Hybrid RSU Management in Cybertwin-IoV for Temporal and Spatial Service Coverage

Yuanzhi Ni, *Member, IEEE*, Chengcheng Zhao, *Member, IEEE*, and Lin Cai, *Fellow, IEEE*

***Abstract*—Roadside Unit (RSU) plays an important role in Vehicle-to-Everything (V2X) service on the Internet of Vehicles (IoV). Due to the limitation of the existing network architecture, the RSU management technology either cannot fulfill the time location-varying service demands or consumes a large number of resource to cover the interested area. To mitigate the gap between the stringent V2X requirements and the limited available resource, a cybertwin-based IoV architecture is proposed to facilitate the RSU management and achieve always-on V2X services. Two types of RSUs, i.e., static RSU (sRSU) and mobile RSU (mRSU), are applied in infrastructure-assisted V2X communications. To evaluate the performance of cybertwin-based RSU deployment and scheduling, the utility maximization problem with coverage constraints is formulated. A three-stage hybrid RSU management strategy is proposed considering the different granularity of service loads. First, sRSUs are deployed to satisfy the basic service demands in different areas. Second, mRSUs are flexibly selected and managed to adapt to real-time variations of service loads. Finally, the RSUs are scheduled based on the real-time load prediction. The case study of Wuxi city illustrates that the proposed solution outperforms the existing strategy in terms of the deployment utility, response ratio, and adaptiveness to demand dynamics.**

***Index Terms*—Internet of Vehicles, cybertwin, roadside unit, always-on service.**

I. Introduction

As A distributed network supporting the data exchanges between vehicles, Internet of Vehicles (IoV) is key to intelligent transportation systems, boosting advanced safety, comfortable and enriched user experiences [1]–[4]. With the development of vehicular wireless communication technology, ultra-reliable, low-latency Vehicle-to-Everything (V2X) communications are expected to enable various IoV related applications [5].

However, there is a gap between today's V2X technologies and stringent service requirements. First, the infrastructure coverage is insufficient to fully support V2X services anytime, anywhere [6]. Second, the bandwidth and energy in IoV are usually limited and costly. Thus, the resource management encounters various challenges to efficiently facilitate the V2X communications. Last, the network dynamics due to vehicle mobility, introduce a significant reliability and scalability issue which is a bottleneck of implementing the always-on services.

Roadside Unit (RSU) is a valuable component in IoV given its stable and high communication, computing and cache capability [7], [8]. For example, RSUs can be used as Internet gateways for nearby vehicles requesting V2X services, and relieve the communication network from resource shortage or traffic congestion [9]. Thus, how to optimize the placement and management of RSU, is a critical issue to realize the V2X service coverage anytime, anywhere.

In the existing literature, the deployment and management of RSUs have been explored extensively [10]–[13]. RSUs can be applied to improve the availability and quality of V2X services [14]. In general, there are two types of RSUs, i.e., the static RSUs (sRSU) and the mobile RSUs (mRSU) [11], [13]. The sRSUs are deployed at the fixed locations with relatively stable quality and capacity, while the mRSUs move following a given path or freely cruising in a desired area. Since different types of RSUs provide different levels of supports to V2X services, both of them are needed to satisfy the requirements of the always-on service and cost-effective deployment. However, most of existing work assumed a static service demand, while in the real cases, the service load follows the distribution of vehicles, which varies with time and location [15], [16]. An unchanged deployment and resource management strategy may lead to the shortage of service capacity and wasting of resource during different hours in a day. Thus, simply applying RSU as a router or storage box without traffic prediction and resource adaption cannot guarantee the performance of V2X service. SDN-based IoV architecture is introduced in [17]–[19] to achieve configurable scheduling decisions for vehicles and RSUs. However, given the large scale of the IoV, the RSU management has an extremely large decision space, and it is challenging to evaluate the utility of each strategy and select the optimal one without extracting global or local information. From the above facts, the deployment of RSUs along with the

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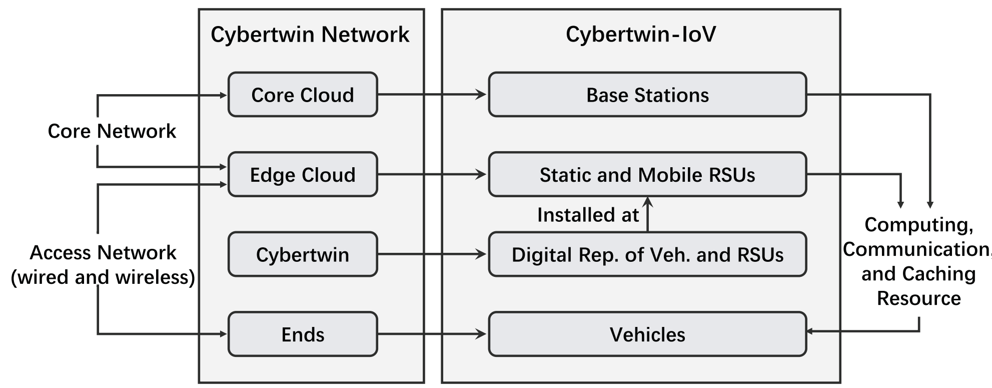

Fig. 1. Cybertwin network and Cybertwin-IoV.

scheduling of service responses should be jointly optimized under a scalable architecture, which motivates this work.

To solve the RSU deployment and management problem while satisfying the time-location-varying demand of V2X service, it is necessary to model the utility and the cost of RSU-assisted V2X services. Furthermore, due to the unbalanced loads of service requests in different time slots and areas, the coverage capacity should also be adaptive to achieve the trade-off between the performance and cost. Thus, the traditional solutions cannot be applied directly.

As shown in Fig. 1, a cybertwin-based cloud-centric network architecture for future generation networks is proposed. The cybertwin is the digital representation of human and things in cyberspace, and serves as a communication assistant to support the always-on service under the architecture of combined core cloud, edge cloud, cybertwin and the ends, with high availability and low latency [20]. By introducing cybertwin into IoV, the network is managed by the centralized controller from core cloud, and the data exchanges between ends are scheduled by edge cloud. Thus, the foundation of scalable network service is laid. In this paper, we apply the cybertwin-based IoV architecture (Cybertwin-IoV) and incorporate the control loop in the twin system to further optimize the scheduling strategies.

The main contributions of this paper are three-folds:

- We propose a novel Cybertwin-IoV architecture that provides scalable and flexible V2X services. A hybrid RSU deployment and management problem is modeled under the proposed architecture, which is an integer programming problem.
- A utility-based hybrid RSU scheduling strategy is proposed leveraging both global information and traffic prediction to obtain the locations of sRSUs and scheduling of mRSUs, respectively. The time-location-varying service demand is considered to achieve the trade-off between the utility and the cost of V2X service.
- The performance of Cybertwin-IoV and the proposed strategy are verified with the case study in Wuxi, China. The results show that the proposed solution outperforms the existing method in terms of the deployment utility, response ratio and adaptiveness to demand dynamics.

The rest of this paper is organized as follows. Section II introduces the related work. In Section III, the preliminaries, including the network architecture and system modeling are presented. The coverage utility maximization problem is formulated in Section III followed by the strategy design in Section IV. Performance evaluation through a case study is presented in Section V. Section VI concludes the paper and discusses the future work.

II. Related Work

In the past few decades, with the increasing presence of infrastructure-based vehicular applications and services, extensive efforts have been devoted into the exploration of the RSU deployment and management.

First, the function and importance of RSUs in IoV have been studied and analyzed extensively. Reis *et al.* [21] studied the benefit of deploying RSUs in one-dimensional vehicular networks with bidirectional traffic. Considering the high cost associated with RSU, the parked cars are used as RSUs in a self-organizing network, and the received signal strength and coverage maps are used to determine if a parked car should be enabled as an RSU [12]. Kim *et al.* [11] introduced three types of RSUs, i.e., static, mobile but not controllable and mobile and fully controllable. Given a limited budget, the viability of vehicular network is tested by deploying heterogeneous RSU and maximizing the coverage. He *et al.* [7] proposed to use Dropboxes to facilitate the message dissemination in two-dimensional vehicular networks, and designed an optimal deployment algorithm to maximize the utility. Jabri *et al.* [22] studied the fuzzy logic based vehicular fog gateway selection approach under the multi-access edge-based vehicular fog computing architecture.

Second, the deployment and management of RSUs with various requirements of V2X services are studied. To improve the success ratio when the number of service requests increases, Abrougui [23] *et al.* introduced a bandwidth-efficient and scalable hybrid adaptive service discovery protocol (VSDP) with the supports from infrastructure. The search for the service provider and its routing information are conducted simultaneously to saving bandwidth. Sorkhoh [24] *et al.* proposed an RSU-assisted workload scheduling scheme where the RSU is responsible for distributing the computational tasks to the vehicles within its range. A mixed integer programming problem maximizing the weight of the admitted tasks is formulated and solved by a

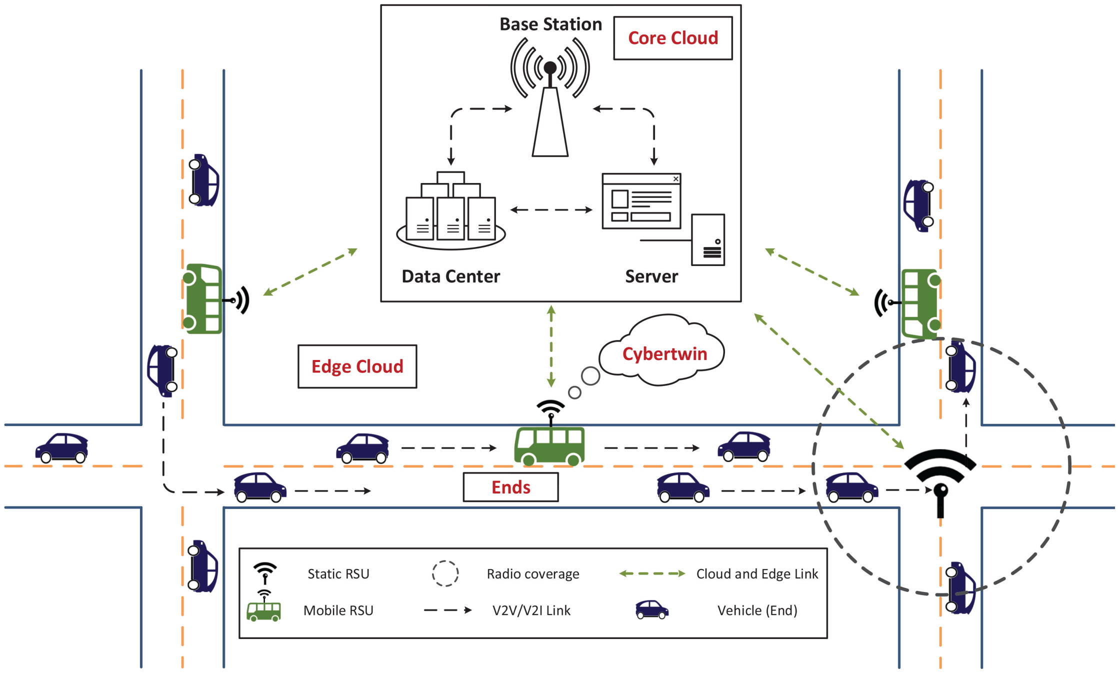

Fig. 2. Cybertwin-IoV scenario.

Dantzig-Wolfe decomposition algorithm. Hui *et al.* [25] focused on collaborative content delivery in Software-Defined Heterogeneous Vehicular Networks (SD-HeVNET) with cellular base stations and RSUs. To maximize the utility and improve the efficiency of the networks, the double auction game is exploited to motivate cellular base stations to cooperate with RSU and the optimal bidding strategies are analyzed.

In the previous works, different RSUs are applied to improve the performance of V2X service. However, The RSU deployment and scheduling satisfying the demand with different granularity in a comprehensive IoV architecture is still an open issue. Furthermore, how to handle the time-location-varying service load while achieving a cost-effective performance has not been discussed yet.

III. System Model and Problem Formulation

In this section, the details of Cybertwin-IoV are introduced first. Graph theory is used to model the evolution and interrelationship of the system. Then, the maximum utility problem with coverage constraint is formulated and analyzed.

A. Cybertwin-Iov

As shown in Fig. 1, Cybertwin-IoV includes four main components, i.e., core cloud, edge cloud, cybertwin, and the ends, which are introduced as follows.

- **Core cloud** is the main infrastructure in IoV, such as base station or central server. They are fully connected and form the core networks to provide resources from different domains including communications, computing and cache.
- **Edge cloud** connects the core cloud and the ends, and serves as a local administrator. It can provide communications, computing and cache resources with a small granularity, and timely responses to the nearby end users. The RSUs including sRSU and mRSU are proper candidates to perform the roles of edge cloud statically or dynamically, respectively.
- **Cybertwin** is the digital representation of the participants in IoV, which is usually located at the edge cloud. It provides communication assistance, network data analytics and other necessary functions, e.g., accurate prediction of the traffic load in a time period based on the twin system in cyberspapce, to facilitate the always-on V2X services.
- **The ends** are the real participants in IoV, including but not limited to vehicles, pedestrians, and other users. They access the IoV network through different links and served directly by the local cybertwin. It is noted that the end-to-end communication is no longer needed in the proposed architecture [20].

The Cybertwin-IoV architecture utilizes the information of different granularity to improve the resource distribution in the whole network. As shown in Fig. 2, the cybertwins deployed at RSUs can handle the information with small granularity and conduct timely responses to network changes in small-scale area. The central controller deployed at the core cloud observes the macroscopic dynamics and schedules the resource according to the actual demands in large-scale view. By introducing cybertwin into IoV, the network is managed by the centralized controller from the core cloud, and the data exchanges between ends are scheduled by the edge cloud. Given the above architecture, different types of network management load can be distributed to different layers with sufficient resource and timely response. For example, the central controller from core cloud focuses on the macroscopic information processing and distributes computing, communication and caching resources to ends. Thus, the system is scalable.

In the proposed architecture, the service requests are launched by the ends, i.e., vehicles on the road, and responded by edge cloud, i.e., the heterogeneous RSUs. To facilitate the V2X service, the network management operated by core cloud includes processing the global information of the whole area, distributing the work load to the edge cloud and allocating resource. The network deployment and management problem is solved in multiple steps by different entities. First, the locations of sRSUs are determined and the paths of mRSUs are selected by central controller in advance. Then, the real-time resource scheduling is solved by the edge cloud based on the information exchanged in local area.

The sRSUs are deployed at proper locations to maximize their service coverage and the connection quality, and the locations will not be changed once deployed. Due to the reliable connection with the network and the power grid, the sRSUs provide stable Internet service and have a sufficient power supply. On the other hand, the mRSUs are installed at the public transportation vehicles, i.e., the buses. Compared with the sRSUs, mRSUs need to deal with the instable Internet connection and limited power supply, which are introduced by the vehicle mobility. Therefore, mRSUs usually cost more energy resource than sRSUs. For the deployed RSUs, the capacity is limited, so the maximum service load one RSU can handle is predetermined by hardware. In summary, the service offered by the RSU is available under two conditions. First, the vehicle is within the service range of the RSU so that the data can be exchanged. Second, the service capacity of the RSU is not fully occupied. To satisfy the service requirements, thanks to the flexibility of edge cloud in Cybertwin-IoV, the massive loads can be distributed to different RSUs to maintain the desired performance.

To achieve a cost-effective performance, the management and scheduling of RSUs are critical. For example, the mRSUs can be turned off to save resource when the neighboring sRSUs provide sufficient service capacity. In reality, with the help of beacon broadcast initiated through access network, the vehicles can detect the availability of mRSUs in its sensing area and launch the requests to the available RSUs.

The proposed cybertwin-enabled architecture offers distinctive advantage in solving the large-scale optimization problem, especially for integer programming problem. On the one hand, the cybertwin can obtain the global information including the locations of vehicles, the real-time service and the traffic states, etc. On the other hand, on top of a network service simulator, the cybertwin with the massive information is able to predict the traffic distribution and service demand in the next period and optimize the resource management and scheduling decisions. Thus, the V2X service is more likely to meet the requirements of the system, and achieves a better trade-off between the benefit and cost.

B. Graph-Based System Modeling

In this subsection, the studied metropolitan area is abstracted as a rectangle area, which is further divided into small squares, as shown in Fig. 3. The side of the squares is $(\sqrt{2}r)$, where r is the communication range of an RSU. Let N_A and $\mathbf{A}$ be the number of areas and the set of areas, respectively. Accordingly, it is assumed that any vehicle travels into the communication range of an RSU is able to launch a service request and be served afterwards under the condition that sufficient resource is allocated. Here, the set of the centers of small rectangles is defined as $\mathbf{S}$, which includes the candidate locations of sRSU deployment. Let N_S be the cardinality of $\mathbf{S}$. A feasible solution is a subset of $\mathbf{S}$, and the set of feasible solutions is defined as

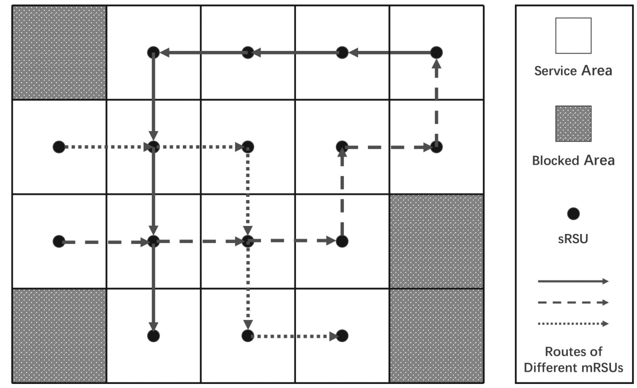

Fig. 3. Spatial and temporal coverage by sRSU and mRSU.

$$\mathcal{S} = \cup C^i_{N_S}, i = \{0, 1, 2, \ldots, N_S\}. \tag{1}$$

Additionally, considering the different capacities of sRSUs, the coverage matrix C^S is defined as follows, where c^s_j is the capacity of the j-th sRSU.

$$C^S_{ij} = \begin{cases} c^s_j, & \text{sRSU } j \text{ is deployed at area } i, \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

Naturally, the locations of mRSUs are determined by the selected bus routes. Let the set of mRSUs be $\mathbf{P}$, whose cardinality is N_P. Accordingly, the set of the feasible mRSU management strategies is $\mathcal{P}$, where both the installation decision $\tilde{p}_k$ and scheduling $p_k(t)$ of mRSUs are included, respectively. Here, one day is divided into T time slots and each mRSU arrives one specific area in one time slot. Given the proper size of area, the stable speed and fixed routes, it is reasonable to assume an mRSU can cover vehicles within the same area.

It is noted that the areas differ from the service load. Due to the dynamics of the vehicle distribution, the service load varies in different time slots during a day. Given the different capacities of mRSUs, the time-varying coverage matrix $C^P(t), t = \{1, 2, 3, \ldots, T\}$ is defined as

$$C^P_{ik}(t) = \begin{cases} c^p_k, & \text{mRSU } k \text{ arrives area } i \text{ at time } t, \\ 0, & \text{otherwise,} \end{cases} \tag{3}$$

where c^p_k is the capacity of k-th mRSU.

Based on the above basics, the studied area can be further modeled as a time-varying graph. At time slot $t \in \{1, 2, \ldots, T\}$, the corresponding graph is denoted as $G(t) = \{V, E, \mathcal{L}(t))\}$, where V and E are the set of nodes and edges, respectively. The nodes are the candidates of sRSUs in the divided area, while the edges are the connections between two adjacent areas. Let $\mathcal{L}_i(t)$ be the service load of area i at the t-th time slot, and it is also the weight for the corresponding area in $G(t)$.

C. Maximum Utility Problem With Coverage Constraint

In this paper, we investigate the hybrid RSU deployment and management problem under the Cybertwin-IoV architecture. The objective of the studied problem is to obtain a strategy for the sRSU and mRSU deployment and management such that the interested area is covered through different time slots.

First, the benefit function $\mathcal{F}(s,p)$ is defined as the sum of the coverage strength through the entire area and the whole time period, as shown in (4).

$$\begin{aligned}\mathcal{F}(s,p) &= \sigma \sum_{i=1}^{N_A}\sum_{t=1}^{T}\left[\sum_{j=1}^{N_S} C_{ij}^S(t)s_j + \sum_{k=1}^{N_P} C_{ik}^P(t)p_k(t)\right]\\ &= \sigma \sum_{i=1}^{N_A}\left[T\sum_{j=1}^{N_S} C_{ij}^S s_j + \sum_{t=1}^{T}\sum_{k=1}^{N_P} C_{ik}^P(t)p_k(t)\right], \end{aligned} \tag{4}$$

where $p_k(t) \in \{0,1\}$ indicates the state of mRSU k switching between on and off to adapt to the time-varying loads. $p_k(t) = 0$ indicates that the mRSU is turned off at time slot t while $p_k(t) = 1$ indicates that the mRSU is turned on. The benefit $\mathcal{F}$ is normalized into a unified monetary unit by introducing an adjusting parameter σ. It is assumed that one mRSU keeps the same state when traveling within the same area to avoid the overhead from frequent switching.

Second, the costs of sRSUs and mRSUs are defined as

$$\mathcal{C}^S(s) = \sum_{j=1}^{N_S} s_j f_j^S \tag{5}$$

and

$$\mathcal{C}^P(p) = \sum_{k=1}^{N_P} \tilde{p}_k \tilde{f}_k^P + \frac{1}{T}\sum_{t=1}^{T}\sum_{k=1}^{N_P} p_k(t) f_k^P, \tag{6}$$

where $\tilde{p}_k \in \{0,1\}$ denote whether the k-th mRSU is installed, $\tilde{f}_k^P$ is the installation cost of the k-th mRSU, and f_j^S and f_k^P are the depreciation and maintenance cost of j-th sRSU and k-th mRSU, respectively.

According to (4)–(6), the utility is defined as the difference between the benefit and the cost, and the maximum utility problem with the coverage constraint is formulated as

$$\begin{aligned} &\max_{s^*\in\mathcal{S},p^*\in\mathcal{P}} \mathcal{F}(s,p) - [\mathcal{C}^S(s) + \mathcal{C}^P(p)]\\ \text{s.t.}\ &\sum_{j=1}^{N_S} C_{ij}s_j + \sum_{k=1}^{N_P} C_{ik}(t)p_k(t) \ge \mathcal{L}_i(t), \quad \forall i,t,\\ &s_j \in \{0,1\}, \quad \forall j,\\ &\tilde{p}_k \in \{0,1\}, \quad \forall k,\\ &p_k(t) \in \{0,1\}, \quad \forall k,\\ &p_k(t) \le \tilde{p}_k, \quad \forall k. \end{aligned} \tag{P0}$$

In this problem, the main constraints is to utilize RSUs to serve the time-varying demand. Additionally, the utility will be maximized to achieve the trade-off between the service benefit and the cost. The dimension of solution for the studied problem includes both the spatial domain and the temporal domain, while these two factors are coupled with each other in the RSU selection and scheduling. Thus, it is challenging to obtain the optimal solution.

IV. Hybrid RSU Deployment and Management Strategy

In this section, the hybrid RSU deployment and Management strategy is introduced to solve the maximum utility problem with coverage constraints. The intuition of strategy design is analyzed followed by the details of the proposed strategy. In general, the problem is solved through three stages on the basis of the Cybertwin-IoV. First, the sRSUs are deployed to offer a basic and stable capability for V2X service. Second, the paths and switching of mRSUs are selected and managed based on the historical time-varying service load. Last, according to the incidental service demands, a real-time RSU scheduling scheme is applied to satisfy the demands with the best efforts.

A. Intuition for Strategy Design

The formulated problem is an integer programming problem, which jointly considers the sRSU deployment and mRSU management strategy. Since the selections of sRSUs and mRSUs are coupled with each other, it is challenging to obtain the optimal solution. On the other hand, the granularity of load variance, i.e., the degree of service load variance, changes significantly due to different time, location, and occasional incident. For example, the service loads during rush hours are usually significantly higher, and the occasional service loads vary in a reasonable range. Consequently, the granularity of load service is quite different under various cases. Thus, traditional static deployment strategies cannot be applied directly. Here are some intuitions for the strategy design.

- The granularity of optimization decision differs from system-level resource distribution to point-to-point transmission scheduling. The solution should take both sides into account.
- The locations of sRSU have significant impacts on the path selection of mRSUs. How to decouple the interrelation between the heterogeneous RSUs is critical to maintain a low cost.
- The main task of the mRSUs is to cover the high-dynamics of the peaks and valleys through different time slots. Also, since the mRSUs will pass multiple road segments, i.e., areas with different service loads, the capacity of them will not always be fully utilized. Thus, the states of them needs to be tuned adaptively to maintain a high efficiency.
- The time-varying and unbalanced service load distribution introduces different resource demands in different areas and time slots. How to schedule the RSUs based on the available information is essential to the service performance.

In summary, to solve the formulated problem (P0) effectively, it is necessary to leverage the advantages of both types of RSUs, i.e., the stable capacity of sRSU and the flexibility of mRSU, and consider the time-location-dependent service demand. Thus, a hybrid RSU deployment and management strategy is proposed in this section. The main idea is to divide the decision process into three stages. First, since the sRSU cannot move once deployed, the algorithm deploys sRSUs to satisfy the basic demand for service through the whole day. Second, the algorithm finds the optimal path for the mRSU without concerning bus routes constraints. According to the optimal path, a cost minimization set cover problem is formulated and solved to obtain the set of selected routes and state switching strategy, respectively. Last, considering the occasional service demand exceeding the estimated range, the available RSUs will be scheduled to satisfy the requirements with best efforts.

In the three-stage strategy, how to adapt to the granularity of load variance is considered in different stages. Generally, the load variance among different periods and locations with a large granularity is handled by the mRSU selection of the second stage, while the real-time small-granularity load variance beyond the estimated range will be compensated by scheduling the available resources in the third stage.

B. Static Deployment Stage

In the first stage, the locations of sRSU are determined based on the expected service load obtained from historical data. The sRSU deployment offers a fundamental coverage capacity for the studied areas. The locations and costs of sRSUs will not change once determined. Thus, in order to avoid unnecessary overhead, the deployed sRSUs should be carefully selected to fulfill the basic demands of the covered area only. It is noted that the peaks and valleys of service load are not the main concerns in this stage.

As shown in Algorithm 1, the expected service load of the i-th area $\bar{\mathcal{L}}_i$ is obtained from historical data. Then, the sRSU deployment algorithm divides the candidate sRSUs into groups according to the located area. For the i-th area, all candidates in this area form a set S_i. Since the deployment between areas is independent, a greedy policy is applied for the sRSU deployment in each area. The candidates are selected following the descending order of the capacity-to-cost ratio and the selected sRSU is removed from S_i. The deployment ends when the total capacity of selected sRSUs, $\sum_{j:s_j=1} C_{ij}^S \geq \bar{\mathcal{L}}_i$ or $S_i = \emptyset$. After the sRSU deployment, $s_j, \forall j$ is returned as the input for the second stage.

C. Mobile Deployment Stage

In the second stage, the mRSUs are selected and scheduled according to the time-location-varying service demand. Given the sRSU deployment strategy $s_j, \forall j$, the original problem (P0) is transferred into (7), where only the mRSU selection and scheduling need to be determined.

$$\max_{p^* \in \mathcal{P}} \quad \mathcal{F}(s^*, p) - [\mathcal{C}^S(s^*) + \mathcal{C}^P(p)] \tag{7a}$$

$$\text{s.t.} \quad \sum_{k=1}^{N_P} C_{ik}(t) p_k(t) \quad \geq \mathcal{L}_i^R(t), \qquad \forall i, t \tag{7b}$$

Algorithm 1: sRSU Deployment Algorithm.

Input: $G(t)$, $\mathcal{L}_i(t)$, C^S, $\forall i, t$
- $\bar{\mathcal{L}}_i = \frac{1}{T}\sum_{t=1}^{T} \mathcal{L}_i(t), \forall i$
- **for** $i \in \mathcal{A}$ **do**
  - $S_i \leftarrow \{C_{ij}^S > 0, \forall j\}$
  - **while** $\sum_j C_{ij}^S s_j < \bar{\mathcal{L}}_i$ & $S_i \neq \emptyset$ **do**
    - $j^* \leftarrow \arg \max_{j:C_{ij}^S>0} C_{ij}^S / f_j^S \leftarrow 1$
    - $s_{j^*} \leftarrow 1$
    - $S_i \leftarrow S_i \setminus j^*$
  - **end while**
- **end for**

Output: $(s_j, \forall j)$

Algorithm 2: mRSU Management Algorithm.

Input: $G(t)$, $\mathcal{L}_i(t)$, C^P and $s_j, \forall i, j, t$
- $\mathcal{L}_i^R(t) = \max\{\mathcal{L}_i(t) - \sum_j c_{ij} s_j, 0\}$
- Solve (7a) without the route constraints
- Obtain $\widehat{P}^* = \{p_k^*(t), \forall k, t\}$
- Formulate the set cover problem (8) with $\widehat{P}^*$
- Obtain $\tilde{p}_k$ by solving (8)
- $p_k(t) \leftarrow p_k^*(t)$

Output: $(\tilde{p}_k, p_k(t), \forall k, t)$

$$\tilde{p}_k \in \{0, 1\}, \qquad \forall k \tag{7c}$$

$$p_k(t) \in \{0, 1\}, \qquad \forall k \tag{7d}$$

$$p_k(t) \leq \tilde{p}_k, \qquad \forall k, \tag{7e}$$

where $\mathcal{L}_i^R(t) = \max\{\mathcal{L}_i(t) - \sum_j c_{ij} s_j, 0\}$ is the remaining service load in the i-th area at time slot t, which should be served by mRSUs.

First, we ignore the constraint of fixed bus routes by removing the condition (7e), and focus on the area and time slots where the mRSUs are needed. The optimal mRSU switching policy $\widehat{P}^* = \{p_k^*(t), \forall k, t\}$ can be obtained by linear programming methods. Then, the constraints of fixed bus routes are recovered, and (7) is simplified into a cost minimization set cover problem as shown in (8).

$$\min_{\tilde{p}_k \in \mathbf{P}} \quad \mathcal{C}^P(p) \tag{8a}$$

$$\text{s.t.} \quad \tilde{p}_k \in \{0, 1\}, \qquad \forall k \tag{8b}$$

$$p_k(t) \leq \tilde{p}_k, \qquad \forall k \tag{8c}$$

In essence, the mRSU management problem is to select the paths of mRSUs with the minimum installation cost while covering $\widehat{P}^*$.

D. Real-Time Scheduling Stage

Considering the uncertainty of service demand, it is possible that the actual service load exceeds the estimated range. Thus, it is necessary to consider how to handle the scalable issue in such cases.

Algorithm 3: Hybrid RSU Scheduling Algorithm.

Input: $G(t)$, $\mathcal{L}_i(t)$, C^S, C^P, s_j, $\tilde{p}_k$ and $p_k(t), \forall i, j, k, t$
1: $V(i,t) \leftarrow Cybertwin(G(t), V_{trace})$
2: $\hat{\mathcal{L}}_i(t+\Delta t) \leftarrow Elman(G(t), V(i,t))$
3: Formulate real-time scheduling problem (9)
4: Obtain $p_k(t+\Delta t), \forall k$ by solving (9)
Output: $\hat{\mathcal{L}}_i(t+\Delta t), p_k(t+\Delta t), \forall i, k$

Once the RSUs are deployed or installed, the maximum capacity of the edge cloud is determined. However, in order to reduce the depreciation and maintenance cost, some mRSUs will be turned off when the existing capacity is enough in the second stage. The capacity of the inactive mRSUs can be released to make up for the shortage of capacity. With the twin system in cybertwin, the real-time service load can be predicted with accurate simulations and learning-based methods [26]–[28]. From the historical data, microscopic pattern of vehicle movement in each area, i.e., transition probability from one area to another, is extracted and used to predict the real-time vehicle movement. Accordingly, the short-term service load can be simulated in advance. Thus, the states of mRSUs can be further scheduled in real cases to serve the burst service load if needed.

As shown in Algorithm 3, given $G(t)$, location-time-dependent area transition probability and the real-time traffic flow obtained by cybertwin, Elman Neural Network is used to predict the real-time traffic in the following time period Δt. Let the predicted service load of i-th area at time slot $(t+\Delta t)$ be $\hat{\mathcal{L}}_i(t+\Delta t)$. The hybrid RSU scheduling problem is formulated in (9).

$$\begin{aligned} &\min_{p_k(t+\Delta t)} \mathcal{F}(s,p) - [\mathcal{C}(s) + \mathcal{C}(p)] \\ &\text{s.t.} \quad \sum_{k=1}^{N_P} C_{ik}(t) p_k(t+\Delta t) \geq \hat{\mathcal{L}_i^R}(t+\Delta t), \quad \forall i, \\ &\qquad p_k(t+\Delta t) \in \{0,1\}, \quad \forall k, \\ &\qquad p_k(t+\Delta t) \leq \tilde{p}_k, \quad \forall k, \end{aligned} \tag{9}$$

where $\hat{\mathcal{L}_i^R}(t+\Delta t) = \max\{\hat{\mathcal{L}}_i(t+\Delta t) - \sum_{j=1}^{N_S} C_{ij} s_j, 0\}$. The scheduling decision $p_k(t+\Delta t)$ is obtained by solving (9).

E. Discussion and Analysis

As mentioned in Section IV-A, the original utility maximization problem (P0) needs to optimize the sRSU deployment and mRSU selection simultaneously while satisfying the time-varying service demand constraints. However, after sRSU are deployed, the original problem (P0) is transformed into (7), where mRSU selection need to be optimized. Finally, Given sRSU and mRSU, only the scheduling decision needed to be obtained in (9). Overall, the original problem illustrates the coupling between sRSU and mRSU management, and is solved in (7) and (9) by decoupling the optimization decision domain. Thus, a feasible and satisfactory solution is obtained.

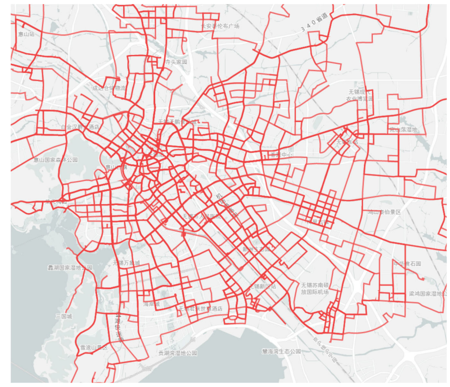

Fig. 4. The bus routes in Wuxi, China.

It is shown in (P0) that the original problem is a mixed integer programming problem, which is not solvable in polynomial time. Additionally, the service demand may exceed the estimated range in real cases. Thus, it is impractical to obtain the optimal solution under this circumstance. In this work, (P0) is solved in three stages. The first stage simplifies (P0) by turning the time-varying demand into the expected ones and obtains the sRSU deployment strategy. In the second stage, the solutions of the linear programming problem (7) and the set cover problem (8) have been studied with a theoretical bound. In the third stage, the optimal real-time scheduling decision is obtained by solving the linear programming problem (9). Overall, although the proposed strategy cannot guarantee an optimal solution, the feasible solution returned is efficient.

V. Experiment

To validate the performance of the proposed hybrid RSU deployment and management strategy, we use the geographic data in Wuxi, China for a case study. The experiments are conducted by Matlab with the following steps. First, based on the geographic information of Wuxi, China, the time-location-dependent traffic load is generated according the popularity of area and the number of active vehicles. Then, the performance of the proposed solution is evaluated by comparing with the benchmark method in terms of the optimality, response ratio, adaptiveness and etc.

A. Geographic Information and Bus Routes in Wuxi

Wuxi is a 4,627 square kilometer city located in east coast of China, with a population of 6 millions and over 2 millions vehicles. The studied metropolitan area is a 10 km $\times$8 km square in the main area of Wuxi, divided into 500 areas. As shown in Fig. 4, the routes of 385 buses cover the most of the city for a period of 24 hours. From the public bus timetable, we can obtain the cruising path and the service time of over 2,400 bus routes, which is the basis for mRSU installation. The processed bus routes are illustrated in Fig. 5.

Given the path and service time of each bus route, the departure interval between two consecutive buses of the same route is set to be 30 minutes. To simplify the simulation setting, each

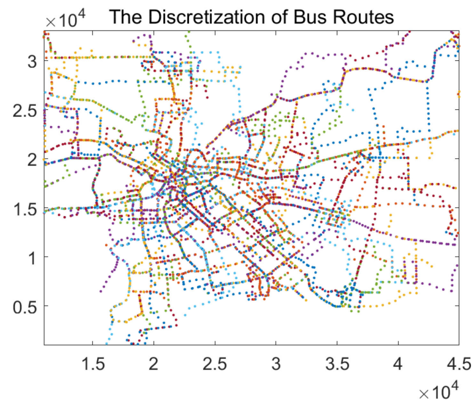

Fig. 5. The processed bus routes.

TABLE I
PARAMETER SETTING OF TRAFFIC LOAD GENERATION

Parameter	Value
Duration of time slot	15 min
Total number of vehicles	10, 000
Speed range of vehicle	[0, 60] km/h
Active ratio of vehicle	[0.01, 1]

bus drives towards the starting point in the next period once it arrives the destination during the service time.

B. Time-Location-Varying Traffic Load Generation

In this subsection, the time-varying traffic load is generated based on the geographic feature of the studied area. First, according to the function division of the city, the popularity of an area depends on the location and time simultaneously [29], [30]. For example, the Central Business District (CBD) attracts a large number of vehicles from residential areas during the morning. To mimic the actual situation, the time-location-dependent vehicle microscopic movement simulation is conducted to generate the time-location-varying traffic load.

Considering the clients of the IoV applications, i.e., the vehicles, will not always travel on the road, the simulation should distinguish the state of a vehicle. From the macro perspective, whether a vehicle is active or not depends on the active ratio, i.e., the probability of a random process. In this paper, the active ratio is manually set based on the peak and valley hour variation. Meanwhile, the active ratio can be obtained from historical data of the studied area if provided. Thus, the number of active vehicles can be estimated accordingly. Given the total number of vehicles and the peak-valley hours, we assume a time-varying vehicle active ratio. However, the geographic distribution of active vehicles cannot be obtained directly. We applied Elman Neural Network to predict the real-time number of active vehicles in each area.

The duration of time slot, total number of vehicles, range of vehicle active ratio and traveling speed are shown in Table I. Then, the microscopic movement of each vehicle is simulated according to the following regulations. Specifically, we define the attraction strength of i-th area to the vehicles in j-th area

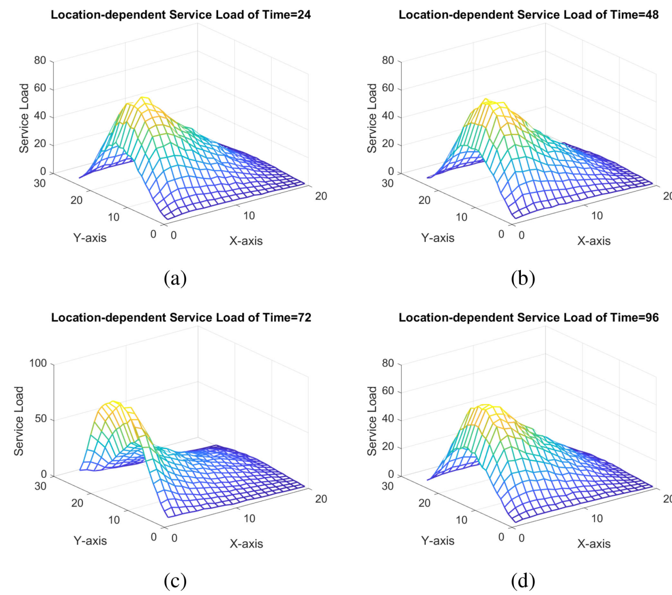

Fig. 6. The location-dependent load at different time slots. (a) time slot = 24. (b) time slot = 48. (c) time slot = 72. (d) time slot = 96.

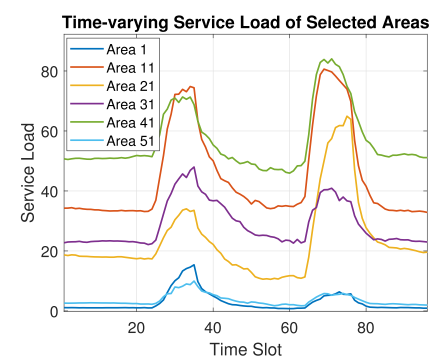

Fig. 7. The time-varying traffic load in different areas.

$A_{ij}(t)$ at time slot t as the follows

$$A_{ij}(t) = \frac{P_i(t)}{D_{ij}}, \tag{10}$$

where $P_i(t)$ is the popularity of i-th area at time slot t and D_{ij} is the distance between area i and j. A vehicle in area j will select area i as the destination with the probability of $\frac{A_{ij}(t)}{\sum_i A_{ij}(t)}$. If $i = j$, the vehicle stays. Otherwise, the vehicle will follow the shortest path in $G(t)$ to the randomly selected destination.

Thus, through 100 simulations, the time-location-dependent traffic load is obtained as shown in Figs. 6 and 7. Fig. 6 illustrates that in the studied area, the service load in different areas is highly-varying. Also, during different time slots, the service load distribution is also different. It is natural to find that the service load at time slot = 72 (6pm) is higher than that at other time slots, due to the peak-hour phenomenon in the afternoon. Fig. 7 shows the service load of selected areas during a day. It is straightforward to find that the service load in different areas is unbalanced, but also follows a similar peak-valley distribution. The service loads between time slots (30–36) and

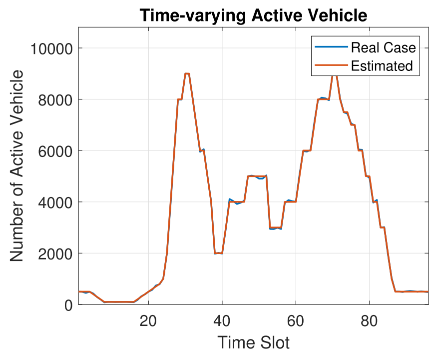

Fig. 8. The time-varying number of active vehicles in a day.

TABLE II
PARAMETER SETTING OF SIMULATIONS

Parameter	Value	Unit
r	200	meter
C^S_{ij}	$[50, 500]$	served vehicles per slot
C^P_{ik}	$[20, 200]$	served vehicles per slot
f^S_j	$[300, 3000]$	\$ per day
f^P_k	$[500, 2000]$	\$ per day
$\tilde{f}^P_k$	$[500, 5000]$	\$ per mRSU

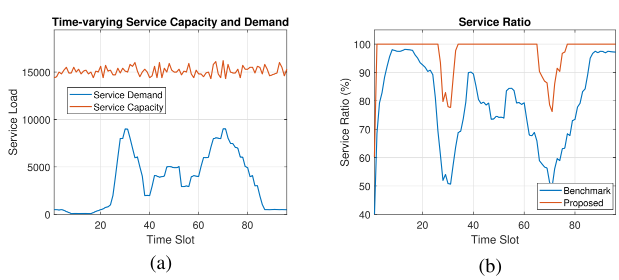

Fig. 9. The time-varying service capacity, demand and ratio. (a) The service capacity and demand. (b) The service ratio.

(68–76) are higher than other periods. In Fig. 8, the estimated number of active vehicles and the actual number in simulations are compared. Generally, the actual number of active vehicles matches the estimated value. However, in some time slots, the actual number of active vehicles slightly exceeds the estimated range, which may lead to a shortage of capacity for RSU scheduling. The result in Fig. 8 is consistent with the previous observations.

C. Performance Evaluation

The parameter settings of the following simulations comparing the proposed solution and benchmark method are presented in Table II.

Based on the proposed strategy, the locations of sRSUs and paths of mRSUs are obtained. Also, the real-time scheduling of RSUs are conducted to satisfy the occasional service demand. As shown in Fig. 9(a), the total capacity and service demand are compared. In general, the service capacity is higher than service demand. This is because the deployed sRSUs provide stable capacity for V2X services through the whole simulation.

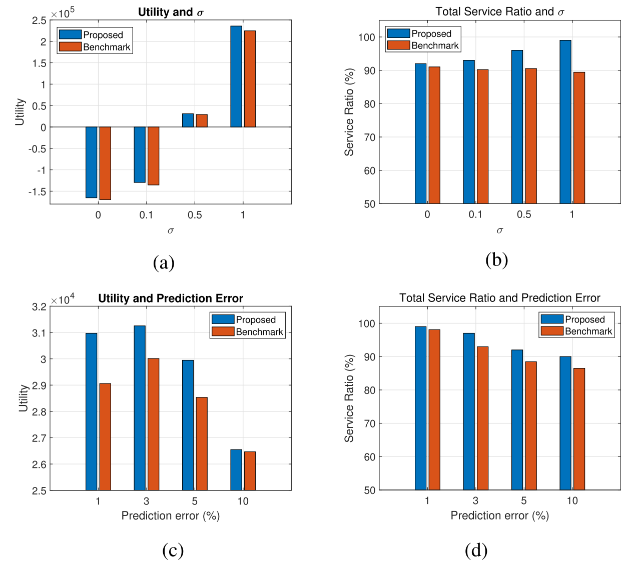

Fig. 10. The comparison between the different σ and prediction error. (a) Utility and σ. (b) Service ratio and σ. (c) Utility and prediction error. (d) Service ratio and prediction error.

On the other hand, mRSUs dynamically change their states to fulfill the time-varying service demands, which is reflected in the fluctuation of the total capacity. To evaluate the performance of the proposed solution, a benchmark method is conducted and compared. Specifically, the formulated utility maximization problem is first solved without integer constraints and selected sRSU and mRSU following the descending order of s_j and $\tilde{p}_k$ until the capacity is sufficient. Then, the locations of sRSUs and paths of mRSUs are determined. In the scheduling stage, the same strategy of the proposed algorithm is applied for fair comparison.

Fig. 9(b) illustrates the service ratio, which is defined as the ratio of the served demand. It is showed that the service ratio varies during different time slots, and the lowest service ratio appears during the peak hours in the morning and afternoon. This is because the most of the capacity is offered by sRSUs for the low cost, and the flexibility of mRSUs is not as sufficient as expected. Thus, when the occasional service load raises, even mRSUs make the best efforts to actively serve the vehicles, the demand cannot be satisfied completely. The service ratio of the proposed strategy outperforms the benchmark methods especially during the peak hours. This is because the proposed solution takes different granularity of load variance into account and optimizes the scheduling decision according to location and time simultaneously.

Fig. 10 illustrates the utility and the service ratio of the proposed solution and the benchmark method under different σ and prediction error. It is noted that due to the traffic prediction error cannot be controlled in the model directly, a random noise is added to the traffic load in the scheduling stage of algorithms. Fig. 10(a) shows that the parameter σ has a significant impacts on the utility. For example, when $\sigma = 0$, the utility maximization problem is simplified as a cost minimization problem. Thus, both algorithms will reduce the number

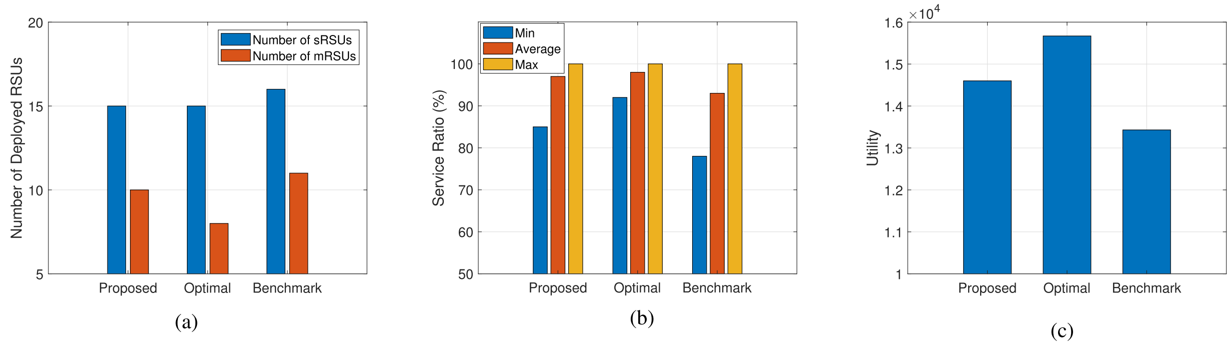

Fig. 11. The comparison in small-scale area. (a) Number of Selected RSUs. (b) Service ratio. (c) Utility.

or the cost of deployed RSUs as any extra deployment leads to more cost only. However, Fig. 10(b) shows the service ratio is not affected greatly since the time-varying service demand constraints should be satisfied. Figs. 10(c) and (d) present the impacts of the prediction error. In general, a higher prediction error leads to a smaller service ratio, since the capacity has been predetermined during the deployment stage and is difficult to always adapt to burst demand. However, the utility increases when the prediction error is 3% since the extra service load can be served by turning on the inactive mRSUs when needed.

To evaluate the optimality of the proposed solution, a small-scale experiment is applied to obtain the optimal solution, which is compared with the proposed algorithm. As shown in Fig. 11, the proposed algorithm achieves similar performance with optimal solution in terms of the number of the deployed RSUs, service ratio and total utility. Fig. 11(a) shows that the proposed strategy deploys a close amount of mRSUs and sRSUs compared with the optimal solution, while the benchmark methods consumes more RSUs in both types. Fig. 11(b) illustrates that the service ratio of the optimal solution is higher than the proposed solution and the benchmark method, especially for the lower bound of the service ratio. However, the proposed strategy also performs closely to the optimal one in terms of the average and maximum service ratio in total, which are both greater than 95%. As shown in Fig. 11(c), the utility of the proposed strategy is above 560 and only 2% less than the optimal one. This is because the proposed three-stage strategy comprehensively considers the benefit and cost the both sRSU and mRSU, and optimizes the coupled selection in each stage.

VI. Conclusion

To facilitate the always-on V2X services, this work has investigated the hybrid RSU deployment and management problem under the Cybertwin-IoV architecture. Considering the time-location-varying service load, the utility maximization problem with coverage constraints have been formulated. A three-stage strategy has been proposed to solve the optimization problem and satisfy the service load with different granularity. Finally, the case study in Wuxi city illustrates that the proposed solution can achieve a trade-off between the benefit and cost, and outperforms the existing method in terms of the deployment utility, the service ratio and the flexibility to fluctuation.

There are some research issues are worth further exploration. For instance, the theoretical performance of the hybrid deployment strategy for multiple objectives needs further investigation. The accurate model of the IoV application and service quality is simplified in this work, which also deserves future efforts.

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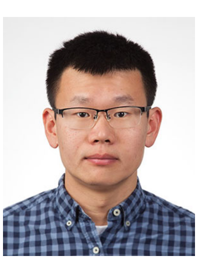

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