Joint Roadside Unit Deployment and Service Task Assignment for Internet of Vehicles (IoV)

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***Abstract*—Internet of Vehicles (IoV) is a promising Internet of Things application, where roadside unit (RSU) plays an important role for network service provisioning. How to select the number and locations of RSUs to deploy and allocate the traffic load to them is a critical and practical open problem. Most of the existing work focused on 1-D scenarios assuming unlimited RSU capacity, while a more practical 2-D case with limited RSU capacity has not been fully considered yet. In this paper, we investigate an RSU deployment problem for 2-D IoV networks considering the expected delivery delay requirements and task assignment. We formulate a novel utility-based maximization problem to solve the RSU deployment problem, where the utility function indicates the total benefit from the RSU deployment. We observe that each RSU has an irregular service area, which makes the problem much more difficult than the traditional facility location problem. Then, we design a utility-based RSU deployment algorithm (URDA), a linear programming-based clustering algorithm, to solve the problem. The gap between URDA and the optimal solution has been analyzed, which proved that the proposed URDA is near optimal if the deployment cost is low. Extensive simulations have been conducted to demonstrate the effectiveness and superiority of the proposed solution for IoV network service guarantee over other approaches.**

***Index Terms*—2-D Internet of Vehicles (IoV) networks, delivery delay requirement, roadside unit (RSU) deployment, service load management, service-centric architecture design.**

I. Introduction

Internet of Vehicles (IoV) is a promising Internet of Things application, and it attracts extensive attention from both the academic and industrial communities. Numerous safety-related services and infotainment applications can be supported in the new IoV paradigm, thanks to the fast development of vehicle-to-everything (V2X) communication technologies [1]–[7]. Roadside unit (RSU) is of great value in IoV given its high communication capacity and complementary features compared with vehicles [8]–[13]. For example, RSUs can be used as content dispatchers exchanging the information with nearby vehicles reliably at fixed locations [14], [15]. Recently, cellular-V2X technologies have been developed [16]–[18], where both RSUs and evolved node B can provide services to vehicles and other users in intelligent transportation systems [19]. In an area with heavy data traffic, deploying RSUs can be an effective solution to relieve the cellular network from severe congestion. How to optimize the placement of RSUs in 2-D IoV networks is a crucial and practical issue.

In this paper, the delivery delay, a general and important performance metric, is selected as the quality of service (QoS) index. The solution of this paper can be easily extended if other types of QoS are considered. There are great efforts devoted to studying the RSU deployment problem by combining the delay analysis and system constraints [20]–[24]. Also, many works in the literature have studied the relationship between the RSU deployment and the network connectivity, service coverage, etc. [9], [25]–[27]. However, most of the existing work focused on 1-D roads and assumed RSUs with unlimited capacity. In the urban scenario, vehicles move in a 2-D area, and RSUs need to serve the vehicles driving toward different directions. Simply applying the existing 1-D solutions to 2-D scenarios may lead to substantial performance degradation. Clearly, the service load from the vehicles, the road topology, and the RSU locations are coupled in the 2-D area. The modeling of the RSU service area and the deployment strategy design along with the service task assignment should be jointly optimized, which motivates this paper.

To solve the RSU deployment problem in 2-D IoV networks, it is necessary to consider the tradeoff between the benefit brought by the RSU service and the RSU deployment cost. How to model the benefit is difficult. Furthermore, due to the uneven vehicle densities in different roads, given the delivery delay requirement, the effective service area of each RSU is irregular. We thus cannot directly utilize solutions to the traditional facility location problem to solve the RSU deployment problem.

To address these challenges in this paper, we consider a practical 2-D RSU deployment problem and propose an efficient and effective algorithm to acquire the deployment strategy. The major contributions are listed as follows.

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1) The RSU deployment problem is modeled as an RSU service coverage problem given the expected delivery delay requirement. The effective service area of a single RSU is obtained based on the delay analysis. Given the varying vehicle density, the service area is irregular.
2) This paper proposes a comprehensive utility function evaluating the RSU deployment strategy in the 2-D dynamic traffic environment, where the utility denotes the difference between the total benefit to all clients and the cost of deployment.
3) A linear programming (LP)-based clustering algorithm is proposed to solve the utility maximization problem. The gap between the obtained solution and the optimal one has been analyzed, which proved that the proposed algorithm is near optimal if the deployment cost is low. Extensive simulations have been conducted to demonstrate the effectiveness and superiority of the proposed algorithm over the existing approaches.

The remainder of this paper is organized as follows. Section II introduces the related work. In Section III, the preliminaries, including the scenario and network modeling are provided. The utility maximization problem is formulated in Section III followed by the proposed algorithm in Section V. Section VI analyzes the gap between the obtained solution and the optimal one. Performance evaluations by simulation are presented in Section VII. Section VIII concludes this paper and discusses the future work.

II. Related Work

The approach and analysis of message dissemination with RSUs in IoV networks have been widely studied considering the following two aspects.

First, the importance of RSUs in vehicular network message dissemination has been studied extensively in [8] and [28]–[33]. Reis *et al.* [8] investigated the benefit of RSU deployment in highway scenarios where both connected RSUs and disconnected RSUs were considered in the analytical model. Wang and Wu [28] proposed an adaptive algorithm to maximize users' satisfaction of downloading by offloading traffic from the cellular links to RSUs in IoV networks. Salvo *et al.* [29] proposed three forwarding algorithms for disseminating the message originated from the RSU in an extended service area in urban scenarios. It was also proposed in [30] and [32] that the parked vehicles can serve as RSUs to provide service to users. Malandrino *et al.* [30] exploited the parked vehicles to extend the content downloading service coverage of RSUs while considering the freshness of the content, the efficiency of the radio resource utilization and the fairness in the vehicle energy consumption. In the vehicular cloud computing system, RSUs are applied to collect the computing tasks and then offload to the associated vehicles based on the proposed multitask replication policy [31]. In [32], a self-organizing network approach was proposed to select the minimum number of parked cars while maximizing the coverage of the support networks. In [33], RSUs at the intersections were used to control data congestion by clustering the message and selecting appropriate parameters for different clusters.

Second, the RSU deployment problem with different requirements and objectives has been considered [9], [20], [21], [23]–[27]. Cavalcante *et al.* [9] formulated a maximum coverage problem with time constraints for the RSU deployment for information dissemination in IoV networks. To provide Internet access for the passengers in the vehicle, Omar *et al.* [20] studied the gateway deployment problem aiming at minimizing the deployment cost while guaranteeing the probability of finding a network path greater than the threshold. Wang *et al.* [21] studied the message delivery problem on a bidirectional road segment and proposed a mathematical model indicating the relationship between the message delivery delay and the RSU deployment distance. Based on the proposed analytical results, the maximum deployment distance was obtained given an information delivery constraint. Zheng *et al.* [23] studied the access point placement problem to provide guarantees on the quality of data service in the urban network. A geometry-based coverage optimization problem maximizing the coverage ratio in urban scenarios was considered in [25]. Considering the uneven distribution of the vehicle traffic, Barrachina *et al.* [26] proposed a density-based RSU deployment policy and compared it with the minimum cost and the uniform mesh deployment policies. The proposed solution outperforms the latter two when the expected vehicle density is greater than certain thresholds. By proposing a dynamic programming and dimension enlargement-based algorithm, He *et al.* [24] obtained the optimal RSU deployment strategy for message delivery in a large-scale vehicular network. For the 2-D urban or suburban RSU deployment problem, Wang *et al.* [27] applied the 0-1 Knapsack algorithm to maximize the total centrality of RSU deployment given a limited deployment budget. More generally, the facility location problem has been studied with different variants since the early 1960s [34]–[36]. For the uncapacitated facility location problem, Charikar and Guha [34] proposed an algorithm-based cost scaling and greedy local improvement, and achieved a bicriteria approximation tradeoff for facility cost versus service cost. The LP-rounding algorithm, which is based on solving the LP relaxation and rounding the obtained fractional solution into integers, has been studied extensively. Shmoys *et al.* [35] presented a polynomial-time algorithm based on the filtering and rounding technique for the facility location problem. The proposed solution provided the first constant performance guarantee for this problem. For the similar problem, Chudak and Shmoys [36] proposed an improved approximation algorithm by using the randomized rounding on the optimal solution to the linear program relaxation. The proposed solution significantly improved the approximation guarantee to $(1 + 2/e)$.

Previous works have justified the importance of RSUs in IoV networks. However, the RSU deployment problem in a 2-D area considering the irregular service areas and limited service capacity has not been discussed yet. Furthermore, an analytical framework is needed to investigate the effectiveness of the deployment strategy in delivery delay guarantee.

III. System Modeling

A. Scenario

This paper investigates where and how many RSUs should be deployed in a 2-D vehicular network in order to guarantee

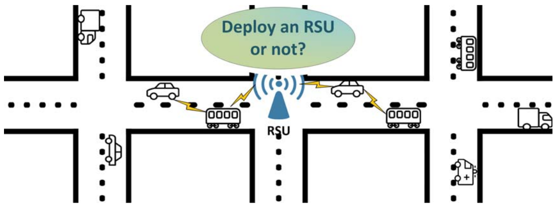


Fig. 1. Scenario of RSU deployment.

the expected delivery delay. As shown in Fig. 1, the deployed RSU can disseminate the message to nearby vehicles by vehicle-to-infrastructure (V2I) communication links. After the vehicle receives a message from the RSU, it broadcasts the message to other vehicles within the vehicle-to-vehicle (V2V) communication range. Following this process, the message can be disseminated to a larger area. The RSU connected with the content providers is responsible for disseminating the message to the vehicles within its V2I communication range. The vehicles which received the message can forward the message to more vehicles out of the communication range of RSU by V2V relay.

The promising V2X technologies, e.g., LTE-V2X technology, can be applied in the proposed system and facilitate the location-relevant information dissemination. As specified in [37], there are two modes of operation for V2X communications over the PC5 interface and the LTE-Uu interface, respectively. For the multihop V2V communication in the proposed system, the PC5 interface is applied such that the message can be transferred between vehicles directly, regardless of whether the vehicles are inside the LTE network coverage or not. On the other hand, the V2I communication relies on the LTE-Uu interface to realize efficient unicast delivery and/or multimedia broadcast/multicast service delivery. Therefore, the message dissemination in the proposed system can be well supported by the LTE-V2X technology.

In the proposed system, RSUs are connected with the application server through wired links. The server is responsible for delivering the data and assigning the task. For the uplink task, the vehicles can report tasks to the server through a nearby RSU or an evolved universal terrestrial radio access network of the LTE network. After receiving the request, the server allocates the task to an available RSU. The downlink tasks can be allocated to different RSUs by the server directly. Thus, the tasks will be handled appropriately while the network load is balanced.

In a real world, the value of a message highly depends on the delivery delay. We assume that the message becomes useless if the delivery delay exceeds a certain threshold. With the increase of the transmission distance and V2V relay hops from RSU, the delay increases. Thus, only the vehicles in a certain area may likely receive the message from the deployed RSU with satisfactory delay performance. We call this area the RSU service area and the formal definition will be given later in this section. Note that the RSU service area is different from the area within RSU's transmission range, as vehicles outside the transmission range of RSU may still receive the message within the delay bound via V2V relays. In order to broadcast the message to as many vehicles as possible, we assume that RSUs are deployed at the intersections such that the message can be propagated in different directions quickly. Due to the limitation of the power, computation, and storage capability, the capacity of an RSU is limited so the number of tasks it can handle simultaneously is limited. Otherwise, the queue of service tasks may be unstable, or many tasks may be dropped due to congestion.

B. Network Modeling

Graph Model: A 2-D area can be modeled as a graph $\mathbf{G} = \{\mathbf{V}, \mathbf{E}\}$, where intersections are abstracted to nodes and road segments between intersections are abstracted to edges. Let $\mathbf{V} = \{v_i : i = 1, 2, \ldots, N\}$ be the node set and $\mathbf{E} = \{e_j : j = 1, 2, \ldots, M\}$ be the edge set. N and M are the number of nodes and edges, respectively.

Message Delivery: In $\mathbf{G}$, a 2-D graph, messages delivered from an RSU to a vehicle may have multiple paths. For each path, the message is first broadcast to the vehicles within the V2I communication range. Let D_b be the delay of broadcasting the message to vehicles through V2I communication links. Then, according to the analysis provided in [38], the expected message delivery delay in the 2-D traffic environment through V2V links can be divided into two categories, i.e., the expected road propagation delay D_p and the expected intersection transfer delay D_t. The expected road propagation delay[1] is the average time of a message being delivered from one end of a road segment to the other. The expected intersection transfer delay is the average time it takes for a message being forwarded from the current road segment to an adjacent road segment once the message carrier arrives the intersection. The intersection transfer delay usually comes from the time of searching for a nearby vehicle going to the intended direction. We refer the reader to [38] for more details. Since the delivery path P from the RSU to the vehicle may consist of several edges and nodes, the expected entire delivery delay D_s is the sum of the broadcast delay, the road propagation delays, and the intersection transfer delays, i.e.,

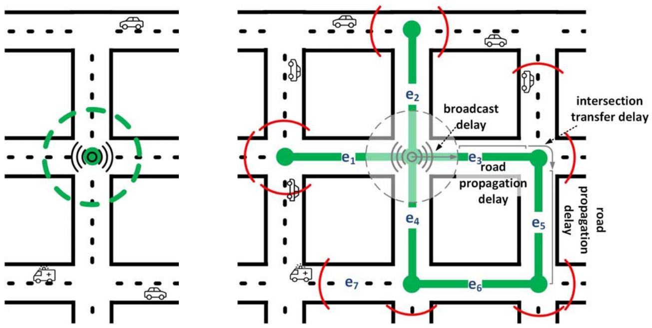
$$D_s = D_b + \sum_{e \in P} D_p(e) + \sum_{v \in P} D_t(v). \tag{1}$$

D_s can be calculated using the existing methods [21], [22], [38]–[40], assuming that the vehicles in each road segment are distributed randomly, and thus the details are omitted in this paper. Compared with the road propagation delay and the intersection transfer delay which are usually in seconds, the queuing delay and the processing delay at the RSUs are negligible in the studied scenario, so they are omitted in this paper.

RSU Service Area: With the requirement of the delivery delay, the message transmitted from an RSU can be propagated no farther than a continuous area consisting of intersections and road segments, which is the RSU service area defined in Definition 1.

Definition 1 (RSU Service Area): The region to where the message can be delivered starting from the RSU through road segments and intersections within the required average delivery delay requirement.

[1]The road propagation delay defined here is different from the definition of the electromagnetic waveform propagation delay, which is the time for an electromagnetic wave to propagate from the sender to its intended receiver.



(a) (b)

Fig. 2. Illustration of RSU radio coverage and service area. The dotted green circle in (a) is the radio coverage of an RSU. It is assumed that the vehicle within the radio coverage can directly communicate with the RSU. The green solid lines in (b) represent the RSU service area set C_1 deployed at v_1. Although part of the vehicles at edge e_7 can receive the message from the RSU within the required delay, e_7 is excluded by C_1 for brevity.

The RSU service area includes not only the area within its V2I communication range but also the area where a message can arrive through multihop V2V links with tolerable delay, i.e., the average delay for a message from the RSU to reach the area is below the delay bound. $\forall v_i \in V$, $i = 1, 2, \ldots, N$, its service area can be presented as an edges set C_i defined as

$$C_i = \left\{e_j^i\right\} = \left[\, e_1^i \quad e_2^i \quad \cdots \quad e_{M_i}^i \,\right]$$

where e_j^i, $j = 1, 2, \ldots, M_i$ is the edge that v_i can cover,[2] and M_i is the number of the edges in C_i. Vehicles traveling on $\forall e_j^i \in C_i$ are able to receive messages disseminated from v_i within the average delay requirement. If part of an edge is not covered, this edge is excluded in the coverage set of the RSU, so that the expected delivery delay constraint can be satisfied in our solution. Note that, in vehicle networks, typically the message should be delivered to a certain area, no matter which vehicles are there. Thus, the coverage area defined above is to cover the area, including road segments and intersections rather than a certain vehicle.

To obtain the service area of each RSU, the following steps are conducted. First, assuming an RSU is deployed at an intersection, the initial delivery delay from the RSU to this intersection is 0. Each RSU broadcasts the message to different directions. If the current delivery delay plus the expected delivery delay from the current intersection to the next intersection is within the required delay, we include the latest road segment into the RSU service area and update the expected delivery delay. The investigation on the neighboring road segments of the newest road segment continues until any of the following conditions happens: 1) it reaches the boundary of the studied area and 2) the expected delivery delay exceeds the required delivery delay. Finally, the set of road segments in the RSU service area is obtained.

The comparison of the radio coverage and service coverage is shown in Fig. 2. Fig. 2(a) presents the traditional radio coverage of an RSU while Fig. 2(b) illustrates the RSU service area defined in this section. Compared with the traditional radio coverage, the service area is a flexible model to represent the relationship between the QoS and the locations. First, the service area can statistically ensure the QoS of delay-tolerant information dissemination. It is adjustable to QoS requirements. Second, it is important that the service area can provide the flexibility to fit different road topologies and traffic conditions, especially in the 2-D urban scenario. The service area shows that how QoS varies with locations while the radio coverage does not contain such information.

[2]For simplicity, we use v_i to represent the RSU deployed at the node v_i.

Remark 1 (Irregular RSU Service Area): Different from the traditional coverage problem, the RSU service area highly depends on the vehicle traffic density and road topology, as well as its own communication ability. Due to the different vehicle traffic densities, the propagation speed of the message delivery in different places is different. Furthermore, the RSU service area must follow road geometry. Thus, the RSU service area is usually irregular.

Given the irregular RSU service area considered in this paper, many traditional approaches cannot be applied directly. For example, how to evaluate the importance of candidate RSUs and assign the service task between RSUs and the covered road segments at the same time is the main challenge.

Deployment and Assignment: Let $Y = \{y_i\}$ be the RSU deployment strategy where $i = 1, 2, \ldots, N$

$$y_i = \begin{cases} 1, & \text{if } v_i \text{ is deployed} \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

Let $X = \{x_{ij}\}$ be the service task assignment strategy, and $x_{ij} \in [0, 1]$ is a continuous variable indicating the portion of service tasks from edge e_j that is assigned to RSU v_i. X and Y are a pair of feasible solutions if the message dissemination tasks of all edges in $\mathbf{G}$ are served.

IV. Utility-Based RSU Deployment Problem

To evaluate the deployment strategy, we should consider two aspects, i.e., the benefit and the cost. Specifically, the deployment strategy is aiming at improving the network performance using the minimum number of RSUs. Thus, a utility-based approach is proposed in this section.

A. Strategy Evaluation

Naturally, the more RSUs the vehicular network deploys, the better performance it has. However, with the increase of the RSU density, the extra benefit of deploying one more RSU may decrease. Hence, the key issue is to maximize the total utility while fulfilling the expected delivery delay requirement.

1) Utility: In the RSU deployment problem, the RSU deployment utility U includes two parts, i.e., the benefit of serving the data dissemination tasks depending on the assignment strategy X and the cost of the deployment strategy Y, as follows:

$$F_U(X, Y) = F_B(X) - F_C(Y) = \sum_{i=1}^{N}\sum_{j=1}^{M}\tilde{b}_{ij}x_{ij} - \sum_{i=1}^{N} f_i y_i \tag{3}$$

where $\tilde{b}_{ij}$ is the benefit from the service to e_j provided by v_i and f_i is the cost of deploying an RSU at v_i. Considering both the installation and maintenance cost, f_i is the depreciation cost plus the maintenance cost of RSU v_i over time period T.

It is noted that both benefit and cost are measured over the same time period of T.

2) Benefit Evaluation: To evaluate the benefit of the task assignment strategy, the following issues are considered in the modeling: a) if the expected delivery delay is smaller, the benefit of the message is higher; b) if the network can serve more vehicles, the total benefit is higher; and c) the benefits of message being received by different vehicles are additive. In this paper, the benefit indicates the RSU service gain without considering the cost, and it is always positive. The utility indicates the total net profit of the deployment and services, which is the difference between the benefit and the cost. Thus, as shown in (3), the utility is positive only when the benefit is larger than the cost.

With the above principles, a comprehensive metric of the deployment benefit can be defined as the sum of the benefit for all vehicles in the network over the time period T. Hence, $\forall e_j \in C_i$, $\tilde{b}_{ij}$ is defined as follows:

$$\begin{aligned}\tilde{b}_{ij} &= T \cdot \int_0^{L_j} f(d_i(x))\mathrm{d}x \cdot r_j \quad \forall e_j \in C_i \\ &= b_{ij} \cdot r_j \end{aligned} \tag{4}$$

where L_j and r_j are the length and the amount of service task of e_j, respectively, $d_i(x)$ is the expected delivery delay from v_i to the position x of e_j if the message is delivered through the shortest-delay path, and $f(\cdot)$ is a decreasing function of delay $d(\cdot)$ indicating the relationship between the benefit and the delay. The shortest-delay routing in [38] is applied to obtain the expected delivery delay over the shortest-delay path. For those $e_j \notin C_i$, $\tilde{b}_{ij} = b_{ij} \cdot r_j$, and b_{ij} is set to a negative number indicating the benefit loss for violating the QoS requirement. Note that the delivery delay may vary due to the time-varying vehicle traffic and randomness in wireless communications. In this paper, the expected delivery delay is applied for delay-tolerant applications in vehicle networks. The influence of the delay variance in real cases will not be significant for two reasons. First, the variances of the road propagation delay and the intersection transfer delay decrease with the increase of the vehicle density. In most of the 2-D scenarios, e.g., the urban area, the vehicle density is relatively high, and thus the variance of the delivery delay will be less significant. On the other hand, for a connected network, the vehicle reduction in a road segment usually means an increase in nearby areas, and vice versa. Thus, the positive and negative variances of the delays following a specific path are expected to compensate each other. To verify the above assumption, we have also investigated the delivery delay distribution in the simulation in Section VII. The results depict that the variance is acceptable and the vast majority of the message can be delivered within the required delay.

3) Delivery Delay From RSU to Vehicle: Before a message is received by a vehicle, the message first passes one end of the road segment where the vehicle is currently located. Thus, to calculate $d(\cdot)$, d_{ij}, the expected delay over the shortest-delay path from v_i to v_j (where v_j is one end of an edge within C_i), should be obtained first. Based on Algorithm 1, d_{ij} is calculated given the deployed RSU v_i and the corresponding service area set C_i.

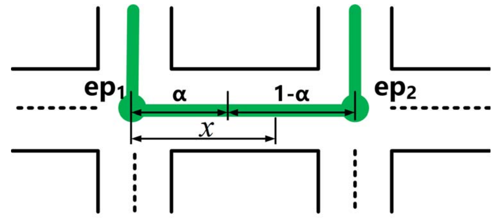


Fig. 3. Road segment division.

Algorithm 1 Shortest Delay Calculation Algorithm

Input: v_i, C_i

Generate a graph G_i based on C_i
$\forall i \neq j, d_{ij} \leftarrow \infty, d_{ii} = 0$
$n \leftarrow$ number of nodes in G_i
$count \leftarrow 0$
while $count < n - 1$ **do**
  for $\forall v_j \in G_i$ **do**
    if v_j has received the message **then**
      Send the message to its neighbors
      Compare and update d_{ij}
    end if
  end for
  $count \leftarrow count + 1$
end while

Output: $d_{ij}, \forall v_j \in G_i$

First, from each deployed RSU, if the node is within its coverage, it corresponds to the smallest expected delivery delay obtained by Algorithm 1. Then, the delivery delay from an RSU to a vehicle can be obtained as follows. Let ep_1 and ep_2 denote the two endpoints of edge e and the smallest expected delays from the RSU to ep_1 and ep_2 are dp_1 and dp_2, respectively. dp_1 and dp_2 can be obtained using Algorithm 1. As shown in Fig. 3, the road segment can be divided into two parts following a portion $\alpha \in [0, 1]$. For the vehicles located in the left portion, the expected delay from ep_1 will be smaller than that from ep_2 by definition, and vice versa. α can be obtained by

$$\alpha = \begin{cases} 1, & \mathrm{dp}_1 - \mathrm{dp}_2 < -\mathrm{dp}_{12} \\ \frac{\mathrm{dp}_{21} - \mathrm{dp}_1 + \mathrm{dp}_2}{\mathrm{dp}_{12} + \mathrm{dp}_{21}}, & \mathrm{dp}_1 - \mathrm{dp}_2 \in \left[-\mathrm{dp}_{12}, \mathrm{dp}_{21}\right] \\ 0, & \mathrm{dp}_1 - \mathrm{dp}_2 > \mathrm{dp}_{21} \end{cases} \tag{5}$$

where dp_{12} (dp_{21}) denotes the expected delivery delay from ep_1 (ep_2) to ep_2 (ep_1). Denote the distance between ep_1 and the vehicle by x as shown in Fig. 3. Thus, the expected delivery delay can be calculated as

$$d(x) = \begin{cases} \mathrm{dp}_1 + \frac{x}{L_j}\mathrm{dp}_{12}, & x < \alpha L_j \\ \mathrm{dp}_2 + \frac{L_j - x}{L_j}\mathrm{dp}_{21}, & x \geq \alpha L_j. \end{cases} \tag{6}$$

Combining (3)–(6), the benefit is obtained.

B. Problem of Interest

To obtain a deployment strategy with the maximum utility, by plugging (4) into (3), an optimization problem is formulated as follows:

$$\max \sum_j \sum_i r_j b_{ij} x_{ij} - \sum_i f_i y_i \tag{P0}$$

$$\text{s.t.} \sum_i x_{ij} = 1 \quad \forall j \tag{7a}$$

$$x_{ij} \leq y_i \quad \forall i, j \tag{7b}$$

$$\sum_j r_j x_{ij} \leq u_i y_i \quad \forall i \tag{7c}$$

$$0 \leq x_{ij} \leq 1, y_i \in \{0, 1\} \quad \forall i, j \tag{7d}$$

where r_j and u_i indicate the task of e_j and the capacity of v_i, respectively.

In this problem, the basic constraint is to use RSUs to serve all the data dissemination tasks in **G** within the required expected delivery delay. In addition, we also want to maximize the deployment utility. The formulated problem not only focuses on whether the requirement is met but also takes the exact service benefit for all clients and the deployment cost into account.

V. Deployment Strategy Design

In this section, we design an LP-based clustering algorithm to solve (P0). First, the formulated problem is analyzed. Then, the single-node instance is introduced as the preliminary of the algorithm design. Finally, the algorithm details are provided.

To design an effective RSU deployment algorithm, there are some aspects should be taken into account. First, although the coverage of one RSU does not affect that of others, the overlapping area of the coverages does affect the task assignment, as the vehicles in the overlapped area may receive services from multiple RSUs and how to properly select the server and client under the capacity constraints will significantly affect the delivery delay. Second, there are 2^N possible deployment strategies given N, the number of location candidates. For each feasible deployment strategy, the service load assignment and the corresponding utility are different. To obtain the optimal solution, all the feasible strategies should be compared, so the complexity increases exponentially with N. Thus, an approximation algorithm with performance guarantee is preferred. Last, to maximize the total utility, there is a tradeoff between the benefit and cost. Furthermore, the assignment is highly related to the deployment strategy as shown in (7b) and (7c). The algorithm needs to comprehensively consider the relationship between the utility maximization and delivery delay requirement, and take care of both deployment and assignment simultaneously.

Based on the above analysis, we propose a utility-based RSU deployment algorithm (URDA) in this section.

A. Single-Node Problem

Before introducing the deployment algorithm in details, we first study the single-node capacitated facility location problem (SNCFL) where there is only one road segment needed to be served by multiple RSUs. The original problem (P0) with only one road segment is simplified as follows:

$$\max \sum_i R b_i x_i - \sum_i f_i y_i \tag{P1}$$

Algorithm 2 Deployment Algorithm for Single-Node Problem

Input: R, f_i, b_i, u_i
1: $x_i, y_i = 0, \forall i$
2: **while** $\sum_{i:y_i=1} x_i < 1$ **do**
3: $\quad k \leftarrow \arg\max_{i:y_i=0} (b_i - \frac{f_i}{u_i})$
4: $\quad x_k \leftarrow \min(u_k/R, 1 - \sum_{i:y_i=1} x_i)$
5: $\quad y_k \leftarrow R x_k / u_k$
6: **end while**
Output: (x, y)

$$\text{s.t.} \sum_i x_i = 1 \tag{8a}$$

$$R x_i \leq u_i y_i \quad \forall i \tag{8b}$$

$$0 \leq x_i, y_i \leq 1 \quad \forall i \tag{8c}$$

where y_i is relaxed to a continuous variable within (0, 1). If $y_i = 1$, the RSU v_i is fully opened while $0 < y_i < 1$ indicates the RSU v_i is fractionally opened. It is noted that the capacity and cost of the fractionally opened RSUs are also scaled down. b_i and x_i is the benefit from the service provided by v_i and the portion of service task assigned to v_i, respectively. R is the amount of the service tasks.

Given any feasible solution (x, y), we can set $\hat{y}_i = (Rx_i/u_i)$ and obtain a feasible solution $(x, \hat{y})$ with no less total utility. Thus, the objective function can be replaced by $\max \sum_i R(b_i - (f_i/u_i))x_i$, and the corresponding constraints (8b) and (8c) are changed to $Rx_i \leq u_i$ for all i. By adding the RSUs following the decreasing order of $b_i - (f_i/u_i)$ and assigning the maximum possible demand to the selected RSUs, i.e., the smaller one among the capacity of the RSU and the remaining demand, until all the demands are satisfied, (P1) is thus solved in a greedy manner as shown in Algorithm 2. The obtained solution is the optimal one and there is at most one RSU is fractionally open [41]. The property is used in the algorithm introduced below.

B. Algorithm Design

In this section, we introduce URDA, an LP-based clustering algorithm to solve (P0). By relaxing the solution region from integer to continuous variables, the original problem can be transformed as follows:

$$\max \sum_j \sum_i r_j b_{ij} x_{ij} - \sum_i f_i y_i \tag{P2}$$

$$\text{s.t.} \sum_i x_{ij} = 1 \quad \forall j \tag{9a}$$

$$x_{ij} \leq y_i \quad \forall i, j \tag{9b}$$

$$\sum_j r_j x_{ij} \leq u_i y_i \quad \forall i \tag{9c}$$

$$0 \leq x_{ij}, y_i \leq 1 \quad \forall i, j \tag{9d}$$

and its dual problem is

$$\min \sum_i z_i - \sum_j \alpha_j \tag{P3}$$

$$\text{s.t. } \alpha_j \leq -r_j b_{ij} + \beta_{ij} + r_j \gamma_i \quad \forall j \tag{10a}$$

$$\sum_j \beta_{ij} \leq f_i + z_i - u_i \gamma_i \quad \forall i, j \tag{10b}$$

Algorithm 3 URDA

Input: $\mathcal{C} = \emptyset$, $\mathcal{S} = E$

Solve (P2) and (P3)
while $S \neq \emptyset$ **do**
  $e_{j^*} = \arg\min_{e_j \in \mathcal{S}} \alpha_j$
  $N_{j^*} = B_{j^*}$
  $\mathcal{C} = \mathcal{C} \cup e_{j^*}$, $\mathcal{S} = \mathcal{S} \setminus e_{j^*}$
  Update $B_j, \forall e_j \in \mathcal{S}$
end while
if $U(= F - \cup_{e_k \in \mathcal{C}} N_k) \neq \emptyset$ **then**
  for $\forall v_i \in U$ **do**
    $e_{j^*} = \arg\max_{e_j \in \mathcal{C}} b_{ij}$
    $N_{j^*} = N_{j^*} \cup v_i$
  end for
end if
for $e_k \in \mathcal{C}$ **do**
  for each $v_i \in N_k$ **do**
    Open v_i with $y_i = 1$
  end for
  $L_k = \{v_i \in N_k : y_i < 1\}$
  $R_k = \sum_{v_i \in L_k} \sum_j x_{ij}$
  obtain $(x^{(k)}, y^{(k)})$ using Algorithm 2 with (L_k, R_k)
end for
$Y = \{y^{(k)}\}_{e_k \in \mathcal{C}}$
Obtain X by solving (P0) given Y

Output: (X, Y)

$$\beta_{ij}, \gamma_i, z_i \geq 0 \quad \forall i, j \tag{10c}$$

where intuitively, α shows the contribution of each road segment to the total utility.

Let (x, y) and $(\alpha, \beta, \gamma, z)$ be the optimal solutions to (P2) and (P3), respectively. Let $F = \{v_i : y_i > 0\}$ be the opened facilities in (x, y) and $F_j = \{v_i : x_{ij} > 0\}$ be the facilities in F that fractionally serve e_j. The algorithm is conducted in three steps as shown in Algorithm 3: 1) RSU clustering; 2) reducing to the single-node instance; and 3) assigning the tasks.

1) *RSU Clustering:*

S1: Let $\mathcal{C}$ be the set of the current cluster centers, which is initially empty, and N_k denote the RSUs clustered around the edge $e_k \in \mathcal{C}$. For those edges $e_j \notin \mathcal{C}$, let B_j be the set of the unclustered RSUs that are more beneficial to e_j than any cluster center, i.e., $B_j = \{v_i \in F_j : i \notin \cup_{e_k \in \mathcal{C}} N_k \text{ and } b_{ij} \geq \max_{e_k \in \mathcal{C}} b_{ik}\}$. Let $\mathcal{S}$ be the set containing all the edges that could be chosen as the cluster centers which send at least half of their demands to the RSUs in B_j, i.e., $\mathcal{S} = \{e_j \notin \mathcal{C} : \sum_{v_i \in B_j} x_{ij} \geq (1/2)\}$. We repeatedly select $e_j \in \mathcal{S}$ with the smallest α_j and form the cluster with $N_j = B_j$. Then, we update the sets $\mathcal{C}$ and $\mathcal{S}$.

S2: After the above process, there may still leave some RSUs in F have not been clustered around any $e_j \in \mathcal{C}$. For these RSUs, we assign them to the existing cluster center to whom the RSU is most valuable, i.e., $N_j \leftarrow N_j \cup \{v_i\}$ where $e_j = \arg\max_{e_k \in \mathcal{C}} b_{ik}$. The tasks served in each cluster are defined as the total tasks served by all the RSUs in it. Note that not only the tasks from the cluster center e_j but also from other edges fractionally served by the RSUs in N_j are counted as the cluster demand, i.e., $\sum_i \sum_j r_j x_{ij}$.

2) *Reducing to the Single-Node Instance:* First, $\forall v_i \in N_k$, v_i is opened if $y_i = 1$ for all clusters. Then for each cluster, an SNCFL is formed with the remaining RSUs and service tasks. Let $L_k = \{v_i \in N_k : 0 < y_i < 1\}$ be the set of remaining RSUs and $R_k = \sum_{v_i \in L_k} \sum_j r_j x_{ij}$ be the total demand, respectively. The greedy algorithm in Section V-A is used to find the optimal solution $(x^{(k)}, y^{(k)})$ for the SNCFL. Let O_k^* be the value of the optimal solution. We open all RSUs with $y_i^{(k)} > 0$. Together with the RSUs opened at the beginning of this step (i.e., those with $y_i = 1$), the RSUs opened now have sufficient capacity to serve all the demand $\sum_{v_i \in N_k} \sum_j r_j x_{ij}$ and thus the total demand can be served. Combine the solutions for all clusters and we have all the RSUs either fully opened or not opened.

3) *Assigning the Tasks:* After opening enough RSUs, we redo the task assignment by solving (P0) to maximize the total utility.

The algorithm operation includes four steps. First, solve a relaxed LP problem (P2) and its dual problem (P3), which can be done by well-studied tools. Second, based on the solutions of (P2) and (P3), group the RSUs into different clusters. Here, as shown in Algorithm 3, the number of clusters will not exceed the number of RSU candidates. Third, solve single-node problem (P1) for each cluster in a greedy manner with a low complexity. Last, combine the solution of all clusters together and solve the task assignment problem which is another LP problem. Overall, the complexity is moderate with the above analysis and will not increase significantly with the network scale. Thus, the algorithm is viable even when the network scale is large.

VI. Algorithm Analysis

In this section, the gap between the proposed URDA and the optimal one is studied. The analysis uses the following two facts. First, Lemma 1 shows that the solution of (P1) is not far away from its optimal solution. Second, Lemma 3 shows that the solution of (P2) obtained by assembling the solutions to each single-node instances is not far away from the optimal solution to the original problem. For convenience, we assume that the service demand $r_j = 1$, $\forall j$. It is straightforward to find the following result also holds for varying r_j. Let $U^* = F_U(x, y)$ and $B^* = F_B(x)$ be the optimal utility and the corresponding total benefit for (P2), respectively.

Recall that $L_k = \{v_i \in N_k : y_i < 1\}$, $(x^{(k)}, y^{(k)})$ is the optimal solution to (P1) found by the greedy algorithm for the single-node instance corresponding to this cluster, and O_k^* is the value of this solution.

Lemma 1: For each $e_k \in \mathcal{C}$, the optimal value

$$O_k^* \geq \sum_j \sum_{v_i \in L_k} b_{ik} x_{ij} - \sum_{v_i \in L_k} f_i y_i \tag{11}$$

and, hence,

$$\sum_{e_k \in \mathcal{C}} O_k^* \geq \sum_j \sum_{i: y_i < 1} b_{ik(i)} x_{ij} - \sum_{i: y_i < 1} f_i y_i. \tag{12}$$

Proof: First, we propose a feasible solution $(\hat{x}, \hat{y})$, where $\hat{y}_i = y_i$, and $\hat{x}_i = \sum_j x_{ij}$ for all $v_i \in L_k$. Note that $\sum_i \hat{x}_i = \sum_{v_i \in L_k} \sum_j x_{ij} = R_k$. The facility cost of this solution is at most $\sum_{v_i \in L_k} f_i \hat{y}_i = \sum_{v_i \in L_k} f_i y_i$. The service benefit is $\sum_{v_i \in L_k} b_i \hat{x}_i = \sum_j \sum_{v_i \in L_k} b_{ik} x_{ij}$. Combining this with the bound on the facility cost, we have that

$$O_k^* \geq \sum_{v_i \in L_k} b_i \hat{x}_i - \sum_{v_i \in L_k} f_i \hat{y}_i$$

$$\geq \sum_j \sum_{v_i \in L_k} b_{ik} x_{ij} - \sum_{v_i \in L_k} f_i y_i. \tag{13}$$

Since N_k are disjoint, by summing up all clusters, we have

$$\sum_{e_k \in \mathcal{C}} O_k^* \geq \sum_j \sum_{i: y_i < 1} b_{ik(i)} x_{ij} - \sum_{i: y_i < 1} f_i y_i. \tag{14}$$

■

Lemma 1 shows that the sum of the optimal solutions of the clusters has a bounded gap to the global optimal solution.

Lemma 2: The cost of opening the (at most one) extra RSU in cluster N_k is at most $2 \sum_{v_i \in N_k} f_i y_i$.

Proof: $\sum_{v_i \in N_k} y_i \geq \sum_{v_i \in N_k} x_{ik} \geq (1/2)$ since N_k was established around k in step S1, and no RSU is removed from N_k in step S2. We open at most one extra RSU from N_k according to the property of the greedy algorithm introduced in Section V-A. Since all RSUs have the same cost f, the cost of opening this facility is $f \leq f \cdot 2 \sum_{v_i \in N_k} y_i = 2 \sum_{v_i \in N_k} f_i y_i$ (this is the only place that we assume the RSU costs are all the same). ■

Lemma 2 demonstrates that the cost of opening the extra RSU is also bounded.

Let $\hat{y}$ be the 0-1 vector indicating which RSUs are opened. Let $\hat{y}^{(k)}$ denote the portion of $\hat{y}$ consisting of the facilities in L_k, i.e., $\hat{y}^{(k)} = (\hat{y}_i^{(k)})_{v_i \in L_k}$.

Lemma 3: The solution $(x^{(k)}, y^{(k)})$ for cluster N_k yields an assignment $\hat{x}^{(k)} = (\hat{x}_{ij}^{(k)})_{v_i \in L_k}$ such that:

1) $(\hat{x}^{(k)}, \hat{y}^{(k)})$ obeys constraints (9b)–(9d) for all $v_i \in L_k$;
2) $\hat{x}$ satisfies $\sum_{v_i \in L_k} x_{ij}$ fraction of the demand of each road segment e_j, that is, $\sum_{v_i \in L_k} \hat{x}_{ij} = \sum_{v_i \in L_k} x_{ij}$ for all e_j;
3) the utility $\sum_j \sum_{v_i \in L_k} b_{ij} \hat{x}_{ij}^{(k)} - \sum_{v_i \in L_k} f_i \hat{y}_i^{(k)}$ is at least $O_k^* - 2 \sum_{v_i \in N_k} f_i y_i - \sum_j \sum_{v_i \in L_k} b_{ik} x_{ij}$.

Proof: See Appendix A. ■

Lemma 3 shows that the optimal solutions of the clusters can be used to construct a solution to the original problem with a bounded benefit loss.

Lemma 4: The utility of opening RSUs v_i with $y_i = 1$ and serving e_j by such v_i following the assignment x_{ij}, is at least $\sum_i z_i - \sum_j \sum_{i: y_i = 1} \alpha_j x_{ij}$.

Proof: See Appendix B. ■

Lemma 4 uses the complementary slackness to connect the utility from those fully opened RSUs, i.e., $y_i = 1$, with the dual objective function. Combining the above conclusions together, we get the following theorem.

Theorem 1: Under URDA, the utility of the solution returned is at least $4 \cdot U^* - 3 \cdot B^*$, which means the gap between the returned solution and the optimal solution is less than $3 \cdot (B^* - U^*)$.

Proof: See Appendix C. ■

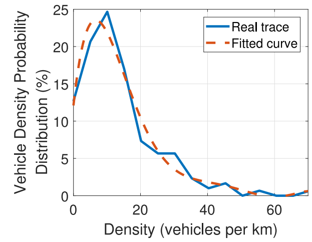


Fig. 4. Vehicle density probability distribution.

As shown in Lemmas 1 and 3, the solutions of all single-node instances (P1) connect the optimal solution of (P2) and the returned feasible solution of (P0) with bounded gaps, respectively. Lemma 1 shows that the total utility of the optimal solution for all the single-node problems has a bounded gap to the optimal solution of (P2), while Lemma 3 shows that the optimal solution of each single-node problem (P1) can be used to construct a feasible solution to the original problem (P0) while losing a bounded term. When constructing the feasible solution of (P0) from that of (P1), the extra cost from fully opening the extra RSU should be considered. Lemma 2 shows that the corresponding cost is bounded. As shown in Lemma 4, when opening the RSUs with $y_i = 1$, the corresponding utility is proved to be a bounded value using complementary slackness. Finally, combining the above facts, Theorem 1 shows that the obtained feasible solution has a bounded gap to the global optimal solution.

Given the fact that the U^* is not necessarily to be a positive value in practice, we cannot bound the returned solution with a constant. However, as shown in Theorem 1, if the deployment cost (i.e., $B^* - U^*$) is small enough, then the returned solution is guaranteed to be close to the optimal value. This is because the algorithm will be less affected by the cost and prefer to achieve a higher benefit from the service.

Furthermore, Theorem 1 provides the guidance for the deployment strategy not only about how to achieve a satisfactory performance, but also on whether it is worthwhile to deploy the vehicular systems in an area. More precisely, it presents the algorithm performance bound after properly selecting the benefit function and evaluating the cost. When the total utility is low in an area, it reflects the low return from the deployment in such an area, and also the algorithm cannot guarantee a promising bound.

VII. Performance Evaluation

To validate the effectiveness of the proposed RSU deployment strategy, extensive simulations have been conducted by using MATLAB. The comparisons with the existing methods are provided in terms of the deployment benefit and utility, under different RSU costs and service requirements.

A. Simulation Setup

An 8×8 Manhattan grid model is adopted in the simulation. To obtain the vehicle density distribution, the real trace collected from about 2300 taxis in Shanghai in 2007 [42]–[44] were analyzed. First, we selected 300 observation spots in Hongkou District in Shanghai, and recorded the number of

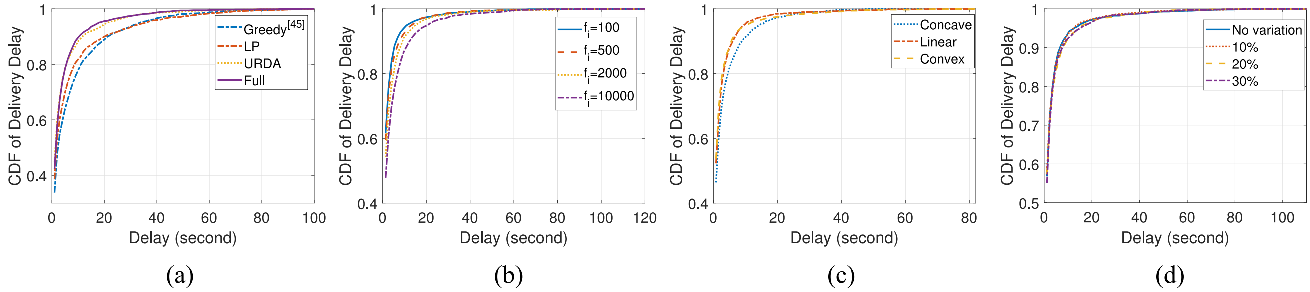


Fig. 5. CDF of delivery delay. Comparison of (a) deployment algorithm, (b) varying f_i, (c) service type, and (d) estimation error.

vehicles passing by each observation spot during mid-day. Then, the distribution of vehicle density is estimated using the polynomial fitting method, and scaled up considering the relationship between the number of taxis in 2007 and that of the vehicles at present. The trace statistics and the estimation result are shown in Fig. 4, which is used for the generation of the vehicle densities of the road segments in the simulation. Finally, according to the vehicle densities of the road segments, the positions of vehicles were randomly generated as in [38]. Note that, we cannot directly apply the taxi trace for simulation because the taxis are only a portion of all vehicles. For the accuracy of the evaluation, the estimation of the density distribution of all vehicles is necessary. In the simulation, the messages are transmitted from the RSU to vehicles randomly located in its designated service area. The message delivery delays from RSU to vehicles are recorded and categorized by road segments. The expected delivery delay requirement is 60 s which is reasonable to ensure the feasibility of the studied problem. Each intersection is connected with its neighbor intersections by a 2000-m road segment, as the arterials in a city. If not stated otherwise, f_i, the cost of deploying an RSU, is 300 and the benefit function is $f(d) = \max(0, 1 - d/60)$. The unit of d is seconds. Benefit $f(d)$ and deployment cost f_i have been normalized into a unified monetary unit. The capacity of RSU and the service tasks of each road segment varies between $[50, 70]$ and $[1, 40]$ per time unit, respectively.

B. Deployment Algorithm Comparison

The performance comparisons among the greedy algorithm improved from [45], the LP-based algorithm improved from [35] and [36], the full deployment algorithm and the proposed URDA are presented in Figs. 5 and 6. Each benchmark algorithm considers both the RSU deployment and the task assignment. The greedy algorithm aims at maximizing the utility increment in each RSU selection step, while still satisfies the capacity constraint. In each iteration, if there is only one unselected RSU that can serve a certain road segment, then this RSU is selected and the service task of that road segment is assigned. Otherwise, the anticipated utility increase by deploying one of the unselected RSUs will be calculated. For example, assuming v_i is an unselected RSU, we assign the service tasks to v_i in the descending order of b_{ij} where $e_j \in C_i$ and r_j has not been fully assigned yet, until either the capacity of v_i is totally occupied or all the possible service tasks are assigned. Then, the RSU with the highest utility increase will be selected and the corresponding task

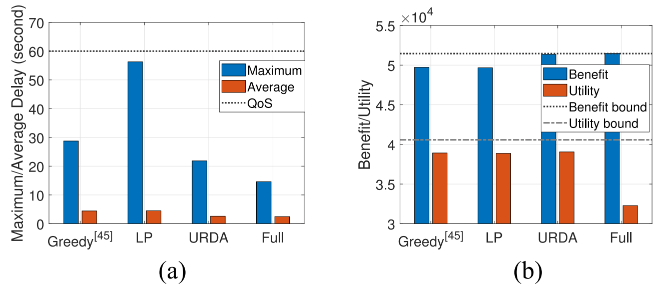
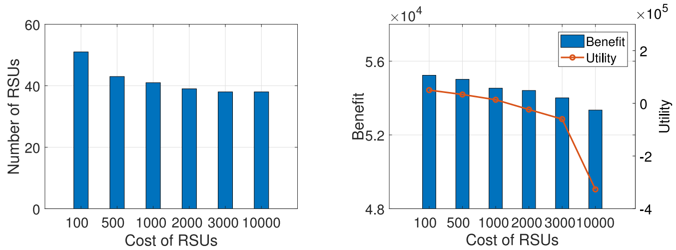


Fig. 6. Algorithm comparison. (a) Maximum and average delay. (b) Benefit and utility.

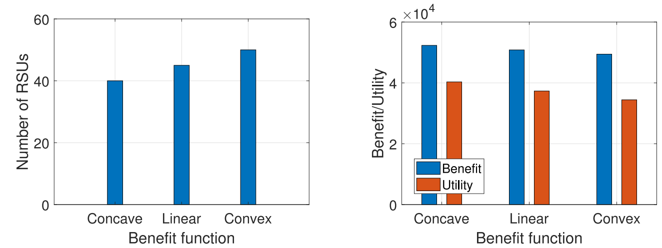
assignment is applied. The iteration ends when all the tasks are assigned. In the LP-based algorithm improved from [36], a simple deterministic rounding scheme is applied. Specifically, the solutions to the relaxed problem (P2) are obtained and the RSUs are selected according to the descending order of y_i until the total capacity is sufficient to serve all tasks. Then, the task assignment is optimized with the selected RSU by solving (P0) given y_i. To achieve the best service performance, the full deployment algorithm ignores the effect of cost and focuses on maximizing the service benefit by setting $y_i = 1, \forall i$. The service assignment is obtained by solving (P0) with $y_i = 1, \forall i$, accordingly.

The delivery delays to the vehicles in each road segment and those to the entire network are averaged first. Fig. 6(a) shows the maximum average delivery delay among road segments and the average delivery delay of the entire network. URDA always has a lower average delay compared with the Greedy algorithm and the LP-based algorithm. When compared with the full deployment algorithm which achieves the best possible performance, the average delay of URDA is only about 0.2 s more than the full deployment algorithm while the number of the RSUs deployed using URDA is 36% less. Fig. 6(b) illustrates that the benefit and utility of RSU deployment strategy. The upper bound of benefit is obtained by solving (9) under $y_i = 1, \forall i$ and the utility upper bound is obtained without integer constraints, respectively. URDA has a higher benefit and utility compared with the Greedy algorithm and LP-based algorithm. When compared with the full deployment algorithm, although the benefit of URDA is slightly lower because of deploying much fewer RSUs, the utility of URDA is much higher than the full deployment algorithm. As shown in Fig. 5(a), the cumulative distribution function (CDF) of the delivery delay of URDA is quite close to the full deployment algorithm. Furthermore, under the URDA deployment



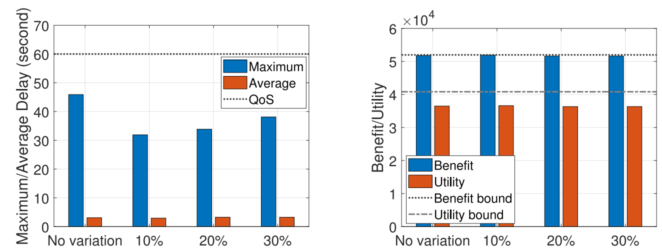
(a) (b)

Fig. 7. Influence of deployment cost f_i. (a) Number of deployed RSUs. (b) Benefit and utility.



(a) (b)

Fig. 8. Influence of benefit function. (a) Number of deployed RSUs. (b) Benefit and utility.



(a) (b)

Fig. 9. Influence of estimation error. (a) Maximum and average delay. (b) Benefit and utility.

and assignment strategy, most of the tasks are served within a short time period and only a tiny portion of them exceed the required delivery delay.

C. Influence of the Deployment Cost

To demonstrate the influence of the deployment cost to URDA, f_i is set to 100, 500, 1000, 2000, 3000, and 10 000, for comparison. As shown in Fig. 7(a), the number of the deployed RSUs decreases with the growth of f_i. When the cost is low, URDA prefers to deploy more RSUs to achieve a better performance. However, when the cost is relatively high, URDA tries to reduce the number of the deployed RSUs while satisfies the requirement. It is found that the number of the RSUs will not keep decreasing with the increase of f_i due to the delay requirement and capacity restriction. When the fewer RSUs are deployed due to the high cost, the total benefit also decreases slightly as shown in Fig. 7(b), while the required expected delivery delay is always met. However, the utility decreases significantly with the increase of f_i, and even below zero when f_i is greater than 2000. To present the results clearly, the CDFs of the delivery delay of $f_i = 100, 500, 2000,$ and $10\,000$ are selected for comparison. As illustrated in Fig. 5(b), the delay performances under different f_i slightly vary. Generally, the smaller f_i is, a better performance the strategy gets thanks to the less influence of the deployment cost, which also verifies the analytical results in Section VI.

D. Different Types of Services

In the real world, different types of message dissemination services may obtain different benefits from the same message delivery delay meeting the QoS requirement. For example, the value of the parking lot availability information decreases rapidly with the growth of the delivery delay since the space may be seized by other vehicles during the message delivery. However, the value of the shopping mall sales advertisement decreases slowly as the information does not change frequently. To illustrate the influence of the benefit function to the deployment strategy, we use three types of benefit functions, including a concave function $f_1(d) = 1 - (d/60)^2$, a linear function $f_2(d) = 1 - d/60$ and a convex function $f_3(d) = 2 - \sqrt{5 - ([d/60] - 2)^2}$ for comparison. Generally speaking, applications more delay-sensitive will choose a convex benefit function over a concave benefit function.

As shown in Fig. 8, the strategy performance highly depends on the benefit function. According to Fig. 8(a), the strategy based on $f_3(d)$ deploys the most RSUs because the benefit decreases rapidly with the growth of the delay in $f_3(d)$. To achieve a higher total utility, URDA gives priority to reducing the delay of the covered area rather than covering more road segments. In addition to the number of deployed RSUs, the benefit/utility evaluation results under different functions are quite diverse. As shown in Fig. 8(b), although convex benefit function-based strategy deploys more RSUs, the benefit is still lower than the former two strategies. Fig. 5(c) illustrates the delay performance of $f_1(d)$ based strategy is relatively worse than the latter two while its total benefit/utility is higher. Even for the similar delay performance, the benefit/utility with $f_2(d)$ is higher than that with $f_3(d)$. This is because the service type significantly affects the evaluation of the benefit. Specifically, the same delay will lead to quite different benefits in different types of services. Thus, it is crucial to choose a proper benefit function when determining the RSU deployment.

E. Time-Varying Traffic

In practice, the vehicle density of the road segment may change with time. As a consequence, the estimation of the vehicle traffic, based on which the algorithm is operated inevitably encounters some errors. To investigate the influence of these estimation inaccuracies, we compare the performance with and without vehicle density variations in Fig. 9. The estimation error rates are set to $\pm10\%$, $\pm20\%$, and $\pm30\%$, respectively, which means the vehicle density of each road segment used in each simulation randomly varies in the given ranges. As shown in Fig. 9(a), even under the estimation error, the maximum average delays are still within the required range and the average delays oscillate slightly. From the above figures, there is no obvious trend that the delivery delay will suffer from the growth of the estimation variation. Thus, it is natural to conclude that the delay performance will not be significantly affected by the time-varying estimation error and URDA still sounds in such cases. It is noted that the traffic statistics used in the algorithm are not restricted to the expected values. Actually, the algorithm is applicable to various inputs when generating the RSU coverage.

Overall, according to the above results, URDA has significant advantages when solving the RSU deployment problem for IoV networks. By properly determining the benefit function according to the service type, URDA can provide an efficient, effective and fair deployment strategy compared with the existing methods.

VIII. Conclusion

This paper investigated the expected delivery delay guaranteed RSU deployment for 2-D IoV networks. We proposed a novel utility function to evaluate the total benefits of the RSU deployment strategy. To obtain an effective solution, an optimization problem is formulated based on the utility function. Then, considering the irregular coverage area of each RSU, an LP-based clustering algorithm is designed to solve the problem. The proposed URDA has a guaranteed performance according to the algorithm analysis. Finally, the simulation results demonstrate the superiority of URDA to other approaches. Besides, URDA can adaptively change the RSU deployment strategy according to different deployment costs and service preferences, and are robust to the inaccuracy of the vehicle traffic estimation.

In practice, there may be some variants of the problem studied above. For example, the capacity of each RSU may not be a constraint with the development of the technology, such that we can simply set a sufficiently large value for each RSU assuming that all RSUs have enough resources to serve all the clients in the network. Hence, the solution will not be affected by the capacity constraint. The problem thus can be solved by our proposed method. In addition, other QoS requirements can also be applied in the proposed framework with a slightly revised coverage generation method. For example, if we take the connectivity probability as the QoS index, the coverage is still an area expanding from the deployed RSU and consisting of road segments and the proposed algorithm is still applicable.

There are many further research issues. For instance, the RSU deployment problems comprehensively considering multiple QoS requirements for the different services in heterogeneous vehicular networks need further research. This paper ignores the details of how the network performance is affected by various network protocols and wireless channel impairments, which also require further investigation. Overall, the work presented in this paper can be an important step toward the future hybrid vehicular network.

Appendix A
Proof of Lemma 3

It is straightforward to see that constraint (9d) is satisfied for $v_i \in L_k$, since $\hat{y}^{(k)}$ is a $\{0,1\}$-vector.

The facility cost $\sum_{v_i\in L_k} f_i\hat{y}_i^{(k)}$ is at most $\sum_{v_i\in L_k} f_i y_i^{(k)} + 2\sum_{v_i\in N_k} f_i y_i$ since every RSU except the extra one is either fully open or not open in the solution $(x^{(k)}, y^{(k)})$ and according to Lemma 2, the cost of opening the extra RSU is at most $2\sum_{v_i\in N_k} f_i y_i$.

The service benefit of the single-node solution is the benefit of serving all the tasks $R_k = \sum_j \sum_{v_i\in L_k} x_{ij}$ from the facilities in L_k to the center e_k. Now we want to move the tasks, $\sum_{v_i\in L_k} x_{ij}$, of road segment e_j from e_k back to e_j. As a consequence, an additional benefit loss $\sum_j \sum_{v_i\in L_k}(b_{ik} - b_{ij})x_{ij}$ is incurred. Specifically, we set $\hat{x}_{ij}^{(k)}$, $v_i \in L_k$ arbitrarily such that, 1) $\sum_{v_i\in L_k} \hat{x}_{ij}^{(k)} = \sum_{v_i\in L_k} x_{ij}$ for each road segment e_j and 2) $\sum_j \hat{x}_{ij}^{(k)} = x_i^{(k)}$ for each RSU $v_i \in L_k$. This satisfies constraints (9b) and (9c)—if $\hat{x}_{ij}^{(k)} > 0$ then $x_i^{(k)} > 0$, so $\hat{y}_i^{(k)} = 1$, and $\sum_j \hat{x}_{ij}^{(k)} = x_i^{(k)} \le u_i = u_i\hat{y}_i^{(k)}$. The service benefit is

$$\begin{aligned}\sum_j \sum_{v_i\in L_k} b_{ij}\hat{x}_{ij}^{(k)} &\ge \sum_{v_i\in L_k}\sum_j b_{ik}\hat{x}_{ij}^{(k)} - \sum_j \sum_{v_i\in L_k}\left(b_{ik} - b_{ij}\right)\hat{x}_{ij}^{(k)} \\ &\ge \sum_{v_i\in L_k} b_i x_i^{(k)} - \sum_j \sum_{v_i\in L_k} b_{ik}x_{ij}. \qquad (15)\end{aligned}$$

We have $O_k^* = \sum_{v_i\in L_k}\left(b_i x_i^{(k)} - f_i y_i^{(k)}\right)$. Combining the bound of the service benefit and facility cost together, we obtained the desired results.

Appendix B
Proof of Lemma 4

By the complementary slackness, each facility v_i with $z_i > 0$ has $y_i = 1$. For each such facility we have that

$$\begin{aligned}\sum_j \alpha_j x_{ij} &= \sum_j -b_{ij}x_{ij} + \sum_j \beta_{ij}x_{ij} + \sum_j \gamma_i x_{ij} \\ &\quad \times \left(x_{ij} > 0 \Rightarrow \alpha_j = -b_{ij} + \beta_{ij} + \gamma_i\right) \\ &= \sum_j -b_{ij}x_{ij} + \sum_j \beta_{ij}y_i + u_i\gamma_i y_i \\ &\quad \times \left(\beta_{ij} > 0 \Rightarrow x_{ij} = y_i, \gamma_i > 0 \Rightarrow \sum_j x_{ij} = u_i y_i\right) \\ &= \sum_j -b_{ij}x_{ij} + f_i + z_i \\ &\quad \times \left(y_i > 0 \Rightarrow \sum_j \beta_{ij} = f_i + z_i - u_i\gamma_i\right). \qquad (16)\end{aligned}$$

Then, we have

$$z_i - \sum_j \alpha_j x_{ij} = \sum_j b_{ij}x_{ij} - f_i. \qquad (17)$$

By summing over all i with $y_i = 1$, we complete the proof.

Appendix C
Proof of Theorem 1

The total utility is bounded at least $4 \cdot U^* - 3 \cdot B^*$ with a feasible solution $(\hat{x}, \hat{y})$ which is constructed as follows. First, we set $\hat{x}_{ij} = x_{ij}$ and $\hat{y}_i = y_i$ for each RSU v_i that $y_i = 1$.

This satisfies constraints (9a)–(9d) for i such that $y_i = 1$. By Lemma 4

$$\sum_j \sum_{i:y_i=1} b_{ij}\hat{x}_{ij} - \sum_{i:y_i=1} f_i\hat{y}_i = \sum_i z_i - \sum_j \sum_{i:y_i=1} \alpha_j x_{ij}. \quad (18)$$

Second, we set $\hat{x}_{ij} = \hat{x}_{ij}^{(k)}$ for $v_i \in L_k$ where $(\hat{x}^{(k)}, \hat{y}^{(k)})$ is the partial solution for the corresponding cluster given by Lemma 3. The remaining $\hat{x}_{ij}$ is then set to be 0. It is apparent that $(\hat{x}, \hat{y})$ is a feasible solution to (P2). Since the clusters N_k are disjoint, from part 3) of Lemma 3 and Lemma 1, we have that

$$\begin{aligned}\sum_j \sum_{i:y_i<1} b_{ij}\hat{x}_{ij} &- \sum_{i:y_i<1} f_i\hat{y}_i \\ &\geq \sum_{k\in\mathcal{C}} O_k^* - 2\sum_{i:y_i<1} f_i y_i - \sum_j \sum_{i:y_i<1} b_{ik(i)}x_{ij} \\ &\geq -3\sum_{i:y_i<1} f_i y_i. \end{aligned} \quad (19)$$

Combining (18) and (19), we obtain that

$$\begin{aligned}\text{Utility} &\geq \left(\sum_i z_i - \sum_j \sum_{i:y_i=1} \alpha_j x_{ij}\right) - 3\sum_{i:y_i<1} f_i y_i \\ &= \left(\sum_i z_i - \sum_j \sum_i \alpha_j x_{ij}\right) - 3\sum_{i:y_i<1} f_i y_i \\ &\quad + \sum_j \sum_{i:y_i<1} \alpha_j x_{ij} \\ &\geq U^* + 3\left(\sum_j \sum_i b_{ij}x_{ij} - \sum_i f_i y_i\right) \\ &\quad - 2\sum_j \sum_{i:y_i<1} b_{ij}x_{ij} - 3\sum_j \sum_{i:y_i=1} b_{ij}x_{ij} \\ &\geq 4\cdot U^* - 3\sum_j \sum_i b_{ij}x_{ij} \\ &= 4\cdot U^* - 3\cdot B^*. \end{aligned} \quad (20)$$

Hence, the gap between the returned solution and the optimal solution is less than

$$U^* - \left(4\cdot U^* - 3\cdot B^*\right) = 3\cdot\left(B^* - U^*\right). \quad (21)$$

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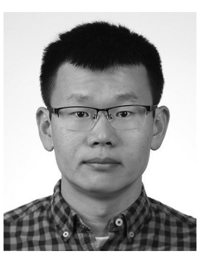

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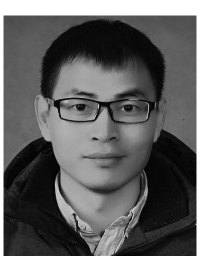

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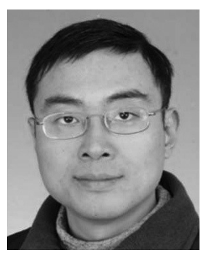

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