_c^k \in R_c$, thus altering the spatial-temporal distribution of the dispatched vehicle. Each vehicle, denoted vehicle c, has its default trajectory represented by r_c^0, which corresponds to the vehicle's trace without any dispatch. The possible trajectory set for a vehicle $\mathcal{R}_c$ and its estimated default trace r_c^0 is given by a mobility predictor altered from [15]. To indicate whether the scheduler selects vehicle c and determines its route, we utilize an indicator variable I_c, defined as follows:

$$I_c = \{D_c == r_c^0\} \in \{0, 1\} \tag{1}$$

Dispatching non-dedicated vehicles has consequences potentially impacting their primary tasks, requiring an incentive cost. If the scheduler aims to alter a vehicle's trajectory ($I_c = 1$), a budget is allocated as compensation. In our case, we simplify the budget limit as the upper bound on quantity of vehicles dispatched, denoted as B.

$$\sum_{c=1}^{C} I_c \leq B \tag{2}$$

Related studies in the field have explored various compensation models to incentivize participation and minimize disruptions to user routine activities [1], [16]. In the Evaluation section, we will further discuss the impact of user acceptability.

C. Problem Formulation

To strike a balance between sensing reliability and sensing coverage, we propose a novel objective function called **aggregated sensing quality (ASQ)**. The ASQ objective function draws inspiration from previous works [14], [17] in the sensing coverage domain, where entropy is used to measure evenness of sensor's spatial distribution. we extend this concept to incorporate sensing reliability. The sensing reliability is originally derived from the paradigm of truth discovery [18], which models the reliability of sensors using the reliability factor w_c. A higher value of w_c indicates a sensor with better sensing reliability, with $w_c = 1$ denoting average reliability. This identifies sensors providing more reliable data and those needing additional vehicle dispatch or more readings to compensate. ASQ is formulated as follows:

$$\phi_w(\mathcal{W}, D^r) = (1 - \beta)E(\mathcal{W}, D^r) + \beta \log Q(\mathcal{W}, D^r) \tag{3}$$

Here, β is a parameter that controls the importance of the two factors(sensing reliability-aware coverage evenness and sensing reliability-aware coverage rate). The entropy of the spatial distribution of sensed areas, $E(\mathcal{W}, D^r)$, is computed as:

$$E(\mathcal{W}, D^r) = -\sum_{x,y,t,\mathcal{W}} P(x, y, t, \mathcal{W}) \log P(x, y, t, \mathcal{W}) \tag{4}$$

The higher the entropy, the more even the sensors are distributed in the area, and sensing coverage is considered better.

We determine $P(x, y, t, \mathcal{W})$ using the aggregated sum of variance factors in the trajectory:

$$P(x,y,t,\mathcal{W}) = \frac{\sum_{c=1}^{C} w_c D_c(x,y,t)}{CT} \tag{5}$$

This equation represents the probability distribution of vehicle agents, where $D_c(x,y,t)$ denotes the presence of vehicle c at location (x,y) and time t, and w_c represents the weight associated with vehicle c. The sensing reliability serves as a weight, providing information on the distribution of sensing reliability on the spatial-temporal map, allowing us to ensure reliable coverage.

The size of sensed areas, $Q(\mathcal{W}, D^r)$, is calculated simply as:

$$Q(\mathcal{W}, D^r) = \left|(x,y,t) : P(x,y,t,\mathcal{W}) > \frac{1}{CT}\right| \tag{6}$$

where $Q(\mathcal{W}, D^r)$ represents the size of the sensed areas in the grid map where the net sensing reliability is greater than an "average sensing reliability " for a sensor.

The reason for selecting a weighted aggregate sum in Equation 5 is that it provides an intuitive and general way to quantify sensing reliability as the evenness of the sensor distributions on the map, while also considering their individual sensing reliability. Although this model is designed to work well with the weighted average data fusion process, further research could explore adapting it to more sophisticated data fusion algorithms.

$$\max_{\substack{I_1,\cdots,I_C \\ D_1,\cdots,D_C}} \phi(\mathcal{W}, D) = (1-\beta)E(\mathcal{W}, D) + \beta \log Q(D)$$
$$\text{subject to} \quad \begin{cases} D_c = r_c^k, k \in \{1,2,\ldots,K\} \\ I_c \in \{0,1\} \\ \sum_{c=1}^{C} I_c \le B \end{cases} \tag{7}$$

The objective function maximizes the quality-informed entropy of sensors' distribution, considering sensing reliability as a weight factor. Physical constraints imposed by agents' mobility and a budget constraint are also considered. The problem is NP-hard, involving combinatorial optimization on discrete variable (I_c) and continuous variable (w_c) under a nonlinear objective function (ϕ_w) and linear constraint $(\sum I_c \le B)$. It's novel for considering both sensing reliability and sensing coverage as important aspects of vehicle sensing performance, incorporating them into a unified framework that jointly optimizes sensors' quantity and reliability.

III. Algorithm Design

In this section, we present our proposed dispatching framework for improving QoI by optimizing ASQ. The algorithm consists of two mutually assisted key steps: sensing reliability inference and dispatch(shown in Fig. 3). The first step focuses on inferring the reliability of sensors(§III-A), while the second step involves dispatching vehicles based on the inferred sensing reliability (III-B). These steps form a loop, with the dispatching process also contributing to sensing reliability inference improvement. Finally, we analyze the algorithm's time complexity(III-C).

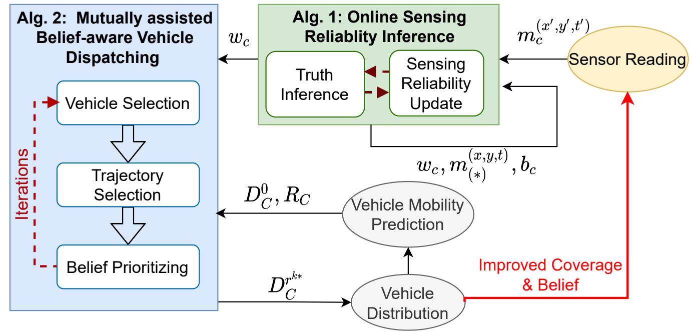


Fig. 3: This figure shows our proposed algorithm's framework.

A. Online Sensing Reliability Inferring

In our framework, we adopt the concept of truth discovery [18] to model the sensing reliability of sensors using the reliability factor w_c. Truth discovery is a method that infers the sensing reliability of sensors by comparing their measurements $m_c^{(x,y,t)}$ with the inferred truth $m_{(*)}^{(x,y,t)}$ from other sensors in correlated sensing scenarios. However, in real-world sensing, different sensors exhibit constant deviations from the true value, introducing bias. This bias impacts data fusion result, especially if all sensors dispatched to one location have the same bias direction, e.g., underestimating. To address this challenge and account for systematic errors, we improve truth discovery by introducing a bias term b_c and redesigning the optimization function as follows:

$$\min_{\mathcal{M}^{(*)},\mathcal{W},\mathcal{B}} f\left(\mathcal{M}_{(*)}, \mathcal{W}, \mathcal{B}\right) =$$
$$\sum_{x,y,t}\{\sum_{c=1}^{C} w_c \| m_{(*)}^{(x,y,t)} - m_c^{(x,y,t)} + b_c \|^2\} \tag{8}$$
$$\text{s.t.} \quad \sum_{c=1}^{C} \exp(-w_c) = 1, \sum_{c=1}^{C} b_c = 0$$

In this optimization function, we consider minimizing the weighted sum of the differences between the inferred truth $\mathcal{M}_*$ and the observed measurements $\mathcal{M}_c$, taking into account the bias terms b_c. The optimization objective is to minimize the overall difference between the aggregated measurement and weighted sensor reading. The first constraint restricts the range of weight to avoid it being trapped to negatively infinite. The second constraint prevents the bias term from taking out all the sensor readings.

To infer sensing reliability, we address the optimization problem described in Equation 8. We employ a similar approach as [18] by using Lagrangian multipliers. The objective is to estimate the sensing reliability values for each sensor. Using Lagrangian optimization, we derive the following equations:

$$\mathcal{M} : m_{(*)}^{(x,y,t)} = \frac{\sum_{c=1}^{C} w_c (m_c^{(x,y,t)} - b_c)}{\sum_{c=1}^{C} w_c} \tag{9}$$

$$\mathcal{W}: w_c = -log \frac{\sum_{(x,y,t)} \|m_{(*)}^{(x,y,t)} - m_c^{(x,y,t)} + b_c\|^2}{\sum_{(x,y,t)} \sum_{c'=1}^{C} \|m_{(*)}^{(x,y,t)} - m_{(c')}^{(x,y,t)} + b_{c'}\|^2} \tag{10}$$

$$\mathcal{B}: b_c = \frac{\sum_{x,y,t}(m_c^{(x,y,t)} - m_{(*)}^{(x,y,t)})}{\|r_c(x,y,t) \neq 0\|} \tag{11}$$

These equations enable inferring sensing reliability values for sensors based on their measurements and the calculated weights.

Algorithm 1 is designed to estimate the reliability factor w_c and constant bias b_c of individual sensors in real-time considering the inferred truth ($m_{(*)}^{(x,y,t)}$) for all sensors in a given time period. It takes the sensing values, error bound ϵ, and past outputs $(m'_{(*)}, w'_c, b'_c)$ as input and returns the updated data quality estimates (w_c, b_c) and the updated inferred truth ($m_{(*)}^{(x,y,t)}$) as output.

For each spatial-temporal cell (x, y, t), the algorithm iterates over all sensors in the corresponding cluster ($s_{(x,y,t)}$) to update their data quality estimates (w_c and b_c). Eq.(10) and Eq.(11) are utilized for this purpose. The inferred truth is then updated using Eq.(9) based on the updated data quality estimates. These equations use past outputs $(m_{(*)'}, w'_c, b'_c)$ as parameters in the summation, effectively incorporating historical data to guide the update process.

The belief of sensing reliability inference is naturally deduced by (10). From the equation we can see that the value of w can be written as $w \propto logk \cdot d(m_{(*)}^{(x,y,t)}, m_c^{(x,y,t)} - b_c)$, while k is the vehicle that participates in the measurement aggregation. Thus, we define the belief of estimate ε_c as follows:

$$\varepsilon_c = \log \left(\sum_{i=1}^{C} \sum_{t=1}^{T} \mathbf{r}_c^k(t) \cdot \mathbf{r}_i^k(t) \right) \tag{12}$$

The definition of $\mathbf{r}_c^k(t)$ is given in Table I, the product of the two tensors indicates the overlap of the trajectories between all vehicles. The sum of all vehicles and all time slots gives the total number of vehicles that have an overlapping trajectory with c. The log of this number is the belief signal ε. If there is no overlap of another vehicle agent with c, the belief ε_c would be 0, meaning that the inference sensing reliability for the vehicle agent c is not reliable at all.

B. Dispatching Algorithm

Algorithm 2 is devised to improve QoI by strategically dispatching vehicles for higher ASQ. Unlike previous work[7], our approach considers sensing reliability and its inference, rather than assuming uniform reliability for all vehicles. We prioritize vehicles with overlapping trajectories, as they're more likely to have accurate inferred sensing reliability. These vehicles are then sent to less populated areas to improve data collection and inference sensing reliability. Once the selection process is completed, dispatching is carried out to improve sensing coverage with sensing reliability, utilizing a V Value-based approach in a similar way. In this way, we optimize both the overall coverage of the data and the quality of the collected data.

Algorithm 1: Online Sensing Reliability Inference

Input : Input: Sensing value of all sensors in a given time period $m_C^{(x,y,t)}, c \in C$, error bound ϵ, past outputs $(m_{(*)'}, w'_c, b'_c)$

Output: Output: Updated data quality estimates w_c, b_c, and inferred truth $m_{(*)}^{(x,y,t)}$

Split the sensors into clusters based on their location, so that $s_{(x,y,t)} = \{c : s_c = (x, y, t)\}$;
Initialization: Set Lagrangian factor $\lambda = 0$;
while $error > \epsilon$ **do**
  $\lambda = \lambda + \sum_c (m_{(*)}^{(x,y,t)} - m_c^{(x,y,t)})^2, c \in s_{(x,y,t)}$;
  for $(x, y, t) \in (M, N, T)$ **do**
    for $c \in s_{(x,y,t)}$ **do**
      Update w_c using equation (10) ;
      Update b_c using equation (11) ;
    end
    Update $m_{(*)}^{(x,y,t)}$ using equation (9) ;
    $error = m_{(*)}^{(x,y,t)} - m_{(*)'}^{(x,y,t)}$;
    if $error \leq \epsilon$ **then**
      break;
    end
    $m_{(*)'}^{(x,y,t)} = m_{(*)}^{(x,y,t)}$;
  end
end

The calculation of V value is given by

$$V_c(D_c, P) = -\frac{\sum_{x,y,t} w_c D_c . P(x,y,t,\mathcal{W})}{\sum_{x,y,t} P(x,y,t,\mathcal{W})} \tag{13}$$

Here D_c^r could be the selected trace of current car, or guessed trace of the car by the mobility predictor.

C. Time Complexity Analysis

To analyze the complexity of our algorithm, we need to mainly consider the time complexity of each step. The time complexity of the initialization step is $\mathcal{O}(C)$ where C is the number of vehicles because we need to set the initialization for all vehicles. The time complexity of the calculation step is $\mathcal{O}(CT^4)$, since we need to calculate the sensing quality for each pair of vehicles, while the trajectory size has an estimated complexity of $\mathcal{O}(T^4)$ according to the Bellman-Ford algorithm for trajectory optimization. Therefore, the overall time complexity of our algorithm is $\mathcal{O}(CT^4)$ in time.

IV. Evaluation

We present the evaluation of *QUEST* with simulated dispatch and map reconstruction experiments using real-world data. Our experiment setup involves a large-scale simulation based on data from a real-world MCS system(§IV-A). We compare how ASQ changes with different factors and show the advantages of *QUEST* over baselines(§IV-B). We further

Algorithm 2: Mutually assisted belief-aware Vehicle Dispatching

Input : estimated trajectory of all vehicles D_C^0, possible trace set of vehicle R_C, dispatching budget B, sensing reliability $\mathcal{W}$

Output: An improved feasible solution $\mathcal{S}^*\{I_C, D_C^{r^{(k^*)}}\}$

Initialize a feasible solution $S = \{I_C, D_C^{k^*}\}$, set $\mathcal{S}^* = \mathcal{S}$, belief ε through eqn. (12) ;
for $iter++ \leq$ *MaxIter* **do**
    $S = S^*$;
    Calculate $P(x, y, t, W)$ by eqn. (5);
    $C^* \leftarrow \{c \mid \varepsilon_c = \max(\varepsilon_C)\}$;
    for $c \in C^*$ **do**
        $k^* = \max_{\varepsilon_c}\{\max_r V(D_c^{r^k}, P), k \in R_c\}$;
        if k^* *is the original trace* **then**
            Cancel c dispatching ;
        end
        if *Total cost* $\leq B$ **then**
            Dispatch vehicle c with trace k^* ;
        else
            continue ;
        end
        $c = c \rightarrow next$
    end
    Select $(c', k') = arg\max_{c,k} V(D_c^{r^{k^*}}, P)$;
    if $k' > 0$ **then**
        Update $\mathcal{S}^*$, $B(c')$ and ε_C
    else
        $I_{c'} = 0, B(c') = 0$;
    end
end

demonstrate the effectiveness of ASQ by evaluating its relations with downstream task(§IV-C). Finally, we showcase the effectiveness of our proposed mutually assisted framework via ablation study(§IV-D).

A. Experiment Setup

1) Data Collection and Processing: We deployed mobile sensors in 29 taxis and collected data for two months in a large city, capturing environmental data such as humidity, temperature, O_3, and particle matter (see Fig. 4). Real-time GPS location data from the taxis, along with accurate sensor readings, were collected every 3 seconds. The data then underwent preprocessing, including outlier removal and handling of missing values using the sliding window approach with a window size of 5 minutes.

2) Simulation Environment: To replicate a real-world scenario, we selected a specific area where the vehicle trajectories were relatively dense, corresponding to a $15\ \text{km} \times 8\ \text{km}$ grid in the city. The spatial resolution was set at $1\ \text{km}$, corresponding to a normal air pollution setup [19], [20]. The temporal resolution(*i.e.*, time period dt) at 2 minutes, and the

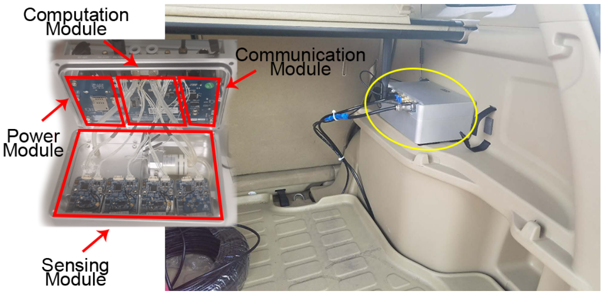


Fig. 4: The sensor platform deployed in our taxi, features a GPS receiver, a gas prompt, and four slacks capable of sensing various physical factors across the city.

TABLE II: Performance by different dispatching and reconstruction algorithms

	NA	PAS	our *QUEST*
ASQ	4.05	5.10	**5.37**
R-RMSE, Linear (ug/m^3)	49.72	28.90	**26.49**
R-RMSE, GPR (ug/m^3)	39.25	28.81	**26.48**
R-RMSE, BGCP (ug/m^3)	26.24	12.24	**9.27**
Err. Reduction(%)	/	53.4	**64.6**

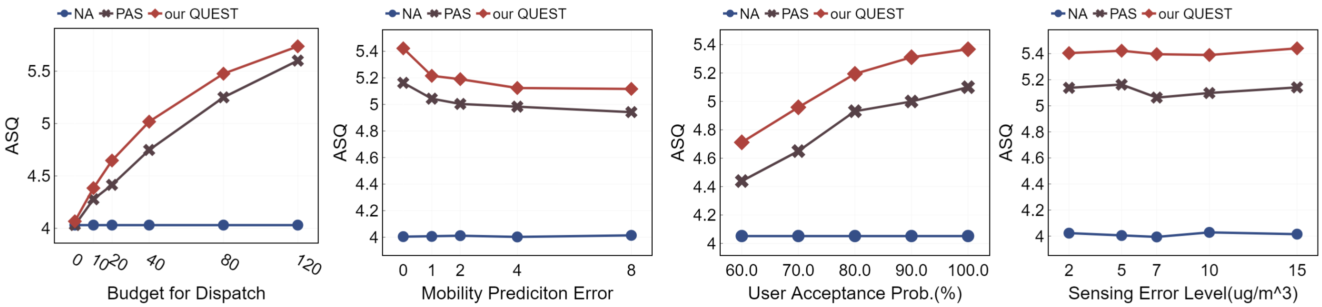
actuation period was set as $5T$ (10 minutes), representing the average time for a taxi to drive 4 km, and ensures that air quality remained static during dispatch simulations. Due to factors such as water bodies, nature reserves, or administrative borders, 42 grids were not covered by any mobile sensor and were marked as 'Excluded Area', thus excluded from our performance-metric calculations.

3) Virtual Taxi Fleet: To create a large taxi fleet and simulate their original trajectories, we utilized the GPS data and parse the trajectory of each vehicle. The trajectories represented actual taxi movements without incentivized dispatch. To simulate a larger taxi fleet for broader coverage, we expand the mobility and distribution of the taxis with respect to the original trajectories to represent 200 virtual taxis. This allowed us to study and evaluate the behavior and coverage of a larger taxi fleet without actually deploying additional physical taxis. Our default dispatch budget was set to $B = 80$ and we assumed a default mobility prediction error of 0 and assumed a 100% dispatch acceptance rate.

4) Sensing Simulations: To simulate low-cost sensors with controllable sensing error, we mainly choose O_3 data from our datasets for evaluation. The low-cost sensor for O_3 has highly variable reliability with many available datasets. We extract error distributions from publicly available low-cost O_3 sensor calibration datasets [21], [22] and applied them to our fine-grained sensing result maps with the corresponding types of sensors. We generate sensing errors according to the error extracted from these datasets and add them to the grid's ground truth as the sensor's measurement.

5) Baselines: Two baseline methods are set to evaluate the improvement of ASQ for *QUEST*.

1. **No Actuation (NA)**, marked by blue dots: This method does not dispatch vehicles and all vehicles follow their original



(a)ASQ VS. Budget (b)ASQ VS. M. Pred. Error (c)ASQ VS. User Acceptance (d)ASQ VS. Error Level

Fig. 5: The performance of *QUEST* under different factors.

trajectories. By comparing NA with our *QUEST*, we investigate the performance improvement from our entire system, which includes two prediction models and a prediction-based actuation planning algorithm.

2. **PAS**, marked by a brown cross: This method dispatches vehicles by a prediction-based actuation planning algorithm [8]. This method is considered the state-of-the-art method used for dispatching non-dedicated vehicles for sensing coverage, and a successor of [7].

6) Performance Metrics: We first use **ASQ** (defined in §II-C) to evaluate dispatch algorithms. To assess the the real-world impact of ASQ as well as dispatch algorithms, we examine their impact through map reconstruction, a downstream task for mobile crowdsensing. Map reconstruction is the process of reconstructing a complete representation of environmental data across a grid map based on data collected by dispatched vehicles. We employ three different map reconstruction algorithms: Linear Interpolation, Gaussian Process Regression, and the BGCP [23] algorithm. We primarily use the **Reconstructed Root Mean Square Error (R-RMSE)** metric to measure the map reconstruction effectiveness. The R-RMSE quantifies the accuracy of the map reconstruction process by comparing the reconstructed map obtained after dispatching with the ground truth data.

B. Evaluation for QUEST

To assess the potential real-world impact of different dispatching algorithms, we also use *Error Reduction Rate (Err. Reduction)*, the maximum reduction rate of R-RMSE among all the reconstruction algorithms, to measure how much improvement the given dispatching algorithm can bring. To analyze how different factors affect the performance of *QUEST*, we mainly use ASQ to evaluate different dispatching algorithms.

Table II shows the performance comparison of sensors and algorithms for sensor readings. Our *QUEST* algorithm outperforms others achieving highest the ASQ score of 5.37 and lowest RMSE among reconstructed algorithms. This means, without additional incentivize cost, our algorithm increases performance by 26% over the previous state-of-art. Furthermore, *QUEST* achieves the highest error reduction rate of 64.6%. These results demonstrate effectiveness and superiority of our proposed algorithm compared to the state-of-art algorithm.

To demonstrate performance under different dispatch budgets, we plot ASQ with the varying amounts of dispatch budget in Fig. 5(a). Our proposed *QUEST* consistently outperforms three baselines across different budget amounts. As the number of scheduled vehicles increases, *QUEST* shows a more significant improvement compared to the PAS algorithm, reaching up to 10% improvement with 80 vehicles. This is because our *QUEST* recognize the sensing reliability and hence utilize the budget for better coverage. However, with increasing budget, the superiority of *QUEST* becomes less significant. This is predictable since the initial distribution is dense, making *QUEST* reaches performance boundary when most vehicles were dispatched to the near surrounding.

We study the impact of mobility prediction error to different dispatch algorithms by adding random error with varying degrees of Euclidian distance bias [24]. As Fig. 5(b) shows, *QUEST* is robust to different accuracy levels of the mobility prediction model. Although ASQ decreases with larger prediction error, *QUEST* outperforms benchmark methods in most cases. Our *QUEST* is more susceptible to mobility prediction error as the cascading effect impacts more on scheduling vehicles with higher sensing reliability.

We consider scenarios where users might refuse to follow dispatched trajectories. Fig. 5(c) shows user acceptance probability impacts algorithm performance. *QUEST* consistently outperforms PAS across acceptance probabilities, achieving higher ASQ indicating better optimization of sensing coverage and reliability.

To explore how different degrees of sensing error impact ASQ, we tune controllable sensing error by adding Gaussian noise, where the sensing error level refers to the standard deviation value. As Fig. 5(d) shows, we observe that the relationship between sensing error level and ASQ is not straightforward and varies by algorithm. There are instances where the ASQ value remains relatively stable or even slightly increases with higher sensing error variance. This is because ASQ is mainly attributed to the relative error of different sensors, so it is not sensitive to overall sensing error changes.

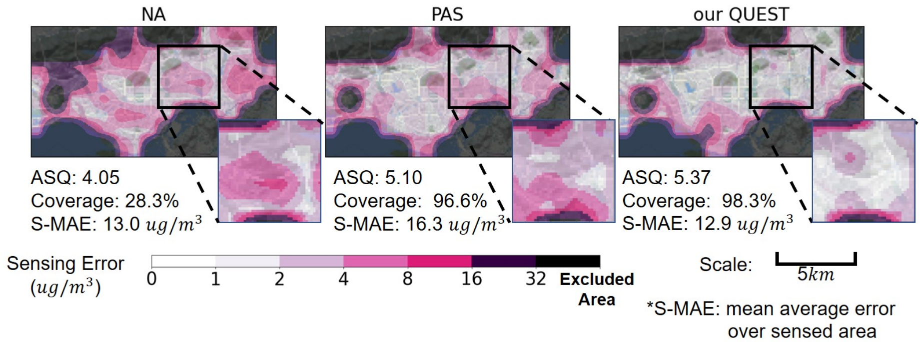


Fig. 6: Sensing error after dispatching. Here we zoomed in on a typical area affected by dispatching algorithms. *QUEST* expanded the sensing coverage without the loss of sensing reliability.

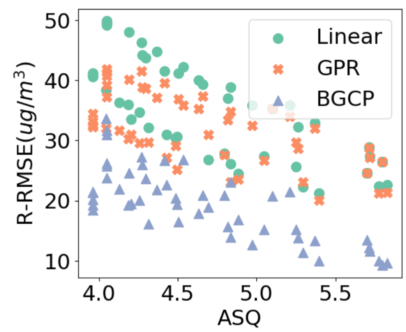


Fig. 7: ASQ shows negative correlations with R-RMSE, among all different reconstruction algorithms.

Fig. 6 visualizes dispatch results with ASQ. PAS and *QUEST* dispatch vehicles from dense to nearby sparse areas. The overall sensing reliability is measured by mean absolute error over sensed area (S-MAE). *QUEST* has the lowest sensing error and highest coverage among algorithms, indicating effective balancing of sensing reliability and coverage. By further observing spatial error distribution, *QUEST* reduces errors in poorly covered areas by NA or PAS. This is because *QUEST* selects vehicles with sufficient net sensing reliability, generating more reliable data than NA or PAS.

C. Evaluation for ASQ

Fig. 7 visualizes the relationship between ASQ and R-RMSE under various experimental conditions, such as different times, budgets, and algorithms. Each dot represents one round of simulation dispatching experiment. The purpose of this analysis is to demonstrate the relevance of the designed ASQ metric in the context of downstream tasks, particularly in map reconstruction. We observe that ASQ is inversely related to R-RMSE values. Dispatching results with higher ASQ scores generally exhibit lower R-RMSE values, suggesting higher QoI in the map reconstruction process. However, actual R-RMSE could still vary within the same ASQ value due to performance differences and statistical variations among map reconstruction algorithms.

D. Ablation Study

We conduct an ablation study to evaluate the effectiveness of our mutually assisted online sensing reliability inference approach. *QUEST*-NI is the naive version of our *QUEST*, where sensing reliability inference is performed before dispatching, which makes dispatching not affect improving sensing reliability inference.

Table III shows the results of the ablation studies. We observe that *QUEST*-NI did have a higher ASQ among the baseline shown in Table II, but the error reduction by dispatching does not show a clear advantage. This is because *QUEST*-NI does not have a well-inferred sensing reliability, leading to sub-optimal dispatching.

TABLE III: Ablation Study

Algorithm	*QUEST*-NI	*QUEST*
ASQ	5.26	**5.37**
R-RMSE, Linear (ug/m^3)	27.40	**26.49**
R-RMSE, GPR (ug/m^3)	27.20	**26.48**
R-RMSE, BGCP (ug/m^3)	11.59	**9.27**
Err. Reduction(%)	55.8	**64.6**

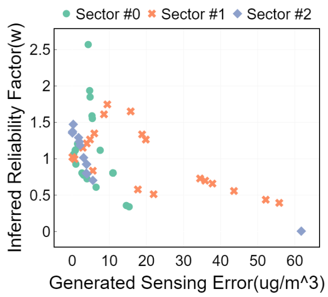
Fig. 8 shows the relationships between the inferred reliability factor w and the generated sensing error in different areas. We selected 3 sectors with varying numbers of vehicle agents. Fig. 8(a) shows the result of reliability inference by *QUEST*-NI. Although the inferred sensing reliability somehow reveals the error induced, the error of local aggregated measurement induces a bias in inferring sensing reliability, leading good sensors to get lower w due to deviation from the local aggregated measurement. On the other hand, Fig. 8(b) shows how the overall result could be optimized by mutually assisted dispatch to help reliability inference. In this figure, although randomness makes little deviations, the result consistently and correctly classifies sensing reliability of each sensor.

V. Discussions

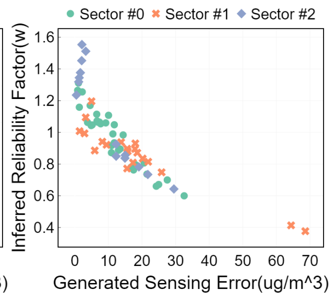
We provide a brief discussion on the generalizability, potential applications, and future directions of *QUEST*. We also address its existing known limits.

Generalize to other MCS applications: While *QUEST* was originally designed for air pollution sourcing tasks, the underlying principles of *QUEST* can be adapted and extended to other sensing scenarios. For example, it could be applied to wireless signal sensing, noise pollution mapping, and various other applications by adjusting the spatial granularity to suit the specific use case. Nevertheless, since *QUEST* adpots truth discovery-based reliability inference that only consider addressing data on the same modality, when facing applications that utilize cross-modality data-fusion for sensing reliability [25], [26], *QUEST* might needs further design to be work appropriately.

Adopting other incentivize model: While *QUEST* assumes a simple incentivize model, different strategies do not impact



(a) Inferred w by *QUEST*-NI



(b) Inferred w by *QUEST*

Fig. 8: These figures visualize the relations between the generated error and inferred reliability factor. *QUEST* utlizes mutually assited dispatching to acquire a more accurate inference.

our main contributions, the modeling of ASQ and the proposed mutually assisted dispatch framework. However, for different incentive models or scheduling approaches, there is potential to develop more budget-efficient strategies.

Sensor Compatibility: Our approach relies on sensors providing data fusion enabling low-cost sensors to compensate for sensing reliability through quantity. However, some types of sensors, like IMUs and GPS, lack this capability. In such cases, *QUEST* approach may not be directly applicable.

Dependency on Accurate Mobility Prediction: As evaluation shows, the performance of *QUEST* is sensitive to the accuracy of the mobility prediction accuracy. Ensuring accurate prediction is crucial for effective real-world application.

VI. Related Work

Non-dedicated Vehicular MCS: Mobile Crowd Sensing (MCS) offers distinct advantages such as high mobility and cost-effectiveness [27]. Non-dedicated vehicular MCS leverages non-dedicated vehicles for sensing purposes, enhancing coverage and operational efficiency. While past research explored data volume [28], multi-object tradeoffs [29], incentivization strategies [30], [31], and data utilization [32], [33], [19], we focus on sensing reliability and coverage challenges in non-dedicated vehicular MCS. Our findings seamlessly integrate into broader MCS research.

Sensing Coverage: To ensure sensing coverage, researchers proposed a spatial-temporal scheduling approach to select MCS agents with consideration of energy efficiency or budget effectiveness [34], [35], [36]. [17] addressed spatio-temporal redundancy when performing MCS tasks in urban cities with high-resolution maps. Researchers also proposed to apply some budget to motivate the MCS agents to cover the area of interest. [7] and [9] proposed incentive systems to guarantee spatial-temporal coverage of non-dedicating ridesharing vehicles. Most of the above methods were assumed to be near perfect sensing reliability. However, such an assumption is impractical in the real world with sensing reliability problems.

Sensing Reliability: Mobile sensors are subject to environmental changes and complicate influence factors [37]. Ensuring MCS sensing reliability requires comparing collected data to ground truth [38], [39], [40], calibrating sensors using external source [10], [41], or using machine learning models to improve reliability [11]. However, these methods face challenges in dynamic,non-dedicated vehicular MCS systems, where sensors vary and references are not always available. In these case, [42], [43] presented historical-data-based comparisons when historical data can serve as pseudo-ground truth for static scenes, [18] proposed truth discovery techniques for correlated sensors and areas. These provide valuable insights, yet still suffer from two issues. First, non-dedicated vehicles are unevenly distributed, so areas with few vehicles lack data, resulting in both uncertain sensing reliability and poor sensing coverage. Second, current methods target finding unreliable sensors without distinguishing constant bias. This necessitates developing new techniques to guide dispatch for better QoI.

VII. Conclusion

To enhance quality of information in non-dedicated vehicular MCS systems, we propose a quality-informed multi-agent dispatching system, *QUEST*. We formulate paradoxically correlated sensing reliability and sensing coverage as an optimization problem. Our framework infers sensing reliability for highly dynamic MCS agents via a dispatch algorithm that also improves sensing coverage. City-scale physical feature-based simulations shows significantly lower error at high coverage. Our solution opens new research avenues for non-dedicated vehicular MCS, such as modeling and optimizing sensing reliability over sensing coverage amid uncertain sensing reliability.

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