UAV-Assisted Vehicular Edge Computing for the 6G Internet of Vehicles: Architecture, Intelligence, and Challenges

Jinna Hu, Chen Chen, Lin Cai, Mohammad R. Khosravi, Qingqi Pei, and Shaohua Wan

Abstract

With the growing intelligence needed on the Internet of Vehicles (IoV), seamless edge computing services for the sixth generation (6G) vehicle-to-everything (V2X) applications require three-dimensional (3D) and ubiquitous networking coverage to realize the intensive computing tasks and data offloading. In the high mobility and fast-changing vehicular environment, the 6G V2X networks supporting vehicular edge computing (VEC) need to be more flexible, smart, and adaptive. In this article, an intelligent unmanned aerial vehicle (UAV)-assisted VEC system is envisioned to satisfy 6G V2X requirements and provide 3D and adaptive service coverage. We indicate that in 6G IoV networks, given the fast-changing and large-scale networks, effectively coordinating and managing massive UAVs incur several problems, which are complex to solve by conventional optimization tools. In this regard, leveraging the big data feature of historical information, artificial-intelligence-based solutions are anticipated to facilitate fast, automatic, and efficient UAV deployment to support 6G V2X applications. An illustrative case study is provided to demonstrate the effectiveness of the proposed intelligent UAV-assisted VEC architecture. We also outline future research directions to realize the vision of UAV-assisted VEC for 6G IoV networks.

Background and Motivations

Future 6G vehicle-to-everything (V2X) applications (e.g., intent sharing, interactive gaming, and coordinated driving [1]) are anticipated to support safer, more diverse, and efficient autonomous transportation [2]. The success of these applications relies on the processing and fusion of massive data from sensors distributed in vehicles, and on roads and other infrastructures to guarantee precise environment perception. The computation and perception ability of the individual vehicle continues to increase. However, it leads to a low price-performance ratio of an intelligent vehicle due to the high price of the powerful CPUs or high-precision sensors. Even ignoring the price-performance ratio, the local perception still limits the performance of 6G V2X applications. Furthermore, the power consumption for perception and computation will also shorten the vehicle's travel mileage. The computation resource-hungry applications pose a significant challenge to the resource-limited vehicular terminals.

To go beyond the limits of an individual vehicle's ability, as a critical technology of 6G wireless networking, vehicular edge computing (VEC) has gained enormous popularity, aiming to provide vigorous computing, storage, and intelligence services by leveraging distributed devices' power with reasonable communication cost [3]. Compared to the traditional cloud-based computing paradigm, the physical proximity between the computing and information sources promises several benefits, including low latency, high energy efficiency, reliable privacy protection, reduced bandwidth consumption, strong context awareness, and so on. VEC relies on advanced wireless technologies to quickly distribute computing tasks and corresponding sensor data from vehicles to network edges (vehicles, roadside units, etc.) to enable intelligent V2X applications for the 6G Internet of Vehicles (IoV).

There are two de facto standards for V2X: dedicated short-range communications (DSRC) based on IEEE 802.11p and cellular V2X (C-V2X) [4, 5]. DSRC was first released in 2010 and has been extensively tested. Driven by the existing cellular systems' coverage, C-V2X has put forth pilot applications with longer transmission distance, broader radio coverage, steadier channel, and dense deployment. The current fifth generation (5G) C-V2X and its next generation are expected to support large data offload to edge nodes by new frequency bands (e.g., millimeter-wave).

Offloading solutions, including task segmentation, offloading edge selection, task migration, and data security, have been widely researched in recent years [3]. It is worth noting that edge computing offloading heavily relies on the coverage and capacity of ubiquitous base stations. However, these works usually assume that the communication resource for edge offloading is sufficient, which is ideal, especially in vehicular networks.

Directly deploying dense base stations can release the overloading problem of VEC. However, it is both costly and inefficient because the service demand in IoV varies with time (rush hour vs. off-peak hour) and location (downtown vs. suburb) dramatically. As a result, in many cases, it is difficult to satisfy the requirements during rush

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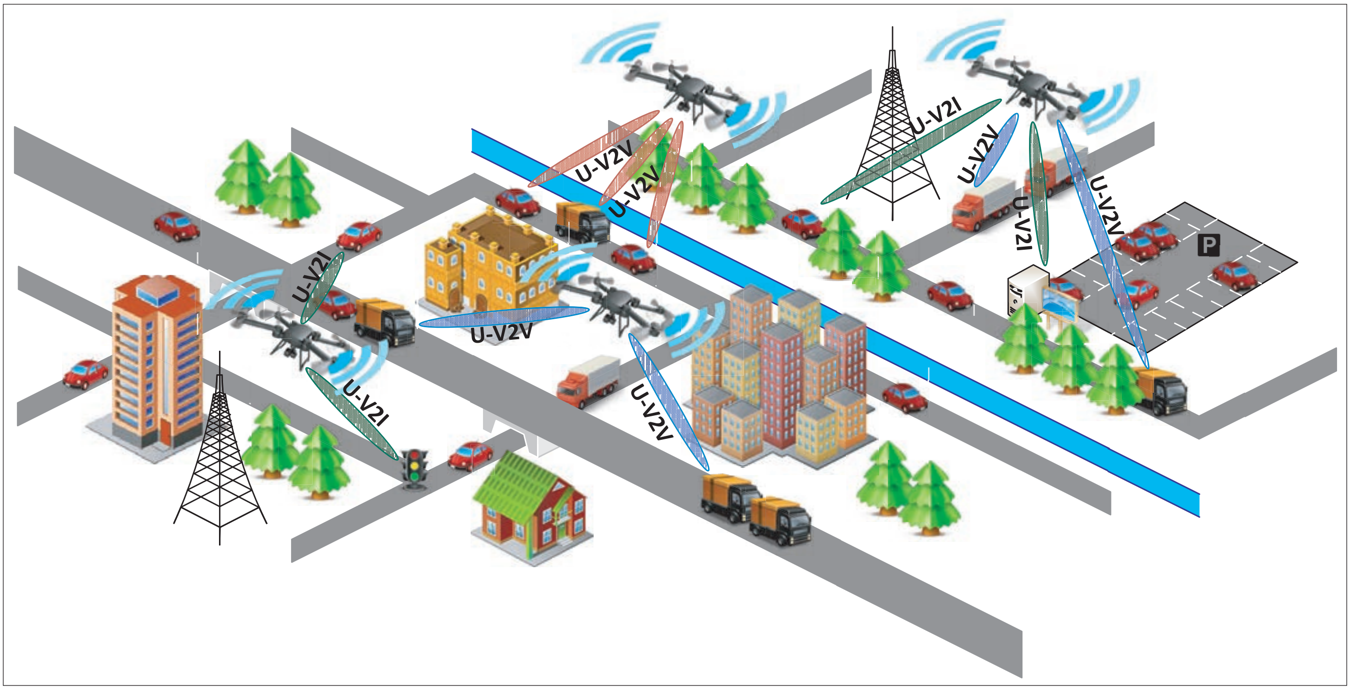

FIGURE 1. UAV-assisted network architecture for 6G vehicular edge computing.

hours, while deploying more base stations may lead to low utilization in off-peak times.

Moreover, with viaducts, bridges, and tunnels, the modern road layout shows a three-dimensional (3D) structure. Thus, the service requests are from 3D spaces instead of 2D areas. The current cellular networks were mainly designed to provide services under 2D networking circumstances. With new high-frequency wireless technology emerging, the base stations should be deployed closer to ground devices to mitigate signal loss and multi-path fading. It is hard to provide seamless and steady 3D coverage for VEC under the V2X environment solely depending on the fixed deployment scheme for base stations.

Due to limited communication rate and the inherent large latency of current satellite networks, UAVs are regarded as effective tools to provide 3D coverage outside terrestrial cellular networks in 6G [6]. However, these works mainly focus on trajectory planning and resource allocation in the general 6G scenarios. As a special 6G scenario, VEC with high dynamic network topology and traffic load requires a specific architecture to provide more flexible infrastructure, ultra-high throughput, 3D radio coverage, and seamless offloading capability. In this article, we introduce an intelligent unmanned aerial vehicle (UAV)-assisted vehicular edge computing system. By involving UAVs and artificial intelligence (AI), a flexible and intelligent V2X network is promising for enabling 3D edge computing service for vehicles with dynamic network topology, intensive computing offloading demands, and massive generated data.

The UAV-Assisted Network Architecture

Given the capability of 3D coverage and adaptability to changing demands, the UAV)-assisted VEC architecture is envisioned as shown in Fig. 1.

Equipped with communication transceivers, UAVs can support ubiquitous broadband wireless communications free from restrictions on road layout and obstacles [7, 8]. For example, the rotary-wing or hybrid fixed-/rotary-wing UAV can hover over a fixed location to provide continuous cellular coverage, and the high maneuverability makes them able to deploy BSs at the desired locations with high precision, or fly in a designated trajectory while carrying BSs [9]. The flying ability allows UAVs to be able to provide 3D multi-angle aerial interfaces for vehicles. Furthermore, by adjusting altitude and positions, a UAV can communicate with vehicles using LoS links with a high chance of success.

On the other hand, to support different lifetime service demands, the network should be flexible to adjust the service capacity of different areas according to the real-time traffic. With high mobility, UAVs can be scheduled to desired positions according to time- and location-varying edge offloading demands to guarantee relatively enough communication resources for vehicular applications, especially for the edge offloading requests from delay-sensitive vehicular applications.

As shown in Fig. 1, multiple UAVs are connected to the cloud center, and they can cooperatively serve overloaded or poor coverage areas to support VEC. In general, edge nodes for vehicles should have stronger computation capacities, larger storage, or free storage and computation resources. Thus, the optimal target edge nodes for vehicle's edge offloading usually are 1) professional edge infrastructures and 2) other vehicles. Through vehicle-to-infrastructure (V2I) and vehicle-to-vehicle (V2V) communications, we can realize the edge offloading from vehicle to vehicle and professional edge infrastructures, which are called V2V and V2I computing offload:

UAV-Assisted V2I Computing Offload: To support high-resolution perception and other

By machine learning technologies, AI can tame the problem complexity by providing pragmatic, yet competitive performances. In addition, AI enables wireless devices to actively and intelligently monitor their environment by learning and predicting the evolution of the various environmental features and proactively take actions that maximize the chances of success for some predefined goal.

enhanced V2X applications, vehicles need to offload intensive computing tasks and massive sensed data to edge infrastructure with high computation and storage capacity. The edge infrastructure is usually equipped with high-performance computing entities, such as a central processing unit (CPU), a graphics processing unit (GPU), a network processing unit (NPU), and a tensor processing unit (TPU), to provide edge computing services for vehicles. By the V2I computing offload, vehicles can use the roadside and sky units' power to speed up the computing tasks. The infrastructure may also leverage the data from other sources (vehicles, clouds, etc.) to further improve AI algorithms' training and learning performance.

However, restricted by the road layout and traffic status, the ground BSs, including the mobile BS vehicle (MBSV), can hardly quickly fill the coverage gap and provide needed VEC data offloading. Using the UAV-assisted networks, a UAV with high altitude can expand radio coverage (equal to raising the antenna height). Moreover, UAVs can provide continuous LoS links to vehicles in dynamic environments by adjusting their impending location, antenna angle, transmitting power, and even modulation scheme.

UAV-Assisted V2V Computing Offload: Besides the V2I computing offload, vehicles may also offload computing tasks to other vehicles by V2V in the following cases:

1. The edge infrastructure is overloaded or not available at that time.
2. The idle computing capacity of neighboring vehicles could be obtained at a lower cost.
3. Distributed coordination or control among vehicles is necessary (e.g., for platooning or content sharing applications)s.

Differing from the V2I computing offload, the source and destination for offloading are mobile and often without LoS opportunity. In addition, for the distributed coordination or control case, any service outage may degrade users' experience and endanger road safety. UAVs can easily track the offloading pairs or clusters to ensure high-quality and timely communications among them.

UAV-assisted communication is desirable, so multiple UAVs should be carefully scheduled and managed to support VEC with desired performance and efficiency. Here, efficiency can be defined according to different metrics (the amount of offloaded data, the throughput in a crowded area, the service satisfaction ratio, etc.). The optimal scheduling is inherently coupled with several mixed-integer optimization problems [10]. The real-time scheduling and management of the multiple UAVs involve traffic analysis, UAV monitoring, and UAV scheduling, which are mutually affected. The complexity makes it hard to solve by conventional optimization solutions.

AI-Enabled Intelligent UAV-Assisted VEC System

Driven by the recent advances in algorithms, computing power, and big data, AI has made substantial breakthroughs in a wide spectrum of fields. By machine learning technologies, AI can tame problem complexity by providing pragmatic but competitive performance. In addition, AI enables wireless devices to actively and intelligently monitor their environment by learning and predicting the evolution of various environmental features and proactively take actions that maximize the chances of success for some predefined goal [11]. In addition, it can adjust the trade-off between performance and complexity during both the training and deployment phases according to applications' requirements. Hence, the AI-based algorithm can flexibly balance the trade-off between prediction accuracy and training complexity. In dynamic vehicular networks, the trade-off can be adjusted according to real-time status inlcuding a UAV's battery level, accuracy requirement, computation resource, and so on.

Several works studied the integration of UAV and V2X communication [12, 13]. However, few proposed a systemic architecture of applying AI to schedule multiple UAVs for VEC. AI can benefit the UAV-assisted network in the following aspects:

- **Pre-scheduling:** UAVs can be scheduled and deployed in advance by AI-based request prediction. AI could provide a robust tool to analyze a time-varying and location-dependent offload request and predict service load from given positions for the next time slot, next minute, and next hour. Based on predictions, the assistance system can find out the potential overload positions in advance.
- **Auto-deployment:** Compared to traditional UAV deployment solutions, the AI-enabled solution enables fully automated deployment. Utilizing AI technology, the heterogeneous optimization problems include UAV choice, deployment topology decision, and route planning. Recharging management can be automatically executed.
- **Large scale:** Based on the powerful deduction, classification, prediction, and ranking ability of AI, a UAV-assisted system can be established in a large-scale area. The automated solution can provide ubiquitous and pervasive VEC offloading services for vehicles in a road segment, a district, and even a city.

As depicted in Fig. 2, an AI-enabled intelligent UAV-assisted VEC system contains two parts, AI-based request prediction and AI-based UAV monitoring and management, which further enable several AI-based services for UAV-assisted VEC. We adopt the cloud-based AI algorithm to realize global optimization and maximize the scheduling efficiency globally [1]. The historic data will be collected in the cloud and utilized to train the AI model. Then the AI model will also be deployed in the cloud to provide global prediction and scheduling based on the global real-time data.

AI-Based Request Prediction

In VEC, the number of offload requests generated by vehicles is affected by traffic density and events. For some basic V2X applications, such as environment perception, an area with high vehicle density generates more offload requests. In some cases, the event-driven V2X applications will create many requests when large-scale or emergent events occur. For instance, sudden road exceptions or traffic accidents will need more complicated coordination and environment perception, thereafter increasing the offload service requests. The request prediction can be long-term or short-term prediction.

The long-term prediction learns the request pattern related to slow or no change (not real-time) parameters, then provides a basic request prediction across a long period of time. The parameters can comprise time, location, number of requests, and more. For example, the requests around a city's CBD have distinguished patterns during weekday and weekend, which commonly consist of very different peak and off periods. The short-term prediction focuses on the relationship between the request and its context (e.g., request frequency, vehicle distribution, channel load, and emergent event) to predict the request load in the next time slot, second, or minute. The long-term prediction attempts to output a rough and macro request estimation, while the short-term prediction tends to generate a precise and micro result. The conventional prediction methods usually require a complex model and may face results' fusion problems. To obtain accurate prediction results with a reasonable complexity, the AI-based request prediction emerges.

AI provides several tools to process the time series data, such as recurrent neural networks (RNNs), spiking neural networks (SNNs), and long short-term memories (LSTMs). For example, as a particular deep learning version of RNNs, LSTMs inherit RNNs' characteristic of efficiency in processing the time-dependent data and analyzing dynamic temporal behaviors, and are capable of storing information for either long or short periods of time. Thus, LSTMs have the ability to make real-time long-term and short-term predictions of the VEC offloading requests.

AI-Based Multi-UAV Monitoring and Management

As mentioned above, UAVs can provide flexible aerial interfaces for vehicles to offload computation and data. However, to realize dynamic UAVs' deployment, the following limitations should be considered:

- **Cost:** Although a UAV provides flexible deployment at a lower cost than a conventional fixed BS, one communication UAV will still cost thousands of dollars plus the operation and maintenance costs. It is desirable to deploy a minimum number of UAVs according to the current network requirements to save cost, especially in highly dynamic vehicular networks.
- **Battery:** A UAV's battery size and weight are limited, which also leads to limited service time. To ensure timely recharging and maintenance, the system should monitor UAVs' real-time states and provide state prediction based on future behaviors.
- **Mobility:** A UAV's flexible deployment relies on its mobility to move to the destination, track a target, or hover around. To avoid conflict and manage battery, UAVs' real-time mobility reactions and states are vital.

Multiple UAVs' scheduling is a continuous control problem with an unlimited action space that requires a series of future state chains to make an optimal decision. Unlike simple information collection, to increase service capacity with a limited number of UAVs, limited battery, and reasonable path planning, the system should make a series prediction of cost, battery states, and mobility states for different scheduling behaviors. Machine learning can be involved to realize intelligent monitoring and management for UAVs, such as RNNs, SNNs, and LSTM.

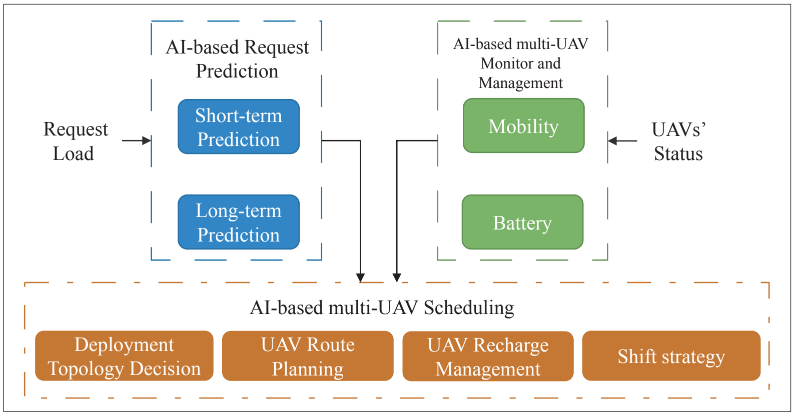

Figure 2. Illustration of general procedures of an AI-enabled intelligent UAV-assisted VEC system.

AI-Based Multi-UAV Scheduling

By leveraging the predictions of requests and a UAV's mobility reactions and states, multi-UAV can be optimally scheduled to improve VEC's efficiency. The scheduling typically involves the following functions:

- **Topology decision:** According to the AI-based offloading request prediction, multiple UAVs can be arranged in appropriate locations to provide offload assistance. An AI algorithm can provide a real-time intelligent decision on these UAVs' topology by considering the current request load, the request load prediction, the current UAV location topology, and the state of those UAVs (working, low battery, or error).
- **Route planning:** In massive VEC networks, a large number of UAVs are involved. The AI-based intelligent route or path planning service is crucial to guarantee timely deployment and avoid flying path conflict. In addition, the enhanced route planning service can support underloaded UAVs to take other edge computing offload requests by detouring to nearby areas, and thus increasing overall offloading efficiency.
- **Recharge management:** Considering the scenario that many UAVs share the limited charging dock, intelligent recharge management is also vital. On one hand, by monitoring UAVs' battery and location, the application can assign low-battery UAVs to the nearest unoccupied charging dock in time. On the other hand, to avoid charging dock overload with many UAVs waiting for charging service, the application should guarantee load balancing throughout all the changing stations and schedule recharging in advance.
- **Task-shifting strategy:** Due to the battery limitation, long-term assistance usually requires

Simulation parameters	Numerical values
Simulation area of Koln	(50.936869, 50.942281) to (6.992264, 7.009435)
Frequency efficiency	12.5 Mb/s/MHz
Bandwidth for offloading service	20 MHz
Required data rate for VEC:	75–125 Mb/s
UAV's average flying speed	20 m/s
The antenna gain of BS, vehicles and UAVs	G_{BS}, G_v, $G_{UAV} = 1$
Receiver threshold	–91 dBm
Transmission power	Vehicles: 50 mW; UAVs: 280 mW

Table 1. Parameters of simulation.

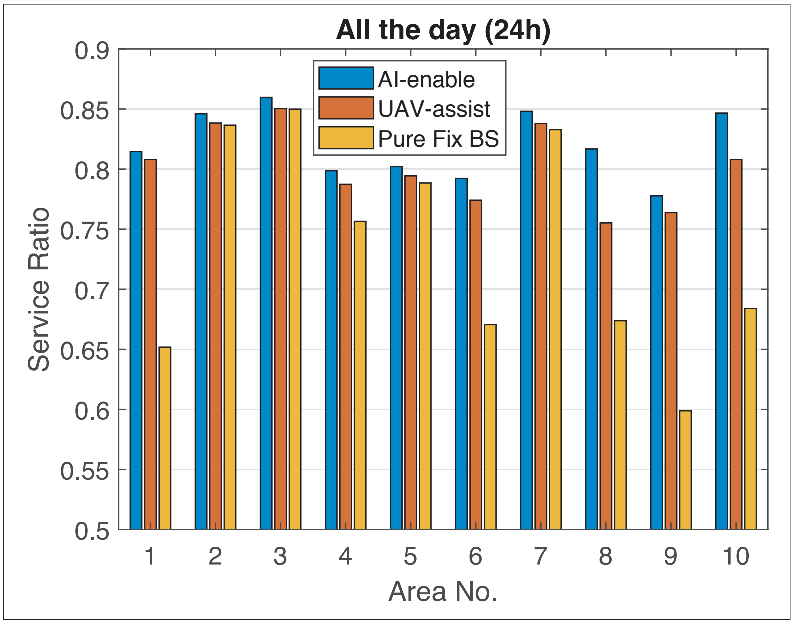

Figure 3. The average service ratio of 10 sub-areas over 24 hours.

several UAVs to relay the task cooperatively. Therefore, an intelligent task-shifting strategy is of great importance. The service should decide which and when UAVs take the shifting to guarantee continuous UAV assistant.

AI-based multi-UAV scheduling mainly focuses on how to schedule limited UAVs to the potential heavy load areas. In most situations, multi-UAV scheduling is a heterogeneous problem that involves several functions. For example, a recharging action requires recharge management and route planning at least. In addition, the problem is a continuous control problem with an unlimited action space. AI provides several strong tools to deal with the dynamic problems that classical centralized or distributed optimization approaches can hardly solve, like actor-critic, deterministic policy gradient, and deep deterministic policy gradient (DDPG). DDPG [14] naturally combines accommodating the continuous space actions and the time-varying problem above. It contains two parts and four neural networks: target network Q′ and critic network Q in the critic part, and target network U′ and actor network U in the actor part. The structure makes the algorithm more stable and easy to converge. By utilizing the strong tools, the multi-UAV scheduling and management can output a specific moving action for every UAV, and the action decision will be evaluated and improved in the process continually.

Case Study

In this part, we discuss a simple case study of LSTM-based request prediction and DDPG-based route planning as a starting point to validate AI-based UAV-assisted VEC. The simulation utilizes the TensorFlow r2.3 platform, which has attracted much attention in the AI field and has high market capitalization. We employ realistic traffic traces and a road layout of Cologne, Germany [15]. We adopt rotary wings or hybrid fixed-/rotary-wing UAVs with 20 m/s average speed as an example, but the simulation results can be extended to a general speed situation. Assume all vehicles are active to request VEC service during driving. We use the service ratio to evaluate our UAV-assisted VEC system's performance, which is defined as the number of served requests before the deadline to the number of total issued requests by vehicles. The main parameters in our tests are listed in Table 1.

The simulation area is further divided into sub-areas according to fixed BS locations. After that, our solution is compared to the BS-only solution and the UAV-assisted systems without AI. For the BS-only solution, all sub-areas are uniformly covered by eight fixed BSs. As for the UAV-assisted solution without AI, four UAVs are launched and scheduled according to real-time traffic load using a greedy algorithm. In the AI-enabled system, we adopted a 2-layer LSTM network with 80 and 50 units, and ReLu activation to predict the request load and UAVs' mobility in the next 15 s. Then, according to the prediction results, we applied DDPG with 0.001 learning rate for actor, 0.002 learning rate for critic, and 0.9 reward discount to schedule the route for UAVs.

Figures 3 and 4 depict the average service ratio of the different sub-areas averaged over daytime and during rush hour only, respectively. Even though only four UAVs are deployed for the UAV-assisted (without AI) system, the average service ratio has been improved in more than six sub-areas. We can find that some sub-areas' performance improvements (e.g., 2, 3, and 7) are not obvious. The UAV-assisted (without AI) system uses a greedy algorithm to maximize the improvement in service ratio. Therefore, the sub-areas with a lower service ratio will be assisted by UAVs first. Compared to the non-AI system, the AI-enabled system shows better performance during rush hours. The AI-enabled system provides a pre-scheduling ability. Thus, it can dispatch UAVs quickly, even before overload occurs. On the other hand, UAVs' intelligent route planning also provides more flexible scheduling. Especially for some sub-areas with "traffic burst" (e.g., areas 6 and 8). DDPG means multi-UAV safer and arrive faster in the demanding areas. In conclusion, AI further harnesses the UAV-assisted system's potential and significantly improves the service ratio compared to the non-AI one.

Open Issues in UAV-Assisted VEC

In this section, we discuss some open issues for enabling UAV-assisted VEC.

Tailored Models for Specific Scenarios: We involve several possible AI application scenarios including traffic prediction, UAV management and monitoring, and UAV scheduling. However, if AI applies to a specific scenario, we need an AI model tailored to the specific scenario. The research on AI algorithms and models for specific scenarios are important and challenging.

Distributed Intelligent UAV-Assisted VEC: As the scale of the UAV-assisted system expands, centralized AI will face latency, data privacy, and confidentiality problems. To support delay- and/or privacy-sensitive VEC application, distributed intelligence is emerging, which pushes the AI to edges. How to incorporate distributed AI nodes and exploit the local data to make real-time global optimization of UAV scheduling is a crucial open issue.

Multi-UAV Coordination: In a UAV-assisted system, multiple UAVs are scheduled by one or multiple scheduling centers. Ideally, the scheduled tasks can be fulfilled by UAVs. However, the wireless channel is vulnerable to fading and interference, especially for the aerial interface in poor weather and/or with 3D road layout. Multi-UAV coordination allows UAVs to work as a team and relay for each other if needed. To ensure reliable multi-UAV coordination, relay selection, scheduling maintenance, and release is a challenging and important topic.

Pre-Computing Offload: Given the high mobility of vehicles, a promising direction is to offload computing among different edge nodes according to vehicles' driving routes. The computing can be directly offloaded to the edge nodes near the location where the vehicle can retrieve computing outcomes. How to split and distribute a computing task according to estimated computing delay, vehicles' driving routes, and edge nodes' (maybe mobile) locations needs further investigation.

Conclusion

This article introduces the potential trends and challenges brought by the upcoming 6G vehicular edge computing. To design a flexible and intelligent computing offloading system to support seamless VEC services for 6G V2X applications, we present an intelligent UAV-assisted VEC system architecture. We present a case study as a starting point to demonstrate the system's effectiveness and discuss the open issues. This article expects to bring more attention to the promising but challenging UAV-assisted VEC system, beckoning further research efforts to address the many open issues to fully realize its potential.

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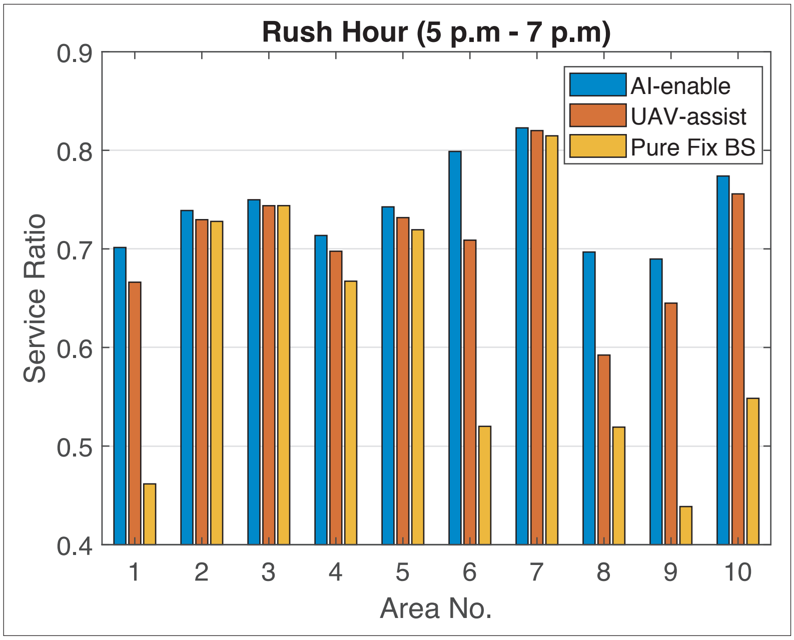

Figure 4. The average service ratio of 10 sub-areas during rush hours (5 p.m to 7 p.m).

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