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Machine learning in vehicular networking: An overview

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A R T I C L E I N F O

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A B S T R A C T

As vehicle complexity and road congestion increase, combined with the emergence of electric vehicles, the need for intelligent transportation systems to improve on-road safety and transportation efficiency using vehicular networks has become essential. The evolution of high mobility wireless networks will provide improved support for connected vehicles through highly dynamic heterogeneous networks. Particularly, 5G deployment introduces new features and technologies that enable operators to capitalize on emerging infrastructure capabilities. Machine Learning (ML), a powerful methodology for adaptive and predictive system development, has emerged in both vehicular and conventional wireless networks. Adopting data-centric methods enables ML to address highly dynamic vehicular network issues faced by conventional solutions, such as traditional control loop design and optimization techniques. This article provides a short survey of ML applications in vehicular networks from the networking aspect. Research topics covered in this article include network control containing handover management and routing decision making, resource management, and energy efficiency in vehicular networks. The findings of this paper suggest more attention should be paid to network forming/deforming decision making. ML applications in vehicular networks should focus on researching multi-agent cooperated oriented methods and overall complexity reduction while utilizing enabling technologies, such as mobile edge computing for real-world deployment. Research datasets, simulation environment standardization, and method interpretability also require more research attention.

1. Introduction

As vehicles increase their awareness of their surrounding environment, combined with improvements in onboard computing power, the potential to support future intelligent Transportation Systems (ITSs) applications [1] grows to enable utility-based onboard services while also improving on-road safety and traffic congestion by interconnecting on-road vehicles, infrastructure, and pedestrians. A particular challenge of vehicular networks is the rapid and continuous position changes demanded by fast network topology changes and short connection times. Conventional wireless networks based on static or low-mobility environment assumptions become less effective in these scenarios. For various Vehicle-to-Everything (V2X) [2] communication types, such as Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I), Vehicle-to-Network (V2N), or Vehicle-to-Pedestrian (V2P), application differentiated Quality of Service (QoS) is necessary for vehicular networks. Safety-related and future support for autonomous driving requirements that utilize V2V demand high reliability and low latency, while Internet infotainment services using V2N require high data rates and large bandwidths. The differentiated QoS requirements of different V2X applications, coupled with the highly dynamic nature of vehicular networks, have introduced new challenges to vehicular networking, including channel fading, Doppler shift problems, differentiated network selection, and resource allocation tasks required by high mobility and heterogeneity.

Previous research on vehicular networks has focused on the IEEE 802.11p-based Dedicated Short-range Communication (DSRC) Radio Access Technology (RAT), but DSRC requires dedicated infrastructure and provides unsatisfactory performance beyond basic safety messaging because it can only broadcast transmissions, has no scheme for feedback or retransmission, and does not have a Doppler shift countermeasure design [3]. As 5G rolls out globally, many RATs offer greater connectivity options [4]. New standardization activity through IEEE (802.11bd) and 3GPP (Release 15) [3] is being developed for V2X, prioritizing QoS and network resource efficiency. These challenges for a vehicular Heterogeneous Network (HetNet) structure are illustrated in Fig. 1, and 5G is a

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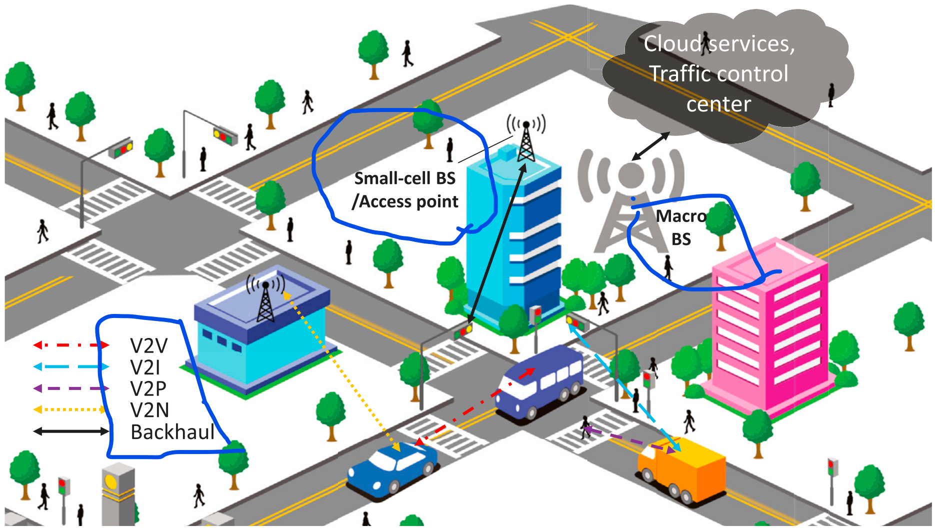

Fig. 1. A heterogeneous V2X network with various communication types and multi-RATs for each type of communication.

strong candidate for vehicular networks requiring efficient and cost-effective deployment as well as cellular network infrastructure exploitation and deployment penetration.

Traditional wireless network systems use parameterized mathematical models under the assumption of a stationary network or low-mobility nodes in the environment with *a priori* knowledge of the environment. Vehicular network environment contains multiple environment types, including one-dimensional (i.e., high-way), two-dimensional (i.e., urban street blocks), and three-dimensional (i.e., roads with flyovers, viaducts, and future Unmanned Aerial Vehicle (UAV) integrated vehicular networks) scenarios [5], plus the uncertainty of temporary obstacles appearing in the environment and blocking possible routing paths make a rigorous parameterized general-purpose design highly complicated. That being said, road vehicles have a much higher velocity compared to pedestrians using cell phones, leading to rapid temporal variation in vehicular wireless channels [6], significant Doppler spread [7], and the aforementioned rapid network topology changes. These highly dynamic properties make tasks such as channel estimation and signal detection for vehicular networks challenging for traditional system designs [8]. Hard-wired control schemes cannot discover and exploit value from rich-information environments that can include vehicular kinematics and traffic flow, while traditional optimization methods face the NP-hard solving issue due to the high complexity of problem formation for these environments, resulting in high sensitivity to rapid environmental changes. Contemporary solutions utilizing Machine Learning (ML) can extract patterns from historical and real-time observed data. ML emphasizes learning and adapting to environmental uncertainties without relying on such *a priori* knowledge, which makes it very suitable for the rapidly changing V2X environment, and extracts value from rich datasets to support new services, such as traffic flow prediction and adaptive network optimization [9].

While many variants exist, ML methods can be classified into three main types: supervised, unsupervised, and Reinforcement Learning (RL); however, some ML systems combine more than one ML method. In recent years, Deep Learning (DL) utilizing artificial Neural Networks (NNs) [10, 11] with multiple hidden layers has become the dominant approach in ML. For interested readers, a detailed background of ML methodologies and algorithms can be found in some well-known treatises [12–14]. In recent years, ML methods have gained increased attention in wireless network research [15–19].

This paper presents an overview of ML methods used in vehicular networks and gives some insight into the challenges and research trends focusing on the network-centric parts of such networks. The major contribution of this paper contains two parts: a comprehensive literature overview, and a set of detailed current challenges and future research directions. Discussion related to ML applications in vehicular networks are also discussed, including network control, which contains handover and routing decision making, resource management, and energy efficiency through network scheduling. While other parts of vehicular networks, such as vehicular communication and security, are also important for vehicular network research, they will not be covered in this review. For interested readers, information on the uncovered topics can be found in some related survey papers [20–22].

The remainder of this paper is organized as follows. Surveyed works are presented in Section 2 and categorized according to the aforementioned topics. Current challenges and possible research directions are presented in Section 3, and the concluding remarks are made in Section 4.

2. ML for vehicular networking

The dynamic nature of vehicular networks and their underlying heterogeneous structure have led to new requirements for networking algorithms that address network control and resource allocation. Network control includes handover, routing, and network traffic offloading, while network resource allocation covers the spectrum, transmission power, and computing resources. As traditional methods cannot capture underlying patterns in vehicular networks, the use of ML methods in this aspect of vehicular networking, as well as a combination of enabling technologies, is presented in this section.

Research utilizing ML methods covered by this overview is categorized according to application with more specific tasks in Table 1. The core algorithm types proposed in these works (with corresponding main ML types) are also summarized in the table with projected task-specific challenges from a network perspective. The 5G development roadmap contains enabling technologies (including Mobile Edge/fog Computing (MEC), Network Function Virtualization (NFV), Control/data plane separation, Software-Defined Networks (SDNs), and network slicing [23–25]) that provide distinct functions addressing current wireless network challenges, such as high network complexity and spectrum resource efficiency. More recent research [26,27] in vehicular networks has also adopted these technologies to tackle such challenges, though not all utilized ML methods.

2.1. Network control

For V2I, typical vehicle velocities (such as 60 km/h in urban areas and 120 km/h on highways) mean a vehicle will traverse a 100 m road

Table 1
Classification of covered work utilizing ML methods with corresponding ML algorithm summary.

Application Category	Task	Work Covered	Utilized ML algorithms	Core ML method utilized	Open challenges specific to V2X
Mobility management	Mobility prediction	[30,31]	Probabilistic models, NNs	Supervised Learning	Accurate but fast future position prediction required to support other predictive tasks, e.g., handover
	Handover optimization	[32–36]	Q-learning, Fuzzy Q-learning, Multi-armed bandits, Support Vector Machine (SVM), NNs, K-nearest Neighbors (K-NN), Kernel-based learning	Supervised Learning RL	Seamless handover required with handover time restriction due to high mobility
Routing	Routing decision, user association	[37–39]	NNs, Q-learning, Multi-armed bandits	RL	Routing in vehicular HetNet according to differentiated QoS requirements
Resource Management	Channel, power, and joint radio resource management	[40–44]	Q-learning, Convolutional NN (CNN), Deep Q-learning	Supervised Learning RL	Resource allocation based on differentiated QoS requirements; System architecture design; Interference and power optimization; Spectrum efficiency through spectrum sharing
	Computation and storage resource management	[45,46]	Deep Q-learning		
Energy efficiency	Base station switch-off	[47,48]	Q-learning, Heuristic	RL	Algorithmic scheduling optimization at a regional central control or on an individual gateway device-level; Large-scale system combining infrastructure with EV real-world deployable ML methods
	Infrastructure and/or Electric Vehicle (EV) energy efficiency through scheduling	[49–53]	Q-learning, Deep Q-learning		

segment covered by a Roadside Unit (RSU) in 6 and 3 s, respectively, while two vehicles driving in opposite directions on a highway can have a relative speed of over 300 km/h, covering a 100 m distance in 1.2 s. However, members of a local vehicular network may change arbitrarily because individual vehicles can choose different destinations and driving paths, resulting in short connection times between vehicular nodes and gateways. This high mobility causes underperformance in conventional reactive routing and handover. ML methods enable vehicle mobility and network traffic prediction, which improve predictive routing and handover control with adaptivity, while predictive information further enables on-road congestion control and network load balancing through ITS applications [28,29].

2.1.1. *Mobility and handover management*

Fast-moving vehicles need to utilize rapid handover with ML-based mobility prediction, while handover management, optimization, and duration can be done based on predicted mobility. Wiest et al. [30] proposed a probabilistic trajectory prediction with Gaussian mixture models. Exploiting observed trajectories, the method produced a distribution of future trajectories where a specific prediction could be given based on statistical properties for more reliable connections. Recent research also implemented a DL-based method using Long Short-term Memory (LSTM), a recurrent NN structure, combined with fully connected NNs for joint trajectory prediction according to different driving styles [31]. The generalization test results of this work showed that this joint method had the lowest root mean square error compared with LSTM only and Kalman filter-based predictions. The performance of mobility prediction has been improved with more sophisticated methods, but the challenge lies in reducing the computational complexity and communication latency.

Vehicles often move in and out of the cover range of other vehicles, infrastructures, and Base Stations (BSs) due to high mobility, causing frequent V2V, V2I, and V2N disconnection, while a fundamental and vital requirement of vehicular networks is seamless communication. Therefore, adaptive handover utilizing ML-based mobility prediction is another major research topic in this area. Xu et al. [32] proposed an online fuzzy Q-learning vertical handover control for heterogeneous vehicular networks, providing optimal handover using real-time received signal strength without *a priori* knowledge. An RL mobility management scheme was proposed by Ref. [33], using non-stochastic bandit theory with handover cost included in the utility function to reduce frequent handovers and overall system energy cost. The recent work of Memon and Maheswaran [34] proposed a combined DL and Support Vector Machine (SVM) prediction technique validated with real-world taxi trace data for optimizing handovers in MEC-enabled vehicular networks.

To date, handover management research has focused on single networks, predominantly 802.11p-based DSRC. With emerging multi-connectivity via different RATs and the development of new standards, addressing networking issues exploiting mixed bandwidth becomes another topic, and recent research has developed a handover control scheme in the mixed bandwidth of sub-6 GHz and mmWave with control/data plane separation [35]. In this work, channel state information of the sub-6 GHz band in the control plane and the Gaussian kernel-based ML method were used to predict future vehicle positions and to activate a target mmWave unit for data plane handover. Historical handover data was also utilized by a K-nearest neighbor algorithm for more agile future handover. Simulation results of an urban intersection scenario showed an improvement in decision-making times from 41 ms maximum to around 2 ms. As traditional handover methods use a break-before-make strategy, the authors also proposed a soft handover for V2I communication via a V2V relay scheme, which improved spectrum efficiency from near zero, due to the hard handover, to over 5 bits/s/Hz. However, this new multi-connectivity feature for vehicular networks has not received much attention, and more research should be committed to these topics as new V2X standards are developed.

2.1.2. *Routing decision making*

Conventional routing protocols mainly use current local information (including location, network topology and relative mobility) and solve for an optimal solution [54]. However, such connections built via static optimization process do not have enough resilience to rapid network topology changes and may fail due to the highly dynamic nature of vehicular networks.

ML methods can leverage collected data, enabling predictive and adaptive routing based on vehicle mobility and future traffic flow prediction. Tang et al. [37] deployed an SDN structure and used one hidden-layer NN-based mobility prediction for routing in heterogeneous vehicular networks to maintain end-to-end connectivity and minimize delays; while Li et al. [38] used Q-learning based hierarchical routing with an adaptive self-built Q-value table built from neighborhood traffic flow, replacing the traditional routing table, to achieve high delivery percentages. A further application for network load balancing was also achieved with adaptive user-association using an online-RL method [39]. The method proposed in this work collected and learned new association information in combination with historical association patterns to achieve HetNet BS load balancing in vehicular networks. Underlying patterns and the regular nature of road traffic can be leveraged for predictive network traffic control, which enables knowledge transfer possibilities and method complexity reduction, such as state-space simplification for RL. More research should be committed to this aspect as current routing and user association are usually implemented from scratch and learned during operation. Agile and cost-efficient algorithmic redeployment, utilizing knowledge of other similar region and transfer learning techniques, is one of the promising directions.

2.2. Resource management

For efficient communication and stable scalability, it is critical to properly manage all kinds of resources, including radio (e.g., spectrum and power), computing power, data storage, and energy consumption. Conventional resource management methods only address spectrum resource allocation and focus on forming optimization problems using mathematical models and solving for optimal or near-optimal solutions with optimality claims or through approximation. High mobility vehicular networks require a rapid response to resource allocation, leaving a short optimization result period with substantial control signal overhead for conventional methods. Differentiated QoS requirements have led to various spectrum resource allocation requirements and priorities for different communication links, while the heterogeneous structure of vehicle networks makes it difficult to form a joint-mathematical optimization object for such methods. Computational and storage resources should also be managed to enable computation offloading for heavy tasks and content caching for infotainment services, saving spectrum resources and reducing communication delay.

ML methods, especially RL, can give solutions to such challenges by interacting with dynamic environments and maximizing numeric rewards. The research of Xiao et al. [40] considered power allocation in a game-theoretic model based on a cooperative crowdsensing scenario, and used a Q-learning-based crowdsensing strategy for a solution to the adaptive transmission power control problem. Recent work in crowdsensing scenarios has considered random user mobility combined with a game-theoretic approach to incentivize crowdsensing. However, instead of using ML methods, a stochastic programming-based solution and an auction-based mechanism were developed for resource allocation and adoption in randomness [55]. By enabling control data plane separation, an SDN-based channel assignment could be developed for traffic load prediction [41]. In this work, the authors used a Convolutional Neural Network (CNN) to tackle traffic burst prediction and thus accomplish an adaptive channel assignment. A solution to computing and storage resource management can also be developed with a double-dueling deep-Q-learning algorithm combined with SDN and MEC for content caching, and that proposed integrated scheme also reduced overall method complexity [45]. More recent research also proposed a double deep-Q-learning method with dynamic pricing to accomplish optimal task allocation for vehicular fog computing task offloading. The central BS learned the task allocation policy with dynamic prices raised to attract vehicles to contribute their computing power, considering the willingness of a real-world service provider [46].

Traditional resource management relies on a centralized controller for calculation and allocation execution, but the highly dynamic nature of a vehicular network will cause more delays and short-term allocation policies because all relative information needs to be sent to the central controller to enable policy optimization, requiring additional communication time and introducing more communication overhead. The time consumed during this process will lead to further network topology changes and result in shorter policy validity periods. Therefore, a decentralized resource allocation mechanism becomes necessary, and a decentralized deep RL algorithm has been developed for V2X communication [42], where every vehicle calculates and optimizes band and radio power levels for channel sharing via both V2I and V2V links. Other research has also leveraged enabling technologies, including MEC and SDN, to achieve a distributed network structure [26] that supports future distributed ML adoption. ML methods have been investigated to tackle the challenges in these enabling technologies, such as the intelligent offloading task in MEC systems introduced in Ref. [27]. Similarly, network slicing, which can benefit V2X systems with heterogeneous QoS requirements, also raises challenges for further research, including service provisioning [25]. Put simply, more possibilities in distributed V2X systems powered by the next generation of mobile networking remain to be explored.

Future vehicular networks will contain multiple radio bands, and more attention should be paid to this feature. The work conducted by Deng et al. [56] constructed a device-to-device relaying scheme in a sub-6 GHz and mmWave 5G for both on-road vehicles and pedestrians. A dedicated hierarchical control framework was proposed in this work with detailed principle setups. However, it also proposed a graph theory-enabled traditional optimization approach to determine its allocation policy, which may not always perform well, as the authors suggested. Exploiting ML techniques for adaptive resource allocation remains an outstanding challenge as less work has been proposed on a similar topic.

2.3. Energy efficiency in vehicular networks

Economic and environmental factors form two major driving forces for new technology development. With the growth of ITS infrastructure and a more significant number of on-road vehicles expected, energy efficiency becomes more critical for large-scale communication systems and sustainable development. One solution is to adaptively switch off unnecessary small-cell BSs for V2N communication, similar to the work by Yu, Chen, and Yin, which used a Markov chain-based, dual-threshold optimization method to put small-cell BSs into sleep mode to avoid frequent mode transactions while saving energy [47]. Recent work by Assad et al. [48] also considered energy consumption with CO_2 emission tracing in 5G HetNets using RL techniques. A Q-learning-based method was proposed for BS network traffic offloading and BS switching to save energy and reduce BS carbon footprints.

In vehicular networks, maximizing battery life for self-powered RSUs is crucial to maintaining on-road traffic service. While networking scheduling, Atallah et al. [49] formed a Markov Decision Process (MDP) model for an RSU's downlink scheduling optimization within a battery charge cycle in V2I communication. The PEARL method proposed in this work was based on ε-greedy Q-learning and aimed to maximize the long-term system reward of total packet download number. The authors further exploit deep RL for general roadside Internet of Things gateway energyefficiency in vehicular networks [50]. The proposed MDP model enabled a central ITS agent to learn an optimal scheduling policy that satisfied operational QoS requirements while minimizing the negative reward of energy consumption.

Battery-powered Electric Vehicles (EVs) form another important aspect of energy efficiency in vehicular networks, as energy management improves the maximum mileage for EVs and maintains infotainment application quality while limiting carbon emissions via green development. Research has been conducted into EV energy saving, such as using ML techniques for driving condition prediction and thus energy management through driving control [51]. The emergence of the Internet of Vehicles (IoV) connecting on-road vehicles with RSUs for information sharing has enabled the possibility of EV energy management through computing task offloading. As individual RSUs possess limited resources while receiving offloading in a dense area can cause serious delay, an energy efficient scheduling framework through load balancing between RSUs in an MEC-enabled IoV was developed for vehicular task offloading [52]. In that framework, an RSU receiving offloaded tasks from a vehicle in its cover range first estimates whether other RSUs are present in that vehicle's moving direction, then forms a group with satisfying candidates. That group subsequently estimates the least energy consuming RSU candidate for computation before forwarding the results to the nearest RSU and returning to the vehicle.

There is also a possibility for cooperative energy management between EVs and RSUs in an IoV vision, and a green IoV framework with an energy harvesting scheme for both EVs and RSUs has been developed in this sense [53]. Self-powered RSUs in this scheme equip wind turbines for energy harvesting and a three-stage Stackerberg game was developed to model the scheme. In the first stage, the RSU stores sufficient electricity and will accept all vehicular requests and sell redundant electricity to EVs in need; In the second state, the battery life reaches a medium level, and RSU turns to buy power via approved EVs while continuing to meet the requests received. The feature of the last stage is that the EVs need to power the RSU at a low battery level to process requests or switch to another RSU for delay-tolerant tasks. The electricity is transmitted via radio frequency energy transfer technology in this scheme and all decisions are made based on Nash equilibrium [57]. Simulation results of this work with real-world taxi trace data suggested a 0.5 improvement of normalized benefit for both RSUs and vehicles compared to a sleep-based solution.

3. Current challenges and opportunities

In this section, several conditions for ML application are elaborated upon, in terms of the type of the problem to be solved, training data, time cost, implementation complexity, and differences between ML techniques in the same category. These conditions should be checked individually before making the final decision about whether to adopt ML techniques and which kind of ML techniques to use.

3.1. Challenges for vehicular networks

Despite advances in both routing and handover in vehicular networking, decision making for network forming/deforming has not received sufficient attention from research communities. Although some research on bio-inspired methods has partially combined ML with routing decision optimization [58], the network node moving speed in vehicular networks is much higher than that of traditional mobile networks, and further limits the time of forming and validating networks. Therefore, future research should focus more on efficient and stable networking in vehicular networks. The development of vehicular HetNets [59] has introduced multiple access technologies for vehicles, RSUs, and BSs, and offered differentiated services fitting different application requirements while maintaining different traffic loads in a specific environment. ML methods used in various recommendation systems can be applied to learn individual node behavior and network traffic loads to match suitable networks, yet this topic currently receives less attention than the surveyed topics in this paper [15]. However, MEC and NFV have been studied extensively, as key technologies for adopting vehicular networks [23]. In vehicular networks, ML must deal with high network dynamics, which needs specific attention from research communities. MEC enables distributed solutions by moving less computationally demanding tasks from cloud computing centers to network edges, improving latency and enabling data exploitation among various network nodes. By contrast, NFV introduces greater flexibility into networks through hardware abstraction, while ML methods can be applied and form a more general solution independent of hardware. In vehicular networks, applying ML methods with these technologies faces major challenges from the aforementioned high network dynamics; this deserves specific attention.

3.2. Distributed learning and multi-agent cooperation for ML in vehicular networks

In contrast to traditional ML application scenarios, data in vehicular networks is generated and stored in different network units, such as vehicles and RSUs. Therefore, individual vehicles usually do not have access to all the rich data sources demanded by certain types of learning tasks. These expectations lead to learning on local partially-observed data while exploiting values from data stored in other devices. A multi-agent setup for ML methods can thus promise better performance at a system level through cooperation in vehicular networks to avoid the aforementioned systematic communication delay and overhead of a purely centralized setup for data transfer. The setup can also utilize the computational power of vehicles to make decisions locally. Research has started investigations in that direction, such as the handover mechanism in a network slicing architecture for mobile networks utilizing multi-agent Q-learning [36]. Attention has also been paid to this aspect in vehicular networks, with a distributed multi-agent deep Q-learning algorithm developed to improve both V2V and V2I communication quality through spectrum sharing [43]. Federated learning is another decentralized ML technique to train models via distributed data and learner cooperation, which can also exploit value through MEC as shown by some recent work [44,60], but given its potential importance to vehicular networks, it is also a key challenge with respect to deployment and needs further exploration.

3.3. ML method complexity issues

NN-based learning methods have achieved continuous performance breakthroughs in various areas. Many current ML solutions in vehicular networks have NN-based methods or combined NNs with different ML techniques, e.g., NN-based prediction with SVM classification, with top performances reaching greater than 99% accuracy in tasks such as mobility prediction [61]. Future vehicular networks will need to extend current two-dimensional scenarios for handover and resource allocation to three-dimensional ones with possible UAV integration, causing overall task complexity to continue to rise. NN-based DL is currently the best solution for its descriptive power. However, the training process of NNs often takes up a significant amount of computation resources because of the deep network structure. Unlike traditional ML methods, NNs can learn directly from raw data while not requiring dedicated feature design or causing large data batches, increasing overall computation complexity. Sophisticated methods have significantly improved performance but can lead to greater latency and reduced energy efficiency. While vehicular onboard vehicle units and RSUs have limited computation power, the requirement of regulating complexity arises for computation alleviation while coping with performance requirements. Another possible solution lies in computation offloading requiring the deployment of mobile cloud and edge computing, where the training is transferred to (and completed by) a remote cloud server or divided into less computational intensive subtasks distributed among network edge nodes while also sharing training results. To conclude, the topic of computation offloading for NN training in vehicular networks needs more research in the future.

3.4. Dataset and environment standardization for ML adoption in vehicular networks

Regarding ML methodology adoption in the field, two existing issues are research datasets and environment standardization. To help researchers focus on learning algorithm design and to simplify performance comparison, common problems should be identified with related datasets, while simulation environments should be standardized as in other Artificial Intelligence (AI) areas; these include the MNIST dataset [62] used for image recognition tasks and the Open AI Gym environment [63] employed for RL methods. Some work has been done in these aspects of vehicular networks, such as Klautau et al.'s [64] presentation of a dataset for mmWave beam-selection and a simulator for vehicle traffic and ray-tracing. Another work developed the first framework for RL research in networking, combining the ns-3 network simulator and Open AI gym [65], and yet another inspired study has developed ns-3 interconnections with popular AI frameworks [66]. However, more research resources are needed to fill this gap, which requires enriched datasets able to perform more networking tasks and standardized networking simulation environments with ML integration.

3.5. Interpretability and trust for ML methods

Another major challenge for ML adoption is the rising “blackbox” problem for more complex methods, such as DL, because decision making procedures presently cannot produce output that can be interpreted directly by humans, creating risk for safety- and security-related applications that cause trust issues involving verification and legal liability confusion when accidents occur. As ML methods have attracted more research interest in vehicular networks, adding interpretability for such systems becomes essential to enable vehicle drivers and network operators to understand system behavior, introducing the possibility of user-based control, justification, and improved performance [67]. Interpretable DL-based systems for vehicular networks should also be developed to assist the legal system with traceable interpretability-founded responsibility made available for legal judgement. A recent advance in CNN hidden-layer neuron activity visualization tools has shown promising means of supporting non-experts in understanding the DL process of CNN training [68]. This can be a valuable example for related research to improve the interpretability of other NN-based methods and help address the potential liability issues.

4. Conclusions

This paper provides a short survey of ML methods in vehicular networking applications as a promising solution to the highly dynamic challenges encountered in vehicular networks providing remarkable performance in various AI-related areas and recent V2X applications. ML has solved most of the underperformance issues faced by traditional networking solutions due to the high dynamics of heterogeneous communication types and differentiated QoS service requirements of vehicular networks. However, current research does not pay sufficient attention to decision making regarding how vehicular networks are formed or deformed, despite this aspect greatly affecting local network validity and resource efficiency. That being said, the high dynamics and overall low tolerance to communication delays and overhead that are part of vehicular networks should drive future research towards decentralized cooperated algorithm deployment and overall method complexity reduction while exploiting value from mobile edge computing for offloading, content caching, and sensor data storage. For ML methods to be adopted by vehicular networks, the standardization of research datasets and simulations needs to be pursued, while ML method interpretability also being necessary.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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