Comprehensive Survey on Machine Learning in Vehicular Network: Technology, Applications and Challenges

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***Abstract*—Towards future intelligent vehicular network, the machine learning as the promising artificial intelligence tool is widely researched to intelligentize communication and networking functions. In this paper, we provide a comprehensive survey on various machine learning techniques applied to both communication and network parts in vehicular network. To benefit reading, we first give a preliminary on communication technologies and machine learning technologies in vehicular network. Then, we detailedly describe the challenges of conventional techniques in vehicular network and corresponding machine learning based solutions. Finally, we present several open issues and emphasize potential directions that are worthy of research for the future intelligent vehicular network.**

***Index Terms*—V2X, vehicular network, machine learning, deep learning, V2V, Internet of Vehicles (IoV), resource allocation, routing, security, mobile cloud computing (MEC).**

I. Introduction

THE FIFTH generation (5G) network is widely deployed and evolved to large-scale commercial applications, and the next generation (6G) is proposed as the potential evolution of 5G to enable the ultra-high and intelligent communication in the future [1]. Even though the specific technologies of 6G is still vague, the networking and communication intelligentization are widely admitted as the key driver towards the 6G network [2]–[4]. Recently, the machine learning is also considered as the key technology to pave the way to the future vehicular network towards 6G [5]. The intelligence enabled vehicle applications such as autonomous driving, Internet of Vehicle (IoV), and air-to-ground (A2G) [6] network have been widely researched in both academia and industry [7], which paves the way to intelligent transportation system (ITS) and intelligent vehicular network in future 6G. Compared with conventional vehicular network, the next generation intelligence-enabled vehicular networks can bring positive impacts on both the transportation and social activity such as smart grid, smart living, and smart travel.

The goal of future vehicular is to develop highly dynamic and intelligent system, allow the network self-adaption to various applications, and mutative requirements of users. To achieve the goal, both the dynamic adaptivity enabling self-learning as well as the rapid response capability improving transmission throughput and reducing end-to-end delay are essential to future intelligence in vehicular network. Furthermore, the advanced hardware in vehicles and vehicular infrastructures provides high computation, caching, and data storage ability [8], [9]. With the stored data and computation ability, various data-driven frameworks are proposed for intelligent applications in vehicular networks [10].

Machine learning, which is a promising data-driven intelligence tool, is widely used in various areas to enable high adaptivity and rapid response capabilities such as image recognition, target tracking, and self-driving. Recently, machine learning is also widely researched for networking and communication intelligentization in future wireless networks [3]. Meanwhile, machine learning also plays a role in network security area [11]. The high mobility and heterogeneous structure of the vehicular network with various types of communication technologies are hard to be adapted in real-time with conventional methods. Machine learning is naturally considered a potential solution for communication and networking optimization for the high dynamic network. Recently many solutions are proposed employing machine learning technologies for the wired/wireless networks, and some survey papers investigate those proposal in terms of different areas and focus. For example, [12] firstly surveys the applications of machine learning and specific deep learning technologies in the generic wireless network. However, This paper mainly focuses on the machine learning of network traffic control in the generic wireless network and not considered the high mobility of the network. The survey [13] surveys the applications of specific machine learning technologies of only neural networks in the generic wireless network. This lacks the introduction of some classical machine learning approaches such as SVM, random forest, and K-means, which are considered more efficient in some tasks for network optimization. Another survey of [14] gives a comprehensive survey of various machine learning technologies for generic wireless networks in terms of different learning tasks. However, this paper focuses on generic wireless

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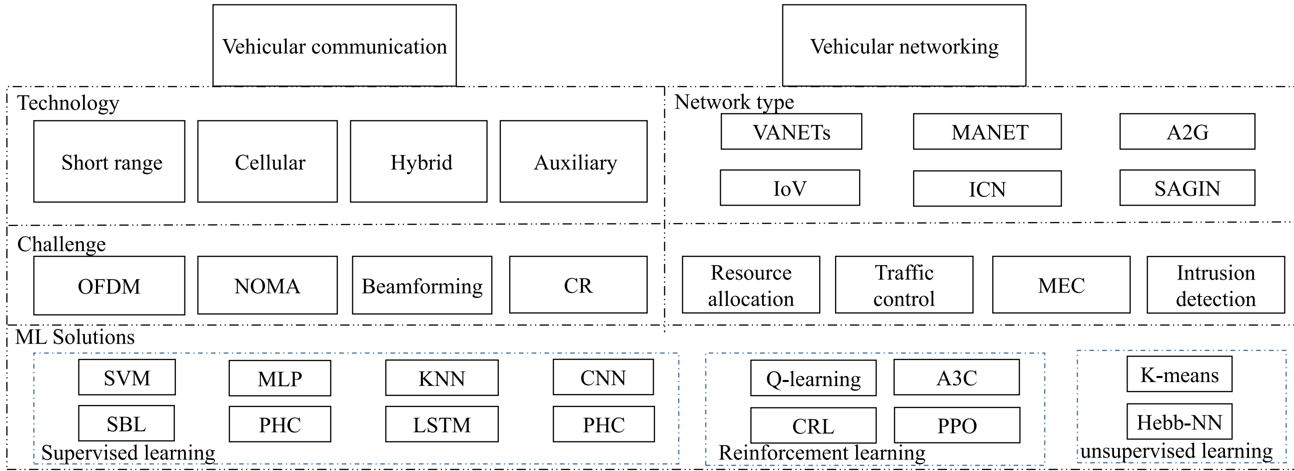


Fig. 1. The technique points in vehicular network we focus on in this survey.

TABLE I
SUMMARY OF EXISTING SURVEYS

Literature	Scope			
	Communication	Networking	Security	Vechiular
[11]	N/A	N/A	√	N/A
[12]	N/A	√	N/A	N/A
[13]	N/A	√	N/A	N/A
[14]	N/A	√	N/A	N/A
[15]	√	√	N/A	N/A
[16]	N/A	N/A	√	√
Our paper	√	√	√	√

network and does not consider the specific types of network such as the vehicular network. Furthermore, this work focuses on the application of machine learning in wireless networking but ignores state-of-art researches of machine learning for basic wireless communications. Besides investigating all types of machine learning technologies for the wireless network, the paper [15] focuses on the applications of reinforcement learning in the wireless network. The survey paper [16] gives a survey and tutorial of machine learning for security issues for Securing Connected Autonomous Vehicles. This paper focuses on the security issue of Connected Autonomous Vehicles. However, the communication and networking issues such as network control and resource allocation are not touched in this work. The detailed information and investigated areas and focus of those surveys are listed in the Table I.

Those survey papers have investigated the applications of machine learning in security, network traffic control in generic networks. However, the vehicular network with high mobility and distinctive features face specific challenges, none of the existing survey papers focus on the solutions of machine learning for vehicular networking and communications by considering the distinctive features including the high mobility, heterogeneous structure, and various communication technologies. Therefore, in this paper, we aim to survey the applications of promising machine learning to enable intelligence in specific vehicular networks in terms of both networking and communication aspects. The flow of this paper is as shown in Fig. 1, we first survey the existing technologies and potential challenges of the vehicular network. And based on the specific challenges, the corresponding machine learning based solutions are investigated by following the choroids of relative researches.

The remainder of the article is organized as follows. Section II introduce the technologies of communication and networking and summarize the challenges in future vehicular network. Section III gives a preliminary of machine learning technologies. In Section IV, we describe the applications of machine learning in vehicular network for solving communication challenges. Then, we investigate the machine learning based approaches for intelligent vehicular networking in terms of four aspects including resource allocation, traffic control, mobile edge computing (MEC) and intrusion detection in Section V. The open research issues and some future research directions are discussed in Section VI. Finally, in Section VII, the article is concluded.

II. TECHNOLOGIES AND CHALLENGES IN VEHICULAR NETWORK

In this section, we survey the technologies of vehicular network in terms of communication and networking aspects, and summarize the challenges in terms of specific technologies, respectively.

A. Technologies of Vehicular Communications

To support the vehicular network, the communication technology between vehicles, as well as between vehicles and other equipments have been widely researched for many years. At the beginning, researchers consider directly using existing communication technique such as Bluetooth, WIFI and Zigbee for vehicular communications [7], [17]. However, due to the high dynamic and the capability limitation of those existing techniques, both the quality of service (QoS) to users and the network performance are unqualified to the new generation of vehicular network [18], [19]. To conquer the challenges, in past years, many direct vehicular communication methods based on classical underlying protocol such as IEEE 1609, SAE J2735, SAE J2945 and IEEE 802.11p are proposed to be applied in vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications [20]. To standardize the definition, such kind of short range wireless protocol based vehicular communication technology for automotive and intelligent transportation system (ITS) applications is widely referred to as dedicated short-range communications (DSRC) [21]. To support the development of vehicular network and DSRC, in 1997, the U.S. Department of Transportation (USDOT) established intelligent vehicle initiative project, and processed the DSRC based vehicular communication test from 2013 [21]. In 2014, the USDOT and the U.S. National Highway Traffic Safety Administration (NHTSA) further proposed the Federal Motor Vehicle Safety Standards (FMVSS) No.150 in U.S. government for supporting the DSRC popularization [22].

By enabling DSRC, the vehicular network ushers in a rapid development. However, many new researches show that the bandwidth and transmission distance of DSRC limite the reliability and efficiency of vehicular communications [21], [23]. Furthermore, with the emergence of vehicle-to-everything (V2X) as the new requirement of vehicular communications which includes V2V, V2I, vehicle-to-pedestrian (V2P) and vehicle-to-network (V2N) connections, the vehicular network becomes more dynamic and heterogeneous and demands more powerful communication techniques in terms of both capacity and connection ability [24]. Cellular network, which is the powerful communication technique in conventional wireless network attracts many attentions in vehicular network area recently. As one of the promising technology of cellular communication, the long-term evolution (LTE) for 4G and 5G is widely deployed over the world and being considered as a powerful wireless access technology to enable vehicular communications [25]–[27]. Considering that LTE can synchronously provide both cellular and device to device (D2D) communications in vehicular network, as shown in Fig. 4, a new architecture with heterogeneous wireless technologies including LTE, DSRC and so forth is proposed as the candidate for future vehicular network [21], [28], [29]. For supporting the new architecture, the 3rd Generation Partnership Project (3GPP) defines this architecture as C-V2X, and considers it as the powerful supplement of conventional DSRC based vehicular network and the road to future intelligent vehicular network in 5G [30].

B. Challenges of Vehicular Communication

The vehicles leverage above technologies to provide potential communication ability to build connections in V2X. However, different from conventional wireless network, the distinctive characteristics such as high dynamic and heterogeneous architecture of vehicular network make the vehicular communication become more challenging and need to be specifically considered.

1) OFDM Challenge: The high mobility of vehicles leads to high dynamic on time, space and frequency domains of vehicular communications. The high dynamic is the primary characteristic of vehicular network and makes the design of vehicular communication more challenging than conventional wireless communication. The wireless technologies of WiFi, DSRC, and LTE all support the OFDM and MIMO modulation technologies. The OFDM configuration (e.g., decoding space-time codes, channel equalization and signal modulation) provides intelligent multiple access for future vehicular network and is mainly based on the channel state information (SCI), which can be predicted with probed feedback (e.g., pilot) from the environment [31]. In conventional wireless communication, the channel estimation and signal detection based OFDM is widely used to improve the spectrum utilization, in which, the channel estimation and signal detection accuracy largely depend on the stability of transmitter and receiver [32], [33]. However, because of the high mobility of vehicles, the high Doppler spread causes extremely fast channel fading and hinders the accuracy of channel estimation. Furthermore, the frequency-domain channel estimation algorithms used in conventional wireless network not considering the inter-carrier interference (ICI) is not suitable for highly dynamic environment [34], [35]. By taking ICI as an important parameter that affects channel condition, Panayirci *et al.* propose a space alternating generalized expectation maximization (SAGE) technique for joint channel estimation, equalization, and signal detection in high dynamic OFDM system [36]. Then, by considering the High Doppler effect, Al-Naffouri *et al.* propose a pilot-aided algorithm for the estimation of fast time-varying channels under high mobility condition [37]. In 2006, Tang *et al.* propose the channel model for channel estimation in high mobility (i.e., high Doppler spreads) OFDM communication should be considered to be time-varying (TV) and can be approximated by a basis expansion model (BEM). In [38], the authors specifically consider the OFDM in high mobility roadside-vehicle environment, and propose an OFDM enabled DSRC for the vehicular communication system, which can achieve less than 10^{-5} bit error rate (BER) when the transmission bandwidth is set to 2.048 Mbps in 5.8GHz frequency. However, all of the above researches either focus on the specific vehicle to infrastructure or consider simple communication without considering the characteristics of MIMO. Besides, the classical pilot based channel estimations depending on pilot symbols cause high signaling overhead [39]. Moreover, those existing methods, which at first estimate the channel state information (CSI) and then recover the signal of transmitter based estimated channel, is time-consuming and causes unexpected latency [40]. In summary, the conventional OFDM configuration methods cannot satisfy the ultra-low delay and high throughput requirement of future vehicular communication, how to intelligently configure the OFDM in high dynamic vehicular communication is a big challenge.

2) Cognitive Radio (CR) Challenge: CR is an intelligent wireless communication system capable of awaring and learning the surrounding environment to adaptively change parameters such as using channel frequency, transmit power and modulation strategy [41]. The CR is widely used in wireless network as a spectrum sensing technology to improve the network performance [42]. However, the high mobility of vehicles is still a big challenge of spectrum sensing with CR technology [43]. In CR assisted vehicular communication, the high mobility of vehicle hinders both the sensing process and channel state estimation process of PU and SU [44]. To deal with the high mobility challenge, Kirsch and O'Connor propose a CR system to increase the throughput and decrease packets loss rate by adding additional channels in VANETs [45]. In this research, to conquer the high mobility problem, the authors give a priority rank to messages based on the critical level and ignore some soft messages. However, such method cannot really solve the high mobility problem but improve the real-time delay by sacrificing other performances. Rawat *et al.* leverages game theory to achieve higher throughput of CR based vehicular communication by considering the high mobility of vehicles [46]. In this research, both the heterogeneous structure and dynamic topology are considered, however the authors not fully consider the channel fading caused by the high mobility, and the widely used vehicular wireless technologies such as DSRC and LTE are not used. In [44], the authors claim that machine learning can be a potential solution to deal with the CR spectrum sharing problem in dynamic vehicle environment, whereas the detailed research directions are not introduced. Even so, a new research direction was discovered that the CR is an intelligent wireless communication technology to adapt to the mutative environment which is similar to the machine learning approach such as reinforcement learning as shown in Fig. 5. Naturally, using machine learning to improve the CR performance emerges as an interesting research topic.

3) Beamforming Challenge: The Millimeter-wave (mmWave) is the frequencies between 30 and 300GHz, which offers greater bandwidths for cellular communication [47]. The 3GPP Release 15 for LTE is proposed to standardize the usage of mmWave for 5G wireless communication [48]. The mmWave is a potential wireless technology for supporting future high QoS vehicular communication [49]. However, since the high frequency mmWave has much higher attenuation than low frequency, direct omnidirectional transmission needs very high transmit power and causes insufficient low gain. Therefore, the beamforming is proposed as a spatial and spectral filter to align the wireless wave to the specific direction for improving transmission efficiency [50]. By employing the LTE, the mmWave antenna system equipped with massive antenna array is widely equipped in the next generation (e.g., 5G) infrastructure which can be the base station to provide beamforming service to vehicles. With the same equipment, the Massive MIMO is further exploited as the spatial filter to improve both the spectral and energy efficiency in mmWave frequency [51]. The massive MIMO with beamforming is researched as the potential wireless communication technique for future vehicular network [52], [53]. As shown in Fig. 2, the mutative vehicular location and high overhead of frequent beam-training is the key drawback to develop mmWave in high mobility vehicular communication system. Gonzlez-Prelcic *et al.* claim that the conventional beam training and corresponding mmWave technologies are infeasible in V2X communication due to the high overhead [54]. Therefore, in their research, a novel beamforming strategy that reduces the beam-training time with the aided configuring by a radar mounted at the road infrastructure is proposed to specify the mmWave technology in the V2I communication. At the

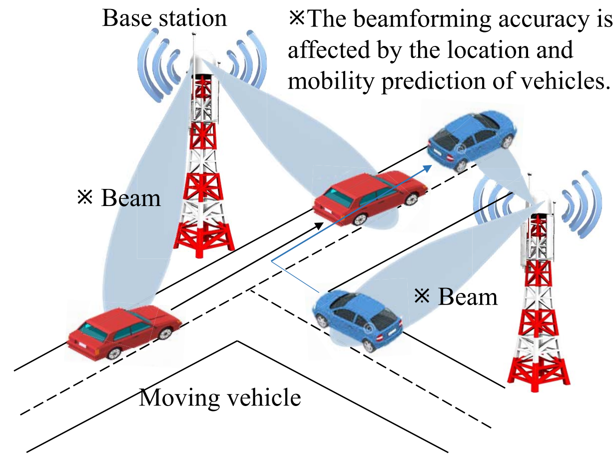


Fig. 2. Illustration of dynamic beamforming in vehicular network.

same year, Choi *et al.* propose the sensor aided mmWave beam alignment strategy to deal with the beam-training overhead in V2V communication [52]. However, the recent researches [49], [55] show that the existing beamforming methods are still with high overload for mmWave in dynamic vehicular communication and are not intelligent to adapt to frequent changing vehicular scenario. To make the mmWave and corresponding beamforming strategy become intelligent, the novel intelligent machine learning technology might be a potential solution.

4) NOMA Challenge: NOMA is a novel multiple access technology proposed by Nippon Telegraph and Telephone (NTT) Docomo company in Japan for cellular future radio access [56]. Instead of the frequency division in above mentioned OFDM in LTE, the NOMA divides frequency, temporal and power domain to multiple users and adopts a successive interference cancelation (SIC) as the baseline receiver scheme for robust multiple access. Comparing with OFDM, the NOMA is more efficient in spectrum and space utilization and trends to be the potential multiple access technology for future mmWave based V2X communications [57]. An illustration of applying NOMA in vehicular network is shown in Fig. 3. Considering the congestion issues in conventional OFDM-based LTE network,Di *et al.* design a NOMA supported cellular V2X system in future 5G vehicular network [58]. In the designed system, the authors propose two corresponding high efficient resource allocation and spectrum scheduling algorithms. With simulation, the proposal shows the NOMA enabled V2X system can achieve low latency and high reliability in ultra-dense vehicular network. Moreover, in [59], Khoueiry and Soleymani propose an efficient V2X communication scheme by using NOMA technology in vehicular network. In this proposal, the graph-based practical encoding and joint BP decoding techniques are considered as the data recovery techniques to reduce decoding failure and iteration times. However, due to the high mobility of vehicles, there are still many problems of employing NOMA for vehicular communications that need to be further addressed. For example, in the high dynamic vehicular communication system, how to adaptively allocate power and frequency to the high mobility

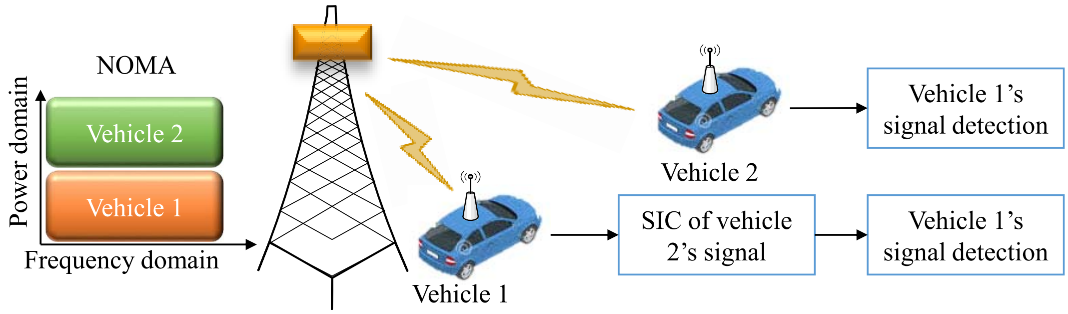


Fig. 3. Spectrum utilization of NOMA in vehicular network.

user when environment changes [60], and how to intelligently allocate resources to the multiple access links for adapting to sharply changing channels with low computational complexity in high dynamic networks [61].

C. State of Vehicular Networking

With various vehicular communication technologies, vehicles are well equipped to provide communications with everything. However, the simple point to point connection is insufficient for providing qualified services to different kinds of users. The vehicle enabled networks are desired to be designed for supporting current high QoS and QoE communication. In this section, we at first introduce the different types of networks constructed with vehicular communications. Then, we overview the challenges in the vehicular networking process and discuss the main research issues for building the vehicular network.

1) Types of Vehicular Networks: Initially, the Vehicular Ad-hoc Networks (VANETs) are proposed to build connections between vehicles to provide various services such as road safety, traffic management, congestion alleviation and autonomous driving auxiliary in the ITS system [62]. The VANET is an advanced ad-hoc network developed from conventional mobile ad hoc networks (MANETs). Different from MANET, VANET is characterized for vehicles, which has higher mobility than conventional mobile nodes and specific features such as the vehicles are restricted by the shape of the road and the infrastructures near the road are used to assist vehicular communications. Then, to extend the usage of VANET, the V2X is proposed to build networks between vehicles and targets of everything including vehicle, infrastructure, pedestrian and network.

To develop VANET to V2X, in 2009, Trullols-Cruces *et al.* proposed a cooperative vehicular network framework, which adopts car-to-road communications to assist data transmission in Delay Tolerant Network (DTN) for reducing packet losses and avoiding congestion [63]. The paradigm that vehicles cooperatively networked to help transmission is widely called as cooperative vehicular networking (CVN) [64]. A series of cooperative networking in vehicular networks are introduced in [65].

For supporting highly intelligent autonomous driving and enabling the efficient data usage, high scalability and low delay transmission in vehicular network, the informative centric

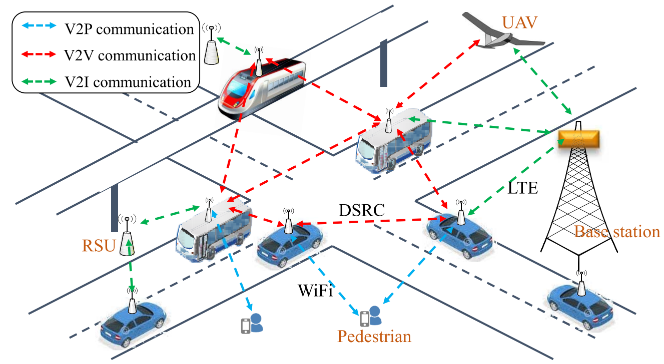
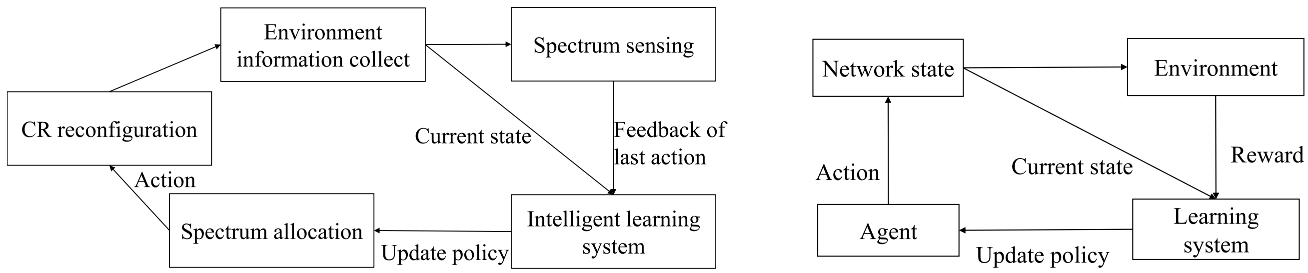


Fig. 4. The heterogeneous structure of future vehicular network.

network (ICN) is proposed to be deployed in vehicular network as the new generation data-driven vehicular network architecture [66]. Compared with conventional vehicular network structure, the ICN totally discards traditional network structure, and decouples transmitter receiver pair to in-network storage-based caching and multiparty communication [10]. The novel ICN-based vehicular network is more suitable for future requirement of heterogeneous and dynamic network structure and flexible for anomaly and failures.

Unmanned aerial vehicle (UAV), as one special kind of vehicle employed to assist transmission and exploit the air space into conventional ground network, attracts much attention recently [67]–[69]. In 2004, the Ad-Hoc UAV Ground Network (AUGNet) is proposed, which is also referred to as air-to-ground (A2G) network and UAV-to-ground (U2G) network [6]. In the A2G, the UAVs acts as mobile air relays that dynamically connect disconnected ground nodes (e.g., vehicle, users, infrastructures) to extend the communication capacity and coverage in rural/disaster areas. To further enhance the communication ability and extend the space utilization, the Space-air-ground integrated network (SAGIN) [70], [71] is proposed to integrate satellite systems (i.e., space), aerial networks (e.g., UAVs, balloons platform), and terrestrial communications (e.g., ground infrastructure, vehicles, devices).

Recently, inspired by the concept of Internet of Thing (IoT), the Internet of Vehicles (IoV) is emerged as the new architecture of vehicular network [72]. The IoV is proposed as a transport fabric capable to intelligently drive people to the



(a) The work flow of intelligent CR

(b) The work flow of RL in network.

Fig. 5. The similar work flow comparing with CR and RL.

desired location. In order to achieve such goal, the IoV should have communications, storage, intelligence, and learning capabilities to understand the intentions of passengers [73]. For achieving such intelligence of IoV, the networking desires high requirements such as ultra-low latency, high reliability, seamless wide-area coverage, high-capacity hot-spot and massive-connections. From initial VANET to the recent IoV, those requirements are continuously addressed by various approaches through different aspects such as network resource allocation, network traffic control, and network content shearing. In the next part, we detailedly introduce those research issues and discuss the corresponding solutions and challenges respectively.

2) State of Network Intrusions in Vehicular Network: The conventional fixed centralized cloud computing deployed in the logical/geometric center of the network is long distance to the remote users. Those centralized clouds do not support the high quality service due to the long distance transmission and cause high overload to the central cloud. Besides providing network service, a vehicle with high mobility, carrying capacity and long power supplication is potential to be the mobile cloud platform for providing computation, traffic and data offloading services. Such kind of vehicle based mobile cloud service is widely referred to as Vehicular Cloud Computing (VCC) [74].

The VCC is widely used in various networks to offer resource offloading services. A series of VCC related researches are introduced in [75]. Recently, the concept of mobile edge computing (MEC) is proposed as the extension of mobile cloud computing, and the vehicles with high mobility are considered as the potential carrier to enable both mobility and computing to edge users. Some rule based MEC scheduling methods and applications are proposed [76]–[79].

3) State of Network Intrusions in Vehicular Network: In the vehicular network, the cyber-physical security is extremely critical as the attack and malicious behaviors may threaten the personal safety. On the other hand, the security issue of vehicular network is much more complex than various conventional networks due to its heterogeneous structure and high mobility. The distinctive features of vehicular network of high mobility, heterogeneous structure, large scaled network result in specific constraints and requirements of vehicular security. For example, the high mobility of vehicles leads to frequent network topology change and distributed data allocation, which makes such ad-hoc system vulnerable to be attacked. Furthermore, without the high fault tolerance of fixed network, the high mobile vehicles require real-time secure information for accident avoidance and quick rescue, which desires ultra low-delay transmission as well as fast attack prevention mechanisms [80]. Meanwhile, the heterogeneous structure with various individual devices is always non-cooperative. The malicious nodes are easy to forge identity and intrude the network without cooperative verification. Besides, the heterogeneous network leads to different resource capacity of nodes. To balance the different types and capacities of resources under the strict security requirement becomes difficult [81].

Considering various attacks, a series of security solutions are proposed for dealing with different kinds of attacks [82]–[85]. Among various security solutions, quick intrusions detection is widely considered as the most efficient way of protecting the network from attacks before the damage was caused. For intrusions detection, researchers found that the leakages and intrusions can be traced with data mining methods from dynamic network traffic patterns [86], [87]. After that, a lot of intrusions detection algorithms with data mining are proposed [11]. The attack detection can be simply categorized into two types. The first one is misuse detection which detects the known attacks by checking the features of signature from the attacks database. On the other hand, the intrusion detection for novel attacks by analyzing the anomaly patterns is referred to as anomaly detection. However, there are many distinctive features of the vehicular network compared with generic wireless networks. The security information including location, velocity, distance, and so on are periodically exchanged between vehicles, which is more vulnerable to be eavesdropped on and attacked. Due to the distributed structure and high dynamic network topology, those passive attacks are much more difficult to be detected. To conquer those specific challenges in the vehicular network. Some existing dynamic attack detection methods are proposed.

For Sybil attack, Zhou *et al.* jointly consider the security and privacy in vehicular network and propose a road-side boxes (RSBs)-assisted Sybil-attack detection algorithm [83]. In [88] the authors consider using the historical trajectories of vehicles to identify the vehicular authorization and propose location-hidden authorized message generation scheme for further recognizing Sybil trajectories.

The detection of traffic attack such as DDoS are widely researched for both conventional network and vehicular network. As the DDoS attack is high resource consumption, the most effective method of any DDoS defense mechanism is to disrupt the attacker close to the source by quick detection [89]. However, one big challenge of DDoS detection is the data collection delay in the heterogeneous and dynamic network, the authors in [90] proposed the soft defined NOX operation system and Openflow for quick DDoS detection. Yu further propose an SDN assisted dynamic framework for real-time DDoS detection in vehicular network [91].

Sedjelmaci and Senouci propose a intrusion detection framework to detect routing attack including blackhole, wormhole, packets duplication and resource exhaustion attacks, which build a robust reputation schema with evaluating trust level of vehicles [92]. Besides, Kurosawa *et al.* propose a dynamic attack detection algorithm for AODV routing based MANET [93], [94].

D. Challenges of Vehicular Networking

1) Network Resource Allocation Challenge: The wireless resources such as channels, power level, computing ability and time slot are uneven distributed in network, and the requirements of users in network are different, how to allocate suitable resources in wireless network is a classical problem in wireless network [95]. Many resource allocation algorithms based on greedy algorithm [96], [97], auction theory [98] and game theory [99] are widely proposed to deal with the resource allocation problem. Different from conventional wireless network, the vehicular network evolves unique characteristics of high mobility nodes, heterogeneous structure, and high QoS requirements from passengers. Conventional static resource allocation methods are insufficient for such complex vehicular networks. For example, a dynamic radio resource allocation problem in vehicular network is shown in Fig. 6. Considering the vehicles are dynamic moving, the radio resources in power, spectrum and time domain should be jointly considered to fit for the mutative scenario. To fit for the special characteristics of vehicular network, a series of researches for conquering the above challenges are proposed. The joint resource allocation based on multiple criteria is an NP hard problem, many researchers try to formulate the problem into sub-problems and solve them in a heuristic manner [100]–[102]. To address the dynamic issue in vehicular network, researchers consider transferring the resource allocation problem into a continuous optimization problem and employ various theoretical tools such as greedy algorithm [103], game theory [104], [105], graph theory [101] and Markov chain to dynamically manage it [105]. Considering the resource allocation in hybrid structure is hard to be processed with central controller and the connection ability between hybrid communication technologies is week. Some researchers consider using the supplemental communication such as D2D, UAV and satellite to enhance the connection ability in VANET and propose corresponding resource allocation algorithms [68], [101], [106], [107].

Above surveyed papers give solutions for resource allocation problem in vehicular network. However, comparing with the high requirement of future vehicular network, there are still many gaps that can be further improved. In summarize, there are three main challenges for employing resource allocation algorithm in vehicular networks:

1) The fast convergence speed of resource allocation algorithm to achieve immediate resources handoffs,
2) The intelligent resource manage ability adapting to distributed heterogeneous system without knowing the global information,
3) The future state prediction and intelligent decision making ability for adapting to the sharply changing environment.

The intelligent machine learning technologies can be potential solutions to further improve the above abilities for intelligent resource allocation in future vehicular network which are detailed introduced in Section V-A.

2) Network Traffic Control Challenge: The network traffic control including network routing, congestion avoidance, and traffic offloading is widely researched in conventional wireless network. In vehicular network, considering the dynamic of network topology, the traffic control strategy becomes more complex. Instead of conventional routing protocols such as Open Shortest Path First (OSPF), Intermediate System-to-Intermediate System (IS-IS) and Routing Information Protocol (RIP), the location information and network topology emerge as important parameters involved in routing protocol design for high dynamic vehicular network.

The most widely used routing protocols in static wireless network such as OSPF [108] and IS-IS [109] are based on the Link-state routing protocol (LSR). Every node in the network need a connectivity graph based on all link-state of the whole network, then the routing tables calculate the node correspondingly. However, different from conventional network, the high dynamic vehicular network makes the established route which is fixed succession in conventional routing protocol easy to be broken. Therefore, the mobility of nodes affected routing is initially widely researched in MANET. In [110], the authors discuss the characteristics such as dynamic topologies, constrained energy and constrained bandwidth may significantly affect the performance of routing protocol. Considering those constraints, a series of classical dynamic routing protocols such as Destination-Sequenced Distance-Vector routing (DSDV) [111], stability-based adaptive routing (SSA) [112] and Dynamic Source Routing (DSR) [113] are proposed for dynamic MANET. Those methods are most dependent on Distance-vector routing (DV) protocol. Even though the Optimized link state routing protocol (OLSR) [114] is proposed in 2003 to extend the LSR into dynamic network, the DV based routing protocols seems more popular in high mobility vehicle related areas. further improved from DV protocol, Charles *et al.* proposed an Ad-hoc On-demand Distance Vector (AODV) protocol for VANET, which soon becomes the most classical routing protocol in vehicular network [115]. After that, a series enhanced

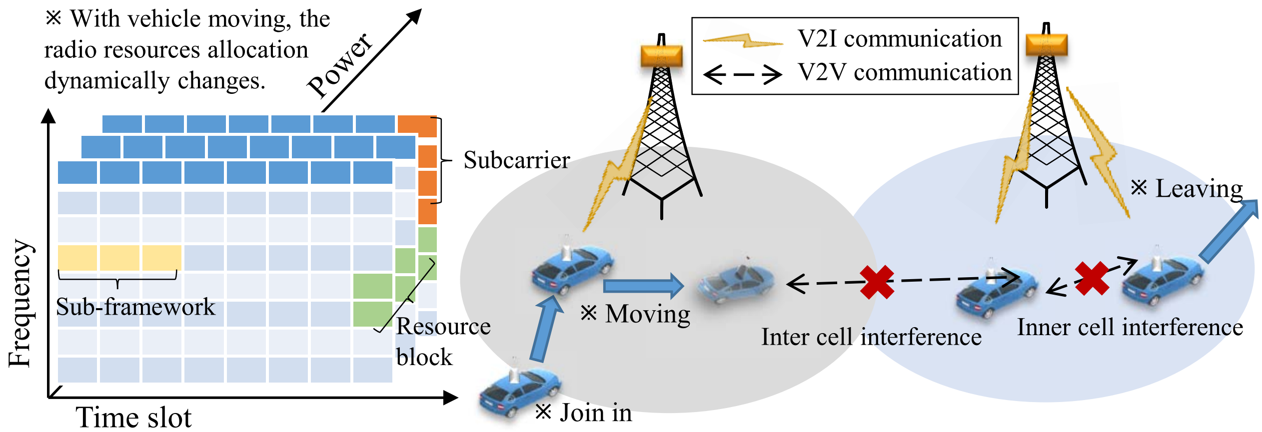


Fig. 6. Illustration of dynamic radio resource allocation in vehicular network.

routing protocols are proposed [116]–[120]. However, it is hard for the distributed routing based on local or neighboring information to reflecting the global state of large-scale vehicular network. Without the powerful correlation recovery ability, both the optimized delay (above 500ms) and throughput (less than 1Mbps) of the rule-based conventional methods do not reach the high demand of the future vehicular network as mentioned in the earlier section.

Network congestion control is a transmission manage strategy to avoid congestion and rebuild the packets transmission for improving network performance, which is widely researched in conventional wireless network [121]. The congestion control strategy is mainly designed in the network layer and can be either included or independent from routing protocol. Different form conventional wireless network, the special requirements of vehicular network such as road safety and road state monitoring demands frequent real-time messages (e.g., beacons/signaling) from vehicles [122]. Besides, the high dynamic and distributed topology of vehicular network cause both high beacons overhead for frequent information updating (causes long queuing time and channel resources wasted) and frequent routing path failure (causes problems such as acknowledgment (ACK) packets loss, hidden node uncovering and invalidation for contention window (CW) changing) [123]. How to adapt to the dynamic topology and control the large amount of beacons become two main challenges in vehicular network.To control the transmission congestion, many rule-based congestion control algorithms are proposed [124]–[129]. All of the above methods focus on detecting the congestion state using feedback messages, which is high-overhead and just reflects the current congestion state, however the traffic patterns and loads change frequently and may suddenly change in the next time slot in the highly dynamic vehicular network. Further more, the decisions of vehicles are highly affected by each other in distributed system. The accurate congestion prediction, multi-agent cooperation and beforehand intelligent transmission scheduling are highly desired for future vehicular network.

In summary, the most required abilities for future routing and congestion control for vehicular network are as follows.

1) The state prediction ability of the high mobility of vehicles,
2) Correlation recovery ability based on partial information in the large-scale network,
3) Distributed Cooperation and intelligent decision ability for heterogeneous network.

3) Vehicular Cloud Computing Challenge: The vehicular MEC brings new computing resources for edge users. However, limited by the power and embedded computing and network resource, there are two main challenges for MEC. The first one is the intelligent computing in MEC. Due to the high mobility of vehicular network, the communication cost and synchronization problem becomes big problem for deploying the intelligence in MEC. The second one is the computing and communication resource allocation problem in MEC. The vehicular MEC not process all computing nodes in centralized manner faces the difficulty of allocating resource precisely and dynamically in the high mobility and heterogeneous network.

4) Vehicular Security Challenge: The conventional data mining technologies such as association rules, auto regressive, and classification are widely used in the above researches for intrusion detection. The data mining algorithms for both misuse and anomaly detection in conventional networks mostly are achieved by defining the normal state from static training data. However, in the high dynamic vehicular network, the existing training data is not efficient for novel intrusions in the changing environment. Machine learning, famous for the dynamic adaption ability and significant fitting performance, is recently proposed to be the promising data mining tool for improving both the data encryption and intrusions detection performance in the vehicular network. In this paper, we in detail introduce the promising machine learning-based intrusion detection methods for the vehicular network in Section V-D.

III. Overview of Machine Learning Techniques

Machine learning (ML) is the promising technology to enable artificial intelligence. Depending on the different data entrance manners, the machine learning algorithms are divided into three categories: supervised learning,

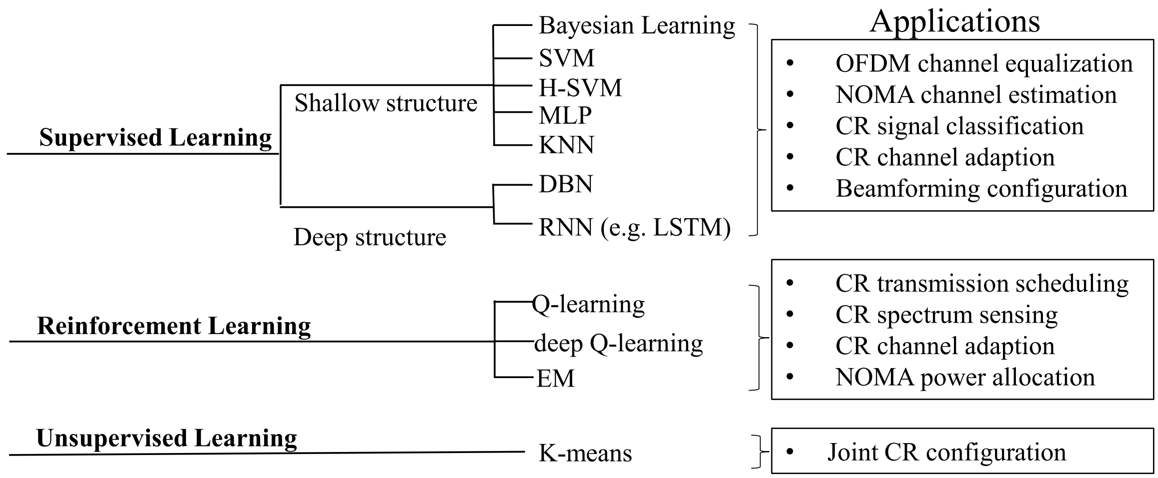


Fig. 7. Applications of machine learning in vehicular communication.

unsupervised learning and reinforcement learning. In this section, we give a preliminary of the three kinds of machine learning technologies respectively.

A. *Supervised Learning*

Supervised learning is the machine learning method that maps the relation from input to output based on labeled data constructed with determined input-output pairs. The supervised learning algorithms are designed for classification, regression and recognition tasks such as image classification, pattern recognition, surveillance, diagnostics and target tracking [12]. The novel applications of the corresponding machine learning technologies for vehicular networks are summarized in Fig. 7 of the next section.

The supervised learning is initially developed from 50 years ago, five classical machine learning algorithms: first Bayesian classifier, Logistic regression, Perceptron model, decision tree and K-Nearest Neighbor (KNN) algorithms are proposed in this period. However, both the convergence speed and scalability are big problems in those algorithms. In 1986, Rumelhart *et al.* first propose the classical back-propagation method to solve both the convergence and scalability problem in conventional machine learning algorithm [130]. Three years later, LeCun *et al.* propose the classical Convolutional Neural Network (CNN) to deal with the handwritten recognition task [131]. Besides CNN, two other classical algorithms: Super Vector Machine (SVM) [132] and Random Forests (RF) algorithm developed from decision tree are respectively proposed [133]. As we know, the classical CNN is famous in dealing with pattern recognition and image classification tasks. Another famous machine learning algorithm, Long Short-Term Memory (LSTM) proposed in 1997, is developed from Recurrent Neural Networks (RNN) which is widely used in time sequence recognition and prediction [134]. Also, the Gradient Boosted Decision Trees (GBDT) developed from decision tree is widely used for data mining and recommendation system [135].

In the early years, the machine learning is mostly sallow or tree framework. Such structure is hard to approximate the complex relations inner the high dimensional data. In 2006, Hinton and Salakhutdinov first propose the concept of Deep Learning (DL), which is a generative deep architecture designed to characterize the high-order correlation properties of the input data for synthesis purposes [136]. It is worth noting that because of the high computational complex and dimension curse in deep structure, the deep structure is hard to be employed in both academia and industry. Until 2012, benefited from the GPU accelerated computing system and new activation functions such as Relu and Softmax, the deep learning structures are proved to be the state-of-art machine learning technology in various areas [137]–[139]. A series of deep learning structures extended from CNN, Deep Belief Network (DBN) and RNN are widely proposed for solving problems in areas of computer vision, speech recognition, robotics, AI gaming, and networking [12]. Recently, some new deep supervised learning structures such as Deep Residual Network (ResNet) [140], capsule network [141], and Graph Neural Network (GNN) [142] are proposed and show outstanding performance comparing with traditional ones.

B. *Unsupervised Learning*

Unsupervised learning is one class of machine learning approach which train unlabeled data to model the probability density of them. The unsupervised learning is mainly used in data clustering and dimension reduction.

1) Clustering: Classical unsupervised learning clustering algorithms are initialized in 1960s. For clustering data by using unsupervised learning, the earliest concept of Hierarchical clustering (HC) is proposed which clusters data by measuring the dissimilarity between data sets and building a hierarchy of clusters [143]. As the most popular unsupervised learning algorithm, the partitioning based K-means algorithm is proposed in 1967 [144]. Then, the Expectation Maximization (EM) algorithm which is a model based clustering method is proposed in 1977 [145]. In 1995, Cheng proposes the density based clustering method called Mean Shift algorithm, which clusters data by shifting each data point to the average of data points in its neighborhood [146]. Besides, the grid-based methods (e.g., STING [147], CLIQUE [148]) and spectral clustering algorithm [149] emerge as the popular unsupervised clustering methods recently.

2) Dimensionality Reduction: Besides clustering, another main task for unsupervised learning is to reduce the dimension of input data. One of the main direction for dimensionality reduction is Principal Component Analysis (PCA), which is proposed one century ago and widely used in various areas. The initial PCA linear maps the data from high dimensional space to low dimensional space through constructed covariance matrix and eigenvectors. However, the linear mapping is hard to approximate complex functions [150]. Then, in [151], the kernel-PCA is proposed to approximate data in a nonlinear manner by using means of the kernel trick. Because of the local symmetries, considering each point can be approximately reconstructed by the linear combination of nearby points, the locally linear embedding (LLL) algorithm is proposed to reduce data dimensionality with linear reconstructions [152]. Another method, called Laplacian eigenmaps (LE), processes data dimensionality reduction by leveraging singular value decomposition for the Laplacian matrix of input data [153]. Some other unsupervised dimensionality reduction algorithms such as Locality preserving projections (lpp) [154], Isometric mapping (Isomap) [155], stochastic neighbor embedding (SNE) [156] and t-distributed Stochastic Neighbor Embedding (t-SNE) [157] are continuously proposed and become classical unsupervised learning methods for dimensionality reduction.

C. Reinforcement Learning

The supervised learning is an approximation method to build connection inner the labeled data, meanwhile the unsupervised learning is a method to model the probability density of unlabeled input data. However, in the real world, the artificial intelligence neither depends on labeled data nor unlabeled raw data. The normal case is that people do corresponding actions based on the reflection of previous temptations. The reinforcement learning (RL) is the kind of machine learning that imitates human behaviors, which trains the agents (people) do actions based on the cumulative reward (reflection from environment) of previous actions (temptations). To mathematically analyze the interaction between agents and environment, the Markov Decision Process (MDP) is proposed to model the state (i.e., environment) and actions transfer process [158]. The initial reinforcement learning is developed from the classical Dynamic Programming (DP) algorithm [159]. The early classical Temporal Differences (TD) based algorithms are proposed in 1980s [160], [161]. The most popular Q-learning developed from TD method is proposed in [162] which is an off-policy control algorithm. Besides TD method, one famous branch of reinforcement learning is Monte Carlo (MC) control method, which is used in the value network of AlphaGo [163].

Even the reinforcement learning is researched for centuries, the wide applications are emerged after the deep learning structure is combined in the reinforcement learning. Combining with deep neural structure and reinforcement learning, the concept of Deep Reinforcement Learning (DRL) is proposed in [164]. As a classical DRL algorithm, the value based double Q-learning enhanced from Q-learning shows significant performance in the game AI area [165]. Besides the value based method, the policy gradient based method is proposed in [166], which focuses on continuous policy updating instead of value matrix optimization. After that, the novel DRL algorithm involves the idea of both value updating and policy gradient referred to as Asynchronous Advantage Actor-Critic (A3C) algorithm is proposed [167]. The most recent breakthrough of DRL is the Proximal Policy Optimization (PPO) proposed by OpenAI lab in 2017, which is widely accepted as the state-of-art one in the game AI and intelligent control related area [168].

IV. Applications of Machine Learning in Vehicular Communications

The vehicular communication is generally defined as direct transmission process from physical layer to MAC layer. The machine learning is widely employed for physical and MAC layer communication intelligentization recently. In this part, we comprehensively review the applications of using machine learning in vehicular communication to address the challenges listed in Section II-B. All the related characteristics of surveyed works are listed in Fig. 7.

A. Machine Learning in OFDM

Channel estimation-based configuration of OFDM is widely researched in wireless network. As we mentioned in Section II-B, the OFDM for high mobility vehicular network requires ultra-low delay and high adaption ability which is hard to be configured with conventional methods. Recently, the machine learning is widely researched to enable intelligence in OFDM configuration. One direction of enabling machine learning in OFDM configuration is employing machine learning to improve the accuracy of channel estimation algorithm, and the other direction is directly using machine learning for adapting the configuration based on the changed environment.

1) Tutorial for Learning Based Equalization in OFDM: Before the review of related works, we give a tutorial and guideline on the machine learning based solutions for physical communication problem. The channel modulation and signal processing is always a big problem in wireless communication. In conventional methods, the Inter-Symbol Interference (ISI) is ideally assumed as certain linear or non-linear function, and the Feed Forward Equalizer (FFE), Continuous Time Linear Equalizer (CTLE) and Decision Feedback Equalizer (DFE) are jointly used to fit for the ideal ISI function. However, those assumptions and fitting methods limited degrees of freedom, which is hard to be used in the real environment as the real ISI is extremely complex and change rapidly [180].

To overcome the shortcomings, inspired by the pattern recognition technology, some researchers proposed that the machine learning technology can be used in signal detection to fit for the unmanageably complex channel environment and the classical problem of curse of dimensionality in signal processing can be solved with advanced deep learning architecture. The work flow of the machine learning based solution

TABLE II
THE DEEP LEARNING BASED OFDM CHANNEL ESTIMATION AND EQUALIZATION FOR VEHICULAR COMMUNICATION

learning type	Communication type	Learning structurte	Input&state	Output&action	Iterature
Supervised	V2I	DNN	Tranmited and received signal	CIR estimation	[169]
Supervised	V2I	LSTM	Historical CSI and estimated CSI	CSI prediction	[170]
Supervised	V2I	CNN-LSTM	Tranmited and received signal	CSI prediction	[171]
Supervised	V2I	CNN	Historical CSI and coordinates	CSI prediction	[172]
Supervised	V2V	LSTM	Inphase and quadrature samples	CSI prediction	[173]
Supervised	V2V	DNN	Tranmited and received signal	Channel equalisation	[174]
Supervised	V2X	DNN	Tranmited and received signal	CSI prediction	[175]
Supervised	C-V2X	CNN	Least-Squares channel matrix	Estimated channel matrix	[176]
Supervised	C-V2X	LSTM	Historical CSI	CSI prediction	[177]
Reinforcement	V2I	Q-Matrix	Normalized spectrum efficiency	Select the CIR predictor	[178]
Semi-supervised	V2V	DNN	Tranmited and received signal	Equalized data	[179]

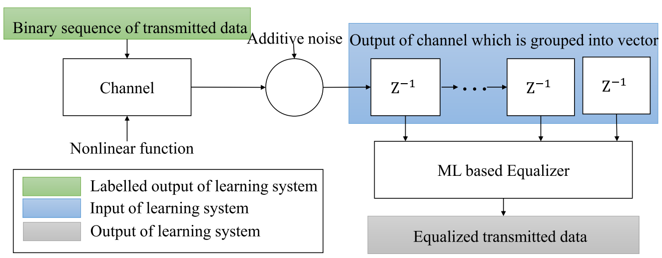


Fig. 8. The work flow of machine learning based signal equalization in vehicular communication.

is shown as in Fig. 8. Here, Z is the vector of variables need to be optimized, the equalized transmitted data is formatted as the input of the machine learning system, the received signal is formatted as the input which mixed with multiple signals and functioned with ISI [181]. The transmitted data (i.e., original and correct data) is formatted as binary vector as labeled output. the learning system is continuously fine-turned to optimize Z for minimizing the gap between the output and labeled output. Such kind of learning process can be modeled as an optimum classifier with the Bayesian maximum likelihood process [180].

2) Shallow Machine Learning for Channel Prediction and Equalization: With both the machine learning technology and computation ability developing, the learning system and training data formatting method evolute step by step. Before the deep learning is emerged as the powerful machine learning tool, the conventional shallow machine learning structures such as supervised multilayer perceptron (MLP), SVM and Sparse Bayesian Learning (SBL) are commonly used. For complex channel equalization, Chen *et al.* first employ supervised MLP to decode and reconstructing the transmitted symbols [181]. Sebald and Bucklew employ machine learning to address the nonlinear equalization problem in wireless network by using SVM to extract the temporal correlation in collected intersymbol interference (ISI) data [180]. In the vehicular network, the MIMO with multiple antennas are widely employed, the mixed noises in such complex environment should be considered. Further considering the space diversity in multi-path transmission process, the authors in [182] propose SVM based multi-regression algorithm to estimate channel states in MIMO environment for optimal OFDM configuration. Also considering the SVM for channel estimation, Feng and Chang proposes a Parallel Hierarchical Support Vector Machines (H-SVM) based parameters determination algorithm for MIMO channel configuration [183]. The above works show the significant performance improvement of machine learning based OFDM configuration than conventional methods such as minimum mean square error (MMSE) based algorithm [32] and maximum likelihood based algorithms [33]. The SVM based estimation can achieve good performance always depends on the assumption of slow fading and ideal ISI conditions, which is not practical in the real high dynamic vehicular network. Therefore, some other machine learning techniques are explored for the OFDM configuration problem. With experiments, Wen *et al.* claim that the link signal in MIMO system is approximately sparse, and the promising Gaussian-Mixture Bayesian Learning is exploited to estimate the channel conditions. The simulation shows that both the channel estimation accuracy and achievable rates of Bayesian Learning based algorithm is much better than conventional methods [184]. Also depending on the sparse feature of signal, the authors in [39], [185] exploit SBL to estimate the OFDM channel condition by modeling the channel with sparse non-zero components. Then, the authors of [186] compare the sparse recovery algorithms for channel estimation considering the similar sparse channel model of OFDM in the underwater environment.

3) Deep Learning for Data Detection and Channel Prediction: The above methods all depends on the assumption that the specific channel model is given. Although the widely used BEM channel model in vehicular network is proved to be a good approximation to the high dynamic environment, in the high dynamic vehicular network, with the high frequency mmWave and high mobility in the high density environment, the channel condition becomes more complex and hard to be modeled by a specific channel model. Furthermore, compared with the conventional quasi-stationery communication system, the vehicular communication faces the fast-varying channel problem with considering the large Doppler effort of vehicles.

Recently, as shown in Table II, the deep learning is proposed as the powerful prediction and configuration tool to overcome the high dynamic changing signal problem in vehicular network [169], [173], [187]. Li *et al.* uses the deep learning to solve the channel impulse response (CIR) prediction problem of dynamic V2I connection where the infrastructure is fixed but the vehicle is moving with high speed [169]. Addition to the historical channel information used in quasi-stationery communication, the vehicle information including position and velocity are characterized as the training date in the deep learning system. The DNN is used in this proposal, which shows higher prediction accuracy from the conventional prediction method. Kim *et al.*, proposes a LSTM based channel tracking algorithm for V2I communication [174]. Yang *et al.* further characterize the signal as a 2-dimensional matrix input and propose a learning structure combined with CNN and LSTM to predict the channel state [171]. The authors in [172] further assuming the 3D scenario of V2I connection and propose a CNN based channel prediction algorithm.

The above works consider the V2I connection which one end of the connection is a fixed station. Some other researchers work on the OFDM channel prediction of V2V connections. The authors in [173] conduct a deep learning based CSI prediction with collecting the wave communication dataset from real V2V driving scenarios. Kim *et al.*, propose that the DNN can be efficient to the both channel equalisation and symbol detection in V2V connections [174]. Then, the deep learning based data detection and channel prediction is further expended to the V2X connections. Sattiraju *et al.*, propose a deep learning based channel prediction algorithm which outputs the channel matrix over different Signal to Noise Ratio (SNR) points [176]. To further reduce the receiver complexity, the authors in [175] propose a data-pilot aided deep learning based V2X channel estimation algorithm. Liu *et al.*, propose a LSTM based channel prediction algorithm under the Raleigh fading channel condition [177].

4) Deep Learning for OFDM Configuration: Furthermore, OFDM configuration based on the estimated channel condition is time consuming and resource wasted. Therefore, some researchers propose that the machine learning especially deep learning can be used to integrate and accelerate the configuration of whole communication process [188]. Daniels *et al.* exploit the KNN to adaptively configure OFDM for intelligent modulation, bit interleaving and coding. In this paper, the proposal is model-free and can adapt the OFDM configuration in one slot to accelerate the whole communication process. Also consider model-free approach, Daniels *et al.* propose a KNN based adaptive OFDMA configuration for multi-radio access [189]. Considering the OFDM connection state is dynaic changing in vehicular network, the authors in [179] propose a integrated channel estimator and equalizer to adaptively configure OFDM. By jointly considering the integrated design of channel prediction, beamforming and configuration for V2I communications, the authors in [178] propose a reinforcement learning based adaptive OFDM configuration system without using pilot signals. To improve the performance of model-free based OFDM configuration, Ye *et al.* propose a DBN based deep learning algorithm for channel estimation and signal detection [40]. Then, Felix *et al.* propose that the deep learning can be employed to replace conventional signal processing blocks to accelerate the OFDM adaptive configuration [190].

B. Machine Learning in CR

CR is the intelligent adaption tool in wireless system to aware and learn from environment, which is widely researched for efficient vehicular spectrum sensing and quick communication [191]. In vehicular network, the complexity of environment is extremely high due to the high mobility and heterogeneous structure of vehicular network. In such complex scenario, several Interrelated influence factors such as transmit power, sensing policy, coding scheme, sensing algorithm, modulation scheme, and communication protocol need to be adjusted simultaneously. The simple formulas is hard to model those parameters simultaneously [192]. Furthermore, The precise information such as vehicles' positions and out-of-band measurements is important for CR configuration in vehicles network. However, the information is hard to be accurately collected in the high mobility network. To adapt to the complex environment and configure the CR process for simultaneously, the machine learning is proposed to be the potential solution for helping CR configuration in vehicular network.

The spectrum sensing is the basic of CR system, in [193], the authors propose a Bayesian Learning based adaptive algorithm to set up the cooperation relationship between local nodes. In this approach, the adaptive learning is used to find the optimal decision threshold, which can be treated as the classification problem with supervised learning. The supervised learning algorithms are widely used in CR for task classification such as SVM for signal classification [194]. Mendis *et al.* proposes a supervised DBN neural network for automated modulation classification for cognitive radio [195]. Also by modeling the parameter setting as classification problem, the machine learning of MLP is used for data transmission parameters optimization in paper [196]. Compared with conventional CR system, one advantage of CR in vehicular network is the predictability of the vehicle trajectory along the road. The authors in [197] propose a Bayesian learning based spectrum prediction algorithm for CR in vehicular network.

The CR configuration is complex in high dynamic vehicular network. The simple classification is not efficient for the quick decision when the environment is dynamic changing. Furthermore, the above approaches model the CR configuration with fixed number of parameters which is not practical in the real word. For considering a model-free approach, Galindo-Serrano and Giupponi consider the channel and interference as a black box, and model the channel adaption and environment changing as MDP [198]. In this paper, the Q-learning method is proposed to adaptively schedule CR parameters by solving the modeled MDP problem in an online manner. For further considering the transfer policy in MDP is unknown, Choi and Hossain model the CR system as a Hidden Markov Model (HMM) and propose an expectation-maximization (EM) algorithm to estimate the primary user parameters in the learning part of cognition cycle [199]. In 2016, Assra *et al.* e.g., further exploit EM algorithm to cooperatively detect spectrum in multi-antenna CR network [200]. Recently, the deep structure of machine learning (i.e., deep learning) is proved to be the powerful tool in various areas including being employed in CR configuration. Zhu *et al.* employ the deep Q-learning for solving the HMM based transmission scheduling of CR [201]. Further considering the variety of V2I and V2V connections, Zhang *et al.*, propose a deep Q-learning based adaptive data transmission algorithm for CR based vehicular communications [202]. Considering the road segments can be clustered to cooperative sensing, the authors in [203] propose a tri-agent reinforcement learning based spectrum sensing algorithm.

The above researches all focus on using supervised or reinforcement learning to optimize one aspect in CR. In [204], Thilina *et al.* jointly consider the supervised and unsupervised learning in CR system. In this paper, the unsupervised learning of K-means algorithm is used to cluster the channel features, and the supervised learning of SVM and KNN is used to approximate the relation function between channel vectors and separating hyperplane.

C. Machine Learning in Beamforming

The complex environment of heterogeneous vehicular network leads to distorted wireless conditions, which is hard to be model with simple mathematical formulas. In the radio access system of vehicular network, the machine learning is widely used as model-free tool to address the problem of beamformer design, beam alignment, and adaptive configuration. Ramon *et al.* model the beamformer design problem as a complex value constrained optimization problem [205]. By using SVM, the authors approximate the optimal value with continuous value iterations to accelerate convergence speed of the beamforming. In [206], the authors also model the beamforming configuration process as a variance minimization problem. Such nonlinear problem is NP-hard and hard to be solved with conventional algorithm. Thus, an SVM based learning algorithm is proposed to configure the array beamforming intelligently. However, all the above proposals are depending on ideal assumptions of that the noise is modeled with specific known function. Furthermore, the high dynamic of vehicular network is not fully considered.

To address the high dynamic of vehicular communications, the authors propose a machine learning based recommendation algorithm to classify and rank the beam pairs, the vehicles choose the corresponding beam pair based on the beam class [207]. Yang *et al.* propose a shallow SVM based beam selection algorithm and analyze the beam convergence of the proposal [208]. Those methods based on the vehicle information and network state may ignore the important features caused by high mobility of vehicles. The work in [209] shows that the coarse user location could be considered to enhance the beam selection performance. By sensing changing environment to collect coarse user location, an online learning algorithm is proposed to improve both network performance and communication stability. Gui *et al.*, further improve the location based beam selection algorithm by considering the location conflict [210].

However, the shallow machine learning is not efficient when the network is large size and with complex channel states [55]. The authors in [55], propose a deep learning based optimal beam selection algorithm for high dynamic V2I communications in 5G vehicular network. In this paper, shallow machine learning and deep learning techniques with both supervised and reinforcement manner are explored for beam selection problem. The simulation shows that the deep learning shows better accuracy and convergence performance than shallow machine learning based approaches. After this, Alkhateeb *et al.* propose a deep learning coordinated beamforming method to improve both the coverage and latency in high mobility wireless network [211]. Echigo *et al.*, propose a CNN based beam quality prediction and selection algorithm [212]. Above proposals focus on the beam for vehicles but laks consideration of pedestrian. The work in [213] takes the pedestrian equipped with handset into consideration and propose a pedestrian position and orientation aided DNN based beamforming algorithm.

The supervised learning provides powerful classification and estimation ability for beam selection. Some other researchers assume that the beam selection can be scheduled with reinforcement learning in online manner automatically. Van Huynh *et al.*, model the beam selection as a semi-MDP problem and propose a parallel Q-learning based beam selection algorithm [214]. The simulation demonstrate that the disconnection time can be continuously reduced with the reinforcement learning online processing. Then, a improved deep reinforcement learning based beam tracking algorithm is proposed in [214]. Besides direct beam connection, to expand the beam coverage, Zhang *et al.*, assume a scenario using tunable reflectors to expand the alternative indirect line-of-sight (LOS) links for vehicles behind the blockages, and propose a deep Q-learning based adaptive beam and reflector configuration algorithm [215].

D. Machine Learning in NOMA

For better utilization of spectrum, the NOMA is widely researched in the wireless communication system. However, the NOMA algorithms designed for conventional wireless network is limited of the high computational complexity and high dependency on the stable channel condition. The problems in OFDM are also exist in the NOMA technology. Furthermore, the high mobility of vehicle derives the sharply changing wireless channel, which requires extremely short process time and changing channel adapting ability. For conquering above challenges, the deep learning based intelligent NOMA system is proposed.

1) ML for Data Detection and Channel Estimation: The authors in [61] model the user data detection problem in NOMA as a nonlinear mapping problem. To solve the nonlinear mapping problem, an LSTM based approximation algorithm is proposed to accelerate the NOMA process. The main idea of the proposal is using deep learning to extract the spatial-temporal correlation between the detected signals and frequently changing channel states. By considering the sparse features of the signals, the authors in [216] propose an SBL based user detection and channel estimation sparse code multiple access (SCMA) system. Besides, Kim *et al.* propose a DBN based channel configuration algorithm to accelerate SCMA and minimize the transmission bite error rate (BER) in high density network [217].

2) ML for Resource Allocation in NOMA: Besides the supervised learning based approaches for data detection and channel estimation, the reinforcement learning is being widely applied for NOMA joint resource allocation in vehicular network. In [60], Xiao *et al.* propose an intelligent power allocation algorithm in NOMA to avoid potential congestion and jamming attacks. Xu *et al.*, model the NOMA resource allocation as a mixed-integer nonlinear programming (MINLP) problem, and propose a multi-agent reinforcement learning to dynamically allocate sub-channels [218]. Some other authors considering the high mobility of vehicles and model the NOMA resource allocation problem as a decentralized Discrete-time and Finite-state Markov Decision Process (DFMDP) [219]. In this paper, the Deep Deterministic Policy Gradient (DDPG) algorithm is employed to maximize the sum-rate of V2I communications and guarantee the communication latency and stability of V2V connections. However, the previous works all focus on the information in physical layer and ignore the end-to-end QoS requirement.To minimize end-to-end delay while satisfying other QoS requirements, Ding and Leung, propose a cross-layer packets delay-aware resource allocation algorithm in [220].

V. Applications of Machine Learning in Vehicular Networking

The networking process in the vehicular network including radio resource assignment, transmit scheduling, transmit power control, traffic offloading, dynamic routing and computing association all can be optimized with promising machine learning technologies. In this part, we survey the applications of machine learning for the above networking functions respectively. Most of the surveyed papers are published recently, which may reveal a research trend.

A. Machine Learning in Resource Allocation

The solutions for resource allocation are widely researched in conventional networks. However, there are strict constraints of the high dynamic vehicular network as mentioned in Section II-D1. To satisfy the specific requirement of vehicular network of fast decision making, estimation and recovering ability based on incomplete information and adaptivity for changing environment, the machine learning based dynamic resources allocation algorithms which are with high adaptivity and self-learning ability are widely investigated recently. The used machine learning algorithms of surveyed papers are listed in Table III.

Why the machine learning is efficient for solving resource allocation problem? The existing resource allocation algorithm for wireless network is commonly categorized into two types, one is fixed assignment based scheme and the other is dynamic scheduling based scheme. The fixed schemes such as [221], [222] is suitable for the network with simple network with fixed topology, which is not satisfy the high dynamic of vehicular network. Such dynamic environment require dynamic scheduling based resource allocation scheme, many dynamic resource allocation algorithm based on greedy algorithm, game theory and graph theory are proposed. However, as mentioned in Section II-D1, the conventional algorithm faces three main challenges, the convergence speed, communication cost and adaptability for sharply changing states. The machine learning based solutions show significant improvement on convergence speed, communication cost and adaptability than conventional algorithms. For example, the supervised learning algorithm such as neural network used for dynamic channel assignment can reduce convergence time and saving communication cost [222]. Because it is impossible to find the exact optimal solution for channel allocation problem which is considered as a NP-complete problem. The machine learning is shown to be the novel solution to approximate the optimum with fast convergence speed. The network state including historical traffic patterns and channel conditions are recorded as input and the labeled date with indexes of assigned channels are formatted as output. Then, the neural network is activated to fine-turn the wights of neural cells and finally approximate a polynomial function to map the relation between input and output. The detailed mathematical model can be found in the papers [222], [223].

In the next part, we introduce proposals for resource allocation in vehicular network to solve different problems with different types of machine learning techniques. The corresponding scenario, advantage and disadvantages for each algorithm are simply summarized.

1) Reinforcement Learning Based Prediction and Intelligent Decision in Resource Allocation: The resource allocation decision based on accurate future state prediction is of cause more efficient than the allocation based on current state. The most difficult point is how to make the prediction accurate especially when the network environment is highly dynamic. The conventional model based prediction methods shows limitation in scenarios with high mobility [224], [225], [225]. For dynamic environment, the reinforcement learning based prediction is firstly explored for dynamic channel resource allocation from 20 years ago [224]. With the high prediction and adaptation ability, the model-free reinforcement learning is efficient for improving the model adaptability for state changing scenarios, and is naturally considered to be the potential tool for high dynamic resource allocation in vehicular network. For example, in the classical radio resource allocation problem in vehicular network, researchers consider multiple criteria including channel interference and traffic conditions as constrains to model the joint channel resources allocation problem. As such joint objective optimization problem with changing state in most cases is NP-hard and difficult to be solved, the value iteration based reinforcement learning is widely considered as the solution to predict future state and approximate the optimal option.

Following the above problem modeling and solving method, in [225], the authors propose a dynamic channel allocation mechanism by considering energy consumption in VANET. In the proposal, a simple machine learning technology called as learning automata (LA) is used to record the reusability of channel resources and dynamically assign the channel to links according to the recorded reusability and energy consumption level. The LA select their current action based on past experiences from the environment which can be treated as one simple kind of reinforcement learning. However, the policy iterators of LA is not so efficient in the scenario of continuously changing state space such as heterogeneous vehicular network. Thus,

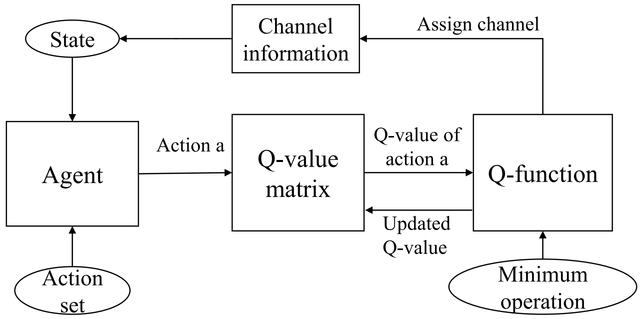


Fig. 9. The Q-learning based dynamic radio resource allocation.

the classical reinforcement learning algorithm referred as Q-learning is employed. As shown in Fig. 9, the reinforcement learning (e.g., Q-learning) based channel resources allocation process is dynamic collect changing states of nodes and collect reflection (i.e., reward) from changing environment (i.e., network states). Based on current states and reflected reward, the nodes change resource allocation strategy to maximize reward continuously. Such prediction and reward based solution is widely exploit in related joint optimization problems in dynamic network. However, due to the constrain of poor computation power and complicity of deeper learning structure, the machine learning based resource allocation mechanisms do not attract many attentions until the advanced deep learning algorithms are widely deployed with powerful computers. With deep structure, the deep reinforcement learning can be adopted in complex and high dynamic environment of generation vehicular networks. The authors in [226], [227] jointly consider radio, caching and computing resources allocation in vehicular network, an SDN and ICN based global multiple tasks targeted joint resource allocation algorithm is proposed. Comparing with conventional algorithms, the proposal with Q-learning to predict future state can avoid potential collision, and the cache utility is improved with constrained computation cost. Also considering the multi-targets optimization problem in large scale dynamic network, Nie and Haykin proposed a Q-learning based dynamic channel assignment algorithm [224].

Besides radio resource, the authors in [228] consider power allocation problem in cooperative sensing vehicular network. In this paper, a Q-learning based mobile crowd-sensing strategy is proposed for efficient power control in high mobility vehicular network. The authors modeled the crowd-sensing problem as a game, the Q-learning is proved of fast convergence to make the game reach Nash equilibrium. Also considering power resource allocation, Atallah *et al.* propose a energy-efficient radio resource scheduling algorithm for V2I down-link scheduling in vehicular network [229]. With the reinforcement learning, the proposal results in 50% performance improvement comparing with state-of-art heuristic algorithm in terms of the percentage of vehicles departing with incomplete service requests. Instead of simple down-link scheduling, Zhou *et al.* propose that the reinforcement learning can be employed for dynamic full-Duplex TDD channel resource allocation for both Up/Down-link scheduling [230]. With simulation, the proposal shows almost 30% performance improvement in terms of global throughput and packets loss rate than heuristic algorithms. To further improve the TDD configuration and adapt to more complex heterogeneous network, the paper of [231] further proposed deep Q-learning to deal with the high mobility environment. In addition, the authors in [232] jointly consider channel and power resources and propose a deep reinforcement learning based algorithm for V2V communications in 5G vehicular network. Besides ground vehicles, Kawamoto *et al.* study the resource allocation problem between high dynamic UAVs and a Q-learning based efficient resource allocation algorithm is proposed [233], which improves completion time of communication demand comparing with conventional algorithm. The authors in paper [234] considering the energy resource allocation problem in vehicular network, and propose deep reinforcement learning based joint energy allocation and routing algorithm. In the proposal, a LSTM is employed to predict the traffic patterns and iteratively fine-tuned with reinforcement learning.

2) Supervised Learning Based Information Recovery, Prediction and Convergence Acceleration in Resource Allocation: The deep reinforcement learning is widely used for joint targets optimization in resource allocation, the supervised learning is usually used for information recovery, prediction and quick resource assignment. Instead of leveraging reinforcement learning to improve adaptability based on the calculated rewards, the supervised learning is widely used to recovery the incomplete information of network and accelerate resource allocation process based on the labeled data (predicted state or recovered information). Due to the high mobility of vehicular network, both the traffic patterns and the channel interferences are high dynamic changing, the conventional resource allocation based on fixed rule or game theory mainly based on the actions information collected from other users, which makes the resource allocation time and signaling cost. The supervised radio assignment algorithm can accelerate the convergence speed of joint resource optimization problem just based on local/incomplete information and reduce signaling overhead. Although the initial works commonly propose the supervised learning based resource allocation algorithms into three optimization objectives of information recovery, state prediction and allocation acceleration [235], [236]. In the recent works, most researchers consider combing different structures of machine learning algorithm to jointly address incomplete information based state prediction and allocation acceleration problem [223].

In [223], the CNN and DBN are proposed to jointly predict the bursty traffic and assign channels to links adaptively. In the proposed algorithm, the first CNN part is used to continuously predict the future traffic load level by extracting features from traffic patterns. Then, the DBN structure which is offline pre-trained with the existing dataset is employed after the CNN part to intelligently assign channels. The full intelligent channel assignment process and the enhanced algorithms are introduced in [237], [238]. The deep learning structure can predict future traffic and channel state based on incomplete information and assign the optimal channel to avoid potential congestion. Also consider DNN, Gao *et al.* employ DNN

TABLE III
THE APPLICATIONS OF USING ML FOR VEHICULAR NETWORK RESOURCE ALLOCATION

ML type	Depth of the ML structure	Problem	ML method	Improvement	paper
Reinforcement learning	shallow	Dynamic radio resource allocation	LA	Packets loss rate, blocking probability, hand-off latency and energy consumption	[225]
Reinforcement learning	shallow	Dynamic radio resource allocation	Q-learning	Call blocking probability	[224]
Reinforcement learning	deep	Multiple tasks joint optimization	Deep Q-learning	Utility of cache	[226], [227]
Reinforcement learning	shallow	Radio resource allocation	Q-learning	Completion time of communication demand	[233]
Reinforcement learning	deep	Power allocation	deep Q-learning	Energy comsuption and sensing utility	[228]
Reinforcement learning	deep	Energy-efficient radio resource scheduling	Deep Q-learning	Capacity of links	[232]
Reinforcement learning	shallow	Energy-constrained downlink scheduling	Q-learning	Network throughput	[229]
Reinforcement learning	shallow	TDD Radio Resource Control	Q-learning	Network throughput and packets loss rate	[230]
Reinforcement learning	deep	TDD Radio Resource Control	Deep Q-learning	Network throughput and packets loss rate	[231]
Reinforcement learning	deep	Energy allocation and routing	Deep Q-learning	energy efficiency and packets loss	[234]
Supervised learning	deep	Traffic prediction and channel assignment	CNN,DBN	Network throughput and packets loss rate	[223], [237], [238]
Supervised learning	deep	Power allocation	DNN	CDF and PDF	[235]
Supervised learning	deep	Joint power and radio resource allocation	CNN	CDF	[236]
Supervised learning	deep	Radio resource allocation	LSTM	Prediction accuracy and training loss	[239]
Supervised learning	deep	Predict channel and avoid packet collisions	LSTM	Packet reception percentage	[240]
Supervised learning	deep	Joint power and radio resource allocation	LSTM	Transmission delay and energy consumption	[241]

to allocate optimal transmit power for maximizing the overall system throughput in the V2X communication system [235]. The simulation shows that the machine learning based solution can significantly improve the cumulative distribution function (CDF) and probability density function (PDF) comparing with the conventional minimum mean square error (MMSE) based method. Besides, the authors in [236] consider CNN as the extractor to decompose the joint power and spectrum allocation problem into a classification sub-problem and a regression sub-problem, which can be solved in much less run-time and resources consumption. The CDF is further improved with the proposed CNN comparing with the DNN learning structure. However, due the importance is not equal to traffic patterns in the time sequence, the structure such as CNN considering translation invariance may not suitable for the kind of traffic patterns which highly dependents on time correlation. The time-series data-oriented LSTM which is good at solving the vanishing gradient problem is considered for intelligent vehicular resource allocation. In [239], the authors proposed the LSTM based resource allocation algorithm for the V2V and V2I communications in the vehicular network. The comparison of the resource allocation algorithm leveraging previous DNN, CNN and the proposed LSTM is processed, the result shows that the LSTM based solution outperforms DNN and CNN in terms of prediction accuracy and training loss. Due to the good prediction performance of LSTM, Khan *et al.* further propose an LSTM aided application scheduler for channel prediction and radio resource allocation [240]. The authors analyze the resource allocation performance with different transmitter and receiver distance. Also employing LSTM, Fu *et al.* predict the traffic pattern and propose a joint power and radio resource allocation algorithm [241]. And the authors compare the performance of LSTM based algorithm with conventional (RMSE) and root mean absolute error (MAPE) based solutions in terms of transmission delay and energy consumption.

In summary, the machine learning methods are recently (those two years) widely exploited in dynamic resource allocation in the vehicular network. We surveyed the resource allocation problems and corresponding machine learning solutions and compared the employed machine learning technology and performance improvement respectively as shown in Table III. Both supervised learning and reinforcement learning are studied for fast decision making, estimation, recovering and adaption of resource allocation in high dynamic vehicular networks, and which may attract more attention in the next few years.

B. Machine Learning in Network Traffic Control

The mobility of vehicle significantly affects both the communication connectivity and routing scheduling in vehicular network. Recently, the machine learning is employed to improve mobility prediction, efficient connection, dynamic

TABLE IV
THE APPLICATIONS OF USING ML FOR VEHICULAR NETWORK TRAFFIC CONTROL

Solved Problem	ML type	Depth	Structure	Paper
Mobility prediction	Supervised learning	shallow	ANN	[243]
		deep	DNN	[245]
		deep	DNN	[251]
		deep	SAEs	[246]
Network flow prediction		shallow	MODWT	[252]
		shallow	SVM	[255]
		deep	CNN	[253]
Dynamic routing		shallow	ANN	[256]
		deep	CNN	[71]
		deep	CNN	[257]
	reinforcement learning	deep	deep Q-learning	[258]
		shallow	Q-learning	[259]
		shallow	Q-learning	[260]
		shallow	CRL	[261]
		shallow	PHC	[262]
Congestion control	unsupervised learning	shallow	K-means	[263]
Vehicles clustering and routing		shallow	K-means	[264]
		deep	AKHM	[265]
		deep	Hebb neural network	[266]

routing, quick handoff and potential congestion avoidance for vehicular network intelligent traffic control. We summarize the proposals as in Table IV, and detailedly survey those proposals by classifying them depending on different tasks.

1) Supervised Machine Learning for Dynamic Routing: The powerful function approximation ability makes the supervised machine learning efficient for information recovering in spectrum and space domain and state prediction in time domain. Based on the different prediction or information recovering methods, we introduce the supervised machine learning based dynamic routing approaches respectively.

- *Vehicle Mobility Prediction Based Mobile Routing:* The built connections and routing paths may frequently be broken due to the high vehicle mobility. To establish and maintain end-to-end connections in vehicular networks, involving the vehicle mobility and vehicular traffic change trends into dynamic routing problem in vehicular network is an essential solution. In [242], considering the vehicular traffic is dynamic changing, to stable network connectivity and improve network performance, an innovative machine learning based Poisson Dependency Networks (PDNs) is proposed to predict future road traffic flow and build the relation between the future traffic and cellular connectivity. Tang *et al.* propose an SDN centralized dynamic routing scheme which involves mobility prediction as the foundation of routing scheduling [243]. In the approach, both the roadside units (RSUs) and moving vehicles are considered as the switches. The time to time traffic information is integrated to the SDN central controller, based on the collected information, the SDN controller predicts the traffic flow with two layers of Artificial neural network (ANN) and computes optimal routing paths for all switches. In the above researches, the vehicles are considered as entire traffic flow, instead of that, Lai *et al.* granulate the vehicles and study the movement of the individual vehicle. By considering the moving vehicles and static RSUs as the relay nodes, the machine learning based routing method is proposed. However, what machine learning structure and training method are not mentioned in this paper. Location information is critical of the mobility prediction, the work [244] employs machine learning based proximation algorithm for location verification in the vehicular network. Above prediction algorithms are all based on shallow machine learning structure, in [245] the authors prove that the deep learning architecture such as DBN, RNN can achieve close to 5% improvements for traffic flow prediction compared with shallow structures. A novel deep learning structure called stacked autoencoders (SAEs) is employed in [246] to predict traffic flow, in which both the spatial and temporal correlations are inherently considered. Also considering the spatio-temporal correlation, the deep CNN which is proved as the efficient image recognition tool is proposed to predict the road traffic situation in [247]. In this proposal, two CNNs are jointly used. After traffic prediction, The authors further formulate the load balancing problem between vehicles as a nonlinear programming (NLP) and propose an additional CNN system to approximate the NLP optimization adaptively when traffic changes.
- *Network Traffic Flow Prediction Based Routing:* The road traffic prediction is normally used in the dynamic topology to adaptively choose relay nodes and routing paths. However, most of the traffic prediction methods are based on the globe information such vehicle locations, speed, and distances, which is not invalid in many scenarios. Furthermore, the routing process after the road traffic is predicted is time consuming, and sometimes leads to delayed decision. In order to make the real-time decision in high dynamic environment, the network traffic flow prediction based routing algorithms are proposed. A network traffic flow is

defined to be a sequence of data packets, which share the same context between source-destination pairs that include Transport Control Protocol (TCP) connections, media stream, and so forth. Considering the temporal collection of network traffic flow, a large amount of time series based traffic flow prediction algorithms are proposed for decades. In [248], the authors survey a bunch of time-series models for the Internet traffic and indicate the traffic flow forecasting has potential application in network traffic control and dynamic resource allocation. Feng *et al.* analyze the prediction accuracy and computational complexity between machine learning based traffic predictors (e.g., ANN) and conventional methods such as Autoregressive integrated moving average (ARIMA) [249], FARIMA [250]. In this paper, the authors compare the performances of those prediction methods by simulating under four wireless network traffic traces and decide the most suitable network traffic predictor based on acceptable performance and accuracy [251]. To enhance the generalization ability of finite-impulse-response (FIR), Alarcon-Aquino and Barria propose a neural network based learning algorithm using the maximal overlap discrete wavelet transform (MODWT) to predict the network traffic flow [252]. However, above traffic flow prediction all based on temporal sequence and missed the spatial connection between traffic flows. Lopez-Martin *et al.* show that the CNN structure is good at extracting the spatio-temporal features from the formatted traffic patterns, and is easy to be extended to network traffic classifier in an easy and natural way [253]. The study also analyzes the impact of the features chosen and the length of the network flows used for training. In our earlier research, a joint CNN and DBN based network traffic prediction and routing algorithm is proposed [254]. In the proposal, the whole algorithm is divided into two parts: the deep CNN is used to construct the award prediction network while the deep DBN constructs the action decision network. The simulation shows the CNN based algorithm achieves improved network performance in terms of packets loss rate and throughput in contrast with those in the conventional routing method.

- *Network Traffic Control in Hybrid Vehicular Network:* As the structure of future vehicular network is heterogeneous, routing between various technologies and nodes becomes a big challenge. In [255], considering the complexity of vehicular network, the authors propose a joint prediction algorithm by considering both transmission rate and vehicle to RSU distance. In the prediction algorithm, the SVM is used to estimate the probability of succcessful receptions, then the prediction based routing strategy is proposed. The simulation in a mimic CSMA-DSRC based vehicular network shows that the proposal can significantly improve network throughput. For considering more complex structure, one of our previous research gives a proof-of-concept that the machine learning assisted traffic control algorithm can improve the network performance in the highly heterogeneous SAGIN network [71].
- *Correlation Recovering Based Network Traffic Control:* In heterogeneous vehicular network, the control system is hard to be deployed in centralized as globe controller. Thus, the distributed or semi-centralized controller need to make a decision based on complicated information. Therefore, to increase decision accuracy and saving signaling overhead, the correlation recovering based network traffic control methods with machine learning are proposed recently. In our previous work, a deep learning based intelligent routing algorithm is proposed to calculate routing paths just based on information of edge regions [267]. In this algorithm, the DBN structure is employed to recover routing information from historical traffic patterns and correspondingly estimate the traffic situation of the whole network. To further improve the route computing performance, the GPU-accelerated deep learning based routing is further proposed for dynamic network [268], [269], and a spatial-temporal value network aided deep learning based traffic control algorithm is proposed for large scale heterogeneous network [270]. Besides recovering incomplete data, deep learning is also good at recovering related information from mixed data filled with redundant information. The collected information form network is complex which is filled with parameters such as spatial distribution pattern, node density and wireless channel conditions, to extract the critical parameters for optimal traffic decision is difficult by using conventional Heuristic methods. naturally, the powerful machine learning is proposed as the extractor to understand the correlation and make quick decision in vehicular networks. In [256], the authors exploit machine learning for multi-hop broadcast fast decision in vehicular networks. For extracting the correlation from social attributes and mobility parametors of vehicles, Gulati *et al.* propose a deep learning based scheme vehicular packets dissemination strategy. In the proposal, the multi-layer CNN is employed for extracting correlations and the gradient descent algorithm is used to approximate the optimal packets dissemination strategy [271].

2) Reinforcement Learning for Dynamic Traffic Control:

- *Reinforcement Learning for Distributed Dynamic Routing:* Conventional routing optimization algorithms require either prior knowledge or centrally managed real-time knowledge of the whole environment, which are not viable in dynamic networks where topology, resource, and node availability are subject to frequent and unpredictable change [261]. In order to deal with the routing problem in dynamic network, In early 1994, Boyan and Littman analyze the feasibility of leveraging reinforcement learning for adaptive packet routing decision in dynamically changing network [260]. Then, series researches about reinforcement learning based dynamic routing emerges. Zeng *et al.* consider the routing problem in vehicle delay tolerant networks. Different from conventional network, the authors consider energy consumption as one constraint as well as congestion occurrence, remained buffer and transmission delay in network performance. For joint optimization of the routing strategy under the four constrains, a Q-learning based directional route scheduling algorithm which exploits the obtained knowledge to adapt changing environment is proposed [259]. Dowling *et al.* propose that, the collaborative reinforcement learning (CRL) can be a potential solution to enable groups of agents (vehicles or vehicles clusters) to online solve the system optimization problem in the dynamic and decentralized MANET [261]. For evaluating the performance of reinforcement learning based routing algorithm in practical scenarios, the authors in [258] propose a joint Q-learning and transfer learning algorithm for intelligent routing in VANET in practical case. The processed real-world experiments demonstrate the proposal can achieve better transmission delay, packets loss rate and signaling overhead than conventional methods.

- *Reinforcement Learning for Cooperative Congestion Control:* Besides the dynamic routing, the reinforcement learning as a classical tool for optimizing cooperative strategies also can be potential solution to model the cooperative congestion control in vehicle network. In vehicular network such as VANET, IoV, nearby vehicles can be clustered with D2D connections. In [272], Liu *et al.* at first propose a dynamic clustering algorithm for information integrating in vehicular network, then, a distributed cooperative reinforcement learning-based network traffic control is proposed to balance the traffic overload between clusters. For offloading traffic from onboard units (e.g., mobile users, vehicles and base stations), the authors in [262] propose a cooperative UAVs-aided data relay system. In such heterogeneous network, the interactions between UAVs and onboard units are formulated as an anti-jamming game. In such game, both the states transfer policy and actions model are unknown. To deal with the mixed-strategy game, a model-free hotbooting policy hill climbing (PHC) algorithm is correspondingly proposed to quickly output the optimal data relay policy. The simulation results show that the bit error rate can be significantly reduced by the proposal comparing with classical Q-learning based algorithm. In the dynamic vehicular network, the traffic patterns frequently change and cause unexpected abnormalities such and so forth. In [257], [273], a real-time deep learning based intelligent network traffic control method is proposed to online control network traffic by adaptively changing routing decision. In the proposal, the network traffic control process is divided into running and training phase. The training data constructed with historical traffic patterns and feedback reward (i.e., congestion level) pairs are continuously collected in the running phase. Then, a deep CNN is exploited to learn the relations between historical traffic patterns and potential congestion. With online learning, the deep CNN can adapt to changing environment and handle new abnormal situations. Then, they further consider the case of dynamic topology, and propose a value iteration architecture based deep learning for intelligent routing, which reduces computation complexity and guarantee more stable network performance when network topology changes [274].

3) Unsupervised Machine Learning for Clustering Based Traffic Control: Clustering for vehicles, packets and infrastructures is a classical approach for efficiency transmission control and information integration. The clustering in vehicular network is obstructed by the high dynamic topology and heterogeneous structure. Furthermore, considering the clusters in vehicular network are dynamic moving, how to efficiently manage traffic flows between moving clusters is still a challenge. In this part, we introduce the advanced applications of unsupervised machine learning for Clustering based Traffic Control.

For efficient messages transmission in MANET, the authors in [263] propose a clustering based data congestion control strategy, which can intelligently choose transmission strategy such as transmit rate and contention window size. In this proposal, the node at first detects congestion by measuring usage level of channels. Then, the unsupervised K-means algorithm is employed to intelligent gather and cluster messages based on size, validity, and type of messages. Finally, the suitable transmission strategy is chosen for different message clusters.

Considering the dynamic of vehicles, the unsupervised learning method is used for dynamic vehicles clustering for efficient information dissemination in V2I [266]. In this paper, a position-based clustering multi-hop routing method is proposed by hierarchically organizing VANETs into clusters with trained Hebb neural network (Hebb-NN). Besides, in the heterogeneous network that contains both cellular and D2D communications, the k-means algorithm is used to cluster vehicles as relay nodes for traffic offloading [264]. With the unsupervised learning, the cellular base station learns the dynamic distribution of devices and adaptively chooses relay strategy for different clusters. Furthermore, an advanced K-means algorithm which is referred to as Adaptive K-Harmonic Means (AKHM) is proposed in [265] for intelligent vehicles clustering in MANET. Compared with both classical K-means and K-Harmonic Means (KHM), the proposed AKHM can better adapt to the dynamic environment of vehicular network.

C. Machine Learning in Vehicular MEC

In MEC, the high mobility vehicles are usually deployed as the mobile edge cloud servers to offer computations to users. Such kind of vehicular MEC has sufficient computation resources for multiple users and is enabled to be embedded with the machine learning algorithms, which can be exploited for assistant in both supplied applications and self-optimization such as resource allocation and network traffic control. We listed the investigated literature in Table V, the different scenario, task and machine learning technology are summarized separately.

1) ML Embedded Applications in MEC: One advantage of the vehicular MEC is the high dynamic topology and strong computing capacity which enabling the computing resources to be distributed allocated in the edge of vehicular network. Meanwhile, the distributed machine learning algorithms such

TABLE V
THE APPLICATIONS OF MACHINE LEARNING IN VEHICULAR MEC

ML type	Depth	Task	ML method	Consider mobility	paper
Supervised learning	deep	Acclerate training process	CNN, DNN	N/A	[275]
Supervised learning	deep	MEC hardware design	ANN	N/A	[9]
Supervised learning	deep	Data validation	CNN	N/A	[276]
Supervised learning	deep	Blockchine improvement	DBN	√	[277]
Supervised learning	deep	Resource scheduling	DBN	√	[278]
Supervised learning	deep/shallow	Joint resource optimization	SVM, K-means, CNN	√	[279]
Reinforcement learning	deep/shallow	Resource scheduling	Q-learnng, deep Q-learning	√	[280]
Reinforcement learning	deep	Resource allocation	deep Q-learning	√	[281]
Reinforcement learning	deep	Content caching schedualing	deep Q-learning	√	[282]
Reinforcement learning	deep	Power resource allocation	D-MARL	√	[283]
Reinforcement learning	deep	Dynamic data scheduling	deep Q-learning	√	[284]
Reinforcement learning	deep	Computing offloading	deep Q-learning	√	[285]

as federated learning is widely employed to slice training tasks into distributed neural networks for accelerating the training process. Naturally, the high dynamic vehicular network is proposed as the distributed paradigm to accelerate the machine learning algorithm and other machine learning based applications. To support the assumption, the authors in [9] firstly verify the feasibility of embed deep learning in vehicular edge computing. In this paper, the real hardware of Intel Movidius Neural Compute Stick is used to embed deep learning algorithm in vehicle, the experiment result shows the proposed system can achieve reasonable computation efficiency and computing overhead. Then, in [8], the authors propose that the deep learning model which is layered can be distributed in the edge of networks, which is extremely suitable for the mobile edge computing architecture. To show the advantage of the vehicular MEC enabled machine learning, in [275], the authors propose the federated learning can be significant accelerated with distributing the training process into individual clients in vehicular edge. The result in this works shows that, compared with conventional fixed network, the vehicular network enabled federated learning is with high dynamic to select suitable federated client to avoid computing conflict. Besides accelerating the general machine learning algorithm, the machine learning is proposed as a candidate for accelerating the data process in vehicular MEC. For example, Zhou *et al.* propose the deep learning can be leveraged for data validation in MEC enabled crowd sensing [276]. Recently, the blockchain is proposed as a distributed security tool for data transactions, cashing and storage. In [277], Wang *et al.* propose a MEC based system to provide computation to blockchain users, and the deep learning with DBN structure is exploited for resource balance in the proposed system. Besides for individual application, Le *et al.* propose a integrated application paradigm for machine Learning in tasks such as object detection, network slicing, and migration services in vehicular MEC [286]. Comparing conventional method, the machine learning based algorithm shows higher accuracy and process speed.

2) ML Assistant Resource Allocation in MEC: In above sections, we have demonstrated the potential of machine learning in joint resource allocation and intelligent traffic control in vehicular network. As shown in Section II-D3, the vehicular MEC also faces big challenges of resource allocation especially the computation resource allocation. The vehicular MEC with powerful edge servers enables tasks with high computational demands but constructed with high mobility and heterogeneous structure. How to dynamic allocate resource to balance resources and adapt to the dynamic structure emerges as a big challenge.

Considering the different task characteristics, changing wireless conditions, and frequent handover caused by the high mobility of vehicles, the authors in [285] model the dynamic resource allocation process in vehicular MEC as a NP hard problem and propose a deep learning based solution to intelligent schedule computing offloading with resource balance. Also considering the high dynamic in vehicular MEC, The authors propose a multi-armed bandit learning algorithm for workload balancing among MEC servers. With the simulation comparing with two conventional online MEC scheduling algorithms, the proposed machine learning algorithm is proved to be a feasible solution for computing offloading in the high dynamic MEC [287]. Then, the He *et al.* consider the joint resource management for networking, caching, and computing offloading in MEC [281]. The content caching is also challenging due to the high mobility of vehicles and dynamic wireless channel condition, a DRL approach is designed to optimize the content caching scheme with taking mobility into account in [282]. The paper shows that the reinforcement learning can efficiently overcome the environment frequent changing problem, which is more efficient than conventional method in terms of both decision making accuracy and speed. To improve data accessing efficiency, Luo *et al.* jointly considering the communication and computation resources, propose an enhanced deep Q-learning algorithm to dynamically schedule the data delivery in the vehicular MEC [284]. The performance shows that the machine learning approach have better data loss rate and higher accuracy of caching proportion than conventional method.

By modeling the joint resource allocation as a multiple tasks optimization problem and formulating the offloading decision problem as a multi-label classification problem, the authors in [278] propose supervised DBN based resource scheduling algorithm to improve the computation speed in user side under constraints of limited channel bandwidth and

TABLE VI
MACHINE LEARNING BASED INTRUSION DETECTION METHODS IN VEHICULAR NETWORK

Solved problem	Paper	ML structure	Tasks	Attack type	Data set or simulator	For dynamic environment	For vehicle network
Misuse detection	[289]	NN	Misuse detection	N/A	DataPro	N/A	N/A
	[290]	DNN	Misuse detection	Sink-hole;DoS; Packet dropper	OCTANE	√	√
	[291]	Q-learning	Secure strategy selection	Eavesdropping; Jamming	N/A	√	N/A
	[292]	DNN	Misuse detection	N/A	N/A	√	√
Anomaly Detection	[293].	Bayes learning	Detecting complex and coordinated attacks	DDoS	DARPA 2000	N/A	N/A
	[294]	NN	Fault detection	Fault data injection	N/A	√	√
	[295]	VSM	Malicious attacks detection	N/A	VanetMobiSim	√	√
	[296]	K-means	Intrusion detection	N/A	CERIAS TR 2000-12	√	N/A
	[297] [298]	Bayes learning; RF; Ada Boost	Malicious attacks detection	N/A	NCTUns-5.0	√	√
	[299]	Bayes learning	Mobility prediction and anomaly detection	N/A	N/A	√	√
Hybrid Detection	[300]	RF	Intrusion detection	Attack-free	KDDpsila99	√	N/A
	[301]	RF	Intrusion detection	Attack-free	Apache Spark	√	N/A
	[302]	SVM	Collaborative intrusion detection	Sybil attack; Worm-hole; Black hole	NS3	√	√

computation resource in network side. Wang *et al.* compare the performance of four gradient-descent based machine learning algorithms (SVM, linear regression, K-means, and deep CNN) for resource allocation in MEC [279]. However, the supervised learning widely depends on the labeled existing data collected from certain scenario which is expensive and hard to be generalized to adapt to the dynamic environment. In [288], the authors firstly employ MDP to model the change states of vehicular MEC and dynamic task offloading process. Which guides a potential direction for using reinforcement learning in vehicular MEC task offloading problem. Instead of using supervised learning, Li *et al.* model the joint resources optimization problem as a single-agent infinite-horizon MDP, and propose two reinforcement learning algorithms with both shallow (i.e., Q-learning) and deep structures (i.e., deep Q-learning) to online approach the optimal option of the MDP [280]. To further consider multi-agent competition problem in vehicular MEC, a distributed multi-agent reinforcement learning (D-MARL) algorithm is proposed for power resource allocation [283], which improves energy consumption, radio coverage and user Fairness comparing with conventional algorithms.

D. Machine Learning in Vehicular Network Intrusion Detection

The cyber security intrusion detection methods are mainly divided into three types, the misuse-based detection, anomaly based detection and hybrid detection. The machine learning is a tool to give computers the ability to learn without being explicitly programmed, which shows great performance for classification, clustering, and prediction. In conventional wireless network, the supervised machine learning is widely exploit for data mining as well as the unsupervised learning is exploit for feature clustering for anomaly detection [303], [304]. As a powerful supplement, the reinforcement learning with accurate prediction is also employed for misuse detection and network QoS and security balancing [291]. Different from the conventional wireless network, the vehicular network with heterogeneous structure and high mobility brings new challenges for the network security. As mentioned in Section II-C3, the high mobility of vehicles break the links frequently and hinders the real-time interaction of secure information. The conventional reputation based secure system is hard to be deployed in such dynamic network [305]. Besides, due to the heterogeneous structure of vehicular network, the various security resources are constrained and compatible with others, the joint security optimization is always NP-hard and hard to be solved in optimal [81]. Furthermore, the extremely large scale vehicular network increases not only the computation and communication overhead of security algorithm, but also the complexity of data mining and design difficulty of machine learning based secure algorithm. Therefore, the intrusion detection and security mechanism for future vehicular network should be more advanced to address the distinctive features of the high mobility and heterogeneous structure.

In this subsection, we introduce how the machine learning based intrusion detection methods conquer those challenges. The novel machine learning based vehicular security methods are summarized in Table VI and categorized into three detection types: misuse detection, anomaly detection, and hybrid detection.

1) Machine Learning for Misuse Detection in Vehicular Network:

- *Supervised Learning Based Misuse Detection:* The misuse detection is benefited from the quick data mining technologies for recorded signature marching, which is well addressed by machine learning algorithms [306]. The neural network is widely used for cyber-physical system misuse detection for almost 30 years [289]. Especially for the adaptation to new and "unknown" environments like the high dynamic vehicular network, the NN shows significantly improved performance than conventional method [307]. Considering the more deep structure of NN, Kang and Kang propose a probability-based feature vectors assisted DNN algorithm to detect misuse in-the high mobility vehicle network [290]. Besides inter-vehicle security, Anzer and Elhadef propose a deep learning based misuse intrusion detection system for inner vehicle network security [292].

- *Reinforcement Learning Based Misuse Detection:* Other than supervised learning, the reinforcement learning is employed for prediction based misuse detection. Al Zamil *et al.* modeled the misuse detection process as an HMM and process binary classification based prediction to detect misuse in vehicular network [308]. In [309], the authors employ the stochastic game to model the QoS and security trade-off problem for dynamic and heterogeneous network. The big challenge of such system is the non-cooperation between vehicles, most of researchers study such problems with game theory. Xu *et al.* modeled the eavesdropping and jamming attacks and corresponding secure strategy selection as a stochastic game [291]. To solve such game and get near-optimal performance, a Q-learning-based multi-agent cooperative security strategy is proposed for high dynamic wireless network.

2) Machine Learning for Anomaly and Hybrid Detection in Vehicular Network: The anomaly detection is a supplement for the novel attack in which the signature is not recorded in the database. The anomaly detection algorithm model the patterns of normal behaviors as benchmark and identify anomalies as deviations [11]. The machine learning is widely used for target tracking and abnormal detection in both image recognition and NLP for many years. However, due to the high dynamic and resource constrain of vehicular network, the high computation based machine learning algorithms are hard to be deployed in the past. Recently, with the deployment of high performance MEC, the machine learning especially deep learning based anomaly detection algorithms explosively emerge.

- *Supervised Learning Based Anomaly Detection:* Benferhat *et al.* propose a Bayes learning based algorithm for detecting complex and coordinated attacks in dynamic network [293]. This initial work does not consider the distinctive structure of the vehicular network. Sargolzaei *et al.* propose a neural network based intelligent security system to detect fault data injection attacks in vehicular network [294]. The simulation with vehicular platoon shows that the proposal can improve both network reliability and security. However, the high mobility of vehicles is not fully considered in this research. Thus, Scalabrin *et al.* propose a Bayesian prediction method by calculating the vehicle moving trajectory to detect anomaly in high mobility vehicular network [299]. And the work of [310] employs Bayesian Neural Network (BNN) to detect the honest or dishonest nodes in vehicular networks. By considering the dynamic machine to machine links, the authors in [311] propose a machine learning based trust evaluation model for detecting malicious activities in the vehicular network. The detection performances of the conventional Extreme Gradient Boosting (XGBoost), Random Forest and the proposed Entropy-Based Feature Engineering coupled XGBoost (EBFE-XGBoost) algorithms are compared in this work. As mentioned above, the limited resources need to be carefully considered in the vehicular network. Wahab *et al.* propose an SVM based malicious attacks detection system by jointly considering resources constraint and security in clustered vehicular network [295]. Besides, considering the privacy of users, the work in [312] proposes a privacy-preserving SVM classifier training scheme for distributed training in vehicular network embedding with block chain technology. Instead of considering inter-vehicle security, Al-Saud *et al.* propose an improved SVM model for anomaly detection for Inner-vehicle security [313]. Based on the controller area network bus protocol, the proposal can increase the searchability and avoid premature convergence reliability. Both reliability and security are improved. The above proposals all consider specific vehicular networks, the authors in [297], [298] analyze the performance of different kinds of machine learning including Bayes learning, RF and Ada Boost for anomaly detection in various high dynamic scenarios. With experiments, the authors show that machine learning based malicious detection methods can achieve reasonable improvement in the vehicular network. Singh *et al.* further analyze the performance of various machine learning technologies to detect the DDoS attacks in SDN based vehicular network [314]. The anomaly detection can further improve misuse detection by recording the signature of novel attacks. Naturally, some hybrid detections including both misuse and anomaly detection are proposed. Zhang *et al.* propose that random forests can be an efficient machine learning algorithm for hybrid detection against both misuse and anomaly in network [300]. The authors in [301] further improve the random forests hybrid detection in the high dynamic network under the real-time constrain.
- *Unsupervised Learning Based Anomaly Detection:* Unlike the supervised learning is highly depending on a lot of labeled data, the unsupervised learning is a data-free approach with low computation overhead and good adaption for high dynamic scenario. For dynamic attacks in vehicular network, Sequeira and Zaki propose an semi-incremental K-means based anomaly detection algorithm to detect various intrusions for dynamic network in real-time [296]. Also improved from classical k-means algorithm, Maglaras proposes a recursive K-means clustering module for distributed intrusion detection in vehicular network [315]. Considering high vehicle mobility may lead to frequent changing topology of VANET, Sedjelmaci and Senouci propose an unsupervised clustering based collaborative intrusion detection framework

to stable the vehicles communication flow and secure vehicular networks [302].

VI. Open Research Issues and Future Directions

In this section, we discuss the open research issues and potential future directions of machine learning in vehicular network.

A. The Scalability of Machine Learning Applications in Vehicular Network

Future vehicular network is large scaled and requires both high communication and computation efficiency. The machine learning algorithms with deep structure are proved more powerful in vehicular network than machine learning with shallow structure [211], [245], [280], [316]. However, the deep learning with high complexity demands high computation ability, which is limited in conventional vehicular network. Even the MEC can be employed to provide computation offloading in vehicular network, the CPU based hardware is still limited for large scale matrix operation based deep learning algorithm. To conquer both the computation and communication scalability problem, the GPU-accelerated hardware such as scalable GPU server [317] and GPU embedded soft define router (SDR) [268] can be considered as the next generation hardware in future vehicular network. Furthermore, the distributed machine learning approach requires a large number of training dataset which needs large storage in distributed vehicles. By considering the storage and quick reading and writing, the high-speed Storage Area Network (SAN) framework [318] may be a viable approach that can provide access to the relevant dataset for training the machine learning system while moving the unwanted dataset to a backup archive storage. However, considering the high dynamic topology and heterogeneous structure, how to design a suitable framework to extend the scalability for machine learning in future large scaled vehicular network needs to be further addressed.

B. The Universality of Machine Learning Applications in Vehicular Network

Machine learning is an artificial intelligent tool to make the target system self-learning and get rid of human intervention. A complete machine learning based system should be applied to handle most of the possible tasks and adapt to any scenarios. However, almost all of the proposed machine learning algorithms in vehicular network are specifically designed just as optimization methods for specific task in assumed scenarios. For example, because the parameters and neural structure are specifically configured in advance, the CNN based machine learning system for mobility prediction in urban vehicular network cannot handle the resource allocation in countryside vehicular network. For conquering those problems, the transfer learning is researched to be exploited in dynamic routing in vehicular network, which can simply transfer the trained neural structure to new tasks avoiding redundant training process and saving resources [258]. However, the transfer learning is only feasible for structure transfer between related tasks and not scalable for multiple tasks. To make the machine learning more intelligent and universal for various tasks and scenarios, the novel concept of meta-learning is proposed recently. The meta-learning is an approach to make machine learning intelligently learn and improve itself by dynamically changing inner parameters and structures [319]. Therefore, using meta-learning to handle multiple tasks and continuously adapt to the future vehicular network which is a non-stationary and competitive environment, should be an interesting research direction.

C. Integrated Intelligence With Vehicular Network and Autonomous Driving

Machine learning is widely used in autonomous driving for image recognition, task tracking, driving decision making and so on. The embedded sensors continuously collect data from the environment in Line-of-Sight (LOS) and transfer the data for machine learning processing in the vehicle. Such local intelligence without interaction with objects Non-Line-of-Sight (NLOS) is not efficient when the environment becomes complex. Recently, the reliable and highly efficient vehicular communications are presented to be the essential foundation for autonomous driving vehicles [320], which provides various required information in NLOS to improve the efficiency of autonomous driving. As the machine learning algorithms are used in both vehicular network and autonomous driving, the authors in [321] jointly consider that the local collected visual information and other information received from V2V communication can be formatted as training data for machine learning and propose a semi-supervised manifold alignment approach for autonomous driving. Moreover, the vehicular related resources such as MEC, UAV, and satellites can also be considered as elements in the integrated intelligent system. However, the resources for specific communication, computing and energy consumption are limited. Besides, the collection of training data is time-consuming, the resource allocation for balance various resources is still a big challenge. The various resource allocation algorithms are proposed, but none of the existing works completely considered the joint optimization of both vehicular communication and autonomous driving. Furthermore, considering the heterogeneous structure of the vehicular network, how to integrate the machine learning based networking, driving and computation into the complex system may emerge as a new challenge.

D. The Theoretical Proof of Deep Learning in Vehicular Network

Recently, the deep structure of machine learning is widely used in vehicular network and proved the high efficiency than shallow structures. However, as the deep learning is treated as a black box for various applications, both the results and calculation process lack of theoretical explanation. Why can the deep learning predict future mobility and traffic flow of vehicles? How can the deep learning recover the correlation among massive data? And in the complex joint learning, which part reflects which parameter? The theoretical proof and transparency of deep learning based algorithms is needed to build trust among researchers.

E. The Distributed Data Access in Vehicular Network

The machine learning based intelligent vehicular network requires a large amount of data for training. However, due to the privacy and security issue of vehicle users, the data access mechanism for the machine learning system need to be designed carefully. How to collect data for training and secure privacy? recently, the new encryption algorithms and consensus mechanisms such as block-chain are widely researched for distributed data access and control in vehicular network [322]. Furthermore, the distributed learning technology of moving the learning from central to the edge such as federated learning [323] and edge learning [324]. However, due to the high communication cost and interaction delay, how to construct an efficient distributed learning system with secured user data is still a big challenge.

F. The Proactive Learning in Vehicular Network

For now, the most efficient learning strategies for vehicular network and autonomous driving are based on supervised learning which is based on the collected data passively collected by humans. However, such a reactive learning process is a simple exploit process with approximated functions which is not efficient for the varying environment. Although many researchers have considered proactive machine learning technologies such as reinforcement learning and imitative learning for vehicular network [325], due to the high process cost of online data collection and interaction, proactive learning is still not widely deployed in the real world.

VII. Conclusion

Machine learning, especially deep learning technology, has proved to be the potential solution for paving the way to future intelligence in various systems. In this paper, we investigate the applications of machine learning technologies in intelligent vehicular network. The survey focus on the distinctive challenges in existing vehicular communication, networking and security, and investigate corresponding machine learning based solutions. In addition, we list some worthy researches which might be interesting for next studies.

References

[1] W. Saad, M. Bennis, and M. Chen, "A vision of 6G wireless systems: Applications, trends, technologies, and open research problems," *IEEE Netw.*, vol. 34, no. 3, pp. 134–142, May/Jun. 2020.

[2] K. B. Letaief, W. Chen, Y. Shi, J. Zhang, and Y. A. Zhang, "The roadmap to 6G: AI empowered wireless networks," *IEEE Commun. Mag.*, vol. 57, no. 8, pp. 84–90, Aug. 2019.

[3] N. Kato, B. Mao, F. Tang, Y. Kawamoto, and J. Liu, "Ten challenges in advancing machine learning technologies towards 6G," *IEEE Wireless Commun.*, vol. 27, no. 3, pp. 96–103, Jun. 2019.

[4] G. Gui, M. Liu, F. Tang, N. Kato, and F. Adachi, "6G: Opening new horizons for integration of comfort, security and intelligence," *IEEE Commun. Mag.*, vol. 27, no. 5, pp. 126–132, Oct. 2020.

[5] F. Tang, Y. Kawamoto, N. Kato, and J. Liu, "Future intelligent and secure vehicular network toward 6G: Machine-learning approaches," *Proc. IEEE*, vol. 108, no. 2, pp. 292–307, Feb. 2020.

[6] T. Brown, B. Argrow, C. Dixon, S. Doshi, R.-G. Thekkekunnel, and D. Henkel, "Ad hoc UAV ground network (AUGNET)," in *Proc. AIAA 3rd Unmanned Unlimited Tech. Conf. Workshop Exhibit*, 2004, p. 6321.

[7] J. Wang, J. Liu, and N. Kato, "Networking and communications in autonomous driving: A survey," *IEEE Commun. Surveys Tuts.*, vol. 21, no. 2, pp. 1243–1274, 2nd Quart., 2019.

[8] H. Li, K. Ota, and M. Dong, "Learning IoT in edge: Deep learning for the Internet of Things with edge computing," *IEEE Netw.*, vol. 32, no. 1, pp. 96–101, Jan./Feb. 2018.

[9] J. Hochstetler, R. Padidela, Q. Chen, Q. Yang, and S. Fu, "Embedded deep learning for vehicular edge computing," in *Proc. IEEE/ACM Symp. Edge Comput. (SEC)*, Oct. 2018, pp. 341–343.

[10] B. Ahlgren, C. Dannewitz, C. Imbrenda, D. Kutscher, and B. Ohlman, "A survey of information-centric networking," *IEEE Commun. Mag.*, vol. 50, no. 7, pp. 26–36, Jul. 2012.

[11] A. L. Buczak and E. Guven, "A survey of data mining and machine learning methods for cyber security intrusion detection," *IEEE Commun. Surveys Tuts.*, vol. 18, no. 2, pp. 1153–1176, 2nd Quart., 2016.

[12] Z. M. Fadlullah *et al.*, "State-of-the-art deep learning: Evolving machine intelligence toward tomorrow's intelligent network traffic control systems," *IEEE Commun. Surveys Tuts.*, vol. 19, no. 4, pp. 2432–2455, 4th Quart., 2017.

[13] M. Chen, U. Challita, W. Saad, C. Yin, and M. Debbah, "Artificial neural networks-based machine learning for wireless networks: A tutorial," *IEEE Commun. Surveys Tuts.*, vol. 21, no. 4, pp. 3039–3071, 4th Quart., 2019.

[14] C. Zhang, P. Patras, and H. Haddadi, "Deep learning in mobile and wireless networking: A survey," *IEEE Commun. Surveys Tuts.*, vol. 21, no. 3, pp. 2224–2287, 3rd Quart., 2019.

[15] N. C. Luong *et al.*, "Applications of deep reinforcement learning in communications and networking: A survey," *IEEE Commun. Surveys Tuts.*, vol. 21, no. 4, pp. 3133–3174, 4th Quart., 2019.

[16] A. Qayyum, M. Usama, J. Qadir, and A. Al-Fuqaha, "Securing connected autonomous vehicles: Challenges posed by adversarial machine learning and the way forward," *IEEE Commun. Surveys Tuts.*, vol. 22, no. 2, pp. 998–1026, 2nd Quart., 2020.

[17] M. Khairnar, D. Vaishali, and D. S. Pradhan, "V2V communication survey wireless technology," 2014. [Online]. Available: arXiv:1403.3993.

[18] C. Chou, C. Li, W. Chien, and K. Lan, "A feasibility study on vehicle-to-infrastructure communication: WiFi vs. WiMax," in *Proc. 10th Int. Conf. Mobile Data Manag. Syst. Services Middleware*, May 2009, pp. 397–398.

[19] A. Tufail, M. Fraser, A. Hammad, K. K. Hyung, and S.-W. Yoo, "An empirical study to analyze the feasibility of WiFi for VANETs," in *Proc. 12th Int. Conf. Comput. Supported Cooper. Work Design*, Apr. 2008, pp. 553–558.

[20] K. Zheng, Q. Zheng, P. Chatzimisios, W. Xiang, and Y. Zhou, "Heterogeneous vehicular networking: A survey on architecture, challenges, and solutions," *IEEE Commun. Surveys Tuts.*, vol. 17, no. 4, pp. 2377–2396, 4th Quart., 2015.

[21] K. Abboud, H. A. Omar, and W. Zhuang, "Interworking of DSRC and cellular network technologies for V2X communications: A survey," *IEEE Trans. Veh. Technol.*, vol. 65, no. 12, pp. 9457–9470, Dec. 2016.

[22] *FMVSS No.150*. Accessed: May 2019. [Online]. Available: https://www.nhtsa.gov/sites/nhtsa.dot.gov/files/documents/v2v_pria_12-12-16_clean.pdf

[23] S. Chen *et al.*, "Vehicle-to-everything (V2X) services supported by LTE-based systems and 5G," *IEEE Commun. Stand. Mag.*, vol. 1, no. 2, pp. 70–76, Jul. 2017.

[24] S. Chen, J. Hu, Y. Shi, and L. Zhao, "LTE-V: A TD-LTE-based V2X solution for future vehicular network," *IEEE Internet Things J.*, vol. 3, no. 6, pp. 997–1005, Dec. 2016.

[25] G. Araniti, C. Campolo, M. Condoluci, A. Iera, and A. Molinaro, "LTE for vehicular networking: A survey," *IEEE Commun. Mag.*, vol. 51, no. 5, pp. 148–157, May 2013.

[26] L. Gallo and J. Härri, "Short paper: A LTE-direct broadcast mechanism for periodic vehicular safety communications," in *Proc. IEEE Veh. Netw. Conf.*, Dec. 2013, pp. 166–169.

[27] S. Kato, M. Hiltunen, K. Joshi, and R. Schlichting, "Enabling vehicular safety applications over LTE networks," in *Proc. Int. Conf. Connected Veh. Expo (ICCVE)*, Dec. 2013, pp. 747–752.

[28] X. Wang, S. Mao, and M. X. Gong, "An overview of 3GPP cellular vehicle-to-everything standards," *Mobile Comput. Commun.*, vol. 21, no. 3, pp. 19–25, Nov. 2017.

[29] M. Gonzalez-Martín, M. Sepulcre, R. Molina-Masegosa, and J. Gozalvez, "Analytical models of the performance of C-V2X mode 4 vehicular communications," *IEEE Trans. Veh. Technol.*, vol. 68, no. 2, pp. 1155–1166, Feb. 2019.

[30] *3GPP:C-V2X*. Accessed: May 2019. [Online]. Available: https://www.3gpp.org/ftp/information/presentations/Presentations_2017/A4Conf010_Din%20Flore_5GAA_v1.pdf

[31] Y. Li, N. Seshadri, and S. Ariyavisitakul, "Channel estimation for OFDM systems with transmitter diversity in mobile wireless channels," *IEEE J. Sel. Areas Commun.*, vol. 17, no. 3, pp. 461–471, Mar. 1999.

[32] Y. Li, L. J. Cimini, and N. R. Sollenberger, "Robust channel estimation for OFDM systems with rapid dispersive fading channels," *IEEE Trans. Commun.*, vol. 46, no. 7, pp. 902–915, Jul. 1998.

[33] J.-J. van de Beek, O. Edfors, M. Sandell, S. K. Wilson, and P. O. Borjesson, "On channel estimation in OFDM systems," in *Proc. IEEE 45th Veh. Technol. Conf. Countdown Wireless 21st Century*, vol. 2, Jul. 1995, pp. 815–819.

[34] Y. Li, "Pilot-symbol-aided channel estimation for OFDM in wireless systems," *IEEE Trans. Veh. Technol.*, vol. 49, no. 4, pp. 1207–1215, Jul. 2000.

[35] B. Yang, K. B. Letaief, R. S. Cheng, and Z. Cao, "Channel estimation for OFDM transmission in multipath fading channels based on parametric channel modeling," *IEEE Trans. Commun.*, vol. 49, no. 3, pp. 467–479, Mar. 2001.

[36] E. Panayirci, H. Senol, and H. V. Poor, "Joint channel estimation, equalization, and data detection for OFDM systems in the presence of very high mobility," *IEEE Trans. Signal Process.*, vol. 58, no. 8, pp. 4225–4238, Aug. 2010.

[37] T. Y. Al-Naffouri, K. M. Z. Islam, N. Al-Dhahir, and S. Lu, "A model reduction approach for OFDM channel estimation under high mobility conditions," *IEEE Trans. Signal Process.*, vol. 58, no. 4, pp. 2181–2193, Apr. 2010.

[38] T. Maehata *et al.*, "DSRC using OFDM for roadside-vehicle communication system," in *Proc. IEEE 51st Veh. Technol. Conf. (VTC-Spring)*, vol. 1, May 2000, pp. 148–152.

[39] R. Prasad and C. R. Murthy, "Bayesian learning for joint sparse OFDM channel estimation and data detection," in *Proc. IEEE Global Telecommun. Conf. (GLOBECOM)*, Dec. 2010, pp. 1–6.

[40] H. Ye, G. Y. Li, and B. Juang, "Power of deep learning for channel estimation and signal detection in OFDM systems," *IEEE Wireless Commun. Lett.*, vol. 7, no. 1, pp. 114–117, Feb. 2018.

[41] S. Haykin, "Cognitive radio: Brain-empowered wireless communications," *IEEE J. Sel. Areas Commun.*, vol. 23, no. 2, pp. 201–220, Feb. 2005.

[42] Y. Liang, K. Chen, G. Y. Li, and P. Mahonen, "Cognitive radio networking and communications: An overview," *IEEE Trans. Veh. Technol.*, vol. 60, no. 7, pp. 3386–3407, Sep. 2011.

[43] M. Di Felice, K. R. Chowdhury, and L. Bononi, "Analyzing the potential of cooperative cognitive radio technology on inter-vehicle communication," in *Proc. IFIP Wireless Days*, Oct. 2010, pp. 1–6.

[44] J. Eze, S. Zhang, E. Liu, and E. Eze, "Cognitive radio technology assisted vehicular ad-hoc networks (VANETs): Current status, challenges, and research trends," in *Proc. 23rd Int. Conf. Autom. Comput. (ICAC)*, Sep. 2017, pp. 1–6.

[45] N. J. Kirsch and B. M. O'Connor, "Improving the performance of vehicular networks in high traffic density conditions with cognitive radios," in *Proc. IEEE Intell. Veh. Symp. (IV)*, Jun. 2011, pp. 552–556.

[46] D. B. Rawat, B. B. Bista, and G. Yan, "COR-VANETs: Game theoretic approach for channel and rate selection in cognitive radio VANETs," in *Proc. 7th Int. Conf. Broadband Wireless Comput. Commun. Appl.*, Nov. 2012, pp. 94–99.

[47] S. Rangan, T. S. Rappaport, and E. Erkip, "Millimeter-wave cellular wireless networks: Potentials and challenges," *Proc. IEEE*, vol. 102, no. 3, pp. 366–385, Mar. 2014.

[48] "Study on LTE support for V2X services in 5G, v15.0.0, 3GPP, Sophia Antipolis, France, Rep. TR 21.915, May 2019. [Online]. Available: https://portal.3gpp.org/desktopmodules/Release/ReleaseDetails.aspx?releaseId=190

[49] V. Va, T. Shimizu, G. Bansal, and R. W. Heath, "Position-aided millimeter wave V2I beam alignment: A learning-to-rank approach," in *Proc. IEEE 28th Annu. Int. Symp. Pers. Indoor Mobile Radio Commun. (PIMRC)*, Oct. 2017, pp. 1–5.

[50] B. D. Van Veen and K. M. Buckley, "Beamforming: A versatile approach to spatial filtering," *IEEE ASSP Mag.*, vol. 5, no. 2, pp. 4–24, Apr. 1988.

[51] L. Lu, G. Y. Li, A. L. Swindlehurst, A. Ashikhmin, and R. Zhang, "An overview of massive MIMO: Benefits and challenges," *IEEE J. Sel. Topics Signal Process.*, vol. 8, no. 5, pp. 742–758, Oct. 2014.

[52] J. Choi, V. Va, N. Gonzalez-Prelcic, R. Daniels, C. R. Bhat, and R. W. Heath, "Millimeter-wave vehicular communication to support massive automotive sensing," *IEEE Commun. Mag.*, vol. 54, no. 12, pp. 160–167, Dec. 2016.

[53] Y. Chen, L. Wang, Y. Ai, B. Jiao, and L. Hanzo, "Performance analysis of NOMA-SM in vehicle-to-vehicle massive MIMO channels," *IEEE J. Sel. Areas Commun.*, vol. 35, no. 12, pp. 2653–2666, Dec. 2017.

[54] N. González-Prelcic, R. Méndez-Rial, and R. W. Heath, "Radar aided beam alignment in mmWave V2I communications supporting antenna diversity," in *Proc. Inf. Theory Appl. Workshop (ITA)*, Jan. 2016, pp. 1–7.

[55] A. Klautau, P. Batista, N. Gonzàlez-Prelcic, Y. Wang, and R. W. Heath, "5G MIMO data for machine learning: Application to beam-selection using deep learning," in *Proc. Inf. Theory Appl. Workshop (ITA)*, Feb. 2018, pp. 1–9.

[56] Y. Saito, Y. Kishiyama, A. Benjebbour, T. Nakamura, A. Li, and K. Higuchi, "Non-orthogonal multiple access (NOMA) for cellular future radio access," in *Proc. IEEE 77th Veh. Technol. Conf. (VTC Spring)*, Jun. 2013, pp. 1–5.

[57] B. Di, L. Song, Y. Li, and G. Y. Li, "Non-orthogonal multiple access for high-reliable and low-latency V2X communications in 5G systems," *IEEE J. Sel. Areas Commun.*, vol. 35, no. 10, pp. 2383–2397, Oct. 2017.

[58] B. Di, L. Song, Y. Li, and Z. Han, "V2X meets NOMA: Non-orthogonal multiple access for 5G-enabled vehicular networks," *IEEE Wireless Commun.*, vol. 24, no. 6, pp. 14–21, Dec. 2017.

[59] B. W. Khoueiry and M. R. Soleymani, "An efficient NOMA V2X communication scheme in the Internet of Vehicles," in *Proc. IEEE 85th Veh. Technol. Conf. (VTC Spring)*, Jun. 2017, pp. 1–7.

[60] L. Xiao, Y. Li, C. Dai, H. Dai, and H. V. Poor, "Reinforcement learning-based NOMA power allocation in the presence of smart jamming," *IEEE Trans. Veh. Technol.*, vol. 67, no. 4, pp. 3377–3389, Apr. 2018.

[61] G. Gui, H. Huang, Y. Song, and H. Sari, "Deep learning for an effective nonorthogonal multiple access scheme," *IEEE Trans. Veh. Technol.*, vol. 67, no. 9, pp. 8440–8450, Sep. 2018.

[62] A. Ullah, X. Yao, S. Shaheen, and H. Ning, "Advances in position based routing towards its enabled fog-oriented VANET—A survey," *IEEE Trans. Intell. Transp. Syst.*, vol. 21, no. 2, pp. 828–840, Feb. 2020.

[63] O. Trullols-Cruces, J. Morillo-Pozo, J. M. Barcelo, and J. Garcia-Vidal, "A cooperative vehicular network framework," in *Proc. IEEE Int. Conf. Commun.*, Jun. 2009, pp. 1–6.

[64] E. Ahmed and H. Gharavi, "Cooperative vehicular networking: A survey," *IEEE Trans. Intell. Transp. Syst.*, vol. 19, no. 3, pp. 996–1014, Mar. 2018.

[65] T. S. Abraham and K. Narayanan, "Cooperative communication for vehicular networks," in *Proc. IEEE Int. Conf. Adv. Commun. Control Comput. Technol.*, May 2014, pp. 1163–1167.

[66] D. Grewe, M. Wagner, and H. Frey, "A domain-specific comparison of information-centric networking architectures for connected vehicles," *IEEE Commun. Surveys Tuts.*, vol. 20, no. 3, pp. 2372–2388, 3rd Quart., 2018.

[67] E. P. de Freitas *et al.*, "UAV relay network to support WSN connectivity," in *Proc. Int. Congr. Ultra Mod. Telecommun. Control Syst.*, Oct. 2010, pp. 309–314.

[68] F. Tang, Z. M. Fadlullah, N. Kato, F. Ono, and R. Miura, "AC-POCA: Anticoordination game based partially overlapping channels assignment in combined UAV and D2D-based networks," *IEEE Trans. Veh. Technol.*, vol. 67, no. 2, pp. 1672–1683, Feb. 2018.

[69] F. Tang, Z. M. Fadlullah, B. Mao, N. Kato, F. Ono, and R. Miura, "On a novel adaptive UAV-mounted cloudlet-aided recommendation system for LBSNs," *IEEE Trans. Emerg. Topics Comput.* vol. 7, no. 4, pp. 565–577, Oct.–Dec. 2019.

[70] J. Liu, Y. Shi, Z. M. Fadlullah, and N. Kato, "Space-air-ground integrated network: A survey," *IEEE Commun. Surveys Tuts.*, vol. 20, no. 4, pp. 2714–2741, 4th Quart., 2018.

[71] N. Kato *et al.*, "Optimizing space-air-ground integrated networks by artificial intelligence," *IEEE Wireless Commun.*, vol. 26, no. 4, pp. 140–147, Aug. 2019.

[72] F. Yang, S. Wang, J. Li, Z. Liu, and Q. Sun, "An overview of Internet of Vehicles," *China Commun.*, vol. 11, no. 10, pp. 1–15, Oct. 2014.

[73] M. Gerla, E. Lee, G. Pau, and U. Lee, "Internet of Vehicles: From intelligent grid to autonomous cars and vehicular clouds," in *Proc. IEEE World Forum Internet Things (WF-IoT)*, Mar. 2014, pp. 241–246.

[74] M. Gerla, "Vehicular cloud computing," in *Proc. 11th Annu. Mediterr. Ad Hoc Netw. Workshop (Med-Hoc-Net)*, Jun. 2012, pp. 152–155.

[75] M. Whaiduzzaman, M. Sookhak, A. Gani, and R. Buyya, "A survey on vehicular cloud computing," *J. Netw. Comput. Appl.*, vol. 40, pp. 325–344, Apr. 2014.

[76] L. Tong, Y. Li, and W. Gao, "A hierarchical edge cloud architecture for mobile computing," in *Proc. 35th Annu. IEEE Int. Conf. Comput. Commun. (IEEE INFOCOM)*, Apr. 2016, pp. 1–9.

[77] J. Feng, Z. Liu, C. Wu, and Y. Ji, "AVE: Autonomous vehicular edge computing framework with ACO-based scheduling," *IEEE Trans. Veh. Technol.*, vol. 66, no. 12, pp. 10660–10675, Dec. 2017.

[78] K. Zhang, Y. Mao, S. Leng, S. Maharjan, and Y. Zhang, "Optimal delay constrained offloading for vehicular edge computing networks," in *Proc. IEEE Int. Conf. Commun. (ICC)*, May 2017, pp. 1–6.

[79] K. Zhang, Y. Mao, S. Leng, Y. He, and Y. Zhang, "Mobile-edge computing for vehicular networks: A promising network paradigm with predictive off-loading," *IEEE Veh. Technol. Mag.*, vol. 12, no. 2, pp. 36–44, Jun. 2017.

[80] B. Parno and A. Perrig, "Challenges in securing vehicular networks," in *Proc. Workshop Hot Topics Netw. (HotNets-IV)*, 2005, pp. 1–6.

[81] T. Alpcan and S. Buchegger, "Security games for vehicular networks," *IEEE Trans. Mobile Comput.*, vol. 10, no. 2, pp. 280–290, Feb. 2011.

[82] W. Li and H. Song, "ART: An attack-resistant trust management scheme for securing vehicular ad hoc networks," *IEEE Trans. Intell. Transp. Syst.*, vol. 17, no. 4, pp. 960–969, Apr. 2016.

[83] T. Zhou, R. R. Choudhury, P. Ning, and K. Chakrabarty, "P2DAP—Sybil attacks detection in vehicular ad hoc networks," *IEEE J. Sel. Areas Commun.*, vol. 29, no. 3, pp. 582–594, Mar. 2011.

[84] H. Hasrouny, A. E. Samhat, C. Bassil, and A. Laouiti, "VANET security challenges and solutions: A survey," *Veh. Commun.*, vol. 7, pp. 7–20, Jan. 2017.

[85] B. Kannhavong, H. Nakayama, Y. Nemoto, N. Kato, and A. Jamalipour, "A survey of routing attacks in mobile ad hoc networks," *IEEE Wireless Commun.*, vol. 14, no. 5, pp. 85–91, Oct. 2007.

[86] H. Nakayama, A. Jamalipour, and N. Kato, "Network-based traitor-tracing technique using traffic pattern," *IEEE Trans. Inf. Forensics Security*, vol. 5, no. 2, pp. 300–313, Jun. 2010.

[87] H. Nishiyama, D. Fomo, Z. M. Fadlullah, and N. Kato, "Traffic pattern-based content leakage detection for trusted content delivery networks," *IEEE Trans. Parallel Distrib. Syst.*, vol. 25, no. 2, pp. 301–309, Feb. 2014.

[88] S. Chang, Y. Qi, H. Zhu, J. Zhao, and X. Shen, "FootPrint: Detecting sybil attacks in urban vehicular networks," *IEEE Trans. Parallel Distrib. Syst.*, vol. 23, no. 6, pp. 1103–1114, Jun. 2012.

[89] S. T. Zargar, J. Joshi, and D. Tipper, "A survey of defense mechanisms against distributed denial of service (DDoS) flooding attacks," *IEEE Commun. Surveys Tuts.*, vol. 15, no. 4, pp. 2046–2069, 4th Quart., 2013.

[90] R. Braga, E. Mota, and A. Passito, "Lightweight DDoS flooding attack detection using NoX/OpenFlow," in *Proc. IEEE Local Comput. Netw. Conf.*, Oct. 2010, pp. 408–415.

[91] Y. Yu, L. Guo, Y. Liu, J. Zheng, and Y. Zong, "An efficient SDN-based DDoS attack detection and rapid response platform in vehicular networks," *IEEE Access*, vol. 6, pp. 44570–44579, 2018.

[92] H. Sedjelmaci and S. M. Senouci, "A new intrusion detection framework for vehicular networks," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Jun. 2014, pp. 538–543.

[93] S. Kurosawa, H. Nakayama, N. Kato, A. Jamalipour, and Y. Nemoto, "Detecting blackhole attack on AODV-based mobile ad hoc networks by dynamic learning method," *Int. J. Netw. Security*, vol. 5, no. 3, pp. 338–346, 2007.

[94] H. Nakayama, S. Kurosawa, A. Jamalipour, Y. Nemoto, and N. Kato, "A dynamic anomaly detection scheme for AODV-based mobile ad hoc networks," *IEEE Trans. Veh. Technol.*, vol. 58, no. 5, pp. 2471–2481, Jun. 2009.

[95] Y. Zhang, C. Lee, D. Niyato, and P. Wang, "Auction approaches for resource allocation in wireless systems: A survey," *IEEE Commun. Surveys Tuts.*, vol. 15, no. 3, pp. 1020–1041, 3rd Quart., 2013.

[96] M. A. Hoque, X. Hong, and F. Afroz, "Multiple radio channel assignement utilizing partially overlapped channels," in *Proc. IEEE Global Telecommun. Conf. (GLOBECOM)*, Nov. 2009, pp. 1–7.

[97] P. B. F. Duarte, Z. M. Fadlullah, K. Hashimoto, and N. Kato, "Partially overlapped channel assignment on wireless mesh network backbone," in *Proc. IEEE Global Telecommun. Conf. (GLOBECOM)*, Dec. 2010, pp. 1–5.

[98] Z. Ji, W. Yu, and K. J. R. Liu, "An optimal dynamic pricing framework for autonomous mobile ad hoc networks," in *Proc. IEEE 25th Int. Conf. Comput. Commun. (INFOCOM)*, Apr. 2006, pp. 1–12.

[99] P. B. F. Duarte, Z. M. Fadlullah, A. V. Vasilakos, and N. Kato, "On the partially overlapped channel assignment on wireless mesh network backbone: A game theoretic approach," *IEEE J. Sel. Areas Commun.*, vol. 30, no. 1, pp. 119–127, Jan. 2012.

[100] C. Ibars, R. Milito, and P. Monclus, "Radio resource allocation for a high capacity vehicular access network," in *Proc. IEEE Veh. Technol. Conf. (VTC Fall)*, Sep. 2011, pp. 1–5.

[101] T. Yang, R. Zhang, X. Cheng, and L. Yang, "A graph coloring resource sharing scheme for full-duplex cellular-VANET heterogeneous networks," in *Proc. Int. Conf. Comput. Netw. Commun. (ICNC)*, Feb. 2016, pp. 1–5.

[102] C. You, K. Huang, H. Chae, and B.-H. Kim, "Energy-efficient resource allocation for mobile-edge computation offloading," *IEEE Trans. Wireless Commun.*, vol. 16, no. 3, pp. 1397–1411, Mar. 2017.

[103] X. Cao, L. Liu, Y. Cheng, L. X. Cai, and C. Sun, "On optimal device-to-device resource allocation for minimizing end-to-end delay in VANETs," *IEEE Trans. Veh. Technol.*, vol. 65, no. 10, pp. 7905–7916, Oct. 2016.

[104] J. Tao, Z. Zhang, F. Feng, J. He, and Y. Xu, "Non-cooperative resource allocation scheme for data access in VANET cloud environment," in *Proc. 3rd Int. Conf. Adv. Cloud Big Data*, Oct. 2015, pp. 190–196.

[105] N. Cheng, N. Zhang, N. Lu, X. Shen, J. W. Mark, and F. Liu, "Opportunistic spectrum access for CR-VANETs: A game-theoretic approach," *IEEE Trans. Veh. Technol.*, vol. 63, no. 1, pp. 237–251, Jan. 2014.

[106] W. Xing, N. Wang, C. Wang, F. Liu, and Y. Ji, "Resource allocation schemes for D2D communication used in VANETs," in *Proc. IEEE 80th Veh. Technol. Conf. (VTC-Fall)*, Sep. 2014, pp. 1–6.

[107] M. N. Soorki, M. Mozaffari, W. Saad, M. H. Manshaei, and H. Saidi, "Resource allocation for machine-to-machine communications with unmanned aerial vehicles," in *Proc. IEEE Globecom Workshops (GC Wkshps)*, Dec. 2016, pp. 1–6.

[108] J. Moy, "OSPF version 2," IETF, Fremont, CA, USA, Rep. RFC 2178, 1997.

[109] R. W. Callon, "Use of OSI IS-IS for routing in TCP/IP and dual environments," IETF, Fremont, CA, USA, Rep. RFC 1195, 1990.

[110] J. Macker, "Mobile ad hoc networking (MANET): Routing protocol performance issues and evaluation considerations," IETF, RFC 2501, 1999.

[111] C. E. Perkins and P. Bhagwat, "Highly dynamic destination-sequenced distance-vector routing (DSDV) for mobile computers," in *Proc. ACM Conf. Commun. Architect. Protocols Appl. (SIGCOMM)*, 1994, pp. 234–244.

[112] R. Dube, C. D. Rais, K.-Y. Wang, and S. K. Tripathi, "Signal stability-based adaptive routing (SSA) for ad hoc mobile networks," *IEEE Pers. Commun.*, vol. 4, no. 1, pp. 36–45, Feb. 1997.

[113] D. B. Johnson and D. A. Maltz, *Dynamic Source Routing in Ad Hoc Wireless Networks*. Boston, MA, USA: Springer, 1996, pp. 153–181.

[114] T. Clausen and P. Jacquet, "Optimized link state routing protocol (OLSR)," IETF, Fremont, CA, USA, Rep. RFC 3626, 2003.

[115] C. Perkins, E. Belding-Royer, and S. Das, "Ad hoc on-demand distance vector (AODV) routing," IETF, Fremont, CA, USA, Rep. RFC 3561, 2003.

[116] M. Mauve, H. Füßler, J. Widmer, and T. Lang, "Position-based multicast routing for mobile ad-hoc networks," *ACM SIGMOBILE Mobile Comput. Commun. Rev.*, vol. 7, no. 3, pp. 53–55. 2003.

[117] B. Karp and H. T. Kung, "GPSR: Greedy perimeter stateless routing for wireless networks," in *Proc. 6th Annu. Int. Conf. Mobile Comput. Netw. (MobiCom)*, 2000, pp. 243–254.

[118] C. Lochert, H. Hartenstein, J. Tian, H. Fussler, D. Hermann, and M. Mauve, "A routing strategy for vehicular ad hoc networks in city environments," in *Proc. IEEE Intell. Veh. Symp. (IV)*, Jun. 2003, pp. 156–161.

[119] J. Nzouonta, N. Rajgure, G. Wang, and C. Borcea, "Vanet routing on city roads using real-time vehicular traffic information," *IEEE Trans. Veh. Technol.*, vol. 58, no. 7, pp. 3609–3626, Sep. 2009.

[120] J. Chang, Y. Li, W. Liao, and I. Chang, "Intersection-based routing for urban vehicular communications with traffic-light considerations," *IEEE Wireless Commun.*, vol. 19, no. 1, pp. 82–88, Feb. 2012.

[121] M. A. Kafi, D. Djenouri, J. Ben-Othman, and N. Badache, "Congestion control protocols in wireless sensor networks: A survey," *IEEE Commun. Surveys Tuts.*, vol. 16, no. 3, pp. 1369–1390, 3rd Quart., 2014.

[122] S. Bastani, B. Landfeldt, and L. Libman, "On the reliability of safety message broadcast in urban vehicular ad hoc networks," in *Proc. 14th ACM Int. Conf. Model. Anal. Simulat. Wireless Mobile Syst. (MSWiM)*, 2011, pp. 307–316.

[123] H. Song and H. S. Lee, "A survey on how to solve a decentralized congestion control problem for periodic beacon broadcast in vehicular safety communications," in *Proc. 15th Int. Conf. Adv. Commun. Technol. (ICACT)*, Jan. 2013, pp. 649–654.

[124] L. Wischhof and H. Rohling, "Congestion control in vehicular ad hoc networks," in *Proc. IEEE Int. Conf. Veh. Electron. Safety*, Oct. 2005, pp. 58–63.

[125] G. Santhi and A. Nachiappan, "Fuzzy-cost based multiconstrained QoS routing with mobility prediction in MANETs," *Egypt. Informat. J.*, vol. 13, no. 1, pp. 19–25, 2012.

[126] M. Torrent-Moreno, J. Mittag, P. Santi, and H. Hartenstein, "Vehicle-to-vehicle communication: Fair transmit power control for safety-critical information," *IEEE Trans. Veh. Technol.*, vol. 58, no. 7, pp. 3684–3703, Sep. 2009.

[127] C. Sommer, O. K. Tonguz, and F. Dressler, "Adaptive beaconing for delay-sensitive and congestion-aware traffic information systems," in *Proc. IEEE Veh. Netw. Conf.*, Dec. 2010, pp. 1–8.

[128] J. He, H. Chen, T. M. Chen, and W. Cheng, "Adaptive congestion control for DSRC vehicle networks," *IEEE Commun. Lett.*, vol. 14, no. 2, pp. 127–129, Feb. 2010.

[129] D. B. Rawat, D. C. Popescu, G. Yan, and S. Olariu, "Enhancing VANET performance by joint adaptation of transmission power and contention window size," *IEEE Trans. Parallel Distrib. Syst.*, vol. 22, no. 9, pp. 1528–1535, Sep. 2011.

[130] D. E. Rumelhart *et al.*, "Learning representations by back-propagating errors," *Cogn. Model.*, vol. 5, no. 3, pp. 696–699, 1988.

[131] Y. LeCun *et al.*, "Backpropagation applied to handwritten zip code recognition," *Neural Comput.*, vol. 1, no. 4, pp. 541–551, 1989.

[132] C. Cortes and V. Vapnik, "Support-vector networks," *Mach. Learn.*, vol. 20, no. 3, pp. 273–297, Sep. 1995.

[133] L. Breiman, "Random forests," *Mach. Learn.*, vol. 45, no. 1, pp. 5–32, Oct. 2001.

[134] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural Comput.*, vol. 9, no. 8, pp. 1735–1780, 1997.

[135] J. H. Friedman, "Greedy function approximation: A gradient boosting machine," *Ann. Stat.*, vol. 29, no. 5, pp. 1189–1232, 2001.

[136] G. E. Hinton and R. R. Salakhutdinov, "Reducing the dimensionality of data with neural networks," *Science*, vol. 313, no. 5786, pp. 504–507, 2006.

[137] Y. Bengio, A. Courville, and P. Vincent, "Representation learning: A review and new perspectives," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 35, no. 8, pp. 1798–1828, Aug. 2013.

[138] Y. Bengio, P. Lamblin, D. Popovici, and H. Larochelle, "Greedy layer-wise training of deep networks," in *Proc. Adv. Neural Inf. Process. Syst.*, 2007, pp. 153–160.

[139] G. E. Hinton, S. Osindero, and Y.-W. Teh, "A fast learning algorithm for deep belief nets," *Neural Comput.*, vol. 18, no. 7, pp. 1527–1554, 2006.

[140] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2016, pp. 770–778.

[141] S. Sabour, N. Frosst, and G. E. Hinton, "Dynamic routing between capsules," in *Proc. 30th Adv. Neural Inf. Process. Syst.*, 2017, pp. 3856–3866.

[142] P. W. Battaglia *et al.*, "Relational inductive biases, deep learning, and graph networks," 2018. [Online]. Available: arxiv.abs/1806.01261.

[143] J. H. Ward, Jr., "Hierarchical grouping to optimize an objective function," *J. Amer. Stat. Assoc.*, vol. 58, no. 301, pp. 236–244, 1963.

[144] J. MacQueen *et al.*, "Some methods for classification and analysis of multivariate observations," in *Proc. 5th Berkeley Symp. Math. Stat. Probab.*, vol. 1. Oakland, CA, USA, 1967, pp. 281–297.

[145] A. P. Dempster, N. M. Laird, and D. B. Rubin, "Maximum likelihood from incomplete data via the EM algorithm," *J. Roy. Stat. Soc. B Methodol.*, vol. 39, no. 1, pp. 1–22, 1977.

[146] Y. Cheng, "Mean shift, mode seeking, and clustering," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 17, no. 8, pp. 790–799, Aug. 1995.

[147] W. Wang, J. Yang, and R. R. Muntz, "STING: A statistical information grid approach to spatial data mining," in *Proc. VLDB*, vol. 97, 1997, pp. 186–195.

[148] R. Agrawal, J. Gehrke, D. Gunopulos, and P. Raghavan, "Automatic subspace clustering of high dimensional data for data mining applications," *ACM SIGMOD Rec.*, vol. 27, no. 2, pp. 94–105, 1998.

[149] J. Shi and J. Malik, "Normalized cuts and image segmentation," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 22, no. 8, pp. 888–905, Aug. 2000.

[150] K. Pearson, "LIII. Onlines and planes of closest fit to systems of points in space," *London Edinburgh Dublin Philos. Mag. J. Sci.*, vol. 2, no. 11, pp. 559–572, 1901.

[151] B. Schölkopf, A. Smola, and K.-R. Müller, "Nonlinear component analysis as a kernel eigenvalue problem," *Neural Comput.*, vol. 10, no. 5, pp. 1299–1319, 1998.

[152] S. T. Roweis and L. K. Saul, "Nonlinear dimensionality reduction by locally linear embedding," *Science*, vol. 290, no. 5500, pp. 2323–2326, 2000.

[153] M. Belkin and P. Niyogi, "Laplacian eigenmaps for dimensionality reduction and data representation," *Neural Comput.*, vol. 15, no. 6, pp. 1373–1396, 2003.

[154] X. He and P. Niyogi, "Locality preserving projections," in *Proc. Adv. Neural Inf. Process. Syst.*, 2004, pp. 153–160.

[155] J. B. Tenenbaum, V. D. Silva, and J. C. Langford, "A global geometric framework for nonlinear dimensionality reduction," *Science*, vol. 290, no. 5500, pp. 2319–2323, 2000.

[156] G. E. Hinton and S. T. Roweis, "Stochastic neighbor embedding," in *Proc. Adv. Neural Inf. Process. Syst.*, 2003, pp. 857–864.

[157] L. V. D. Maaten and G. Hinton, "Visualizing data using t-SNE," *J. Mach. Learn. Res.*, vol. 9, pp. 2579–2605, Nov. 2008.

[158] R. A. Howard, *Dynamic Programming and Markov Processes*. Cambridge, MA, USA: MIT Press, 1960.

[159] H. Sakoe, S. Chiba, A. Waibel, and K. Lee, "Dynamic programming algorithm optimization for spoken word recognition," *Read. Speech Recognit.*, vol. 159, p. 224, May 1990.

[160] R. S. Sutton, "Learning to predict by the methods of temporal differences," *Mach. Learn.*, vol. 3, no. 1, pp. 9–44, 1988.

[161] C. J. C. H. Watkins, "Learning from delayed rewards," Ph.D. dissertation, Dept. Psychol., Cambridge Univ., Cambridge, U.K., 1989.

[162] C. J. C. H. Watkins and P. Dayan, "*Q*-learning," *Mach. Learn.*, vol. 8, no. 3, pp. 279–292, May 1992.

[163] D. Silver *et al.*, "Mastering the game of go with deep neural networks and tree search," *Nature*, vol. 529, no. 7587, p. 484, 2016.

[164] V. Mnih *et al.*, "Playing Atari with deep reinforcement learning," 2013. [Online]. Available: arxiv.abs/1312.5602.

[165] H. Van Hasselt, A. Guez, and D. Silver, "Deep reinforcement learning with double *Q*-learning," in *Proc. 13th AAAI Conf. Artif. Intell.*, 2016, pp. 2094–2100.

[166] R. S. Sutton, D. A. McAllester, S. P. Singh, and Y. Mansour, "Policy gradient methods for reinforcement learning with function approximation," in *Proc. Adv. Neural Inf. Process. Syst.*, 2000, pp. 1057–1063.

[167] V. Mnih *et al.*, "Asynchronous methods for deep reinforcement learning," in *Proc. Int. Conf. Mach. Learn.*, 2016, pp. 1928–1937.

[168] J. Schulman, F. Wolski, P. Dhariwal, A. Radford, and O. Klimov, "Proximal policy optimization algorithms," 2017. [Online]. Available: arxiv.abs/1707.06347.

[169] T.-H. Li, M. R. A. Khandaker, F. Tariq, K.-K. Wong, and R. T. Khan, "Learning the wireless V2I channels using deep neural networks," in *Proc. IEEE 90th Veh. Technol. Conf. (VTC-Fall)*, 2019, pp. 1–5.

[170] Y. Guo, Z. Wang, M. Li, and Q. Liu, "Machine learning based mmWave channel tracking in vehicular scenario," in *Proc. IEEE Int. Conf. Commun. Workshops (ICC Workshops)*, 2019, pp. 1–6.

[171] J. Yang, L. Li, and M.-J. Zhao, "A blind CSI prediction method based on deep learning for V2I millimeter-wave channel," in *Proc. IEEE 28th Int. Conf. Netw. Protocols (ICNP)*, 2020, pp. 1–6.

[172] P. Qi, Y. Zhang, Z. Yuan, L. Yu, P. Tang, and J. Zhang, "Channel modeling based on 3D scenario information for V2I communications," in *Proc. 15th Eur. Conf. Antennas Propag. (EuCAP)*, 2021, pp. 1–5.

[173] J. Joo, M. C. Park, D. S. Han, and V. Pejovic, "Deep learning-based channel prediction in realistic vehicular communications," *IEEE Access*, vol. 7, pp. 27846–27858, 2019.

[174] S. Kim, B. J. Kim, and B. Park, "Environment-adaptive multiple access for distributed V2X network: A reinforcement learning framework," in *Proc. IEEE Veh. Technol. Conf. (VTC)*, 2021.

[175] S. Han, Y. Oh, and C. Song, "A deep learning based channel estimation scheme for IEEE 802.11p systems," in *Proc. IEEE Int. Conf. Commun. (ICC)*, 2019, pp. 1–6.

[176] R. Sattiraju, A. Weinand, and H. D. Schotten, "Channel estimation in C-V2X using deep learning," in *Proc. IEEE Int. Conf. Adv. Netw. Telecommun. Syst. (ANTS)*, 2019, pp. 1–5.

[177] G. Liu, Y. Xu, Z. He, Y. Rao, J. Xia, and L. Fan, "Deep learning-based channel prediction for edge computing networks toward intelligent connected vehicles," *IEEE Access*, vol. 7, pp. 114487–114495, 2019.

[178] T. E. Bogale, X. Wang, and L. B. Le, "Adaptive channel prediction, beamforming and scheduling design for 5G V2I network: Analytical and machine learning approaches," *IEEE Trans. Veh. Technol.*, vol. 69, no. 5, pp. 5055–5067, May 2020.

[179] E. Salazar, C. A. Azurdia-Meza, D. Zabala-Blanco, S. Bolufé, and I. Soto, "Semi-supervised extreme learning machine channel estimator and equalizer for vehicle to vehicle communications," *Electronics*, vol. 10, no. 8, p. 968, 2021. [Online]. Available: https://www.mdpi.com/2079-9292/10/8/968

[180] D. J. Sebald and J. A. Bucklew, "Support vector machine techniques for nonlinear equalization," *IEEE Trans. Signal Process.*, vol. 48, no. 11, pp. 3217–3226, Nov. 2000.

[181] S. Chen, G. Gibson, C. Cowan, and P. Grant, "Adaptive equalization of finite non-linear channels using multilayer perceptrons," *Signal Process.*, vol. 20, no. 2, pp. 107–119, 1990. [Online]. Available: http://www.sciencedirect.com/science/article/pii/016516849090122F

[182] M. Sanchez-Fernandez, M. de-Prado-Cumplido, J. Arenas-Garcia, and F. Perez-Cruz, "SVM multiregression for nonlinear channel estimation in multiple-input multiple-output systems," *IEEE Trans. Signal Process.*, vol. 52, no. 8, pp. 2298–2307, Aug. 2004.

[183] V. Feng and S. Y. Chang, "Determination of wireless networks parameters through parallel hierarchical support vector machines," *IEEE Trans. Parallel Distrib. Syst.*, vol. 23, no. 3, pp. 505–512, Mar. 2012.

[184] C. Wen, S. Jin, K. Wong, J. Chen, and P. Ting, "Channel estimation for massive MIMO using Gaussian-mixture Bayesian learning," *IEEE Trans. Wireless Commun.*, vol. 14, no. 3, pp. 1356–1368, Mar. 2015.

[185] R. Prasad, C. R. Murthy, and B. D. Rao, "Joint approximately sparse channel estimation and data detection in OFDM systems using sparse Bayesian learning," *IEEE Trans. Signal Process.*, vol. 62, no. 14, pp. 3591–3603, Jul. 2014.

[186] Y. Huang, L. Wan, S. Zhou, Z. Wang, and J. Huang, "Comparison of sparse recovery algorithms for channel estimation in underwater acoustic OFDM with data-driven sparsity learning," *Phys. Commun.*, vol. 13, pp. 156–167, Dec. 2014.

[187] S. Stainton, W. Ozan, M. Johnston, S. Dlay, and P. A. Haigh, "Neural network equalisation and symbol detection for 802.11p V2V communication at 5.9 Ghz," in *Proc. IEEE 91st Veh. Technol. Conf. (VTC-Spring)*, 2020, pp. 1–5.

[188] T. Wang, C. Wen, H. Wang, F. Gao, T. Jiang, and S. Jin, "Deep learning for wireless physical layer: Opportunities and challenges," *China Commun.*, vol. 14, no. 11, pp. 92–111, Nov 2017.

[189] R. C. Daniels, C. M. Caramanis, and R. W. Heath, "Adaptation in convolutionally coded MIMO-OFDM wireless systems through supervised learning and SNR ordering," *IEEE Trans. Veh. Technol.*, vol. 59, no. 1, pp. 114–126, Jan. 2010.

[190] A. Felix, S. Cammerer, S. Dörner, J. Hoydis, and S. T. Brink, "OFDM-autoencoder for end-to-end learning of communications systems," in *Proc. IEEE 19th Int. Workshop Signal Process. Adv. Wireless Commun. (SPAWC)*, Jun. 2018, pp. 1–5.

[191] R. Pal, A. Prakash, R. Tripathi, and K. Naik, "Regional super cluster based optimum channel selection for CR-VANET," *IEEE Trans. Cogn. Commun. Netw.*, vol. 6, no. 2, pp. 607–617, Jun. 2020.

[192] M. Bkassiny, Y. Li, and S. K. Jayaweera, "A survey on machine-learning techniques in cognitive radios," *IEEE Commun. Surveys Tuts.*, vol. 15, no. 3, pp. 1136–1159, 3rd Quart., 2013.

[193] S. Gong, W. Liu, W. Yuan, W. Cheng, and S. Wang, "Threshold-learning in local spectrum sensing of cognitive radio," in *Proc. IEEE 69th Veh. Technol. Conf. (VTC Spring)*, Apr. 2009, pp. 1–6.

[194] M. M. Ramón, T. Atwood, S. Barbin, and C. G. Christodoulou, "Signal classification with an SVM-FFT approach for feature extraction in cognitive radio," in *Proc. SBMO/IEEE MTT-S Int. Microw. Optoelectron. Conf. (IMOC)*, Nov. 2009, pp. 286–289.

[195] G. J. Mendis, J. Wei, and A. Madanayake, "Deep learning-based automated modulation classification for cognitive radio," in *Proc. IEEE Int. Conf. Commun. Syst. (ICCS)*, Dec. 2016, pp. 1–6.

[196] X. Dong, Y. Li, C. Wu, and Y. Cai, "A learner based on neural network for cognitive radio," in *Proc. IEEE 12th Int. Conf. Commun. Technol.*, Nov. 2010, pp. 893–896.

[197] X.-L. Huang, J. Wu, W. Li, Z. Zhang, F. Zhu, and M. Wu, "Historical spectrum sensing data mining for cognitive radio enabled vehicular ad-hoc networks," *IEEE Trans. Depend. Secure Comput.*, vol. 13, no. 1, pp. 59–70, Jan./Feb. 2016.

[198] A. Galindo-Serrano and L. Giupponi, "Distributed *Q*-learning for aggregated interference control in cognitive radio networks," *IEEE Trans. Veh. Technol.*, vol. 59, no. 4, pp. 1823–1834, May 2010.

[199] K. W. Choi and E. Hossain, "Estimation of primary user parameters in cognitive radio systems via hidden Markov model," *IEEE Trans. Signal Process.*, vol. 61, no. 3, pp. 782–795, Feb. 2013.

[200] A. Assra, J. Yang, and B. Champagne, "An EM approach for cooperative spectrum sensing in multiantenna CR networks," *IEEE Trans. Veh. Technol.*, vol. 65, no. 3, pp. 1229–1243, Mar. 2016.

[201] J. Zhu, Y. Song, D. Jiang, and H. Song, "A new deep-*Q*-learning-based transmission scheduling mechanism for the cognitive Internet of Things," *IEEE Internet Things J.*, vol. 5, no. 4, pp. 2375–2385, Aug. 2018.

[202] K. Zhang, S. Leng, X. Peng, L. Pan, S. Maharjan, and Y. Zhang, "Artificial intelligence inspired transmission scheduling in cognitive vehicular communications and networks," *IEEE Internet Things J.*, vol. 6, no. 2, pp. 1987–1997, Apr. 2019.

[203] M. A. Hossain *et al.*, "Machine learning-based cooperative spectrum sensing in dynamic segmentation enabled cognitive radio vehicular network," *Energies*, vol. 14, no. 4, p. 1169, 2021. [Online]. Available: https://www.mdpi.com/1996-1073/14/4/1169

[204] K. M. Thilina, K. W. Choi, N. Saquib, and E. Hossain, "Machine learning techniques for cooperative spectrum sensing in cognitive radio networks," *IEEE J. Sel. Areas Commun.*, vol. 31, no. 11, pp. 2209–2221, Nov. 2013.

[205] M. M. Ramon, N. Xu, and C. G. Christodoulou, "Beamforming using support vector machines," *IEEE Antennas Wireless Propag. Lett.*, vol. 4, pp. 439–442, 2005.

[206] C. C. Gaudes, I. Santamaria, J. Via, E. Masgrau Gomez, and T. S. Paules, "Robust array beamforming with sidelobe control using support vector machines," *IEEE Trans. Signal Process.*, vol. 55, no. 2, pp. 574–584, Feb. 2007.

[207] Y. Wang, M. Narasimha, and R. W. Heath, "Towards robustness: Machine learning for mmWave V2X with situational awareness," in *Proc. 52nd Asilomar Conf. Signals Syst. Comput.*, 2018, pp. 1577–1581.

[208] Y. Yang, Z. Gao, Y. Ma, B. Cao, and D. He, "Machine learning enabling analog beam selection for concurrent transmissions in millimeter-wave V2V communications," *IEEE Trans. Veh. Technol.*, vol. 69, no. 8, pp. 9185–9189, Aug. 2020.

[209] A. Asadi, S. Müller, G. H. Sim, A. Klein, and M. Hollick, "FML: Fast machine learning for 5G mmWave vehicular communications," in *Proc. IEEE INFOCOM Conf. Comput. Commun.*, Apr. 2018, pp. 1961–1969.

[210] J. Gui, Y. Liu, X. Deng, and B. Liu, "Network capacity optimization for cellular-assisted vehicular systems by online learning-based mmWave beam selection," *Wireless Commun. Mobile Comput.*, vol. 2021, Mar. 2021, Art. no. 8876186.

[211] A. Alkhateeb, S. Alex, P. Varkey, Y. Li, Q. Qu, and D. Tujkovic, "Deep learning coordinated beamforming for highly-mobile millimeter wave systems," *IEEE Access*, vol. 6, pp. 37328–37348, 2018.

[212] H. Echigo, Y. Cao, M. Bouazizi, and T. Ohtsuki, "A deep learning-based low overhead beam selection in mmWave communications," *IEEE Trans. Veh. Technol.*, vol. 70, no. 1, pp. 682–691, Jan. 2021.

[213] S. Rezaie, C. N. Manchon, and E. de Carvalho, "Location- and orientation-aided millimeter wave beam selection using deep learning," in *Proc. IEEE Int. Conf. Commun. (ICC)*, 2020, pp. 1–6.

[214] N. Van Huynh, D. N. Nguyen, D. T. Hoang, and E. Dutkiewicz, "Optimal beam association in mmWave vehicular networks with parallel reinforcement learning," in *Proc. GLOBECOM IEEE Global Commun. Conf.*, 2020, pp. 1–6.

[215] L. Zhang, X. Chen, Y. Fang, X. Huang, and X. Fang, "Learning-based mmWave V2I environment augmentation through tunable reflectors," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, 2019, pp. 1–6.

[216] Y. Wang, S. Zhou, L. Xiao, X. Zhang, and J. Lian, "Sparse Bayesian learning based user detection and channel estimation for SCMA uplink systems," in *Proc. Int. Conf. Wireless Commun. Signal Process. (WCSP)*, Oct. 2015, pp. 1–5.

[217] M. Kim, N. Kim, W. Lee, and D. Cho, "Deep learning-aided SCMA," *IEEE Commun. Lett.*, vol. 22, no. 4, pp. 720–723, Apr. 2018.

[218] S. Xu, C. Guo, and Z. Li, "NOMA enabled resource allocation for vehicle platoon-based vehicular networks," in *Proc. IEEE Globecom Workshops (GC Wkshps)*, 2019, pp. 1–6.

[219] Y.-H. Xu, C.-C. Yang, M. Hua, and W. Zhou, "Deep deterministic policy gradient (DDPG)-based resource allocation scheme for NOMA vehicular communications," *IEEE Access*, vol. 8, pp. 18797–18807, 2020.

[220] H. Ding and K.-C. Leung. *Resource Allocation for Low-Latency NOMA-V2X Networks Using Reinforcement Learning*. Accessed: Jun. 2021. [Online]. Available: https://www.eee.hku.hk/ kcleung/papers/conferences/NOMA-V2X:GI_2021/2021040367.pdf

[221] M. Duque-Anton, D. Kunz, and B. Ruber, "Channel assignment for cellular radio using simulated annealing," *IEEE Trans. Veh. Technol.*, vol. 42, no. 1, pp. 14–21, Feb. 1993.

[222] D. Kunz, "Channel assignment for cellular radio using neural networks," *IEEE Trans. Veh. Technol.*, vol. 40, no. 1, pp. 188–193, Feb. 1991.

[223] F. Tang, Z. M. Fadlullah, B. Mao, and N. Kato, "An intelligent traffic load prediction-based adaptive channel assignment algorithm in SDN-IoT: A deep learning approach," *IEEE Internet Things J.*, vol. 5, no. 6, pp. 5141–5154, Dec. 2018.

[224] J. Nie and S. Haykin, "A *Q*-learning-based dynamic channel assignment technique for mobile communication systems," *IEEE Trans. Veh. Technol.*, vol. 48, no. 5, pp. 1676–1687, Sep. 1999.

[225] S. Misra, P. V. Krishna, and V. Saritha, "LACAV: An energy-efficient channel assignment mechanism for vehicular ad hoc networks," *J. Supercomput.*, vol. 62, no. 3, pp. 1241–1262, Dec. 2012.

[226] Y. He, F. R. Yu, N. Zhao, H. Yin, and A. Boukerche, "Deep reinforcement learning (DRL)-based resource management in software-defined and virtualized vehicular ad hoc networks," in *Proc. 6th ACM Symp. Develop. Anal. Intell. Veh. Netw. Appl. (DIVANet)*, 2017, pp. 47–54.

[227] Y. He, N. Zhao, and H. Yin, "Integrated networking, caching, and computing for connected vehicles: A deep reinforcement learning approach," *IEEE Trans. Veh. Technol.*, vol. 67, no. 1, pp. 44–55, Jan. 2018.

[228] L. Xiao, T. Chen, C. Xie, H. Dai, and H. V. Poor, "Mobile crowdsensing games in vehicular networks," *IEEE Trans. Veh. Technol.*, vol. 67, no. 2, pp. 1535–1545, Feb. 2018.

[229] R. F. Atallah, C. M. Assi, and J. Y. Yu, "A reinforcement learning technique for optimizing downlink scheduling in an energy-limited vehicular network," *IEEE Trans. Veh. Technol.*, vol. 66, no. 6, pp. 4592–4601, Jun. 2017.

[230] Y. Zhou, F. Tang, Y. Kawamoto, and N. Kato, "Reinforcement learning based radio resource control in 5G vehicular network," *IEEE Wireless Commun. Lett.*, vol. 9, no. 1, pp. 611–614, May 2020.

[231] F. Tang, Y. Zhou, and N. Kato, "Deep reinforcement learning for dynamic uplink/downlink resource allocation in high mobility 5G HetNet," *IEEE J. Sel. Areas Commun.*, vol. 38, no. 12, pp. 2773–2782, Dec. 2020.

[232] H. Ye, G. Y. Li, and B. F. Juang, "Deep reinforcement learning based resource allocation for V2V communications," *IEEE Trans. Veh. Technol.*, vol. 68, no. 4, pp. 3163–3173, Apr. 2019.

[233] Y. Kawamoto, H. Takagi, H. Nishiyama, and N. Kato, "Efficient resource allocation utilizing *Q*-learning in multiple UA communications," *IEEE Trans. Netw. Sci. Eng.*, vol. 6, no. 3, pp. 293–302, Jul.–Sep. 2019.

[234] T. Fu, C. Wang, and N. Cheng, "Deep-learning-based joint optimization of renewable energy storage and routing in vehicular energy network," *IEEE Internet Things J.*, vol. 7, no. 7, pp. 6229–6241, Jul. 2020.

[235] J. Gao, M. R. A. Khandaker, F. Tariq, K. Wong, and R. T. Khan, "Deep neural network based resource allocation for V2X communications," in *Proc. IEEE 90th Veh. Technol. Conf. (VTC-Fall)*, Sep. 2019, pp. 1–5.

[236] M. Chen, J. Chen, X. Chen, S. Zhang, and S. Xu, "A deep learning based resource allocation scheme in vehicular communication systems," in *Proc. IEEE Wireless Commun. Netw. Conf. (WCNC)*, Apr. 2019, pp. 1–6.

[237] F. Tang, B. Mao, Z. M. Fadlullah, and N. Kato, "On a novel deep-learning-based intelligent partially overlapping channel assignment in SDN-IoT," *IEEE Commun. Mag.*, vol. 56, no. 9, pp. 80–86, Sep. 2018.

[238] F. Tang, B. Mao, Z. M. Fadlullah, and N. Kato, "Deep spatiotemporal partially overlapping channel allocation: Joint CNN and activity vector approach," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Dec. 2018, pp. 1–6.

[239] S. K. Tayyaba *et al.*, "5G vehicular network resource management for improving radio access through machine learning," *IEEE Access*, vol. 8, pp. 6792–6800, 2020.

[240] M. I. Khan, F. Aubet, M. Pahl, and J. Härri. (2019). *Deep Learning-Aided Application Scheduler for Vehicular Safety Communication*. [Online]. Available: http://arxiv.org/abs/1901.08872.

[241] T. Fu, C. Wang, and N. Cheng, "Deep learning based joint optimization of renewable energy storage and routing in vehicular energy network," *IEEE Internet Things J.*, vol. 7, no. 7, pp. 6229–6241, Jul. 2020.

[242] C. Ide *et al.*, "LTE connectivity and vehicular traffic prediction based on machine learning approaches," in *Proc. IEEE 82nd Veh. Technol. Conf. (VTC-Fall)*, Sep. 2015, pp. 1–5.

[243] Y. Tang, N. Cheng, W. Wu, M. Wang, Y. Dai, and X. Shen, "Delay-minimization routing for heterogeneous VANETs with machine learning based mobility prediction," *IEEE Trans. Veh. Technol.*, vol. 68, no. 4, pp. 3967–3979, Apr. 2019.

[244] U. Ihsan, R. Malaney, and S. Yan, "Machine learning and location verification in vehicular networks," in *Proc. IEEE/CIC Int. Conf. Commun. China (ICCC)*, 2019, pp. 91–95.

[245] W. Huang, G. Song, H. Hong, and K. Xie, "Deep architecture for traffic flow prediction: Deep belief networks with multitask learning," *IEEE Trans. Intell. Transp. Syst.*, vol. 15, no. 5, pp. 2191–2201, Oct. 2014.

[246] Y. Lv, Y. Duan, W. Kang, Z. Li, and F. Wang, "Traffic flow prediction with big data: A deep learning approach," *IEEE Trans. Intell. Transp. Syst.*, vol. 16, no. 2, pp. 865–873, Apr. 2015.

[247] J. Li *et al.*, "An end-to-end load balancer based on deep learning for vehicular network traffic control," *IEEE Internet Things J.*, vol. 6, no. 1, pp. 953–966, Feb. 2019.

[248] S. Basu, A. Mukherjee, and S. Klivansky, "Time series models for Internet traffic," in *Proc. IEEE INFOCOM Conf. Comput. Commun.*, vol. 2, Mar. 1996, pp. 611–620.

[249] G. Zhang, "Time series forecasting using a hybrid arima and neural network model," *Neurocomputing*, vol. 50, pp. 159–175, Jan. 2003.

[250] J. Ilow, "Forecasting network traffic using farima models with heavy tailed innovations," in *Proc. IEEE Int. Conf. Acoust. Speech Signal Process.*, vol. 6, Jun. 2000, pp. 3814–3817.

[251] H. Feng and Y. Shu, "Study on network traffic prediction techniques," in *Proc. Int. Conf. Wireless Commun. Netw. Mobile Comput.*, vol. 2, Sep. 2005, pp. 1041–1044.

[252] V. Alarcon-Aquino and J. A. Barria, "Multiresolution fir neural-network-based learning algorithm applied to network traffic prediction," *IEEE Trans. Syst., Man, Cybern. A, Syst., Humans*, vol. 36, no. 2, pp. 208–220, Mar. 2006.

[253] M. Lopez-Martin, B. Carro, A. Sanchez-Esguevillas, and J. Lloret, "Network traffic classifier with convolutional and recurrent neural networks for Internet of Things," *IEEE Access*, vol. 5, pp. 18042–18050, 2017.

[254] Z. M. Fadlullah, F. Tang, B. Mao, J. Liu, and N. Kato, "On intelligent traffic control for large-scale heterogeneous networks: A value matrix-based deep learning approach," *IEEE Commun. Lett.*, vol. 22, no. 12, pp. 2479–2482, Dec. 2018.

[255] M. Sangare, S. Banerjee, P. Muhlethaler, and S. Bouzefrane, "Predicting transmission success with machine-learning and support vector machine in VANETs," in *Proc. 7th IFIP/IEEE Int. Conf. Perform. Eval. Model. Wired Wireless Netw. (PEMWN)*, Toulouse, France, Sep. 2018, pp. 1–5.

[256] M. Slavik and I. Mahgoub, "Applying machine learning to the design of multi-hop broadcast protocols for VANET," in *Proc. 7th Int. Wireless Commun. Mobile Comput. Conf.*, Jul. 2011, pp. 1742–1747.

[257] F. Tang *et al.*, "On removing routing protocol from future wireless networks: A real-time deep learning approach for intelligent traffic control," *IEEE Wireless Commun.*, vol. 25, no. 1, pp. 154–160, Feb. 2018.

[258] C. Wu, Y. Ji, F. Liu, S. Ohzahata, and T. Kato, "Toward practical and intelligent routing in vehicular ad hoc networks," *IEEE Trans. Veh. Technol.*, vol. 64, no. 12, pp. 5503–5519, Dec. 2015.

[259] Y. Zeng, K. Xiang, D. Li, and A. V. Vasilakos, "Directional routing and scheduling for green vehicular delay tolerant networks," *Wireless Netw.*, vol. 19, no. 2, pp. 161–173, Feb. 2013.

[260] J. A. Boyan and M. L. Littman, "Packet routing in dynamically changing networks: A reinforcement learning approach," in *Proc. Adv. Neural Inf. Process. Syst.*, 1994, pp. 671–678.

[261] J. Dowling, E. Curran, R. Cunningham, and V. Cahill, "Using feedback in collaborative reinforcement learning to adaptively optimize manet routing," *IEEE Trans. Syst., Man, Cybern. A, Syst., Humans*, vol. 35, no. 3, pp. 360–372, May 2005.

[262] L. Xiao, X. Lu, D. Xu, Y. Tang, L. Wang, and W. Zhuang, "UAV relay in VANETs against smart jamming with reinforcement learning," *IEEE Trans. Veh. Technol.*, vol. 67, no. 5, pp. 4087–4097, May 2018.

[263] N. Taherkhani and S. Pierre, "Centralized and localized data congestion control strategy for vehicular ad hoc networks using a machine learning clustering algorithm," *IEEE Trans. Intell. Transp. Syst.*, vol. 17, no. 11, pp. 3275–3285, Nov. 2016.

[264] W. Song, F. Zeng, J. Hu, Z. Wang, and X. Mao, "An unsupervised-learning-based method for multi-hop wireless broadcast relay selection in urban vehicular networks," in *Proc. IEEE 85th Veh. Technol. Conf. (VTC Spring)*, Jun. 2017, pp. 1–5.

[265] R. Chai, X. Ge, and Q. Chen, "Adaptive *k*-harmonic means clustering algorithm for vanets," in *Proc. 14th Int. Symp. Commun. Inf. Technol. (ISCIT)*, Sep. 2014, pp. 233–237.

[266] D. Tian, Y. Wang, H. Xia, and F. Cai, "Clustering multi-hop information dissemination method in vehicular ad hoc networks," *IET Intell. Transp. Syst.*, vol. 7, no. 4, pp. 464–472, Dec. 2013.

[267] N. Kato *et al.*, "The deep learning vision for heterogeneous network traffic control: Proposal, challenges, and future perspective," *IEEE Wireless Commun.*, vol. 24, no. 3, pp. 146–153, Jun. 2017.

[268] B. Mao *et al.*, "Routing or computing? The paradigm shift towards intelligent computer network packet transmission based on deep learning," *IEEE Trans. Comput.*, vol. 66, no. 11, pp. 1946–1960, Nov. 2017.

[269] B. Mao *et al.*, "A tensor based deep learning technique for intelligent packet routing," in *Proc. GLOBECOM IEEE Global Commun. Conf.*, Dec. 2017, pp. 1–6.

[270] F. Tang, B. Mao, Z. M. Fadlullah, J. Liu, and N. Kato, "ST-DeLTA: An novel spatial–temporal value network aided deep learning based intelligent network traffic control system," *IEEE Trans. Sustain. Comput.*, vol. 5, no. 4, pp. 568–580, Oct.–Dec. 2020.

[271] A. Gulati, G. S. Aujla, R. Chaudhary, N. Kumar, and M. S. Obaidat, "Deep learning-based content centric data dissemination scheme for Internet of Vehicles," in *Proc. IEEE Int. Conf. Commun. (ICC)*, May 2018, pp. 1–6.

[272] W. Liu, G. Qin, Y. He, and F. Jiang, "Distributed cooperative reinforcement learning-based traffic signal control that integrates V2X networks dynamic clustering," *IEEE Trans. Veh. Technol.*, vol. 66, no. 10, pp. 8667–8681, Oct. 2017.

[273] B. Mao, F. Tang, Z. M. Fadlullah, and N. Kato, "An intelligent route computation approach based on real-time deep learning strategy for software defined communication systems," *IEEE Trans. Emerg. Topics Comput.*, early access, Feb. 14, 2019, doi: 10.1109/TETC.2019.2899407.

[274] Z. M. Fadlullah, B. Mao, F. Tang, and N. Kato, "Value iteration architecture based deep learning for intelligent routing exploiting heterogeneous computing platforms," *IEEE Trans. Comput.*, vol. 68, no. 6, pp. 939–950, Jun. 2019.

[275] D. Ye, R. Yu, M. Pan, and Z. Han, "Federated learning in vehicular edge computing: A selective model aggregation approach," *IEEE Access*, vol. 8, pp. 23920–23935, 2020.

[276] Z. Zhou, H. Liao, B. Gu, K. M. S. Huq, S. Mumtaz, and J. Rodriguez, "Robust mobile crowd sensing: When deep learning meets edge computing," *IEEE Netw.*, vol. 32, no. 4, pp. 54–60, Jul./Aug. 2018.

[277] J. Wang, L. Zhao, J. Liu, and N. Kato, "Smart resource allocation for mobile edge computing: A deep reinforcement learning approach," *IEEE Trans. Emerg. Topics Comput.*, early access, Mar. 4, 2019, doi: 10.1109/TETC.2019.2902661.

[278] S. Yu, X. Wang, and R. Langar, "Computation offloading for mobile edge computing: A deep learning approach," in *Proc. IEEE 28th Annu. Int. Symp. Pers. Indoor Mobile Radio Commun. (PIMRC)*, Oct. 2017, pp. 1–6.

[279] S. Wang *et al.*, "When edge meets learning: Adaptive control for resource-constrained distributed machine learning," in *Proc. IEEE Conf. Comput. Commun. (IEEE INFOCOM)*, Apr. 2018, pp. 63–71.

[280] J. Li, H. Gao, T. Lv, and Y. Lu, "Deep reinforcement learning based computation offloading and resource allocation for MEC," in *Proc. IEEE Wireless Commun. Netw. Conf. (WCNC)*, Apr. 2018, pp. 1–6.

[281] Y. He, F. R. Yu, N. Zhao, V. C. M. Leung, and H. Yin, "Software-defined networks with mobile edge computing and caching for smart cities: A big data deep reinforcement learning approach," *IEEE Commun. Mag.*, vol. 55, no. 12, pp. 31–37, Dec. 2017.

[282] Y. Dai, D. Xu, K. Zhang, S. Maharjan, and Y. Zhang, "Deep reinforcement learning and permissioned blockchain for content caching in vehicular edge computing and networks," *IEEE Trans. Veh. Technol.*, vol. 69, no. 4, pp. 4312–4324, Apr. 2020.

[283] M. F. Pervej and S.-C. Lin, "Eco-vehicular edge networks for connected transportation: A distributed multi-agent reinforcement learning approach," in *Proc. IEEE 92nd Veh. Technol. Conf. (VTC-Fall)*, Oct. 2020.

[284] Q. Luo, C. Li, T. H. Luan, and W. Shi, "Collaborative data scheduling for vehicular edge computing via deep reinforcement learning," *IEEE Internet Things J.*, vol. 7, no. 10, pp. 9637–9650, Oct. 2020.

[285] W. Zhan *et al.*, "Deep-reinforcement-learning-based offloading scheduling for vehicular edge computing," *IEEE Internet Things J.*, vol. 7, no. 6, pp. 5449–5465, Jun. 2020.

[286] L. V. Le, S. Do, B.-S. P. Lin, and L.-P. Tung, "Big data and machine learning driven Open5GMEC for vehicular communications," *Trans. Netw. Commun.*, vol. 6, no. 5, p. 103, 2018.

[287] P. Dai *et al.*, "Multi-armed bandit learning for computation-intensive services in MEC-empowered vehicular networks," *IEEE Trans. Veh. Technol.*, vol. 69, no. 7, pp. 7821–7834, Jul. 2020.

[288] X. Zhang, J. Zhang, Z. Liu, Q. Cui, X. Tao, and S. Wang, "MDP-based task offloading for vehicular edge computing under certain and uncertain transition probabilities," *IEEE Trans. Veh. Technol.*, vol. 69, no. 3, pp. 3296–3309, Mar. 2020.

[289] J. Cannady, "Artificial neural networks for misuse detection," in *Proc. Nat. Inf. Syst. Security Conf.*, vol. 26, 1998, pp. 343–348.

[290] M.-J. Kang and J.-W. Kang, "Intrusion detection system using deep neural network for in-vehicle network security," *PLoS ONE*, vol. 11, no. 6, pp. 1–17, Jun. 2016.

[291] Y. Xu, J. Xia, H. Wu, and L. Fan, "*Q*-learning based physical-layer secure game against multiagent attacks," *IEEE Access*, vol. 7, pp. 49212–49222, 2019.

[292] A. Anzer and M. Elhadef, "Deep learning-based intrusion detection systems for intelligent vehicular ad hoc networks," in *Proc. Adv. Multimedia Ubiquitous Eng.*, 2019, pp. 109–116.

[293] S. Benferhat, T. Kenaza, and A. Mokhtari, "A Naive Bayes approach for detecting coordinated attacks," in *Proc. 32nd Annu. IEEE Int. Comput. Softw. Appl. Conf.*, Jul. 2008, pp. 704–709.

[294] A. Sargolzaei, C. D. Crane, A. Abbaspour, and S. Noei, "A machine learning approach for fault detection in vehicular cyber-physical systems," in *Proc. 15th IEEE Int. Conf. Mach. Learn. Appl. (ICMLA)*, Dec. 2016, pp. 636–640.

[295] O. A. Wahab, A. Mourad, H. Otrok, and J. Bentahar, "CEAP: SVM-based intelligent detection model for clustered vehicular ad hoc networks," *Exp. Syst. Appl.*, vol. 50, pp. 40–54, May 2016.

[296] K. Sequeira and M. Zaki, "ADMIT: Anomaly-based data mining for intrusions," in *Proc. 8th ACM SIGKDD Int. Conf. Knowl. Disc. Data Min. (KDD)*, 2002, pp. 386–395.

[297] J. Grover, N. K. Prajapati, V. Laxmi, and M. S. Gaur, "Machine learning approach for multiple misbehavior detection in VANET," in *Proc. Adv. Comput. Commun.*, 2011, pp. 644–653.

[298] J. Grover, V. Laxmi, and M. S. Gaur, "Misbehavior detection based on ensemble learning in VANET," in *Proc. Adv. Comput. Netw. Security*, 2012, pp. 602–611.

[299] M. Scalabrin, M. Gadaleta, R. Bonetto, and M. Rossi, "A Bayesian forecasting and anomaly detection framework for vehicular monitoring networks," in *Proc. IEEE 27th Int. Workshop Mach. Learn. Signal Process. (MLSP)*, Sep. 2017, pp. 1–6.

[300] J. Zhang, M. Zulkernine, and A. Haque, "Random-forests-based network intrusion detection systems," *IEEE Trans. Syst., Man, Cybern. C, Appl. Rev.*, vol. 38, no. 5, pp. 649–659, Sep. 2008.

[301] H. Zhang, S. Dai, Y. Li, and W. Zhang, "Real-time distributed-random-forest-based network intrusion detection system using apache spark," in *Proc. IEEE 37th Int. Perform. Comput. Commun. Conf. (IPCCC)*, Nov. 2018, pp. 1–7.

[302] H. Sedjelmaci and S. M. Senouci, "An accurate and efficient collaborative intrusion detection framework to secure vehicular networks," *Comput. Elect. Eng.*, vol. 43, pp. 33–47, Apr. 2015.

[303] T. Shon and J. Moon, "A hybrid machine learning approach to network anomaly detection," *Inf. Sci.*, vol. 177, no. 18, pp. 3799–3821, 2007.

[304] R. Sommer and V. Paxson, "Outside the closed world: On using machine learning for network intrusion detection," in *Proc. IEEE Symp. Security Privacy*, May 2010, pp. 305–316.

[305] Q. He, D. Wu, and P. Khosla, "SORI: A secure and objective reputation-based incentive scheme for ad-hoc networks," in *Proc. IEEE Wireless Commun. Netw. Conf.*, vol. 2, Mar. 2004, pp. 825–830.

[306] I. H. Witten, E. Frank, M. A. Hall, and C. J. Pal, *Data Mining: Practical Machine Learning Tools and Techniques*. San Francisco, CA, USA: Morgan Kaufmann, 2016.

[307] D. Papamartzivanos, F. G. Mórmol, and G. Kambourakis, "Introducing deep learning self-adaptive misuse network intrusion detection systems," *IEEE Access*, vol. 7, pp. 13546–13560, 2019.

[308] M. G. Al Zamil *et al.*, "False-alarm detection in the fog-based Internet of connected vehicles," *IEEE Trans. Veh. Technol.*, vol. 68, no. 7, pp. 7035–7044, Jul. 2019.

[309] Z. M. Fadlullah, C. Wei, Z. Shi, and N. Kato, "GT-QoSEC: A game-theoretic joint optimization of QoS and security for differentiated services in next generation heterogeneous networks," *IEEE Trans. Wireless Commun.*, vol. 16, no. 2, pp. 1037–1050, Feb. 2017.

[310] E. Eziama, K. Tepe, A. Balador, K. S. Nwizege, and L. M. S. Jaimes, "Malicious node detection in vehicular ad-hoc network using machine learning and deep learning," in *Proc. IEEE Globecom Workshops (GC Wkshps)*, 2018, pp. 1–6.

[311] E. Eziama, S. Ahmed, S. Ahmed, F. Awin, and K. Tepe, "Detection of adversary nodes in machine-to-machine communication using machine learning based trust model," in *Proc. IEEE Int. Symp. Signal Process. Inf. Technol. (ISSPIT)*, 2019, pp. 1–6.

[312] M. Shen, J. Zhang, L. Zhu, K. Xu, and X. Tang, "Secure SVM training over vertically-partitioned datasets using consortium blockchain for vehicular social networks," *IEEE Trans. Veh. Technol.*, vol. 69, no. 6, pp. 5773–5783, Jun. 2020.

[313] M. Al-Saud, A. M. Eltamaly, M. A. Mohamed, and A. Kavousi-Fard, "An intelligent data-driven model to secure intravehicle communications based on machine learning," *IEEE Trans. Ind. Electron.*, vol. 67, no. 6, pp. 5112–5119, Jun. 2020.

[314] P. K. Singh, S. K. Jha, S. K. Nandi, and S. Nandi, "Ml-based approach to detect DDoS attack in V2I communication under SDN architecture," in *Proc. TENCON IEEE Region 10 Conf.*, 2018, pp. 144–149.

[315] L. A. Maglaras, "A novel distributed intrusion detection system for vehicular ad hoc networks," *Int. J. Adv. Comput. Sci. Appl.*, vol. 6, no. 4, pp. 101–106, 2015.
[316] F. Tang, B. Mao, Z. M. Fadlullah, J. Liu, and N. Kato, "On extracting the spatial–temporal features of network traffic patterns: A tensor based deep learning model," in *Proc. Int. Conf. Netw. Infrastruct. Digit. Content (IC-NIDC)*, Aug. 2018, pp. 445–451.
[317] H. Cui, H. Zhang, G. R. Ganger, P. B. Gibbons, and E. P. Xing, "GEEPs: Scalable deep learning on distributed GPUs with a GPU-specialized parameter server," in *Proc. 11th Eur. Conf. Comput. Syst. (EuroSys)*, 2016, pp. 1–4.
[318] R. Telikepalli, T. Drwiega, and J. Yan, "Storage area network extension solutions and their performance assessment," *IEEE Commun. Mag.*, vol. 42, no. 4, pp. 56–63, Apr. 2004.
[319] M. Al-Shedivat, T. Bansal, Y. Burda, I. Sutskever, I. Mordatch, and P. Abbeel, "Continuous adaptation via meta-learning in non-stationary and competitive environments," 2017. [Online]. Available: arxiv.abs/1710.03641.
[320] K. Zheng, Q. Zheng, H. Yang, L. Zhao, L. Hou, and P. Chatzimisios, "Reliable and efficient autonomous driving: The need for heterogeneous vehicular networks," *IEEE Commun. Mag.*, vol. 53, no. 12, pp. 72–79, Dec. 2015.
[321] Y. Maalej, S. Sorour, A. Abdel-Rahim, and M. Guizani, "VANETs meet autonomous vehicles: A multimodal 3D environment learning approach," in *Proc. GLOBECOM IEEE Global Commun. Conf.*, Dec. 2017, pp. 1–6.
[322] J. Kang *et al.*, "Blockchain for secure and efficient data sharing in vehicular edge computing and networks," *IEEE Internet Things J.*, vol. 6, no. 3, pp. 4660–4670, Jul. 2019.
[323] J. Konecný, H. B. McMahan, F. X. Yu, P. Richtárik, A. T. Suresh, and D. Bacon. (2016). *Federated Learning: Strategies for Improving Communication Efficiency*. [Online]. Available: http://arxiv.org/abs/1610.05492.
[324] G. Zhu, Y. Wang, and K. Huang, "Broadband analog aggregation for low-latency federated edge learning," *IEEE Trans. Wireless Commun.*, vol. 19, no. 1, pp. 491–506, Jan. 2020.
[325] F. Codevilla, M. Müller, A. López, V. Koltun, and A. Dosovitskiy, "End-to-end driving via conditional imitation learning," in *Proc. IEEE Int. Conf. Robot. Autom. (ICRA)*, 2018, pp. 4693–4700.

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