Deep Reinforcement Learning based Intelligent Power and Radio Resource Allocation for Heterogeneous QoS requirements in 5G, toward 6G Vehicular Network: A Survey

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Abstract—**The emergence of Vehicular Network (VNET), especially Vehicle-to-Vehicle (V2V) communication aims to make everyday vehicular operation safer, greener, and more efficient. The characteristics of VNET are to serve diverse services with different QoS requirements such as ultralow-reliable low latency, high throughput requirements. Resource management including radio resource and transmit power has become a complex and challenging objective to gain expected outcomes in a vehicular environment. Recently, Machine Learning (ML) is the best technique to support heterogeneous VNET. In this paper, I focus on overview of approaches and techniques to allocate radio resource and transmit power for 5G VNET to guarantee safety requirement with the helps of machine learning, especially Deep Reinforcement Learning (DRL). Finally, I analyze the benefits of Federated Machine Learning (FML) to 6G VNET.**

Keywords: **Deep Reinforcement Learning (DRL); Federated Machine Learning (FML), Internet of Vehicles (IoV); Machine Learning (ML); intelligent transmission power allocation; intelligent resource allocation; resource slicing; Quality of Service (QoS); Heterogeneous Vehicular Network (HetVNET), 5G, 6G**

I. Introduction

The 5G New Radio (NR), driven by the demand for large volume of data due to the rapid growth of cellular mobile and vehicles combined with heterogeneous requirements, allows numerous applications and conveniences to make lives easier, smoother and more comfortable with the better QoS at low cost and complexity. After the 5G wireless network, the AI-enable next-generation (6G) network will be proposed for the future evolution of network intelligentization [1]. The prevalent vision is that vehicles will in the future be highly connected with the aid of ubiquitous wireless networks at anytime and anywhere which is expected to lead to improved Intelligent Transportation System (ITS) safety, increased experience comport, reduced traffic congestion, and lower air pollution. Vehicular communications include vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), and vehicle-to-pedestrian (V2P) communication, which are collectively referred to as vehicle-to-everything (V2X) communication [2], [3]. The use of AI may support the strict requirements, such as ultra-low latency, high reliability, high security, and massive connections in 6G vehicular network.

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The fifth-generation New Radio (5G NR) supports new service classes targeting ultra-reliable low-latency communication (URLLC), machine-type communication (MTC), and enhanced mobile broadband (eMBB) [4]. In the sixth generation (6G) [5] is expected will be proposed and deployed by 2030. Some scenarios predicted for 6G network are described as an improvement of the scenarios defined for 5G networks, like FemBB (Further-eMBB) where a peak through of 1 Tb/s will be necessary for 6G (1000 times faster than 5G). In addition, the delay requirement in 6G is defined as Event Defined Ultra - reliable Low-latency Communication (EDURLLC) which is reduced by at least 10 times compared to 5G where the latency will be reduced from 1 ms to less than 50 ns.The reliability in 6G needs to be guaranteed of 99.99999% to support unmanned systems such as autonomous driving. The spectrum and energy efficiency must be achieved over 10 times efficiency improvement. 6G requires connection density which increases to 1000 times to reach 10^7 to $10^8\ \mathrm{km}^2$. Mobility requirement enhances from 500 km/h to subsonic 1000 km/h (airplane).Further, 6G demands extremely Low Power Communication (ELPC) and Long-distance and High Mobility Communication (LDHMC) [6], [7], [8] .In addition, new application scenarios towards 2030 in 6G are intelligent life, intelligent production and intelligent society [9].

There are various evolution in 6G vehicular network over 5G vehicular network that should be addressed. Firstly, the structure in 6G vehicular network will be deployed with space-air-ground even underwater vehicles replacing the only ground vehicles which are connected to each other in 5G vehicular network. Secondly, in 5G, vehicles are connected to each other to support for transportation purpose. For more experience comfort, 6G AI-enabled vehicular networks not only keeps the same purpose of transportation, but also it allows interaction between humans and the worlds such as smart living, smart grid, and human socialization. To satisfy characteristics and QoS requirements in 5G, some advanced techniques, such as Network Slicing (NS) on a unified physical in-

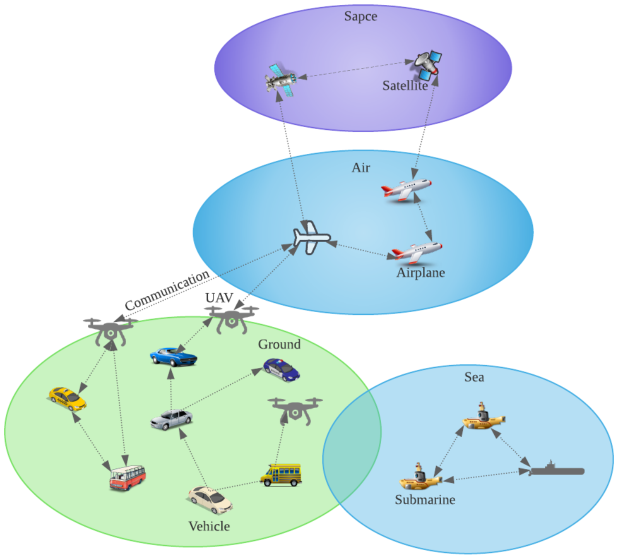

Figure 1. Heterogeneous 6G Vehicular Network

frastructure via software-defined network (SDN), function virtualization (NFV) [10], [11], [12], and cloud computing, and Cognitive Radio (CR) which makes use of spectrum more intelligently and flexibly are proposed. However, in 6G, Intelligent Radio (IR) and self-learning with proactive exploration will be constructed.

Transmission power and resource allocation should be considered as a joint optimization problem for communication in network. In one hand, spectrum is limited and need to be shared between multiple mobile operators. In other hand, transmission power also should not be wasted. In addition, with the high mobility characteristics of vehicular network, resource management must be investigated to support the stochastic vehicular environment with time-varying service demands. Thus, an optimization problem in a joint of transmission power and resource utilization need to be addressed to support heterogeneous QoS requirements in vehicular network. In 5G, to meet the strict reliability requirements of vehicular applications, many studies have been carried out. A radio resource management (RRM) [13], [14] issues have been investigated in vehicular networks and the total capacity of V2I links is maximized while guaranteeing the signal-to-noise-plus noise ratio (SINR) of V2V links [15], [16]. In [17], the optimal Resource Block (RB) allocation and power control by JRPSV algorithm to obtain at each time slot according to the current network state to achieve URLL vehicular networking. In [18], the author worked on large-scale fading channel information to perform a joint of spectrum and Power Allocation (PA) to maximize the sum ergodic capacity for V2I links to achieve URLLC combined with retransmitting the dropped or error packet. However, with this technique, the system could not satisfy real-time communication due to delay of packet retransmission. To achieve the satisfaction in heterogeneous QoS requirements along with stochastic environment vehicular network and to effectively utilize transmission power and resource allocation, the optimal problem defined as a joint power and resource management need to be investigated.

Reinforcement learning (RL), an area of machine learning, is suitable for autonomous vehicle area. RL requires a small labeled dataset which take advantages in a dynamic vehicular network. Moreover, RL allows online learning which support in real-time signal communication between V2I, V2V, and V2X. In addition, RL takes advantage as adaptable machine learning algorithm which does not require retraining because it adapts to new environments automatically. RL has many applications in various areas such as healthcare [19], [20], finance [21], manufacturing [22], [23], [24] and so on. In autonomous vehicle, RL algorithm is applied in both academy and industry [25], [26], [27], [28]. To solve a joint transmission power and resource allocation for 6G intelligent vehicular network, RL need to be deployed with the advantages.

In this survey, I give a comprehensive survey of the employment of reinforcement learning for 5G vehicular network and toward 6G in autonomous vehicle area. The recent advancement techniques in solving optimization problem of an optimal joint of transmission power and resource allocation to guarantee heterogeneous QoS requirements will be presented.

This survey is organized as follows. The related work will be provided in Section II. Section III presents the heterogeneous QoS requirements in 5G and toward 6G. A joint of transmission power and resource allocation will be discussed in Section IV. Deep Reinforcement Learning for resource allocation in VNET will be investigated in section V. In section VI, the open issues are given. Finally, in Section VII, this survey is concluded.

II. Related Survey Papers

To optimize resource while guaranteeing QoS in vehicular network. There are various related survey articles which work in this area.

In [29], the authors worked in a survey of a self-organizing network of connected vehicles as Vehicular Ad-Hoc NETworks (VANETs). They presented the issues related to the heterogeneous vehicular communication environment with resource allocation consideration. However, in this survey, machine learning and reinforcement learning to support resource allocation is not investigated.

The work [30], discussed a Heterogeneous Vehicular Network (HetVNET) which integrates cellular network with dedicated short-range communication. In addition, the authors studied on both the Medium Access Control (MAC) and network layers in HetVETs. However, they did not discuss about resource allocation based on artificial intelligent as reinforcement learning.

In addition, the work [31] studied in visible light communications (VLCs) usage in vehicle applications. The authors mentioned the recent advancements in VLC and envisioned the challenges and solutions for in this area. However, the QoS requirements with the help of reinforcement learning in resource allocation is not studied in this article.

In [32], the authors studied in resource management in vehicular cloud computing regarding to the unique characteristics of vehicular nodes such as high mobility,

Table I
SUMMARY OF THE RELATED SURVEY PAPERS

Survey	Year	QoS	RL	PA	RA	5G	6G	Contributions
[30]	2018	x			x	x		HetVNET in (VANETs)
[31]	2015	x			x			HetVNET in MAC and network layer
[32]	2017	x			x			Recent advancements in VLC with RA
[33]	2020	x			x	x		Resource management in vehicular cloud computing
[34]	2019		x		x	x		Secure and efficient conveyance considered in VANET
[35]	2020		x		x	x		RA in DSRC and CelVNET and ML based RA
[36]	2020	x	x			x		ML pipeline of CAV and adversarial ML attacks
[37]	2020		x		x	x	x	Q-learning based mobile for PA in a in HetVNET
[38]	2020	x	x		x	x		ML methods in CR-VANET scenario

resource heterogeneity and intermittent network connection among vehicular nodes. However, the application of reinforcement learning is not considered in this article.

In [33], the authors studied in machine learning techniques such as deep Q learning, support vector machine (SVM), and K nearest neighbor based VANETs with resource allocation issue. However, this paper is not investigated in a joint transmission power and resource allocation for vehicular network.

In [34], the authors presented a comprehensive survey on resource allocation for the two dominant vehicular network technologies as dedicated short-range communication (DSRC) and cellular vehicular networks (CelVNET). However, with the lack of toward 6G vehicular network and AI, the paper is not as an advance paper.

In [35], the work focuses on connected and autonomous vehicles (CAVs) and intelligent transportation system (ITS) combined with machine learning. However, the paper mainly discusses about security issue.

In [36], the authors investigated intelligent and secure vehicular network toward 6G. Moreover, machine learning applied in vehicular network is discussed. However, detail power and resource management are not studied in this article.

In addition, the work [37] studied machine learning integrated with cognitive radio vehicular ad hoc network (CR-VANET). In this article, current advancements in the amalgamation of prominent technologies and future research direction are discussed. However, a joint of transmission power and resource allocation based on reinforcement learning is not studied in this survey.

Table 1 is a summary of the related survey articles. The issue of a joint PA and RA is not received much attention when considering radio RA for HetVNET Taking advantages of effective resource management to achieve the satisfaction of heterogeneous QoS requirements in 6G vehicular network, there are various related survey articles which work in this area. However, to have the overall view in combination among intelligent transmission power allocation (PA) and resource allocation (RA) to guarantee different QoS requirements in vehicular network based on machine learning, particularly reinforcement learning-enable the sixth generation, there is a survey which covers all list requirements needed to be completed.

III. HETEROGENEOUS QOS REQUIREMENTS IN 5G AND TOWARD 6G

5G is built to support 3 categories including ultra-reliable low latency communications (URLLC), enhanced mobile broadband (eMBB), and massive machine type communications (mMTC). The V2X application scenarios were defined in the standard of enhanced 5G V2X services to support advanced applications including extended sensor and state map sharing, vehicle platooning, remote driving, advanced driving.

5G connectivity is built upon the Packet Data Unit (PDU) Session concept from information-centric networks. Each PDU Session comprises of multiple QoS flows which defines the finest granularity of QoS differentiation within a PDU Session. In conclusion, a QoS metric defines as a set of parameters including Packet Delay Budget (PDB) (ms), Packet Error Rate (PER) (%), and the Guaranteed and Maximum Bitrate (GMB) (kps). Vehicle platooning services have the requirements of End to End (E2E) latency down to 10 ms with 99.99% of reliability, while advanced driving services requires communication channels which support bitrate up to 1 Gbps with the E2E latency down to 3 ms and reliability up to 99.999%. In general, the LoA can be provided with different level of QoS requirements.

6G supports a fully connected, intelligent digital world. This communication system is expected to associate with services which has different requirements. Ultra-high-speed with low-latency communications (uHSSLC) has feature of the E2E delay of less than 1 ms [38], more than 99.99999% reliability [39]. With ultra-high data density (uHDD), 6G is expected to provide Gbps coverage everywhere with the coverage of new environment such as sky (10,000 km) and sea (20 nautical miles) [40]. Ubiquitous mobile ultra-broadband (uMUB) requires 1 Tps peak data rate. 6G will provide massive connected devices (up to 10 million/ km^2).

In autonomous driving, to guarantee passenger safety, 6G is expected to support levels of reliability of >99.99999% and levels of E2E delay down to <1 ms in ultra-high mobility (even up to 1000 km/h) with Terabytes generated per driving hour [40].

IV. A JOINT OF TRANSMISSION POWER AND RESOURCE ALLOCATION

In the aforementioned heterogeneous QoS requirements in 5G Vehicular Network, radio resource allocation and tramsmit power allocation have been investigated widely to guarantee QoS requirements including stringent insensitive latency combined with high throughput, and massive connected vehicles. One of the most strict requirements in VNET is latency. By effectively utilizing radio resource and transmit power, the latency can be guaranteed. Along with the development of modern techniques, resource allocation and resource computation to organize the VNET system, researchers mainly focus on Vehicle Cloud Computing (VCC), Vehicle Fog Computing (VFC), Vehicle Edge Computing (VEC). In this part, I mainly summary resource management via VCC, VFC, and VEC in VNET.

A. Resource Allocation in Vehicle Cloud Computing

Vehicle Cloud Computing, VCC, utilized as a cloud node within neighbourhood cars, is developed to utilize VNET resources efficiently, which enables on-demand service to consumers through various cloud service providers. Vehicles provides a phenomenal computing resource in terms of storage and processing. The VCC composed of three layers of communication such as board layer, communication layer, and cloud computing layer, respectively. The power of the VCC is on the sensors in vehicles. By keeping information on the vehicle, the cost of uploading the information to the web and the associated storage is reduced.

In [41], the motivation is how to manage various radio resources to satisfy different user's QoS. The objective of this article aims to improve the user's service experience and the spectrum efficiency by maximizing the system utility through resource scheduling. Basic safety services (beacon message), advanced safety services (cameras) and traffic efficiency services (dynamic map update and intersection speed advisory) are consider in this work to guarantee QoS based on Resource Blocks (RBs) allocation. Further, resource scheduling based on a dynamic programming to improve user's service experience and the spectrum efficiency by maximizing the system utility. With the approach, the results show a better performance in average delay and packet loss ratio of basic safety message (BSM) and video streaming compared to conventional approach. In addition, the delay jitter of BSM service also is significantly reduced. However, all of these above aforementioned works used the conventional mathematics approach which are not suitable to the significantly increase in number of vehicles. Therefore, we need a new approach such as machine learning. In [42], stringent latency requirements on safety-critical information transmission in Internet of Vehicle (IoV). However, it lacks instantaneous channel state information due to high mobility which drops transmission packets. Packet retransmission mechanism is used to provide reliable communication by considering spectrum and power allocation to maximize the ergodic capacity of V2I links while guaranteeing the latency requirements of V2V links. V2V users reuse radio spectrum of V2I users. A polynomial time solvable bipartite matching problem is applied to optimize reused spectrum and then optimal transmission power is provided for spectrum reusing pair. The results show that with the increasing in the number of V2Vs' packet arrival intensity, the V2Is' sum ergodic capacity is improved compared to other algorithms. In addition, the V2Vs' average packet queueing time plus the service time is guaranteed with the increasing of V2Vs' packet arrival rate. Reusing techniques can partially support reliable communication. However, it also brings the interference which was not discussed in this paper. One more disadvantage in this paper is flexibility due to reusing radio spectrum. In addition, all of these above aforementioned works used the conventional mathematics approach which are not suitable to the significantly increase in number of vehicles. Therefore, we need a new approach such as ML. In [43], due to high-density and high-mobility architectures of Cooperative Automated Drivings (CAVs), to meet the URLL vehicular communications. A position-based user centric radio resource management (RB management) needs to be investigated to guarantee URLL vehicular communications. Virtual cell (VC) member association by proposing a strategy of VC member selection and time-frequency resource block (RB) allocation are identified and related three performance metrics are defined including congestion ratio (CR), outage ratio (OR), and packet delivery ratio (PDR), in other word meaning packet loss ratio (PLR). More than 2 AVs uses the same RB. The results shows that the higher packet arrival rate and the stricter queuing, the bigger congestion ratio. However, when the packet arrival rate and queuing are given, CR can be significantly lowered by reducing the distance between 2 AVs. Even though, the authors discussed the system model of mobile edge computing (MEC) which are deployed near small base station (SBS) to local distributed processing. However, multi AVs uses the same RB leads to interference and congestion issues that impact a lot in URLL vehicular network and safety-critical requirements in AVs environment. In addition, a scenario of AVs' movement was not discussed in a strategy of VC member selection. Moreover, the real world scenarios includes different sizes of packets and packet arrival rate which were assumed to be equal packet size and periodically arrived in the article. ML should be used to this problem. In [44], efficient data delivery among V2V could be assured to ensure safety. However, in case, vehicles appear in the out-of coverage that means the connection to the network infrastructure is not guaranteed such as in tunnels determined as the delimited out-of coverage area (DOCA). Radio resource allocation is used to guarantee the reliability of v2V communication in the DOCA. They consider both aperiodic V2V communication which transmits triggering unexpected events for safety-warning purpose and periodic V2V communication which periodically transmits velocity and position of vehicles. The reliability of v2V communication is defined as the level of signal-to-interference-plus-noise ratio (SINR) at the receiving vehicle, which must be at least equal to a predefined threshold. The reliability of V2V communication is defined as a signal-to-interference-plus-noise ratio (SINR) which is achieved at the receiver side, which must be guaranteed to be at least equal to a predefined threshold.The SINR is guaranteed when the distance between the Tx and its Rx is less than or equals to the distance d and another vehicle does not use the same RB. From the arrival rate prediction of ad hoc services with a probability that a vehicle generates an ad hoc service, the RBs to pre-schedule for unexpected event inside DOCA are defined. Pre-scheduling the services in DOCA. The results show the improvement in reliability while considering the network system with two case of events. However, with the extreme increment in number of vehicles with heterogeneous services. The normal algorithms to predict arrival rate of vehicles with diverse services can not guarantee the exact values. Thus, the RBs which are scheduled after prediction may not be sufficient and effective.

In [45], the authors formulate a platooning problem for vehicular network. To have a safe traffic driving in platooning, an effective V2V communication needs a good radio resource allocation strategy. In other hand, to keep the stability among these vehicles, the control problem would be considered as well. Therefore, a joint optimal radio resource and control problem is formulated to ensure the stability and reliability in vehicular network. The authors divided the formulation problem into 2 subproblems due to communication channel and control theory. The resource allocation for communication subproblem is solved by bipartite graph. In other hand, by guaranteeing the string stability, the control parameters are adapted by using Heuristic Gradient Descent Algorithm for Nonconvex Optimization Problem. By combining both radio resource allocation for communication channels and control parameters for vehicle platooning, the results shows that the joint optimal communication-control scheme can significantly reduce the tracking error of platooning members while guaranteeing the communication-control requirements. Every possible V2X communication needs transmission power to transmit data along with radio resource allocation. Obviously, transmission power at each vehicle is limited. In addition, packet error or drop by dynamic networks (i.e, network channel condition, load, and so on) impact the transmission power at the transmitter. Therefore, the authors should consider this problem in the paper to improve the overview of vehicular network. In the other hand, the radio resource allocation subproblem is solved by a conventional optimization problem which is not satisfied in the heterogeneous services and increment of vehicles at present and in the future. In [46], an age of information (AoI) is defined as the time elapsed since the generation of the last received status update. If the AoI exceeds a predefined threshold, the network system will be unstable due to violation of the historical data with the current data that lead to unreliable communication. The trade off between maximizing reliability by minimizing the probability that the AoI exceeds a predefined threshold and maximizing the knowledge gain about the network dynamics.The prediction of future AoI exceeding a predefined threshold requires the knowledge of the network dynamics (i.e, wireless channels and interference). The authors developed an approach based on Gaussian Process Regression (GPR) to actively learn the network dynamics, estimate the future AoI, then proactively allocation transmission power and resource block in an online decentralized manner for enabling ultra reliable and low latency vehicular communication. The simulation result shows the reduction of 50 percent of AoI violation probability. The same authors discuss about the average AoI measurement. However, it fails to characterize the performance of urll vehicular communication. Because, in urllc in vehicular network, the average AoI estimation can not count for extreme AoI events which occur with very low probabilities. Objective aims to improve urllc with transmission power minimization in a vehicular communication network by characterizing and controlling the AoI tail distribution. An approach in mapping between AoI and queue-related distribution is proposed in this paper. The tail distribution of AoI is modeled by Extreme Value Theory (EVT) to characterize the violation probability and Lyapunov optimization techniques to solve the problem by considering both long and short packet transmissions. The results in this paper shows a significant improvements in terms of AoI and queue length with the consideration of transmission power control and optimal radio resource block allocation. However, with the dynamics of the AoI distribution, and the increment in number of vehicle, the requirement of a better optimization algorithm is needed to deal with the heterogeneous network with diverse requirement. Thus,the Lyapunov optimization can not satisfies the present vehicular network. Machine learning could be a good approach for the real practical vehicular network. In [47], the authors' purpose is aims to guarantee the urllc in vehicle by characterizing the tail distribution of queue length expressed by EVT in limited transmission power and radio resource allocation. A novel distributed Federated Learning (FL) algorithm based on a Maximum Likelihood Estimation (MLE) is proposed to predict the tail distribution of queue length in individual vehicle user equipments (VUEs). Lyapunov optimization is used to derive the JPRA policies enabling urllc in vehicles. In this paper, the results show that by applying FL as distributed learning in this system model achieves the same accuracy estimation level as using centralized learning. In addition, the overhead of signaling is reduced because the data is processed and estimated at each vehicle instead of center server. The transmission power in each vehicles are also reduced compared to the system model solved by centralized learning machine learning.

In [48], the medium and long blocklength of channel codes is not suitable for ultra-reliable and low-latency in vehicular communication, which leads to high-latency communication along with the increment in number of vehicles in the present and in the future. A short blocklength of channel codes is proposed to deal with low-latency in data transmission where the energy efficiency (EE) is maximized by optimizing resource block and power control under the latency and reliability requirements.The EE is achieved by considering the optimal power control, bandwidth allocation, and optimal number of active antennas. The short blocklength regime is employed to achieve the achievable rate with the maximum EE while guaranteeing the reliable and low latency requirements. However, along with the increment of vehicles and the heterogeneous services in vehicular network, the approach solution can not handle the situation at present and in the future. In [49], network Function Virtualization (NFV) and software defined networking (SDN) are techniques in 5G, which provide a platform for autonomous vehicles. A policy framework for resource allocation in SDN-based 5G networks including SDN core network

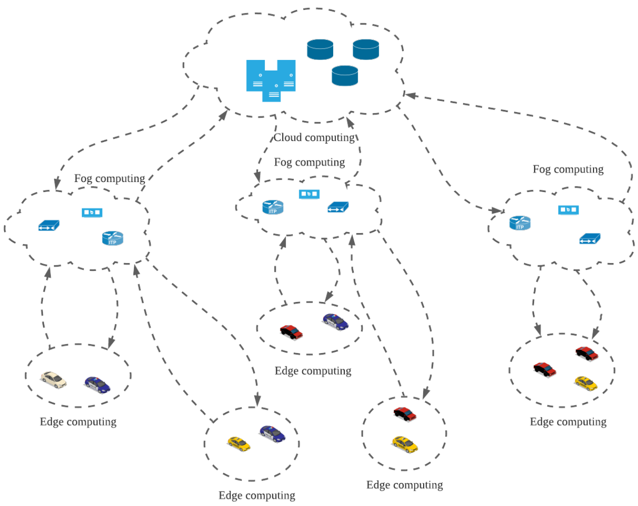

Figure 2. Heterogeneous 6G Vehicular Network

and SDN-enabled wireless data plane. The authors design an adaptive policy generator for creating network policies. In addition, the resource management module (RMM) is used to estimate the radio resource for each slices in vehicular network. Moreover, the traffic adaptive scheduling (TAS) is designed in the SDN controller for collecting the network information. In the last, the authors use machine learning such as Concurrent Neural Network (CNN), Deep Neural Network (DNN), and Long Short Term Memory (LSTM) to classify the traffic of vehicles. Then, the system model proactively allocate radio resource for individual slice. The results in this paper shows that the accuracy in classification by LSTM is higher than CNN and DNN. Even though the authors use machine learning approach to predict traffic, then allocate radio resource for each slices, the transmission power in each vehicle needs to be consider as well to get an effective communication. In [50], the authors proposed a pricing-based resource allocation strategy in virtualized Cloud Radio Access Network (CRANs). Radio resource pool from a mobile network operator (MNO) is shared among multiple mobile virtual network operators (MVNOs). The problem is formulated as two levels. The first level is the upper level spectrum leasing problem that the MNO seeks to find the optimal prices that maximized its revenue. The second level is channel allocation problem in which each MVNO needs to assign channels to its users t maximize its benefit. The channel allocation problem is analyzed by Lagrangian, then the authors propose a fixed point algorithm to solve this optimization problem. Besides, the authors also analyzes revenue and propose pricing algorithm to deal with this spectrum leasing problem. In this paper, the authors gets the results in improvement over the benchmark algorithm.

B. Resource Allocation in Vehicle Fog Computing

Vehicular fog computing (VFC) is a solution to relieve the overload on base station and reduce the processing delay during the peak time, the responding time to end users, and signaling overhead in heterogeneous VNET. The processing and computation can be offload from the base station ti vehicular fog nodes by leveraging the under-utilized computation resources of nearby vehicles.

In [51], to achieve low transmission delay in Vehicular Network (VNET). The authors design a network model which consists of a cloud layer and a fog later. The cloud layer takes responsibility of global traffic management and large-scale traffic light control while the fog layer is used to perform user association in signal processing, resource management, and local scheduling. The authors try to minimize transmission delay subject to QoS requirements and transmit power constraints. In particular, a joint optimization of user association and radio resource allocation, and transmit power are investigated. An iterative algorithm is proposed in this paper to achieve the global optimal solution. The author in [52] discuss how to achieve low-latency QoS in Internet of Vehicles (IoV) under the limitation of fog resources by utilizing both slow moving and parked vehicles along with static RSUs. In this paper, the authors analyze resource allocation problem for vehicular fog computing (VFC) in both a short-term and a long-term resource allocation. Then, the authors propose a heuristic algorithm combined with a Reinforcement Learning-based power control algorithm proposed for spectrum sharing. In addition, the authors employ an LSTM-based DNN to predict vehicles' movement and parking status. The proposed approach is evaluated with a simple vehicular mobility model and in a realistic vehicular mobility model. The results show that the proposed VFC resource allocation outperforms traditional resource allocation schemes along with service satisfaction. In [53], [54] the objective is to offload for cloud layer to fog layer for guaranteeing low latency combined with location awareness distribution, mobility and improving QoS. Vehicles are considered as the end users. Firstly, a probability model is used to estimate resources based on classification of the premium users and non premium users, and the mobility of vehicles. Secondly, the system allocates resource using game theory. The result shows that with the increasing in numbers of tasks, there will be increasing latency. However, by evaluating for users in fog layer, the latency and the response time are reduced compared to that evaluation at cloud layer. In addition, with the simulation, the data transfer cost is lower when processing data at fog nodes. However, obviously, these two methods do not satisfy the present situation in heterogeneous vehicular network. In [55], the authors discuss a fog resource scheduling mechanism to minimize perception-reaction time by applying deep reinforcement learning. The results outperform over those traditional approach which is not suitable for heterogeneous VNET. Even though, the authors solve radio resource allocation, transmit power for transmitting data at individual vehicle is among vehicles. However, due to channel state information and characteristics of data services in the present and in the near future, the power should be consider as different among vehicles to ensures the QoS of each services. In [56], the authors aim to solve the lack of efficient incentive and task assignment mechanisms to minimize the latency due to a contract-matching integration perspective. The authors design a contract-based incentive mechanism and matching-based computation task assignment. Then, these problem is solved by a pricing-based stable matching algorithm. The results is achieved with a network delay demand with a much lower complexity. However, in the practical VNET system, the precise knowledge of channel and vehicle states is unknown. There must be an approach to deal with these issues. Moreover, machine learning to optimize the long-term delay performance.

C. Resource Allocation in Vehicle Edge Computing

Vehicular edge computing (VEC), is a solution of bring the processing, computing, and resource management from the cloud layer to the edge of network, which reduces the delay jitter caused by remote cloud computing. Massive low time-constrained and computation-intensive vehicular computing operations bring new challenges to vehicles, such as excessive computing power and energy consumption. Computation offloading technology provides a sustainable and low-cost solution to these problems.

Recently, the rapid advance of vehicular networks has led to the emergence of diverse delay-sensitive vehicular applications such as automatic driving, auto navigation. Note that existing resource-constrained vehicles cannot adequately meet these demands on low / ultra-low latency.

In [57], the authors formulate an Software-defined networking-assisted MEC network for VNET, which aims to reduce the overhead of the network system. The author study optimal offloading decision, transmission power control, subchannel assignment, and computing resource allocation in this paper by Q-learning to allocate transmission power, subchannels and computing resources in MEC-based VNETs. In addition, the authors model the offloading decision as a potential game. In this article, the results show the reduction in system overhead, network load, and spectrum utilization compared to other approaches. However, without known knowledge about the traffic flow, there must be a hard problem to deal with the burst increment in numbers of vehicles joining the network system. It could be effectively allocated resource, if the authors the traffic forecasting. In [58], the authors aim to minimize a dual-side cost of a smart vehicular terminal by optimizing offloading decision, allocating radio resource and transmit power, provisioning server on the server side, while guaranteeing the network stability. The results show the trade off between cost and queue backlog. Moreover, the iterative radio resource allocation algorithm brings the outperformance in numerical simulation. In [59], this article aims to serve all the incoming requests from end users at the base stations. Thus, the authors develop an uncertainty-aware resource allocation that assigns arriving requests to a base station so that all the requests are severed on time. Base stations are federated to each others. The authors design a system model to solve the probability of meeting deadline in a federated V2V communications, then allocate radio resource to meet the on-time services. By maximizing serving request on time among base station under the scare radio resource constraints, the authors show the good results in radio resource allocation. In [60], an adaptive resource allocation is studied to enhance user experience in vehicular edge computing network. To exploit the computational resources, they propose a system model for balancing computing ability and resource consumption. Thus, the radio resource allocation and computing resources due to the unknown network states are researched in this article. adaptive resource allocation for enhancing user experience (ARAEUE), an online algorithm, is designed to minimize the computing quality loss. The results show that the algorithm achieves the optimality of computing quality while guaranteeing queueing delay. However, in these two articles, transmit power at base is assumed to be equal among all requests which are not suitable for diverse services.

In [61], the authors formulate a computation offloading process at the minimum assignable wireless resource block level in vehicular edge cloud computing (VECC) for guaranteeing QoS of VNET. Value density function is studied to measure the cost-effectiveness of allocated resources and energy savings. These problems are solved by theoretical discovery-based a low-complexity heuristic resource allocation algorithm. The paper shows the results in energy consumption and computing time consumption between vehicular edge cloud computing and local computing. The proposed approach shows a good improvement compared to local computing. In [62], the authors investigate a software-defined vehicular edge computing where a controller has responsibility of task offloading strategy and edge cloud resource allocation strategy. They propose a mobility-aware greedy algorithm to determine the amount of edge cloud resources for individual vehicle. The results show that the success probability of total task execution verus the number of vehicles, vehicular mobility, and completion time limit significantly improve compared to other approaches. In [63], in this paper, the authors investigate a collaborative approach that consider both MEC and cloud computing through a joint optimal computation offloading decision and computation resource allocation. The authors propose a distributed computation offloading and resource allocation algorithm to achieve the optimal solution. By considering a joint optimal problem, the results showed the improved performance than other schemes in terms of the computation time and system utility.

In [64], the authors aim to minimize the processing delay of vehicles' computation tasks, under the constraints of their maximum permissible delays, the authors propose a SDN based load-balancing task offloading scheme in fiber-wireless (FiWi) techniques to enhance vehicular edge computing networks. They propose two game theory to verify the effectiveness of the load balancing scheme.The results show that the proposed approach achieved a superior performance on processing delay reduction as well as the running time reduction. In [65], the authors propose an information-centric heterogeneous networks framework to enable content caching and computing. A system model is considered with a virtualization technique, the designed network system allows sharing communication, computing, and caching resources among users with heterogeneous virtual services. Alternating direction method of multipliers (ADMM), a distributed algorithm, is proposed to solve the resource allocation problem. The performance improvement is achieved with the proposed schemes. In [66], a proposal of a multi-platform intelligent offloading and resource allocation algorithm to dynamically organize the computing resources. To select the task offloading platform such as cloud computing, mobile edge computing, or local computing, the use of K-nearest neighbor algorithm is proposed. In addition, reinforcement learning is applied to allocate computational resource and system complexity in non-local computing. The proposal saved 80 percent of the average system cost while reducing the latency compared to the baseline algorithm. In [67], the authors design a mobility-aware task offloading processed by Vehicular edge computing server which is deployed at the access point. If there is overload at one access point, this access point will share the collected overloading tasks to the adjacent servers at the next access point by cooperative MEC servers scenario on the vehicles' moving direction. The results show that the proposal is achieved by cost reduction while guaranteeing latency.

Even though, all of these aforementioned approaches achieved better performance over baseline algorithm, due to the increasing in numbers of vehicles, we need another algorithms to suit with the diverse services at present and in the future of vehicular network. Recently, machine learning is one of the best algorithm which supports vehicular network.

V. Deep Reinforcement Learning for Resource Allocation in VNET

A neural network (NN), known as an artificial neural network (ANN), a network of neurons, composes of artificial neurons which are organised in layers. There will be three types of layers which are an input layer, a hidden layer, and an output layer. For more complicated problem, the numbers of hidden layers can be varied. ANN has many applications (i.e, text classification and categorization, part-of-speech tagging, speech recognition, spell checking, and so on). A simple neural network is illustrated in Figure 3.

Reinforcement Learning (RL), a computational approach of learning from action in the absence of a training data set. RL consists of three primary components which are the agent, the environment, the action. An agent learns from the environment by interacting with it and receiving rewards for performing actions. A RL model is illustrated in Figure 4.

Deep Reinforcement Learning (DRL), combination of ANN and RL, enables software-defined agents to learn the best actions in virtual environment in order to attain their goals. DRL has many applications (i.e, self-driving cars, industry automation, trading and finance, natural language processing, and so on). A DRL network is illustrated in Figure 5.

In [68], the authors propose a RL based radio resource allocation algorithm to consider the future network status when changing Time Division Duplex configuration in learning phase and to choose action with considering future network status. From predicting the future network status to maximize the reward for the agent. The results

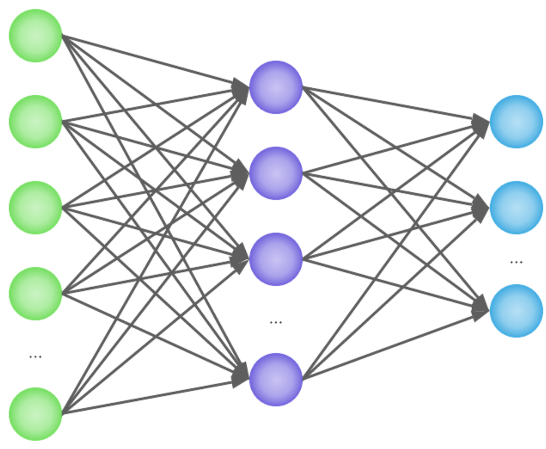

Figure 3. A simple neural network

outperform in throughput of VNET and reduce packet loss rate. In [69], a double-scale deep reinforcement learning (DSDRL) is studied to solve a joint problem of communication, computing, and caching resource allocation to improve user satisfaction, and to reduce cost in heterogeneous services.The results show the reduction in the revenue of network operators compared to different schemes and different number of vehicles. In addition, the latency requirements of diverse services also has a significant reduction as well as cost. In [70], the authors propose a deep reinforcement learning based optimal channel selection for training the network according to the previously sensed data to find optimal available CR channel in CR-VANET. In [71], the authors discuss Age of Information-aware radio resource management problem in VNET. The problem is formulated as a single-agent Markov decision process (MDP). Due to the increasing in numbers of Vehicle User Equipment (VUE) pairs, the MDP problem is decomposed into centralized offline training at RSU and a decentralized online testing at the VUE-pairs by Long Short Term Memory (LSTM) and Deep Reinforcement Learning (DRL) which enables frequency band allocation and packet scheduling decisions at RSU with only partial network state observations but without a priori statistics knowledge of network dynamics. The average transmit power and average packet drops per VUE-pair is reduced compared to baseline algorithm.

In [72], the authors discuss about DRL-assisted optimization for resource allocation which is considered as a joint spectrum and power allocation in VNET in both single-Agent RL and multiagent RL. Because the multiagent RL enables a centralized decision making with very low signaling overhead. Thus, the authors design a learning phase at each V2V transmitter which is constructed a Deep Neural Network (DNN) that learns to compress its local observation and then feeds back to the central base station, which are the input of Deep Q-Network. With the combination of RL and DQN enables the network system

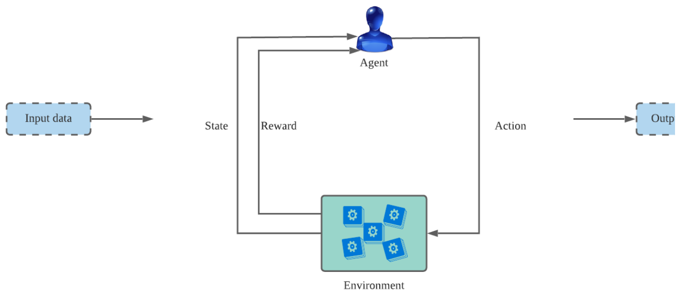

Figure 4. A Reinforcement Learning model

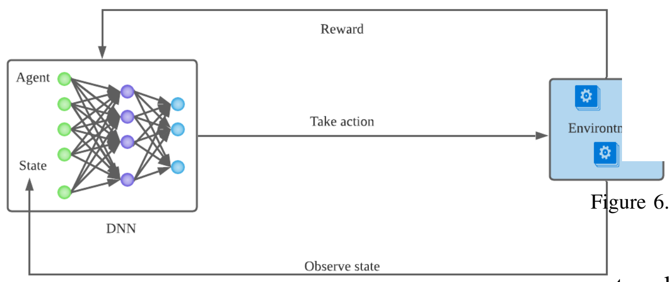

Figure 5. A Deep Reinforcement Learning model

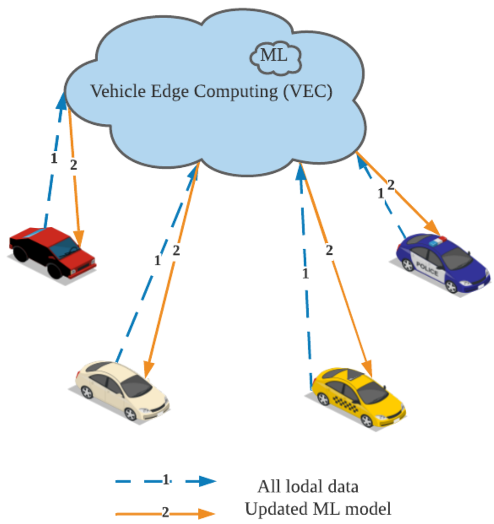

Figure 6. A conventional machine learning model

to transmit at a high rate to finish early and figure out a clever strategy of alternating transmission to void strong mutual interference. In [73], the authors design a network system allows vehicles providing computation services for user equipments (UEs) as the traditional edge server. In addition, the delay and limited computation capabilities of vehicles and edge servers are investigated in this article. The proposal of Q-learning based RL and DRL approaches is applied to find the policies of computation offloading and radio resource allocation. In [74], the authors propose a distributed user association algorithm for network load balancing in VNET by online reinforcement learning approach (ORLA) based on the historical user association. Then the base station allocates its resources among its associated vehicles. The results show that the overall service rates of the proposal approach in this problem achieved better performance than other baseline algorithms. In [75], the authors design a MDP in which consider the impacts of task characteristics, wireless transmission and queue dynamics, and vehicle terminals mobility. A convolutional neural network (CNN) is embedded in the DNN which is used to approximate the offloading scheduling policy and value function. DRL-based offloading scheduling method (DRLOSM) in this network system not only reduces the number of retransmitted tasks and cost, but also energy consumption.

VI. Open Issue

In 6G, vehicular network has characteristics of heterogeneous and large-scale structure which make difficult to efficiently deploy machine learning algorithms. Recently, software defined network and network functions virtualization is proposed to enable software network functions and networking slicing to deal with heterogeneous networks and diverse services.

Even though, to satisfy latency requirements, to reduce signaling overhead, and to improve energy efficiency, vehicle edge computing is proposed. Federated Learning (FL), a machine learning technique, trains an algorithm across multiple end devices or servers which holds local data samples without exchanging the data. However, with the QoS requirements of 6G network that is mentioned in section III, Federated Learning (FL) is a good candidate to deal with the latency requirement.

Conventional machine learning is deployed in VEC layer. The edge devices as vehicles upload all raw data to VEC layer. The machine learning in VEC layer process and compute, then the resultant updated machine learning model is pushed down into the vehicles.

Federated machine learning is that the machine learning algorithm is deployed in both the VEC layer and end devices. The machine learning algorithm runs in vehicles and it then provides updated machine learnings up to the VEC layer. The VEC layer refines these updated machine learnings and pushs it back to the vehicles. Federated machine learning brings benefits of reduction in latency and signaling overhead, increment of privacy and security.

In general, 6G network is with ultralow delay and superhigh network capacity while the resources are limited. The combination among resource slicing for network slicing, machine learning, especially FL at MEC layer is expected to be a worthy research direction toward the 6G VNET.

VII. Conclusion

In this paper, I have summarized deep reinforcement learning based radio resource and transmission power allocation in 5G vehicular network and propose the direction in research for 6G vehicular network. The emerge 6G VNET can be satisfied by applying the combination of vehicle edge computing, network slicing, and federated machine learning.

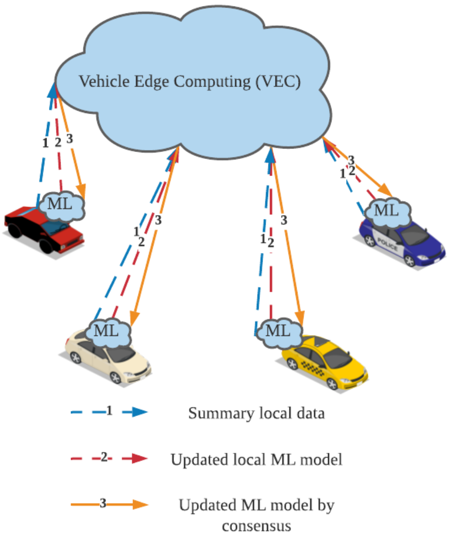

Figure 7. A federated machine learning model

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