A Survey on Resource Allocation in Vehicular Networks

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Abstract—Vehicular networks, an enabling technology for Intelligent Transportation System (ITS), smart cities, and autonomous driving, can deliver numerous on-board data services, e.g., road-safety, easy navigation, traffic efficiency, comfort driving, infotainment, etc. Providing satisfactory quality of service (QoS) in vehicular networks, however, is a challenging task due to a number of limiting factors such as hostile wireless channels (e.g., high mobility or asynchronous transmissions), increasingly fragmented and congested spectrum, hardware imperfections, and explosive growth of vehicular communication devices. Therefore, it is highly desirable to allocate and utilize the available wireless network resources in an ultra-efficient manner. In this paper, we present a comprehensive survey on resource allocation (RA) schemes for a range of vehicular network technologies including dedicated short range communications (DSRC) and cellular based vehicular networks. We discuss the challenges and opportunities for resource allocations in modern vehicular networks and outline a number of promising future research directions.

Index Terms—Intelligent Transportation System, Vehicular network, Autonomous Driving, DSRC V2X, Cellular V2X, Resource Allocation, Network Slicing, Machine Learning.

I. INTRODUCTION

The prevalent vision is that vehicles (e.g., cars, trucks, trains, etc.) will in the future be highly connected with the aid of ubiquitous wireless networks, anytime and anywhere, to provide unprecedented travel experiences and offer a series of far-reaching benefits such as significantly improved road safety, enhanced situational awareness, less traffic congestion, reduced pollution emission, and lower capital expenditure. Central to this vision is a scalable and intelligent vehicular network which is responsible for efficient information exchange among vehicles and/or between vehicles and infrastructure.

As an instrumental enabler for ITS, smart cities, and autonomous driving, vehicular networks have attracted significant research interests in recent years both from the academic and industrial communities [1] [3]. In particular, the concept of connected vehicles, also known as vehicle-to-everything (V2X) communications, has gained substantial momentum by bringing in increased data throughput and enhanced road safety along with novel onboard computing and sensing technologies. So far, there are two major approaches for V2X communications: DSRC and cellular based vehicular communication [6] [7]. DSRC is supported by a family of standards including the IEEE 802.11p amendment for Wireless Access in Vehicular Environments (WAVE), the IEEE 1609.1~0.4 standards for resource management, security, network service, and multi-channel operation [8]. On the other hand, cellular based vehicular communication, also called C-V2X, designed over cellular networks such as Long-Term Evolution (LTE) and 5G new radio (5G NR), allows every vehicle to communicate with different types of communication entities, such as pedestrians, roadside units (RSU), satellites, internet/cloud, and other vehicles. Both V2X techniques have their respective advantages and limitations when they are adopted in vehicular environments. As a result, an integration of such heterogeneous vehicular networks has been suggested to exploit their unique benefits, while addressing their individual drawbacks.

Wireless networks suffer from a wide range of impairments like shadowing, path loss, time- and/or frequency- selectivity of wireless channels, jamming and/or multi-user interference, etc. To deal with these impairments, radio resources (such as time slots, frequency bands, transmit power levels, etc.) should be allocated in an optimized manner to cater for instantaneous channels and network conditions. Dynamic Resource Allocation (RA) schemes are preferred as they give rise to significantly improved performance (compared to the Static RA schemes) by efficiently exploiting diversities from various dimensions [2] [11]. For instance, authors in [12] [16] studied RA schemes for device-to-device (D2D) V2X networks by taking into account fast vehicular channel variations. Nevertheless, RA in vehicular networks are far more challenging due to the following reasons:

1) Highly dynamic mobility from low-speed vehicles
This article is organized as follows. We start our discourse in Section II by a high-level overview of vehicular networks which include DSRC network, C-V2X network and heterogeneous network. Detailed literature surveys on these three types of vehicular networks are presented in Sections III-V, respectively. As machine learning is gaining ever-increasing research attention in numerous areas such as data-driven decision making, we provide a dedicated survey in Section VI on applications of machine learning for RA in vehicular networks. In Section VII, we summarize three important future directions of the RA research by taking advantage of network slicing, machine learning, and context awareness. Finally, this article is concluded in Section VIII.
mechanism, IEEE 802.11p adopts Enhanced Distributed Channel Access (EDCA) mechanism, which allows four access categories in a vehicle with different priorities.

B. Cellular based Vehicular Network (C-V2X)

Despite of the fact that DSRC is generally considered as the de facto technique for vehicular networks, cellular/LTE based vehicular communications (also known as C-V2X) have recently attracted significant attention due to its large coverage, high capacity, superior quality of services, and multicast/broadcast support. An overview of cellular based vehicular network is shown in Fig. 1b. LTE-V2V communication exploits LTE uplink resources while utilizing single carrier frequency division multiple access (SC-FDMA) at the PHY and MAC layers [22]. According to the LTE specifications, the available bandwidth is subdivided into equally-spaced (spacing of 15 kHz) orthogonal subcarriers. A resource block (RB) in LTE is formed by 12 consecutive subcarriers (i.e., 180 kHz) and one time slot (i.e., 0.5 ms). The number of data bits carried by each RB depends on specific Modulation and Coding Schemes (MCS).

To utilize the available radio resources, two sidelink modes are defined by 3GPP standard release 14: Mode 3 and Mode 4. In Mode 3, it is assumed that the vehicles are fully covered by one or more evolved NodeBs (eNBs) who dynamically assign the resources
being used for V2V communications through control signalling. This type of resource assignment is called dynamic scheduling. An eNodeB may also reserve a set of resources for a vehicle for its periodic transmissions. In this case, the eNodeB defines how long resources will be reserved for the vehicle. In Sidelink Mode 4, vehicles are assumed to be in areas without cellular coverage and hence, resources are allocated in a distributed manner. A sensing based semi-persistent transmission mechanism is introduced in Sidelink Mode 4 to enable distributed resource allocation.

The distributed algorithm is implemented among vehicles, which optimizes the use of the available channels by increasing the resource reuse distance between vehicles that are using the same resources. A distributed congestion control mechanism is also applied which calculates the channel busy ratio and the channel occupancy ratio. Then, a vehicle reserves resource for a random interval and sends a reservation messages using Side link Control Information (SCI). The reservation message is also called Scheduling Assignment (SA). Using SA, other vehicles which sense and listen to medium find out the list of busy resources and avoid selection of those resources. To increase the reliability, a vehicle may send a data message more than once in this mode. In Release 14, 3GPP mentioned that D2D communications included in Releases 12 and 13 can also be applied to vehicular networks as the localization characteristics of vehicular networks are similar to D2D networks [14], [23].

C. Heterogeneous Vehicular Network

Despite the potential of DSRC vehicular networks, DSRC technology suffers from several drawbacks [6], [24], [25] such as limited coverage, low data rate, and limited QoS guarantee, and unbounded channel access delay. As a matter of fact, the PHY and MAC layers of DSRC are inherited from IEEE 802.11 standards which have been originally optimized for wireless local area networks with low mobility. As concluded in [25], although the current DSRC technology is shown to be effective in supporting vehicular safety applications in many field trials, significant challenges remain for employing DSRC technology in some hostile vehicular environments.

While cellular based vehicular networks can provide wide coverage and high data rate services, they may not be able to support decentralized communication as the networks may become easily overloaded in situation with very high vehicle density, e.g. traffic jams, etc. Thus, both DSRC and cellular based vehicular networks have their respective advantages and limitations when used in vehicular environments. A depiction of a heterogeneous vehicular network in shown in Fig. 1c. A range of efforts [26],[35] have been made towards the integration of both DSRC and cellular based vehicular networks (e.g., LTE) for enhanced vehicular communications. Besides

the integration of DSRC and cellular based vehicular networks, emerging V2X applications require efficient utilization of heterogeneous access technologies, such as Wi-Fi and TV broadcasting networks.

III. RESOURCE ALLOCATION IN DSRC NETWORKS

In this section, we review a number of resource allocation approaches for DSRC based vehicular networks. Previous works on the resource allocation strategies for DSRC network are mainly focused on MAC parameter allocation, channel allocation and rate allocation techniques. Hence, in the following, we classify all the resource allocation approaches for DSRC network in those three categories.

![Fig. 2: Comparison between default DSRC and the scheme proposed in [36] in terms of data transfer ratio (for fast and slow vehicles) versus mean velocity of slow vehicles.](image)

A. MAC Parameter Allocation

In a traditional DSRC network, all vehicles adopt identical MAC parameters by default and hence have equal opportunity to access the network resources. However, this setting may be unfair for high-mobility vehicles which in turn could significantly degrade the network performance. For example, the data throughput of a vehicle with high velocity may degrade severely compared to that of a slowly moving vehicle because the latter is expected to have a better chance to communicate with its RSU (due to its long residence time in the coverage area of the RSU). Several studies have been carried out on MAC parameter allocation in DSRC networks to enhance reliability, throughput, and fairness. [36] presented a contention window allocation strategy to resolve the aforementioned unfairness problem. Specifically, an optimal selection on the minimum contention window (required for any vehicle) has been derived by taking into consideration the mean speed of vehicles in
the network. Fig. 2 compares the DSRC default scheme and the scheme proposed in [36] in terms of the data transfer ratio (for fast and slow vehicles) versus mean velocity of slow vehicles. It is observed that for the DSRC default scheme, the data transfer ratio increases as the mean velocity of slow vehicles increases. In fact, in this case, the residence time of slowly moving vehicles decreases within RSUs coverage and hence the data transfer decreases correspondingly. On the other hand, a relatively flat data transfer ratio is maintained with their proposed contention window allocation scheme which ensures equal chances of communication with the RSU for both slow and fast vehicles. A modified MAC scheme was proposed in [36] to dynamically adapt the MAC parameters based on the residence time of vehicles.

To maximize the throughput among neighboring vehicles, a stochastic model was proposed in [37], [39] to find the optimal maximum contention window using the surrounding vehicle density. Fig. 3 shows that the proposed protocol in [37], [39] offers much lower average transmission delay as well as significantly improved throughput (compared to the standard DSRC protocols) due to reduced packet collision with optimized contention window size.

In [40], two dynamic contention window allocation schemes have been proposed to improve the network performance in high mobility environments. The first scheme is the p-persistent based approach which dynamically assign the contention window based on the number of neighboring vehicles, while the second scheme performs contention window adaptation based on the vehicle's relative velocity. Fig. 3 compares their proposed schemes in terms of the packet delivery ratios and network throughput. It is observed that both schemes provide enhanced performance (compared to the default DSRC one) as they give rise to reduced packet collisions. Moreover, each scheme provides better performance than the other in certain scenarios. For example, the first scheme exhibits better packet delivery ratio when the number of vehicles in the network is large. In terms of network throughput, the second scheme outperforms the first when the number of vehicles is higher than 80.

B. Channel Allocation for Emergency Messages

DSRC/WAVE uses orthogonal frequency bands to support multi-channel operation while considering equal share of available channels to all messages. Emergency messages (e.g., mission critical messages that carry safety-related information) in vehicular networks need to be processed with high priority, ultra reliability, and low latency. Ryu et al. [42] proposed a multi-channel allocation strategy called DSRC-based Multi-channel Allocation for Emergency message dissemination (DMAE) by first identifying the available bandwidth of channels and then allocating the channel with the largest bandwidth to the emergency message while maintaining QoS between RSU and OBU through periodic channel switching. Fig. 5 compares the packet delivery ratio (PDR) and end-to-end delay between DMAE and the traditional allocation scheme adopted by WAVE. It is observed that the emergency PDR of DMAE is higher than the PDR of WAVE as DMAE assigns available SCH.
with maximum bandwidth to the emergency messages. Moreover, DMAE outperforms WAVE in terms of delay performance as it can assign emergency messages to reserved channels in the event of heavy traffic scenario.

C. Rate Allocation

IEEE 802.11p based communication supports multiple MCS to allow a wide range of data transmission rates ranging from 3 Mbps to 27 Mbps. The data rates and transmission ranges for different MCS are shown in Table I. For the sake of simplicity, a constant MCS is often assumed in previous works on vehicular communications. This strategy may deteriorate the communication performance as constant MCS may not be suitable for diverse traffic environments in different roadway scenarios. As a solution, [43] proposed a new vehicular channel access scheme (VCAS) to maintain a trade-off between overall throughput and fairness. In this scheme, a number of vehicles with similar transmission rates are grouped into one channel to achieve the overall throughput requirement, while the fairness requirement is achieved by controlling the group sizes. By adopting a
TABLE I: Different MCS and their corresponding data rates.

| MCS Index | Modulation | Code rate | Data rate (Mbps) | Communication range (m) |
|-----------|------------|-----------|------------------|-------------------------|
| 1         | BPSK       | 1         | 3                | 1000                    |
| 2         | BPSK       | 3         | 6                | 800                     |
| 3         | QPSK       | 1         | 2                | 700                     |
| 4         | 16-QAM     | 3         | 12               | 600                     |
| 5         | 64-QAM     | 2         | 24               | 400                     |
| 6         | 64-QAM     | 4         | 27               | 300                     |

 marginal utility model to allocate appropriate transmission rate per SCH (determined by predefined transmission distance thresholds), it is shown in [43] that their proposed scheme can simultaneously achieve enhanced fairness and overall system throughput over the existing scheme adopted in DSRC system. More recently, [44], [45] presented allocation of variable MCS (i.e., variable data rates) in network coding-assisted heterogeneous on-demand data access, in which the MCS for disseminating data items were assigned based on the distance of the requested vehicles from the RSU. Simulation results show that the schemes proposed in [44], [45] are capable of improving the on-demand requests serving capability and reducing the system response time.

IV. RESOURCE ALLOCATION IN C-V2X

The capability of supporting diverse vertical industries/applications is a major feature of 5G communication systems and beyond. Examples of vertical industries include smart homes/cities, e-health, factories of the future, intelligent refineries and chemical plants, and Cellular V2X (C-V2X). A strong catalyst for deeper and wider integration of wireless communications into our lives, C-V2X has been advocated by many mobile operators under the evolution of 3GPP’s LTE and 5G NR [46]. Compared to DSRC, C-V2X acts as a “long-range sensor” (aided by sophisticated cameras, radar, lidar, RSUs, cellular infrastructure and network) to allow vehicles to see/predict various traffic situations, road conditions, and emergent hazards several miles away.

From a network point of view, there are three major 5G use cases to be supported: enhanced mobile broadband (eMBB) communications, massive machine-type communications (mMTC), ultra-reliable and low-latency communications (URLLC). As far as C-V2X is concerned with, eMBB, aiming to provide data rates of at least 10 Gbps for the uplink and 20 Gbps for the downlink channels, plays a pivotal role for in-car video conferencing/gaming, various multimedia services, or high-precision map downloading, etc; mMTC will allow future driverless vehicles to constantly sense and learn the instantaneous driving environments using massive number of connected sensors deployed in-car or attached to the infrastructure; URLLC, targeting to achieve 1 ms over-the-air round-trip time for a single transmission with reliability of at least 99.999% is instrumental for autonomous emergency braking and hazard prevention.

That being said, C-V2X has to share and compete with other vertical applications for system resources (e.g., spectrum/network bandwidth, storage and computing, etc) under a common physical infrastructure. RA for C-V2X therefore is a trade-off with a variety of data requirements from different vertical applications. A central question is how to design an efficient network to provide guaranteed quality of service (QoS) for C-V2X while balancing the data services to other vertical applications.

A. RA for Traditional Cellular System

Graph based interference aware RA strategies have been proposed in [47], [48], where the weights of the edges are assigned according to the interference terms between the related vertices. The scheme in [47] formulates an optimization problem with the objective of maximizing the network sum rate with low computational complexity. It is shown in Fig. 6 that their proposed scheme exhibits higher network sum rate than traditional orthogonal communication mode. In contrast, the work in [48] aims at improving the connectivity of vehicular communications by introducing a metric called connectivity index, which is obtained from the percentage of vehicles in the network being assigned with resources while satisfying the interference constraints. With the aid
of the minimum spanning tree approach [49]. Meng et al. [48] proposed a RA algorithm to improve the connectivity of the network. Fig. 7 shows the performance of the RA scheme proposed in [48]. The connectivity index performance is presented in Fig. 7a with varying number of vehicles, whilst the performance of brute force search algorithm is shown as a benchmark. We observe that the connectivity index of [48]'s algorithm is only 17.1% away from the optimum solution obtained from the brute force search algorithm. In Fig. 7b, we present the full connectivity performance of the algorithm proposed in [48] and compare with the greedy graph coloring algorithm [50]. We observe a similar full connectivity performance for both algorithms, while graph coloring algorithm exhibits high computational complexity. As expected, the full connectivity percentage decays with the increase of vehicle arrival rate (i.e., denser vehicular network).

By exploiting geographical information, [52] proposed a joint RA and power control scheme for reliable D2D-enabled vehicular communications by considering slow fading channel information. Queuing dynamics was also considered in [52] in order to meet the requirements of different QoS in vehicular networks. [14] developed a heuristic algorithm, named Separate resOurce bLockand powEr allocatioN (SOLEN), under large-scale vehicular fading channels to maximize the sum rate of cellular users while satisfying the vehicular users’ requirements on latency and reliability. Similar to [14], [51] incorporated dynamic MCS in the process of RBs and transmit power allocation for guaranteed reliability and latency. A latency performance comparison between the works of [14] and [51] is shown in Fig. 8. By adopting dynamic MCS in the allocation algorithm, the algorithm proposed in [51] outperforms that of [14] in terms of average outage probability and packet latency. To support D2D-based safety-critical vehicular communication, a cluster-based RA scheme was proposed in [15] by maximizing the cellular users’ sum rate. This is achieved by a three-step heuristic algorithm with the knowledge of the slowly varying channel state information of uplink channel.

The work in [53] proposed a centralized RA algorithm by utilizing the spectral radius estimation theory. Their proposed algorithm maximizes the number of concurrent reuses of resources by multiple vehicles instead of maximizing the sum rate (a method often used in traditional allocation algorithms). With eNodeB centrally deciding the resource reuse for the vehicles in the network, the scheme proposed in [53] exhibits significant improvement in the spectrum efficiency and demonstrates the capability of maintaining the required QoS when the vehicle density is high.

[54] proposed a RA scheme to support V2X communications in a D2D-enabled cellular system, where the V2I communication is supported by a traditional cellular uplink strategy and the V2V communication is enabled by the D2D communications in the reuse mode. [54] formulated an optimization problem to maximize the sum ergodic capacity of the vehicle-to-infrastructure (V2I) links while satisfying the delay requirements of V2V links. The optimization problem was solved by combining the bipartite matching algorithm and the effective capacity theory.
B. RA for Vehicular Computing System

In recent years, integration of vehicular network with cloud computing, also known as vehicular computing system, has attracted increasing attention for its capability of providing real-time services to on-board users [55], [56]. RA for vehicular computing systems has been investigated in [57], [58]. A semi-Markov decision process based RA scheme was proposed in [57] for a vehicular cloud computing system while considering heterogeneous vehicles, i.e., vehicles with different amounts of computing resources. In particular, [57] integrated the computational resources of vehicles and RSUs in the vehicular cloud computing system to provide optimum services. [58] aimed to reduce the serving time by optimally allocating the available bandwidth in a vehicular fog computing system. The optimization problem of [58], formulated based on the requirements of the serving methods, was solved in the following two steps: 1) finding the sub-optimal solutions by applying the Lagrangian algorithm; 2) performing selection process to obtain the optimum solution.

C. RA for Secured Vehicular Network

RA may also be exploited to enhance the secrecy of cellular vehicular networks. By observing that LTE-based V2X communication cannot properly preserve the privacy, [59] evaluated the message delivery with specified security. A joint channel and security key assignment policy was presented in [59] to enable a robust and secure V2X message dissemination. In [60], a RA scheme was proposed to enhance the physical layer security in cellular vehicular communication. A max-min secrecy rate based problem was formulated to allocate power and sub-carrier while taking into account the outdated channel state information (CSI) due to the high mobility. The problem was solved in two stages: (i) with fixed sub-carrier assignment, allocating the power level by using a bisection method allocation problem; (ii) finding suboptimal sub-carrier allocation by using greedy algorithm.

D. RA for Vehicle Platooning

In recent years, vehicle platooning networks have been gaining growing research interest as they can lead to significant road capacity increase. In [61], the authors proposed a RA scheme for D2D based vehicle platooning to share control information efficiently and timely. A time-division based intra-platoon and minimum rate guaranteed inter-platoon RA scheme was proposed to allocate the resources within the platoon, while ensuring optimized cellular users’ rate. Moreover, to obtain a stable platoon, a formation algorithm was proposed in [61] based on a leader evaluation method. Authors in [62] presented a RA strategy to reduce the re-allocation rate that enhances the number of guaranteed services in vehicle platooning network. A time dynamic optimization problem was formulated in [62] under the constraint of a network re-allocation rate. To further reduce the computational complexity, their proposed optimization problem was converted into a deterministic optimization problem using the Lyapunov optimization theory [9]. Joint optimization of communication and control in vehicle platooning was proposed in [63]. An improved platooning system model was developed by taking into account both control and communication factors in a
vehicle platooning. A safety message dissemination scenario was considered under an LTE based vehicular network, where the platoon leader vehicle coordinates the allocation of available communication and control resources. A joint optimization problem of RB allocation and control parameter assignment was formulated with the constraints of communication reliability and platoon stability. Through simulation results, it was shown that their proposed RA algorithm reduces the tracking error while maintaining the stability of the platoon.

E. RA for Out-of-Coverage Scenario

A two-step distributed RA scheme was proposed in [64] for out-of-coverage (i.e., out of eNodeB coverage) LTE V2V communication. In the first step, RBs are assigned based on the heading directions of vehicles. In other words, the same set of RBs are assigned to the vehicles moving in the same direction. In the second step, a channel sensing based strategy is utilized to avoid the packet collision between the vehicles which travel in parallel on the road. Recently, authors in [65] studied RA scheme for delimited out-of-coverage scenario, where the network infrastructure assigns the resources to vehicles based on the estimated location of vehicles. More recently, authors in [66] analyzed and evaluated the safety message broadcasting performance of LTE-V2V out-of-coverage mode in an urban intersection scenario, where two resource allocation strategies were presented to improve the broadcasting performance through vehicle assisted relaying.

V. RA FOR HETEROGENEOUS VEHICULAR NETWORKS

A graph based resource scheduling approach was proposed in [67] for cooperative relaying in heterogeneous vehicular networks. In LTE, vehicles close to the base station usually enjoy high data rates due to favourable radio links, while vehicles far away from the base station suffer from lower data rates due to poor channel conditions. To tackle this problem, cooperative relaying may be adopted to establish V2V communications for distant vehicles through DSRC. [67] proposed a bipartite graph based scheduling scheme to determine the transmission strategy for each vehicle user from base station (i.e., cooperative or non-cooperative) and the selection of relaying vehicles. The scheme proposed in [67] consists of the following three steps: 1) construct a weighted bipartite graph, where the weight of each edge is determined based on the capacity of the corresponding V2V link, 2) solve the maximum weighted matching problem using the KuhnMunkres algorithm, and 3) optimize the number of messages that need to be relayed, where binary search was utilized to find the optimal solution. The proposed approach guarantees fairness among vehicle users and can improve the data rates for the vehicles far away from the base station.

Very recently, a cascaded Hungarian channel allocation algorithm was presented in [54] for non-orthogonal multiple access (NOMA) based heterogeneous vehicular networks. [54] addressed the channel assignment problem in high-mobility environments with different user QoS requirements and imperfect CSI by formulating a chance constrained throughput optimization problem. In Fig. 9, the overall throughput is compared with that of the RA method reported in [68]. Enhanced performance is observed for the allocation scheme of [54], thanks to an efficient user scheduling algorithm which fully utilizes the transmit power to maximize the throughput. It is also observed that the method proposed in [54] provides
more benefits with increasing transmit powers.

Xiao et al. [70] investigated the spectrum sharing for vehicle users in heterogeneous vehicular networks by exploiting available white space spectrum such as TV white space spectrum. A non-cooperative game theoretic approach was proposed with correlated equilibrium. Their proposed approach allows macrocell base stations to share the available spectrum with the vehicle users and improves the spectrum utilization by reusing the white space spectrum without degrading the macrocell performance. By sharing the available spectrum from the LTE and Wi-Fi networks, [69] presented a quality of experience (QoE) based RA scheme for a software defined heterogeneous vehicular network. The system model considered in [69] is shown in Fig. 10. To maximize the QoE of all vehicles, the proposed scheme exploits the CSI of vehicles to extract transmission qualities of the vehicles with different access points. A heuristic solution was proposed to allocate the available resources (in LTE and Wi-Fi networks), which can be used in both centralized and hybrid software defined network systems. Fig. 11 presents the performance comparison between the proposed SDN based scenario and non-SDN based scenario. In the non-SDN based scenario, the optimization for the allocation of LTE and Wi-Fi resource is carried out separately. Due to the joint optimization of RA, the proposed method effectively allocate the resources and hence outperforms its non-SDN counterpart.

VI. MACHINE LEARNING BASED RA FOR VEHICULAR COMMUNICATIONS

In vehicular networks, whilst vehicles are expected to employ various facilities such as advanced on-board sensors including radar and cameras and even high-performance computing and storage facilities, massive amounts of data will be generated, processed and transmitted. Machine Learning (ML) is envisaged to be an effective tool to analyse such a huge amount of data and to make more data-driven decisions to enhance vehicular network performance [73]. For details on machine learning, readers can refer to [74–76].

For resource allocation, the traditional approach is to formulate an optimisation problem and then obtain an optimal or suboptimal solution depending on the trade-off between target performance and complexity. However, in vehicular networks where the channel quality and network topology can vary continuously, the conventional optimization approach would need to be rerun whenever a small change happens, thus incurring huge overhead [77]. While the ML approach could be an alternative to the prevalent optimisation method, research on applying ML in vehicular networks is still at an early stage [73].

In the existing literature [72], [78–81], machine learning considering the dynamic characteristics of vehicular networks has been applied to channel and power allocation, user association and handoff for load balancing,
In [72], for V2V communications in a cellular network, a distributed channel and power allocation algorithm employing deep reinforcement learning (RL) [76] has been proposed. With the assumption that an orthogonal resource is allocated for V2I links beforehand, the study focuses on resource allocation for V2V links under the constraints of V2V link latency and minimized interference impact to V2I links.

The structure of reinforcement learning for V2V links is shown in Fig. 12. While the agent corresponds to each V2V link, it interacts with the environment which includes various components outside the V2V links. The state for characterising the environment is defined as a set of the instantaneous channel information of the V2V link and V2I link, the remaining amounts of traffic, the remaining time to meet the latency constraints, and the interference level and selected channels of neighbours in the previous time slot. At time epoch $t$, each V2V link, as an agent, observes a state $s_t$ from the state set $S$, and depending on its policy $\pi$, takes an action $a_t$ among the action set $A$. The action is to select the sub-band and transmission power. Following the action, the agent receives a reward $r_t$ calculated by the capacity of V2I links and the V2V latency. The decision policy $\pi$ is determined by deep learning. At the beginning, the agent tends to select actions randomly. However, with an exploration and exploitation strategy, the agent prefers to exploit the effective actions yielding good rewards in the past and it also explores new actions that may produce higher rewards in the future. Since the proposed approach can adjust the power and channel dynamically considering the latency constraints, the proposed algorithm is shown to outperform reference schemes in terms of the probability to satisfy the latency constraint of V2V links.

In [78], the ML approach is exploited to develop the user association algorithm for load balancing in heterogeneous vehicular networks. Considering the regularity characteristics of the data flow (generated from vehicular networks) in the spatial-temporal dimension, a two-step association algorithm is proposed. The initial association decision is made by a single-step reinforcement learning (RL) [75]. Subsequently, base station (i.e., macro, pico and femto cells) uses historical association patterns to make decisions for association. In addition, a base station, as an agent of learning, keeps accumulating feedback information and update the association results adaptively. While each base station runs the proposed algorithm in a distributed manner, in the long run, it is shown that both the real-time feedback and the regular traffic association patterns help the algorithm deal with the network changes.

In [79], a vertical handoff strategy has been devised by using a fuzzy Q-learning approach [75] for heterogeneous vehicular networks consisting of a globally covered cellular network complemented by the V2I mode. From the OBU side, various information including average received signal strength (RSS) level, vehicle velocity and the amount of data is sent to the RSU side. Then, the RSU side considers the delivered information as well as the traffic load (i.e., the number of users associated with the target network) and makes handoff decisions by using the fuzzy Q-learning method. With the simu-
In [80], [81], a machine learning approach is exploited to devise the virtual resource allocation in vehicular networks. Vertical clouds [83] consisting of various OBUs, RSUs, and remote cloud servers can provide a pool of processing, sensing, storage, and communication resources that can be dynamically provisioned for vehicular services. The importance of resource allocation in the vehicular cloud is highlighted in [80]. Poorly designed resource allocation mechanisms could result in QoS violation or under-utilization of resources, whereas dynamic resource provisioning techniques are crucial for meeting the dynamically changing QoS demands of vehicular services. Against this background, a reinforcement learning framework has been proposed for resource provisioning to cater for dynamic demands of resources with stringent QoS requirements. In [81], a two-stage delay-optimal dynamic virtualisation radio scheduling scheme has been developed. Based on the time-scale, the proposed algorithm is divided into two stages, macro allocation for large time-scale variables (traffic density) and micro allocation with short time-scale variables (channel state and queue state). The dynamic delay-optimal problem is formulated as a partially observed Markov decision process (POMDP) [74] and is then solved by an online distributed learning approach.

VII. Future Research Directions

A. Network Slicing based Resource Allocation for C-V2X

Network slicing (NS) is a new paradigm that has arisen in recent years which helps to create multiple logical networks tailored to different types of data services and business operators [84]. NS offers an effective way to meet the requirements of all use cases and enables individual design, deployment, customization, and optimization of different network slices on a common infrastructure [85]. In addition to providing vertical slices (for vertical industries), NS may be used to generate horizontal slices which aim to improve the performance of user equipment (UE) and enhance the user experience [86]. Although initially proposed for the partition of core networks (CN) using techniques such as network function virtualization (NFV) and software defined networking (SDN), the concept of NS has been extended to provide efficient end-to-end data services by slicing radio resources in radio access networks (RANs). The slicing of radio resources has mainly involved dynamic allocations of time and frequency resources based on the characteristics of multiple data services. This is achieved by providing multiple numerologies, each of which constitutes a set of data frame parameters such as multi-carrier waveforms, sub-carrier spacings, sampling rates, and frame and symbol durations. For example, an mMTC slice in C-V2X is allocated with relatively small subcarrier spacing (i.e., for massive connectivity) and hence large symbol duration. In contrast, URLLC requires large subcarrier spacing to meet the requirements of ultra-low latency and stringent reliability. Fig.
Fig. 14: Network slicing for a C-V2X network consisting of RSUs, high-speed trains, railway stations and moving vehicles.

Fig. 14 depicts the NS for a C-V2X network consisting of RSUs, high-speed trains, railway stations and vehicles.

A step-wise approach for designing and applying function decomposition for NS in a 5G CN has been proposed in [87]. Their main idea is to identify those functions which could be merged in different network elements as well as their corresponding implications for procedure and information storage. [88] presented a concrete NS example in the vehicular network domain on efficient distribution of unexpected road conditions among cars within a certain range. By properly configuring the SDN switch and controller, it is shown in [88] that a network slice for such inter-car communication can be readily created. In [89], the impact of NS on a 5G RAN, such as the CN/RAN interface, the QoS framework, and the management framework, has been discussed. It is pointed out in [89] that dynamic NS is preferred in order to cater for rapid change of traffic patterns. A comprehensive work on applications of NS to support a diverse range of C-V2X use cases has been proposed in [90]. Major C-V2X slices identified in [90] are: autonomous driving, tele-operated driving, vehicular infotainment, and vehicular remote diagnostics and management. For example, the slice for supporting tele-operated driving enables URLLC and the slice for vehicular infotainment may use multiple random access technologies (RAIs) to support higher throughput. Moreover, slicing may be carried out in different vehicular devices according to their storage and computing capacities as well as the nature of the data services, a scenario similar to mobile edge computing [90].

It is noted that NS can be carried out not only at higher levels of wireless networks, but also in the physical layer (PHY). In 2017, a multi-service system framework implemented in both time and frequency domains has been proposed in [91], [92]. A major issue here is how to select and design multicarrier waveforms with good time-frequency localization, low out-of-band power emission, low inter-carrier interference (ICI) among different sub-bands using different numerologies, and capability to support multi-rate implementation. Multicarrier waveform design for PHY NS such as filtered orthogonal frequency-multiple access (F-OFDM), windowed-OFDM, and universal filtered multi-carrier (UFMC) have been studied in [91], [93], [94]. In the context of C-V2X, the design of multiple numerologies for modest and high mobility environments is an interesting and pressing research issue. In this case, one needs to deal with doubly selective fading channels which could lead to severe ICI and inter-symbol interference. Another interesting research is direction is how to design and optimize network slices to provide guaranteed quality of services (QoS) for C-V2X while balancing the services of other vertical applications under the constraint of limited radio resources.

B. Machine Learning Perspective in Resource Allocation

Whilst the strong potentials of applying ML in vehicular networks have been discussed with the initial efforts in Section VI, how to adapt and exploit ML to account for the peculiar characteristics of vehicular networks and services still remains as challenges and represents a promising research direction [7]. Vehicular networks significantly differ from the scenarios where machine
learning has been conventionally exploited in terms of strong dynamics in wireless networks, network topologies, traffic flow, etc. How to efficiently learn and predict such dynamics based on historical data for the benefit or reliable communications is still an open issue [73]. In addition, data is supposed to be generated and stored across various units in vehicular networks, e.g., OBUs, RSUs, and remote clouds. It could be interesting to investigate whether traditional centralised ML approaches can be exploited to work efficiently in a distributed manner. For collective intelligent decision making in learning-capable vehicular networks, the overhead for information sharing and complexity of learning algorithms need to be taken into account [95].

C. Context Aware Resource Allocation for Vehicular Communications

Existing work on resource allocation for vehicular networks mostly deals with efficient allocation of resource blocks such as frequency carriers or time-slots. However, most of the prior work on resource allocation did not consider context-aware/on-demand data transfer applications in vehicular networks. On-demand data transfer applications need to meet constraints such as deadline of the requested data items or priority of data items, to ensure a reliable service, there is a need for research to consider those more thoroughly. Although there is a lot of prior work [76, 98] on performance evaluation of on-demand data dissemination scenarios in terms of the above constraints, they do not deal with the allocation of resource blocks, which is important for 5G networks.

VIII. CONCLUSIONS

In this paper, we have surveyed radio resource allocation schemes in vehicular networks. We have categorized these schemes into three categories based on the types of vehicular networks, i.e., DSRC vehicular network, cellular vehicular network, and heterogeneous vehicular network. For each category, the available literature is reviewed and summarized while highlighting the pros and cons of the resource allocation schemes. We have also discussed several open and challenging future research directions for radio resource allocation in vehicular networks. It is anticipated that this paper will provide a quick and comprehensive understanding of the current state of the radio resource allocation strategies in vehicular networks while attracting and motivating more researchers into this challenging area.

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