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Artificial Intelligence for Vehicle-to-Everything: A Survey

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ABSTRACT Recently, the advancement in communications, intelligent transportation systems, and computational systems has opened up new opportunities for intelligent traffic safety, comfort, and efficiency solutions. Artificial intelligence (AI) has been widely used to optimize traditional data-driven approaches in different areas of the scientific research. Vehicle-to-everything (V2X) system together with AI can acquire the information from diverse sources, can expand the driver's perception, and can predict to avoid potential accidents, thus enhancing the comfort, safety, and efficiency of the driving. This paper presents a comprehensive survey of the research works that have utilized AI to address various research challenges in V2X systems. We have summarized the contribution of these research works and categorized them according to the application domains. Finally, we present open problems and research challenges that need to be addressed for realizing the full potential of AI to advance V2X systems.

INDEX TERMS Artificial intelligence, machine learning, VANETs, V2X, predictions, platoon, VEC.

I. INTRODUCTION

The latest developments in the AI techniques have opened up new opportunities for the Intelligent Transportation Systems (ITS). The vehicular sensors are also becoming smarter with time, resulting in an ability of the vehicles to better assess the environment. This advancement has led to the possibility of realizing autonomous driving that is based on the idea of imitating human driving behavior while mitigating human faults. A plethora of applications have been developed starting from active and passive road safety to the optimizing traffic, ranging from autonomous vehicles to the Internet of vehicles [1].

The V2X paradigm is essentially based on sharing of information in the form of Vehicle-to-Infrastructure (V2I), Vehicle-to-Vehicle (V2V), Vehicle-to-Pedestrian (V2P), Vehicle-to-Self (V2S) and Vehicle-to-Road side units (V2R), as shown in Figure 1. There are three main aspects of a V2X communication system: traffic efficiency, road safety and energy efficiency. One important use case of V2X is the traffic flow information. Vehicular applications can use this information to intelligently execute tasks such as traffic congestion rectification, better utilization of Plug-in Electric Vehicle (PEV) charge [2], minimizing fuel consumption and improving location based services. The traffic flow dataset can be acquired from multiple sources such as Closed-Circuit TeleVision (CCTV) cameras, induction loops, crowd souring based information services and vehicles. Designing highly accurate traffic flow prediction algorithms using conventional traffic flow estimation techniques is a big challenge [3].

Moreover, due to very few traffic data and its accessibility, the research and experimentation are also limited to those datasets. There are relatively very few datasets available publicly for the researchers to design and execute their traffic flow prediction algorithms and to compare their results. AI has been widely applied for designing prediction algorithms in fields such as computer vision, data science, robotics, medical, and natural language processing [4], [5]. AI is an efficient data-driven approach that makes it more robust to handle sparse and heterogeneous data. AI together with V2X can enable unconventional applications such as real-time traffic flow prediction and management, location-based applications, autonomous transport facilities, vehicular platoons, data storage in vehicles, and congestion control in Vehicular Ad-hoc NETworks (VANETs). However, the exploitation and

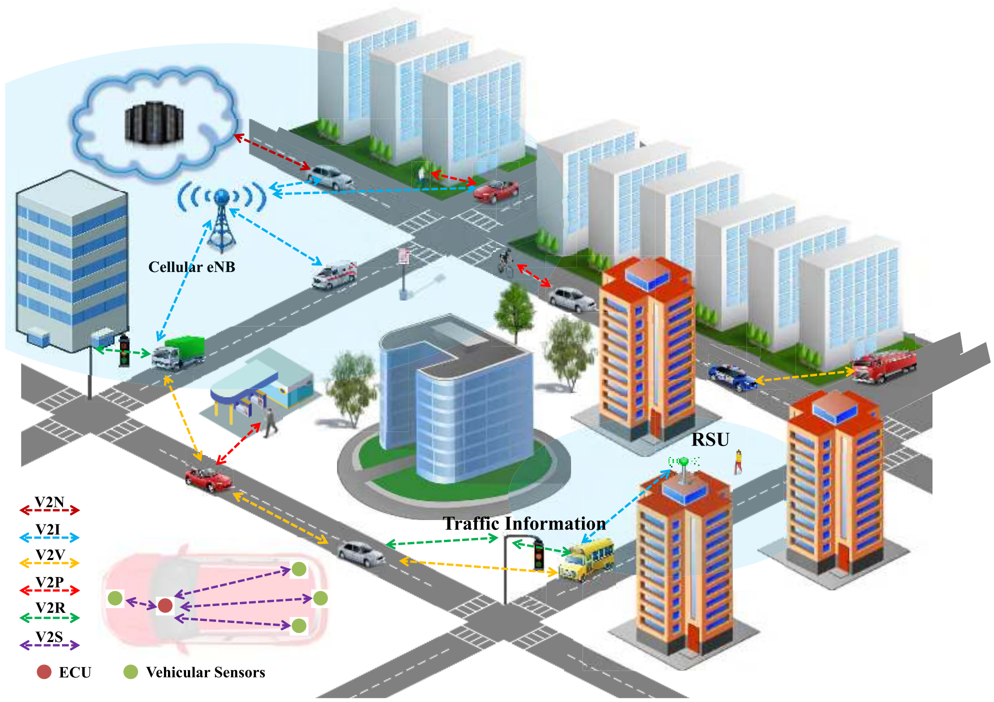

FIGURE 1. An overview of V2X scenario.

adaptation of AI development tools to meet the challenges pertaining to the vehicular networks is still a research area in its infancy.

This article provides a comprehensive survey on this emerging paradigm of AI for V2X, and lists open research challenges that need more work to realize this powerful platform. The rest of the paper is organized as follows. In Section II we give an overview of the V2X communication technologies. We present the key foundation and algorithms for AI, and then provide an overview into the data-driven AI use cases and their potential towards V2X paradigm in Section III. In Section IV, we discuss the tools available for the design and deployment of AI algorithms. In Section V, we present AI based applications in the V2X. Finally, section VI presents open issues and research challenges in the context of integrating the AI and V2X platforms for fully realizing possible benefits from the integration. Section VII concludes the article with future directions.

II. V2X COMMUNICATION TECHNOLOGIES

There are two potential communication technologies that enable V2X. The first one is known as Dedicated Short Range Communication (DSRC) [6], which is based on IEEE 802.11p [7] and was standardized in 2012. The second is based on Long-Term Evolution (LTE) cellular communications and known as cellular-V2X or in short C-V2X [8], which was released by the 3rd Generation Partnership Project (3GPP) in 2016. Both DSRC and C-V2X support V2V and V2I communications. However, C-V2X also supports wide area communications called Vehicle-to-Network (V2N), enabled by 5th Generation (5G) services. The challenges and various solutions to connected vehicles are discussed in detail in [9].

DSRC enables VANET. VANET does not require any infrastructure for vehicles to communicate, which is a key to ensure safety in the remote and little developed areas, especially for accident prevention in foggy highways. In DSRC, vehicles transmit messages known as Common Awareness Messages (CAM) and Basic Safety Messages (BSMs) with a latency of less than 100 ms. DSRC is a slight modification of IEEE 802.11 protocol, and it can be easily used to deploy VANETs. Although VANET devices can access the network quickly, but the Medium Access Control (MAC) protocol of DSRC is based on Carrier-Sense Multiple Access with Collision Avoidance (CSMA/CA), that may cause some unbounded latency and reliability [10].

On the other hand LTE is highly reliable, and have higher bandwidth, and requires modifications before its deployment in the V2X system [11]. According to the latest 3GPP technical specifications of LTE V2X, the physical link of LTE (Sidelink) is introduced, which is different from the traditional LTE uplink and downlink network traffic. In Sidelink the LTE V2X can work in two modes: 1) LTE-V-Cell mode, where eNodeB (eNB) will be used, and 2) LTE-V-Direct mode, where Sidelink will be used as a physical link [12]. In the LTE-V-Direct mode, a self-organized Time Division Multiple Access (TDMA) is used as a MAC protocol, where the time resource is divided in slots. The communication nodes at first need to listen to the channel for a period of time to acquire the frame information, while accessing the channel, and then randomly select an idle slot to access the channel. However, the collisions cannot be avoided completely due to simultaneous channel selection.

In LTE-V-Direct, devices will communicate in half-duplex mode, therefore, collisions cannot be detected immediately. These collisions will continue if the devices continue using the same slot. Thus, in a self-organized TDMA the devices will change the slot several times after sending packets [13]. The Frame Information Loss Rate (FILR) in LTE-V-Direct, is a probability that, the two vehicles within the radio range will fail to acquire the frame information of each other. The Inter-Reception Gap (IRG) is the interruption between successful data transmission. Both FILR and IRG are important factors that indicate the reliability of the LTE-V-Direct system. A Markov chain based Media Access Process Model of LTE-V-Direct Communication is introduced in [10], where the models for FILR and IRG are derived and verified.

In C-V2X, when the wireless link is not necessary from the cellular base station, an alternative mode called PC5 [14] interface can be used. PC5 is a direct communication channel between two vehicles in the absence of base station coverage. In addition to the PC5 based V2V communication, C-V2X also allows a logical interface called Uu [15] between the vehicle and the base station. The cellular communication capabilities have been added to millions of cars and this number is growing. The European Telecommunications Standards Institute (ETSI) ITS specification has described various use cases for the integration of communication capabilities in the vehicles. Many of these use cases have already been implemented using the existing cellular network connections. Examples include safety hazard warning, traffic ahead warning, road work warnings, collision avoidance, speed advisory, and parking assistance. Therefore, Release 14 of the LTE standard supports V2X services according to the parameters defined by the ETSI ITS, United States (US) Society of Automotive Engineers (SAE), and other similar organizations across the world.

III. ARTIFICIAL INTELLIGENCE AND V2X

V2X is an extension of vehicular networks, which aims to promote safety and efficiency of transportation systems by sharing information among vehicles, pedestrians and infrastructures. Recently, V2X platform has received tremendous amount of interest from academia, industry and Government bodies alike. Recent advancements in computation technology and hardware have led to AI being an integral part in almost every engineering related research area. Autonomous driving is one such application where AI plays a crucial role in enabling basic features of human driving. V2X can play a vital role in enhancing both safety and efficiency in autonomous vehicles.

The research related to AI is described as the study of intelligent agents [16]. The field of AI research was started from 1956 at Dartmouth college [17]. AI has been widely applied by modern machines for applications such as competing at the highest level in strategic games (e.g. Go, Chess), understanding human speech, autonomous vehicles, and intelligent network routing in content delivery networks etc. Figure 2 gives an overview of the terms and techniques within the AI research area. Some of the most widely used AI techniques are: Heuristic Techniques, Robotics, Swarm Intelligence, Expert Systems, Turning Test, Logical AI, Planning, Schedule and Optimization, Natural Language Processing, Game Theoretic Learning, Evolutionary Algorithms, Inference, Fuzzy Logic, and Machine Learning etc. We will briefly discuss these techniques in the next subsections.

A. SWARM INTELLIGENCE

Swarm intelligence can be described as a collective behavior of self-organized and decentralized systems. The term Swarm Intelligence (SI) was first introduced by Beni and Wang [18] for the cellular robotic systems. In the context of V2X paradigm, the swarm intelligence is shown by a population of vehicular agents that interact locally with one another and their environment. The vehicles follow simple rules without any centralized control system. The behavior of ant colonies, flocks of birds, schools of fish, animal herding, microbial intelligence, and bacterial growth all are based on swarm intelligence. In an experiment performed by Deneubourg in 1990, a group of ants was given two paths (short/long) that connect their nest to the food location. It was discovered from their results that ant colonies had a high probability to collectively select the shortest path. More detail on Swarm Intelligence for wireless communication can be found in [19]. The most widely accepted use cases of Swarm Intelligence are 1) Particle Swarm Optimization (PSO), 2) Ant Colony Optimization (ACO) and 3) Swarmcasting.

1) PARTICLE SWARM OPTIMIZATION

PSO is regarded as a global optimization algorithm. It can be used to solve a problem whose solution can be described as a point or a surface in an n-dimensional space. Seeded with an initial velocity, various potential solutions are plotted in this solution space. The particles move around this space with certain fitness criteria, and with the passage of time, particles accelerate towards those locations that have better fitness values. In the upcoming Section IV, we discuss the works that have utilized PSO for the VANET applications in more detail.

2) ANT COLONY OPTIMIZATION

ACO was first proposed by Dorigo [20]. ACO finds near optimal solutions to different problems which can be described as graph optimization problems. Just as stated earlier, the ants in ACO try to find the shortest path. A famous application in wireless communication routing is known as AntNet [21]. In this routing, near optimal routes are selected without global information.

3) SWARMCASTING

Swarmcasting exploits the concept of distributed content downloading to provide high resolution video, audio and

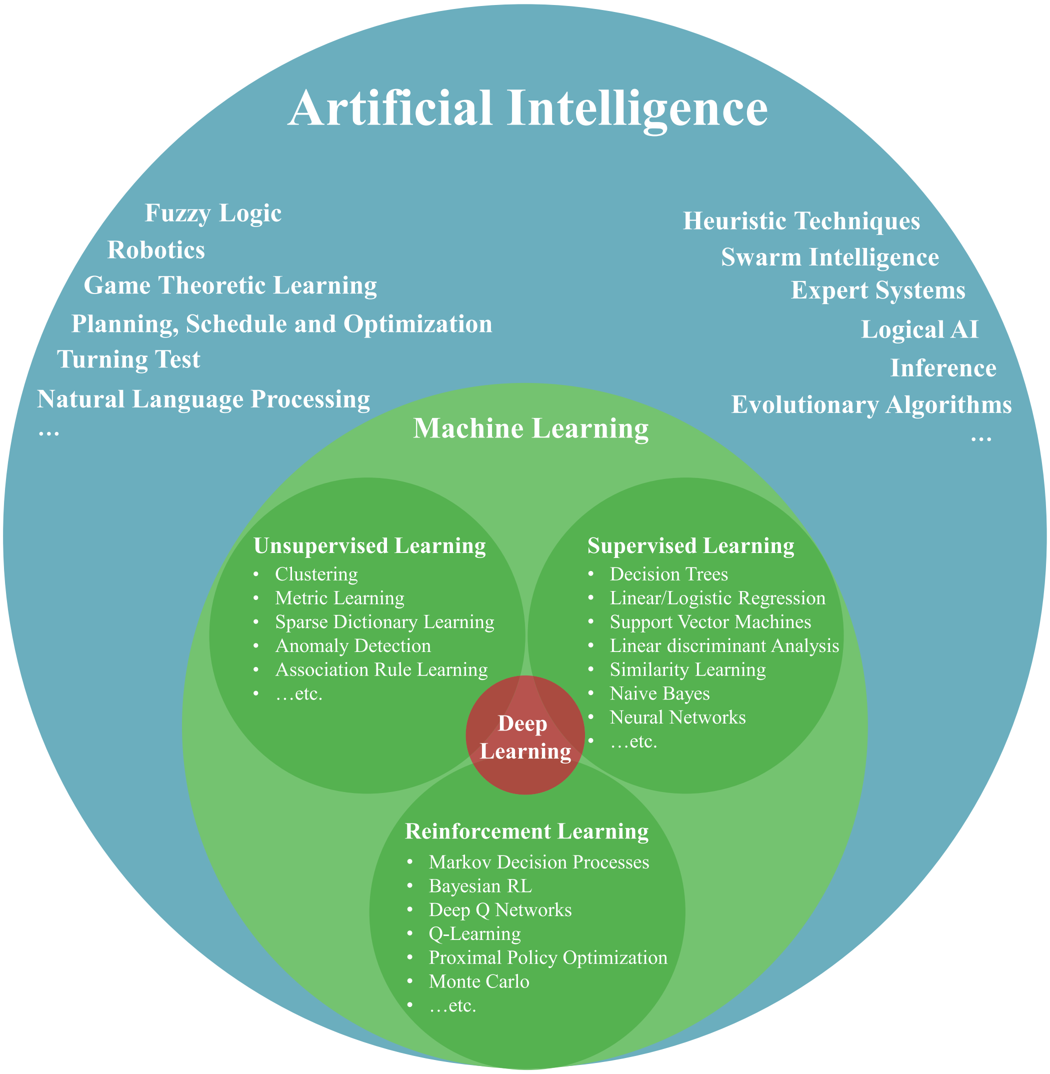

FIGURE 2. AI and its branches.

Peer-to-Peer (P2P) data streams, which contributes in reducing the required bandwidth. It applies the Swarm Intelligence to break down large data into small parts, so that the system can download these parts from different machines simultaneously, which enables a user to start watching the video before downloading is complete. This use case has great potential for enabling and enhancing content delivery and file sharing solutions for the V2X paradigm.

B. MACHINE LEARNING (ML)

ML covers a big part of AI. ML techniques can be described into three types: Unsupervised learning, Supervised learning, and Reinforcement learning. There are some other kinds of ML schemes such as Transfer learning and Online learning, which can be subcategorized in the form of these basic three ML schemes. ML basically consists of two important stages: training and testing. Based on the realistic data, a model is trained in the training phase. Then in the testing phase predictions are made based on the trained model.

1) UNSUPERVISED ML SCHEME

In the unsupervised ML, training is based on unlabeled data. This scheme tries to find an efficient representation of the unlabeled data. For example, the features of a data can be captured by some hidden variables, that can be represented by the Bayesian learning techniques. Clustering is a form of unsupervised learning that groups samples with similar features. The input features of each data point can be its absolute description or a relative similarity level with other data points.

In the wireless networks paradigm, the cluster formation for the hierarchical protocols is of great importance in terms of energy-management, where each member just needs to communicate with the cluster head before communicating with the members of other clusters. Some traditional clustering algorithms are k-means, spectrum clustering, and hierarchical clustering. Dimension reduction is another subclass of unsupervised ML scheme. The main idea behind dimension reduction is to down-sample the data from a higher dimension to a lower dimension without any significant data loss. Applying machine learning for most applications require dimension reduction due to a number of reasons.

Curse of data dimensionality is the first reason. In clustering, classification and optimization, the overall model complexity increases dramatically with the increase in feature dimensions. The second reason is the hurdle in the learning process. In most of the cases the features of the data samples are correlated in some aspects, but if the feature value is affected by noise or interference then the respective outcome of the correlation will be corrupted and the learning process will be affected. Such kind of dimension reduction in the vehicular social networks is the formation which leads to a vehicular cluster. The cluster head collects and transmits the information to the eNodeB to reduce the communication cost. The curse of dimensionality can be reduced by the dimension reduction methods. Dimension reduction methods are grouped in two categories: 1) linear projection methods such as: Principal Component Analysis (PCA) and Singular Value Decomposition (SVD), and 2) nonlinear projection methods such as: manifold learning, local linear embedding (LLE) and isometering mapping.

2) SUPERVISED ML SCHEME

The supervised learning learns from a set of labeled data. Supervised learning can be divided into two categories: 1) Regression, and 2) Classification. If the training data only includes discrete values then it is a classification problem and the output of the trained model is a classification which is also discrete. On the other hand if the training data contain continuous values, then it is the regression problem and the output of the trained model will be a prediction. Two widely used examples of supervised ML are Decision Trees and Random Forest.

The output of regression algorithms is a continuous value that may represent prediction of the house price, stock exchange, banking customer transactions, State Of Charge (SOC) of an electric vehicle battery, level of traffic congestion at various intersections, and jamming prediction. In vehicular social networks, regression can be used to predict parameters such as network throughput. Two classic regression algorithms are: 1) Gaussian Process for Regression (GPR) and 2) Support Vector Regression (SVR). In vehicular networks the classification algorithms can be used for intrusion or malfunction detection. Moreover, classification algorithms are also beneficial in the traffic safety applications such as: Augmented Reality Head Up Display (AR-HUD), active driver information systems, obstacle detection, and predicting complex traffic types.

3) REINFORCEMENT LEARNING (RL)

Reinforcement Learning actively learns from the actions of the learning agent from the corresponding reward. It means in order to maximize the reward, inexplicit mapping the situations according to the actions by trial and error. The Markov Decision Process (MDP) is an example of reinforcement learning. Q function model-free learning process is a classic example to solve MDP optimization problem that does not require information about the learning environment.

Actions and their rewards generate policies of the choice of a proper action. In a given state the Q function estimates the mean of the sum reward. The best Q function is the maximum expected sum reward that can be achieved by following any of the policies. Reinforcement leaning is a perfect candidate for addressing various research challenges in vehicular networks. For example, cooperative optimization of fuel consumption for a given geographical region, handling the spatial and temporal variations of the V2V communications, optimum path prediction of electric vehicles, and reduction in traffic congestions.

C. DEEP LEARNING (DL)

Deep learning is closely related to the above three categories of ML. It is a deeper network of neurons in multiple layers. It aims to extract knowledge from the data representations, that can be generated from the previously discussed three categories of ML. The network consists of input layer, hidden layers and an output layer. Each neuron has a non linear transformation function, such as ReLU, tanh, sigmoid, and leaky-ReLU. The scaling of input data is very crucial as this can severely affect the prediction or classification of a network. As the number of hidden layers increases, the ability of the network to learn also increases. However, after a certain point, any increase in the hidden layers gives no improvement in the performance. The training of a deeper network is also challenging because it requires extensive computational resources, and the gradients of the networks may explode or vanish. The deployment of these resource hungry deeper networks has raised the importance of edge computing technology. Vehicles on the move can get benefit from mobile edge computing servers. Figure 3 illustrates the idea of neurons, input layer, hidden layers and output layer in a Deep neural network. It is also known as Multi-Layered Perceptron (MLP).

D. EXPERT SYSTEMS

Expert systems emulate the human ability to make decisions. The Expert systems solve complex problems by reasoning which is extracted from human knowledge. This reasoning is represented by IF-THEN rules, instead of procedural coding [22]. An Expert system is divided into two parts: Knowledge base and Inference engine. 1) Knowledge base: The knowledge base is composed of rules extracted from human knowledge. Inference engine: 2) The inference engine applies the extracted rules from knowledge base to known facts to deduce new facts. They can also include explanation and debugging abilities. There are further two modes of an inference engine such as forward chaining and backward chaining. More detail on Expert systems can be found in [23].

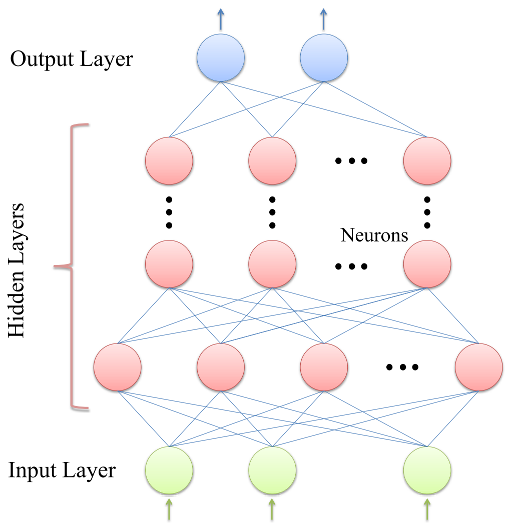

FIGURE 3. A typical Deep neural network.

E. PLANNING, SCHEDULING, AND OPTIMIZATION

This branch of AI deals with the realization of strategies or action sequences, for the execution by intelligent agents. The planning is also related to decision theory, and unlike traditional control and classification problems, the complex solutions must be discovered in an optimized manner from the n-dimensional space. Planning can be performed offline in a known environment with available models, and the solutions can be evaluated prior to the execution. In a highly dynamic and partially known environment of V2X paradigm, the strategy needs to be revised online. The models and related policies must be adapted accordingly. The languages used to describe the scheduling are known as action languages. There are different algorithms of planning, such as Classical planning, Temporal planning, Probabilistic planning, Preference-based planning, and Conditional planning. More details about Planning, Scheduling, and optimization can be found in [24].

IV. SOFTWARE TOOLS AVAILABLE FOR AI

Recently, a number of development tools have been made available online by the AI research community. These tools are a collection of computer programs, with the related AI functionality, and sharing a similar user interface and the ability to easily exchange data with each other. They can be categorized into two libraries, i.e. 1) open source and 2) proprietary based tools. We will briefly discuss these two categories.

A. OPEN SOURCE TOOLS FOR AI

There are quite a few open source tools that can be used for AI based V2X applications. One of the most popular tools is TensorFlow [25] developed by Google. It is a software library for data-flow programming for a range of AI tasks. It has been extensively used for deep learning networks, in autonomous vehicular systems. Tensorflow can run on multiple CPUs and (Graphical Processing Units) GPUs. It is available on various OS and mobile computing platforms such as iOS and Andriod. Apache Spark [26] is a distributed general-purpose framework for cluster-computing. It provides an interface for programming entire clusters. Spark core provides, distributed task dispatching, scheduling, and basic I/O functionalities, exposed using an application programming interface such as Java, Python, Scala, and R. Vehicular edge computing is getting huge usage of the Spark cloud computing. It is due to the fact that Spark can be used in traditional data centers and cloud.

Scikit-learn [27] is a free ML based library for Python. It features various classification, regression and clustering algorithms, that makes it a perfect candidate for ML applications in V2X scenarios. The included algorithms are Support Vector Machine (SVM), random forest, gradient boosting, k-means, and Density-Based Spatial Clustering of Applications with Noise (DBSCAN). A recent Python and NS3 based framework known as PySNS3 [28] can readily import Scikit-learn tools for V2X simulations. The Scikit or also known as SciPy Toolkit is written in Python with some algorithms written in faster Cython.

PyTorch [29], is another open source library for Python used for applications such as natural language processing. It was developed primarily by Facebook AI research group and Uber's ‘‘Pyros’’ software team. It provides high level features such as, Tensor computation with strong GPU acceleration, Deep Neural Networks (DNN) built on a tape-based autodiff system. Tensors are multidimensional arrays, that can be computed on Graphics Processing Units (GPUs) supported by Nvidia's Compute Unified Device Architecture (CUDA) toolkit. PyTorch is a powerful candidate for vehicular cyber social computing, as it uses a technique called automatic differentiation. This technique records what operations have been performed, and then it replays it backwards for gradient computing. This technique is also powerful while building neural networks in order to save time on one epoch by calculating differentiation of the parameters at the forward pass itself. This time saving approach is perfect for the highly time critical V2X scenarios.

Big vehicular data traces can also be efficiently analyzed using another powerful tool known as H2O [30]. It allows users to fit thousands of potential models as part of discovering data patterns. It can be run using R and Python. It is used for exploring and analyzing huge datasets held in the cloud computing systems such as Apache Hadoop Distributed File System. Big vehicular traffic datasets are too large to be analyzed using traditional software like R. Therefore, H2O provides data structures and methods that are suitable for this kind of V2X generated data. H2O contains statistical algorithms such as K-means clustering, generalized linear models, distributed random forests, gradient boosting machines, naive Bayes, and PCA, etc. H2O uses iterative methods that provide quick answers using all the vehicular client's data. A vehicular client running short of time can interrupt the computations and can use an approximate solution. Other DL frameworks are: Keras, Theano, Torch, Caffee, Deeplearning4j, OpenNN, PaddlePaddle, DataMelt, Dlib, BigDL, Seq2SeqSharp and OpenNN.

B. PROPRIETARY SOFTWARE TOOLS FOR AI

One of the most popular software tools in this category is known as Amazon Web Services (AWS) [31]. It is a subsidiary of Amazon.com that provides on-demand cloud computing platforms for the AI research community based on paid subscription. This allows the subscribers to have a virtual cluster of computers, available all the time via internet. Every AWS system also visualizes its own console inputs/outputs. It allows AWS subscribers to connect to its AWS system using any modern browser. This paid and time efficient facility is suitable for the faster development of ML applications for V2X paradigm.

Google prediction [32], is a set of application programming interfaces (APIs), that allows communication with Google Services and their integration to other vehicular services. Especially for the V2X applications the embedded Google map on a website and the traffic information retrieval can be done using Google Earth API. The API supports various languages, such as, Java, .NET, Objective-C, PHP, and Python. Autonomous vehicles are already getting huge benefit from the dynamic loading or auto-loading feature which is supported by Google to enhance performance of the applications using the loaded APIs [33].

Microsoft Azure [34] is another cloud computing web service for AI, created by Microsoft. It can be used for building, training, testing, and deployment of V2X AI applications. It provides Software-As-A-Service (SAAS), Platform-As-A-Service (PAAS) and Infrastructure-As-A-Service (IAAS). It also supports multiple programming languages, and Microsoft specific softwares and systems. The Microsoft Azure ML service is a part of Cortana intelligence Suite that enables natural human machine interaction. Microsoft connected vehicular platform, is already helping auto-makers to transform cars, where the Microsoft's cloud is performing heavy lifting by ingesting bigger volumes of data from connected vehicles. This allows auto-makers to utilize their data in powerful ways.

IBM Data Science eXperience (DSX) [35], is another potential candidate platform for the V2X paradigm. In this platform an ML developer can create project with a group of collaborators who have access to different analytics models and various programming languages. DSX also cooperates with some open source tools such as RStudio, Spark and Python in an integrated environment. DSX also provides access to datasets that are available through Watson Data Platform in the cloud. It has a large community and embedded resources such as datasets on the latest developments from the data science community.

V. AI IN V2X APPLICATIONS

AI can be used in the traditional vehicular communications based applications to overcome their challenges effectively. The sensors, data computation and storage abilities of vehicles can be utilized for data mining and predictions to enhance ITS solutions. We review the studies on the following applications/use cases:

- Safety, comfort and efficiency
- Network congestion control
- Demand and supply oriented applications
- Navigation of autonomous vehicles
- Security in VANETs
- Vehicular edge computing
- Content delivery and offloading
- Vehicle platoons

A. SAFETY AND COMFORT

1) SAFETY AND COMFORT

Information such as driving safety status, road safety index, and road visibility conditions, are of great importance, in terms of passengers safety and route planning. Traditional research on driving safety analysis still needs better accuracy in terms of driving safety assessment. The advancement in computing technology and the edge computing paradigm has made possible the real-time safety analysis on the move. The work in [36], identifies two main challenges in this context: 1) driving safety analysis, and 2) road safety analysis. They proposed a new deep learning framework known as DeepRSI, to conduct real-time predictions of the road safety. These predictions are made based on data obtained from vehicle GPS trajectories and the mobile sensing data collected by the VANETs. The results show that DL has outperformed the traditional methods by intelligent utilization of mobile sensing data.

Another work [37], applied deep learning to improve vehicle safety and comfort by performing human factors assessment and displaying the surrounding information to the drivers. Providing the surrounding information to the drivers is among one of the various solutions to prevent road-side accidents. Their work shows that AR-HUD can be beneficial as a new form of a dialog between the driver and vehicle. This dialog keeps the driver's attention on the road while also providing the surrounding information. A real-time DL based solution is proposed in this work for object detection, identification and recognition of road obstacles in complex traffic situations. They deployed a single convolutional neural network that predicts the region of interest and class probabilities from the single image frame. This information processed by one vehicle can be passed to the vehicle behind through V2X to improve the overall safety factor. Hundreds of people died in the chain of accidents caused by poor visibility e.g., due to fog, or bad weather. The V2X paradigm can play a crucial role in mitigating such accidents as well.

Figure 4 gives an illustration of AI oriented V2X applications. A steering assistance system known as Steer-By-Wire (SBW), is one of the most promising approaches that can improve vehicle safety and comfort. SBW system has been considered as the next generation steering system equipped

TABLE 1. Safety and comfort.

Citation	Platform	Proposed	Traffic	Dataset	AI Domain	Remarks
[36]	Own	Deep RSI	Urban	Urban [134], [135]	DL	Predicts safety index
[37]	SUMO+NS3, Caffee	AR-HUD	Urban	ImageNet	CNN, DL	FCW, ADAS
[38]	Simulink-Carsim	DPDC	Urban	Rules: 32, Params: 5	Fuzzy Logic	SBW, ADAS
[39]	Own	linear MPC	Highway	Odometric [136]	Expert systems	DMA, ADAS
[40]	Own	CA using GPR	Urban	30 minutes data [137]	Unsupervised ML	Predicts collision
[41]	ChronoVeh. [138]	Cooperative CA	Urban	Urban [139]	Expert Systems	CA with TCS
[60]	OLSIMv4	PDNs	Freeway	54000 data points	Decision Trees	Predicts traffic flow
[61]	Own	SAETLP	Freeway	PeMS 80640 dataset	DL	Predicts traffic flow
[63]	Own	Seq2Seq model	Urban	Q-Traffic Data	DL	Predicts traffic jams

FIGURE 4. An illustration of AI oriented V2X applications.

on the vehicles for the overall safety improvement. Recently, in [38], a fuzzy steering assistance control for path following vehicles is introduced, that considered characteristics of a human driver.

Another safety critical task is overtaking, that requires better driving skills. In a complex scenario when multiple participants are involved in the overtaking process, it is very important to understand, coordinate and predict the future actions of other vehicles. Therefore, the prediction of safe future states is an import factor in the V2X paradigm. A recent research [39], has addressed this situation for the connected and automated vehicles, and proposed an overtaking expert system, based on a linear model predictive control approach for multiple vehicles. Their approach dynamically adapts the trajectory for the maneuver in the case of unexpected situations.

An intelligent vehicle should be able to anticipate its surrounding environment in the near future and thus plan ahead accordingly. This ability is essential for Collision Avoidance (CA). For example, if a vehicle knows the projected trajectories of its surrounding vehicles, then it can easily make timely decisions to warn or avoid a potential accident. A research work [40] based on Gaussian process regression model has focused on the long term (particularly more than one second) trajectory prediction of the nearby vehicles, in a dynamically changing and uncertain V2X scenario. The most important and critical systems of a vehicle such as, Anti-lock Braking System (ABS), Electronic Stability Program (ESP), and Traction Control System (TCS), rely on the low-level data from various vehicular sensors. The research work in [41], introduced an extension to the Basic Safety Message (BSM) set in DSRC to prevent potential future collisions among vehicles. This work used Expert System controller which intelligently utilized the low-level sensor data of the neighboring vehicles to collaboratively avoid collisions with the vehicles that were experiencing instabilities. The work demonstrated the sustainability of the proposed system for three scenarios such as, 1) aggressive neighboring vehicles, 2) loss of control among neighboring vehicles, and 3) lane changing among multiple vehicles. A summary of related work on the traffic safety and comfort is shown in Table 1.

2) COOPERATIVE PARKING

During the rush hours a large number of vehicles struggle to find car parking spots in the same location, which can lead to traffic congestion. Without vehicular cooperation, the vehicles might compete with one another for the similar areas, even if there are other alternative spots available. In [42], a decentralized coordination approach was introduced to search the car parking spots, which is applicable to large car park areas. This approach takes into account the walking distance and parking search time in a V2V scenario. A vehicle is assumed to have communication capabilities to extend its observation area by receiving messages from other vehicles, and can make rational decisions based on messages received. Every vehicle updates its knowledge-base and selects the target slot based on strategical cooperation with the neighboring vehicles. The vehicular decision-making takes into account the walking distance to the parking spot, e.g., a building entrance, and the car park searching time.

3) SPEED ADVISORY

The Green Light Optimal Speed Advisory (GLOSA) is a system which allows vehicles to communicate with traffic lights. GLOSA informs drivers about the speed they should drive as they approach junctions to avoid the red lights. The adoption of V2X will therefore, prevent the drivers from rapid driving in order to catch the traffic lights. This will also improve the air quality by reducing the overall harsh accelerating or braking vehicles near the signals. This V2X technology is currently under trails on a Jaguar F-PACE, as part of a £20 M collaborative project [43]. Katsaros *et al.* [44] proposed an AI based GLOSA application and introduced metrics such as, average fuel consumption, and average stop time behind the traffic light. In [45], a new Genetic Algorithm (GA) oriented approach based on multi-segment GLOSA was introduced. In this approach several TLs in a sequence are considered for the route of vehicles. It is assumed that vehicles have the access to the phase schedules of all TLs that they will encounter.

4) SPATIO-TEMPORAL NETWORK TRAFFIC ESTIMATION IN VANETs

The network traffic estimation in time and space has recently, attracted the VANET research community, due to its greater influence in the ITS. The reliability and security of VANET is important to guarantee the successful deployment of VANET's applications. The complex environment of VANET has made the network anomaly detection more challenging due to mobility, buildings, and short-lived links. Recently, Laisen *et al.* [46] demonstrated the importance of convolutional neural networks, by using the fully connected architecture as the output layer and extracting the spatio-temporal features of the traffic matrix. Their preliminary experiments have shown that ML based method is effective as compared to the traditional anomaly detection methods.

5) TRAFFIC LIGHTS CONTROL IN VEHICULAR NETWORKS

Traditionally, the dynamic traffic light control has been deployed using Fuzzy logic and linear programming due to limitations of computational resources and simulation tools. In [47], a scheme was proposed where the learning state is based on position and speed of vehicles, the action uses 4 phases and the reward is a change in cumulative delay using Convolutional Neural Network (CNN). In another work [48], the state is represented by the Queue length and the action uses 2 phases, the reward is a difference between flows in two traffic directions, using Stacked Auto-Encoders (SAE).

In [49], the state is chosen as the position of vehicles, the action is composed of 2 phases and the action includes wait time, stop, switch and delay, using Double Q-Network (DQN) Prioritized experience replay. The work in [50], has used the position and speed as states, the action is composed of 4 phases and the reward is a change in cumulative staying time, using convolutional neural network experience replay. As compared to the discussed research work [50], an improved value based reinforcement learning algorithm to traffic lights control scheme is proposed in [51]. In this work the traffic intersection scenario contains multiple phases, which represents a high-dimension action space. The work also guarantees that the traffic signal time smoothly changes between two neighboring actions.

Another work [52], has introduced a deep RL agent that takes advantage of the real-time GPS data and learns how to control the traffic lights at an isolated traffic intersection. They have combined the Recurrent Neural Network (RNN) with Deep Recurrent Q-Network (DRQN), and compared its performance with the standard Deep Q-Network for a partially observed isolated traffic intersection. This work also shows that the recurrent Q-learning method provides better result compared to the standard Q-Learning method, by achieving lower average vehicle waiting time. Table 2 summarizes the research works where the AI is used in the intelligent traffic light control along with vehicular communications.

6) PREDICTION OF ROAD TRAFFIC FLOW

The information about time efficient traffic flow is important prior to the deployment of various ITS applications. These applications can efficiently use this information for the tasks such as, traffic congestion rectification, better utilization of PEV charge, minimizing fuel consumption and improving location based services. The traffic flow data can be acquired from multiple sources, such as traffic cameras, crowd souring based information services, vehicles etc. This data can be accessed in real-time or in offline e.g., hourly, weekly, monthly or yearly. This data can be very useful for the predictions of various ITS applications by using AI techniques.

The traffic prediction methods are divided into classes, 1) parametric methods, and 2) non parametric methods. One of the most commonly used parametric methods is known as AutoRegressive Integrated Moving Average (ARIMA) [53]. ARIMA assumes that traffic prediction is in a stationary process. However, due to high computational requirements of ARIMA and its subclasses, they are not suitable for the predicting large-scale traffic. Non parametric methods have gained popularity due to stochastic and non linear nature of traffic. Such research works include [54] that used Random Forest (RF), [55] that used Support Vector Regression (SVR), [56] that used OnLine SVR (OL-SVR), [57] that used Bayesian network, [58] that Artificial Neural Networks (ANN) and [59] that used deep belief network.

Obtaining high accuracy of traffic flow predictions is a big challenge for conventional traffic flow estimation techniques. Some research on traffic flow prediction shows excellent performance improvement over conventional approaches. The work in [60] is based on Poisson Regression Trees (PRT) which is a probabilistic graphical model. It has been used for two correlated tasks: 1) prediction of

TABLE 2. Efficiency (Intelligent traffic light control).

Citation	Platform	Proposed	Lanes	Dataset	AI Domain	Remarks
[47]	SUMO, Keras	DQTSCA	4	Dataset [150], [151]	Q-learning, RL	Good TLC policy
[48]	PARAMICS	Deep RL-TLC	4	100 to 200 veh./hr	DL	Minimal deployment cost
[49]	SUMO	Coordinated TLC	2,3,4	Data set [147], [148]	Deep RL	Outperform earlier work
[50]	SUMO	Adaptive TLC	4	1.5hr data [149]	RL	Better TLC policy
[51]	SUMO	3DQN	3	Dataset [147], [148]	Q-learning, RL	Good learning speed
[52]	SUMO, Keras	DRQN TLC	4	Dataset [150], [151]	Recurrent-Q, RL	Best TLC policy

LTE communication connectivity, and 2) the prediction of vehicular traffic. PRT is similar to decision trees and it is used for modeling the count data. In PRT each inner node represents splitting criteria. The prediction performance is enhanced by using the congestion information, vehicular traffic information and the performance of communication system. In [61], a novel stacked auto encoder based traffic flow prediction method is introduced. The auto encoders are used as building blocks to represent features of traffic flow that are used for the Deep Learning and predictions with improved accuracy.

Most of the previously discussed research focused on the prediction of traffic flow for the highways, where the traffic flow is relatively smooth. However, in the urban city scenario the traffic lights would have greater influence on the traffic flow due to speed variations of vehicles. Ma *et al.* [62] predicted traffic speed using Long Short Term Memory Network (LSTM), considering the two points to perform their experiments. The traffic flow prediction is a challenging task without incorporating the crowd-sourced information, due to the complex nature of interaction between the crowd and the vehicles. The most recent research work [63] performed real-world experiments on the Baidu traffic data set. This work proposed an encoder decoder sequence learning framework, which integrates three important factors: 1) road intersection information, 2) offline geographical and social attributes, and 3) online queries from the crowd. The demonstrated results have shown the effectiveness of the framework.

B. NETWORK CONGESTION CONTROL

The traffic and network congestion is common at the cross sections in the urban environment. An unsupervised learning algorithm [64], which is based on k-means clustering, uses a central controlled approach to manage the congestion. This work is focused on vehicles stopping at the red light at the intersections. The Road Side Infrastructure (RSI) measures and controls the wireless channel congestion at the intersections. The transmission data is clustered into different groups by using k-means clustering approach based on the features. These features include size of message, duration of message, V2I distance, message types and directions of message sending vehicles. The independent communication parameters such as transmission rate, transmission power, congestion window size, and Arbitration Inter-Frame Spacing (AIFS), are provided to each cluster. The channel must be made available before transmission to avoid the collision of packets. A recent work [65] has proposed a swarm intelligence based distributed congestion control scheme in VANET. This scheme maintains the level of channel usage under the network malfunctioning limit, while keeping the Quality of Service (QoS) of VANET high. The results demonstrate that this scheme improves network throughput, channel usage, and stability of communication compared to other competing congestion control schemes such as Swarm Distributed Intelligent Fair Rate Adaptation (DIFRA) [66].

In V2X scenarios, the highly dynamic communications, complex correlation among various transmission modes competing for the limited spectrum resources, time varying data rates, and vehicle-mobility, make it challenging to optimally allocate the available spectrum. Cognitive Radio (CR), which is a context-aware intelligent radio, can improve spectrum efficiency by detecting and reutilizing of the under-utilized spectrum [67]. The existing DSRC spectrum may not be sufficient to fulfill the stringent delay constraints required for V2X [68].

A recent work on cognitive vehicular communication [69], has proposed a Q-learning approach to design an optimal data transmission scheduling system that minimize the transmission costs while fully utilizing different communication modes and resources. Furthermore, they have shown that the Deep Q-learning based approach outperforms V2I-only mode and transmission with cognitive radio mode, in terms of average transmission loss. Table 3 gives a summary of the research work related to the congestion control in VANETs.

C. DEMAND AND SUPPLY ORIENTED APPLICATIONS

The V2X paradigm has also proved itself beneficial for the taxi drivers and passengers. Most of the existing works only concentrate on maximizing the taxi driver's profit while giving less importance to passenger prospectives. However, the work in [70], constructs a recommendation system by considering benefits for both sides. They have used improved DBSCAN to first investigate the taxi demand-supply level in real-time, and then studied the tradeoff between the benefits

TABLE 3. Congestion control in VANETs.

Citation	Platform	Proposed	Traffic Lanes	Control	AI Domain	Remarks
[64]	SUMO, NS2	ML-CC	4 lanes	Centralized	Unsupervised ML	Better than CSMA/CA
[66]	Matlab	DIFRA	6 Lanes	Distributed	Swarm Intelligence	Channel load estimation
[65]	Matlab	FREDY	6 Lanes	Decentralized	Swarm Intelligence	Better than DIFRA

of the two parties for different hotspots. They demonstrated that the taxi GPS data set analysis is very useful for making decisions related to the recommendation of the qualified candidates to the drivers and vice versa.

The term Vehicle-to-Grid (V2G) is a network that enables bidirectional communications and energy flow between the electric vehicles (EVs) and the power grid. V2G network can provide smart energy sharing among EV users [71]. Smart pricing can lead to optimal demand response for EVs where EV user can adjust their charging based on their State-Of-Charge (SOC) and pricing information. However there is a problem that the demand from and surplus available with EVs changes dynamically over time. Therefore this problem of both bidirectional V2G and unidirectional V2G is commonly formulated as programming problem.

Unlike linear, quadratic and dynamic programing, the work in [72] has introduced a PSO based optimization to address this problem. This technique considers the EV energy scheduling as a stationary problem. However, in reality the demand as well as mobility pattern of each EV can be different per day. EV energy scheduling is a dynamic process and the prior knowledge is often unavailable. Xie *et al.* [73] have proposed a fair energy scheduling scheme by using Adaptive Dynamic Programing (ADP), which learns from the outside environment and performs estimation of long term future system cost. ADP consists of three networks: action, model, and critic network. All these networks can be implemented by neural network training.

D. NAVIGATION OF AUTONOMOUS VEHICLES

V2V in autonomous vehicles can be envisioned as a machine-to-machine paradigm. In this paradigm the QoS aware architectures are of great importance. QoS architecture, standards and its importance in a machine-to-machine network is reported in [74]. In general the host automated vehicle [75] drives along the predefined path while encountering an expressway toll gate. If there is only one surrounding vehicle present, then the host vehicle can control its speed to avoid the collision by predicting the near-collision point in its path. Using V2V, the host vehicle gets the speed and heading direction of the surrounding vehicle and then calculates the time which is required by the surrounding vehicles to reach the near-collision point.

If the number of surrounding vehicles is greater than two then this collision point calculation becomes much more complicated. Since the host vehicle can (or cannot) pass both near-collision points by acceleration. In these situations the host vehicle needs more advanced approaches to deal with these kind of situations. In [75], a decision tree based ML is applied for controlling the speed of the host vehicle in such a complex situation with the help of V2V. There are five levels of automation that are strictly concerned with the safety of the automated vehicles, as defined by the National Highway Traffic Safety Administration (NHTSA) [76].

- **Level 0**: Driver has complete control of all functions of the vehicle.
- **Level 1**: Only one function is automated.
- **Level 2**: More than one function is automated simultaneously e.g., acceleration and steering control, but the driver remains constantly attentive.
- **Level 3**: Sufficiently automated conditions under which driver can safely engage in other activities.
- **Level 4**: The vehicle can drive by itself without any human driver.

Autonomous Intersection Management (AIM) is another important aspect of ITS. AIM is going through revolutionary changes which are brought by the V2X paradigm to the automated vehicles. In [77], a cooperative motion planning method is introduced for a group of connected and automated vehicles, which may cross a lane-free intersection without using explicit traffic signaling. It is known as Near Optimal Online motion Planning (NOOP). This kind of motion planning scenario for multiple vehicles was formulated as a centralized optimal control problem. However, such a problem is numerically intractable due to high dimensionality of the collision-avoidance constraints plus nonlinearity of the vehicle kinematics. Therefore, a two stage planning, scheduling and optimization strategy is applied to solve this problem. In the first stage the vehicles are requested to reach a standard formation before entering the traffic intersection. The vehicles cross the intersection in the second stage. In this two-stage approach the difficulties in the optimal control problem is significantly reduced. Hence the real-time performance achieved for the AIM. Table 4 presents summary of research works related to the navigation of autonomous vehicles.

The main advantage of deep RL is its model-free characteristics, which removes the burden of complex policy making. The real world scenario for autonomous vehicles consists of some complex sequential decision making processes. However, such processes have inherent distinct behaviors, and the simple forward deep RL algorithm can not learn a good policy. Therefore, in [78], a hierarchical neural network policy

TABLE 4. Navigation of autonomous vehicles.

Citation	Platform	Proposed	Scenario	Lanes	Dataset	AI Domain	Remarks
[75]	Matlab	NAV for Toll gate	Expressway	4	96 paths	Decision trees	CA for uncertain obstacles
[77]	[141], [143]	NOOP for CAVs	TL passing	4	24 CAVs	PSAO	Intelligent merging with CA
[78]	Panda3d API	DHRL for AVs	TL passing	2	500K	R	Trained SMDP
[79]	Matlab	CDM for AV	Ramp merging	2	dataset [142]	Perception	Deterministic obstacles
[132]	Own	DCP for AVs	Double merging	2, 3	30K	RL	Explicit modeling MAs

gradient method, known as Deep Hierarchical Reinforcement Learning (DHRL), is devised to train the network with Semi Markov Decision Process (SMDP). They have shown better decision results over flat deep RL approach.

Although recent developments for autonomous driving have been significant, vehicles need to have advanced decision making abilities for dynamic scenarios that need real-time assessment of the environment where uncertainty is an inherent component. A good decision making vehicle must be in a generic form to cover a huge variety of scenarios, and it should be able to interact with the neighboring obstacles (mobile or stationary). Chen *et al.* [79] have introduced a Maximum Interaction Defensive Policy (MIDP), which finds the best action to interact with the stochastic moving objects in a safety first paradigm.

This policy should be optimized for the most likely future scenarios that result from an interactive, probabilistic motion model for the neighboring vehicles. The possible future measurements about the neighboring vehicles allow the ego vehicle to incorporate the estimated changes in the accuracy of future predictions, in the optimized policy. Thus a compact representation results in a low-dimensional state-space, and the problem can be solved online for varying vehicle counts and road conditions. Such an online solution was introduced in [80]. The convergence of the algorithm was evaluated with a search heuristic. The results demonstrated that this planning, scheduling and optimization approach performs nearly as good as with full prior-information regarding the intentions of other vehicles and also outperforms reactive approaches.

E. SECURITY IN VANET

Security in VANET mostly concerns with the routing protection against potential threats such as jamming attacks. The traditional frequency-hopping based anti jamming techniques are less beneficial in the complex mobility and large scale network environments of VANETs. Xiao *et al.* [81] have used Unmanned Aerial Vehicles (UAVs) to relay the OBU message and improve communication in VANETs against smart jammers. These smart jammers observe the vehicle's On Board Unit (OBU) and UAV link status, and try to make the UAVs to only use a specific relay strategy and then they initiate the attack. Typically the UAV relays the OBU message to another Road Side Unit (RSU) with better radio transmission conditions if the current RSU is jammed or interfered. This situation leads to an anti jamming game between UAV and the smart jammer. They have used reinforcement learning to make a hot-booting policy hill climbing-based UAV relay strategy to help the VANET to resist jamming in the dynamic gaming by considering the VANET and Jamming model as a black box.

The two common and most difficult to detect VANET routing attacks are, 1) black hole, and 2) wormhole. In a black hole attack, a malicious vehicle can destroy all the packets that it receives for subsequent transmission. In the wormhole attack, a malicious vehicle receives data packets and replays them to another malicious vehicle by using a high speed link, which ultimately affects the discovery of valid routes. A Swarm Intelligence algorithm for VANET protection against such kind of routing attacks is introduced in [82]. In [83]–[88], the use of Swarm Intelligence algorithms in dynamic VANETs is introduced for better routing. These include Ant-Colony-Based routing, geographic algorithm based on Cat Swarm optimization for VANET, Particle Swarm Optimization algorithms, Bee-Inspired Approach, and Fuzzy Logic. A detailed survey on geographic routing protocols in VANETs can be found in [89].

The research works [90]–[93] have employed ANN, K-NN, Feed forward Neural Network (FFNN), and SVM to devise schemes against various kinds of attacks in VANETs. These attacks include Denial Of Service (DOS) attack, internal attacks in driverless cars, packet dropping attacks, Gray hole, Rushing attacks, and Sybil attacks. Berlin *et al.* [94] introduced a DL based technique for anomaly detection in a single vehicle or a fleet of vehicles. This technique is suitable for attacks with stolen credentials in a privacy-friendly approach. Studies in [95]–[99] have utilized Fuzzy logic, ANN, Unsupervised learning and game theory, respectively to devise an Intrusion Detection System (IDS) for VANET. Zhang *et al.* [88] have introduced a security aware routing protocol against black holes, and flooding attacks, using Fuzzy logic and ACO. Tables 5 presents a brief summary of the research works where AI is utilized in different forms to the domain of security in VANETs.

F. VEHICULAR EDGE COMPUTING

The ETSI, defines mobile edge computing as: an IT service environment and cloud computing capabilities at the edge of the mobile network, within the Radio Access Network

TABLE 5. Security in VANET.

Citation	Platform	Focus	Protocol	Approach	Algorithm	Privacy	AI Domain	Remarks
[81]	Own	Intrusion	Any	PHC	Q-learning	Yes	RL	Resists Smart jamming
[82]	NS3	Intrusion	AODV	Decentralized	PSO	Yes	SI	Protocol independence
[83]	Own	Intrusion	AODV	Centralized	PSO	No	SI	Only for stable phase TL
[84]	NS2	Routing	AntHocNet	Decentralized	ACO	Yes	SI	Dynamic topology
[85]	Own	Routing	CSO-GR	Geographic	CSO	No	SI	Improved normalized load
[86]	Matlab	Intrusion	Unknown	Centralized	PSO	No	SI	Prevent DOS attacks
[87]	NS2	Broadcast	RSU-based	Centralized	Bee-inspired	Yes	SI	Better than decentralized
[88]	NS3	Intrusion	Any	SAFERACO	ACO	Yes	Fuzzy Logic+SI	Flooding, Black holes
[90]	NS2	Intrusion	AODV	Centralized	Classification	Yes	ANN	Prevent DOS
[91]	Own	Intrusion	Any	ICMetricIDS	Classification	Yes	KNN	Prevent DOS, Sybil
[92]	NS2	Intrusion	AODV	Petri Nets	Prediction	Yes	Fuzzy logic	Prevent Packet dropping
[93]	NS2	Intrusion	AODV	FFNN	Classification	Yes	SVM	Rushing, Black,Gray holes
[94]	Own	Intrusion	Any	Data driven	Detection	Yes	DL	Stolen credentials
[95]	WEKA	Intrusion	Any	FSTS	Detection	Yes	Fuzzy Logic	Prevent Sybil attacks
[96]	Own	Intrusion	Any	Centralized	Classification	Yes	ANN	Prevent Cyber attacks
[97]	NS2	Intrusion	AODV,DSR	Clustering	Classification	Yes	Unsupervised	Prevent Sybil attacks
[98]	NS3	Intrusion	DSRC	Bayesian	Prediction	Yes	Game theory	Prevent Cyber attacks
[99]	NS2	Intrusion	Any	BUSNet	Classification	Yes	ANN	Monitors anomalies

and in close proximity to mobile subscribers. The computational capabilities in vehicular environments can be enhanced using Edge computing [100]. Different applications that may exist in a vehicle can be divided to three classes: 1) critical applications, 2) high priority applications, and 3) low priority applications. Critical applications include the vehicle control system, system monitoring, and accident prevention. The high priority applications are related to vehicle navigation, information services and optional safety applications. Low priority applications are related to multimedia and passenger entertainment. Automobile manufactures are now providing computational capacity in their on board units. The low priority applications and high priority applications can be deployed using Vehicular Edge Computing (VEC) such as speech recognition, video processing, cloud-based video games and multimedia.

Besides critical applications, other applications may not run all the time in the vehicles and the resources of connected vehicles can be utilized to benefit the service provider and the user [101]. A recent work [102], has targeted the local cloud or VEC resources based on the properties such as sharable resources, movement pattern, energy, and incentives to the service providers and to the users for sharing their idle resources. Feng *et al.* [102] proposed an autonomous framework that can provide computation services in dynamic V2X environments. Information collected from neighboring vehicles is utilized to devise a scheduling algorithm based on ant colony optimization. Extensive simulations have demonstrated the effectiveness of vehicular edge computing.

In [103], a vehicular neighboring group based edge computing architecture was introduced. This architecture separates the whole network into three planes, 1) social plane, 2) data plane, and 3) control plane. It also extends programmability for the 5G network and data transmission. By utilizing planning, scheduling and optimization, this architecture simplifies network management, improves utilization of resources and provides a sustainable network. In [104], the authors have described a scenario of Deep Learning handled with VEC. They have used Intel Movidius Neural Computing Stick (MNCS) along with Raspberry Pi 3 Model B to analyze the objects in the real-time images and videos for vehicular environments [105].

The connected vehicle paradigm have fueled a plethora of innovations including networking, caching, and computing. An RL based framework [106] is introduced, which can enable dynamic orchestration of networking, caching and computing resources to improve the performance of next generation vehicular networks. Table 6 presents a summary

TABLE 6. AI applied to VEC.

Citation	Platform	Proposed	Protocol	Algorithm	Dataset	Scenario	AI Domain	Remarks
[102]	Veins, [144]	AVE	DSRC	ACO	[144]	Urban/Highway	SI	Minimal deployment cost
[103]	Own	5G-SDVN	Any	V2N	[145]	Urban	PSAO	Platform independence
[106]	Tensorflow	DRL framework	Any	3DQN	Own	Urban	RL	Caching and Computing
[137]	Multiple OS	EDL-VEC	Any	MLP	[146]	Urban	DL	VEC on multiple OS

of the works where AI is deployed for VEC, in terms of the proposed solutions, platform used, algorithms, and datasets.

G. CONTENT DELIVERY AND OFFLOADING

The rapid growth of mobile data traffic has already started provoking changes in the architecture of the overall wireless network. It is expected that future 5G system will support 1000 times larger mobile data volume and 10 to 100 times increased number of connected devices [107]. Vehicular content delivery is an important and challenging task in the V2X paradigm. Data offloading through WiFi may not be able to guarantee the required level of performance due to limited range of WiFi and highly varying mobility of vehicles. A relatively small amount of data can be delivered to a vehicle for every hotspot on the move, and the offloading performance can improve if the the data service can tolerate delays, because the fast moving vehicle will drive through more hotspots. The term Game-theoretic Learning naturally combines Game theory and ML and has been discussed in [108]–[110]. Game-theoretic Learning has recently received considerable attention from the V2X research community, and they have addressed it in the downloading and resource allocation.

Asadi *et al.* [111] have addressed opportunistic traffic offloading where cellular traffic of the users inside the vehicles, is offloaded through carrier WiFi networks. This work jointly considers the users satisfaction, the cellular network operator's revenue, and the offloading performance, and devises a mechanism called Congestion Game-based Offloading (CGO). With CGO mechanism, a vehicle user finds its utility and makes adaptive offloading decisions by considering strategies of other vehicles. The results have shown that CGO can achieve better performance in terms of average vehicular user utility, fairness, and lower average service delay. Another work [112] proposed a distributed iterative learning algorithm to explore pure strategy Nash Equilibrium (NE) point also ensuring fairness. In [113], a cloud-based MEC framework was introduced to reduce latency and transmission cost for computation offloading for the Internet of vehicles. Various computation transfer approaches were introduced with V2V and V2I modes and game-theoretic learning.

Parked vehicles are also incorporated by some works to deliver content in VANETs. These vehicles can form social communities to exchange information through V2V or V2I. In this context, the incentive-based scheme should be addressed with the optimal pricing strategy. In [114], a pricing based framework was proposed in the form of a Stackelberg game. Then a gradient based iteration algorithm was proposed to obtain the Stackelberg equilibrium. The work [115] has addressed the limitations of the existing wireless wide area networks that are coupled with delay tolerant property of some non-real-time applications such as email or file download and which are dependent on the RSUs to provide internet access to the users in vehicles. They proposed a joint multi-flow scheduling and cooperative downloading protocol with a goal to maximize the amount of data packets.

The mobility of vehicles is random and the connections are continuously changing in a VANET environment. However, the information such as road status and traffic cameras information is region-specific and can be used for local information of traffic and estimation. This information is useful for load-balancing. In VANETs data is stored locally among vehicles, RSUs, and the cloud. Wu *et al.* [116] developed an algorithm to store data in vehicles without any infrastructure based support. The region-specific data always remains in that region due to unicast transmission. In this work the initial relay hop selection is based on fuzzy logic and it is further improved through RL. Then the data carrier node selection is again based on fuzzy logic based short term evaluation. The short term evaluations guarantee the long-term rewards with the help of Q-Learning. Then the application of RL is further applied to obtain the efficient routing strategy for the transfer of data from the source node to the data carrier node.

H. PLATOON OF VEHICLES

The platooning is considered as one of the most important applications using V2X. Vehicle platoons bring multiple advantages. These advantages include: 1) reduction in air drag, 2) increase in fuel efficiency, 3) reduction in traffic congestion, 4) and reduction in average travel time. Along with these advantages, the blocking of the vision of the drivers that follows the leading vehicle is a big issue in vehicle platoons. Although the Advanced Driver-Assistance Systems (ADAS) and V2V can help prevent vehicle collisions, vision blocking can cause anxiety in the following drivers due to the blocked view [117]. Some research works have addressed this problem. In [118], an application that detects vehicles, pedestrians, and obstacles, using the video streaming through V2V communication was implemented to benefit Light Detection And Ranging (LIDAR), in platooning. Also, in a few works like [119] and [120], surveillance applications were implemented based on video streaming through V2X communications. This kind of video streaming among vehicles of a platoon can increase driving safety and comfort by providing visual information to the drivers via front and rear-view cameras.

Despite these developments, video streaming in vehicle platoons bring in new and unprecedented challenges, e.g., bandwidth limitations for the leader vehicle, which may broadcast using the MAC layer transmission in the IEEE 802.11. The member vehicles will play this stream in front of the drivers, but the performance of the one-hop broadcasting can be affected by the varying gap between the vehicles, the surrounding environment, and channel utilization. AI is a promising approach planning, scheduling and optimization to address these problems of video streaming performance degradation in the IEEE 802.11p [117].

The accuracy of the low-level vehicular sensors is very important from the perspective of platoon stability. The on board accelerometers may not maintain the orientation in the long term deployment, and their calibration is difficult [121], [122]. Moreover, the accelerometers, inherent drifts in their outputs due to variation in factors such as, mechanical stress, temperature and humidity. Although works such as [123] and [124] have proposed solutions to tackle these inaccuracy problems by estimating them based on the reliable information but a good margin for improvement still exists. In this context, the recent work such as [125] has investigated platoon control in connected vehicles while focusing on the effect of random MAC protocol and unmeasurable accumulations. Their proposed work assumed that the accelerator measurements are inaccurate, and used an observer to estimate the acceleration, which is based on the position and velocity information of the vehicle and its preceding vehicle obtained through DSRC. The stochastic nature of the MAC protocol of each vehicle is modeled by the Markov chain, and a set of backward recursive Riccati difference equations are solved to obtain sufficient condition which guarantees stable error tracking of the acceleration values.

Clusters in VANET are formed by association of vehicular nodes which is an important aspect of vehicular platoons. Generally, a rule set defines the selection of the head of this group or cluster, known as Cluster Head (CH). The CH acts as a wireless access point for the whole group. The functions of a CH are application specific. Any clustering algorithm must satisfy end-to-end communication performance requirements in the VANET while being able to capture sudden changes in the mobility, network, and cluster topology [126]. Common procedures to initiate clustering among the vehicles are: 1) Neighbor discovery, 2) CH selection, 3) Affiliation, 4) Announcement, and 5) Maintenance of the cluster. More detail on clustering in VANET can be found in the survey paper [127].

However, to the best of our knowledge only few works have utilized AI for clustering in VANET, e.g., [128]. In this

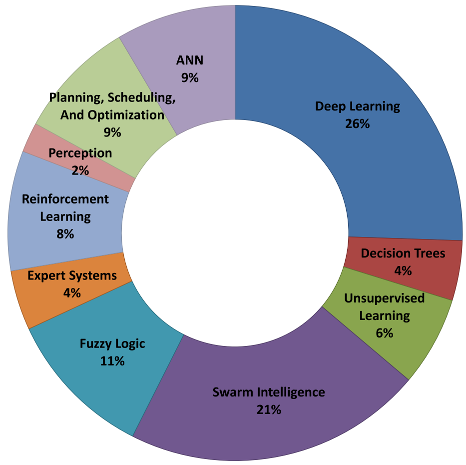

FIGURE 5. Percentage of AI techniques used in V2X applications.

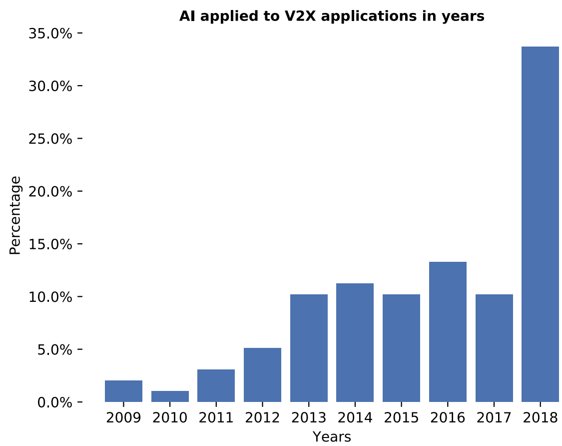

FIGURE 6. Progress of AI applied to V2X applications.

work, a learning algorithm is used to select the CH based on the relative velocities of vehicles. At the traffic intersection, agents are deployed which determine the behavior and velocity of vehicles entering and exiting the intersection. A learning factor is introduced that is increased for the rewards with positive results that is selection of Cluster Head with longest life span and higher PDR. Similarly, the learning factor is penalized or decreased for negative results such as poor performance of the CH. This mechanism progressively finds the best CH selection strategy. Another work [129] is based on Fuzzy logic, which also used the relative velocities between the vehicles as the CH selection criteria. The algorithm determines the driver intentions in order to find out the long term variations in assessing the eligibility for being the CH.

VI. CHALLENGES AND DISCUSSION

The complex and dynamic challenges of V2X paradigm have been addressed using different techniques of AI. Figure 5 shows various AI techniques used in the V2X research presented in this survey. It can be easily seen

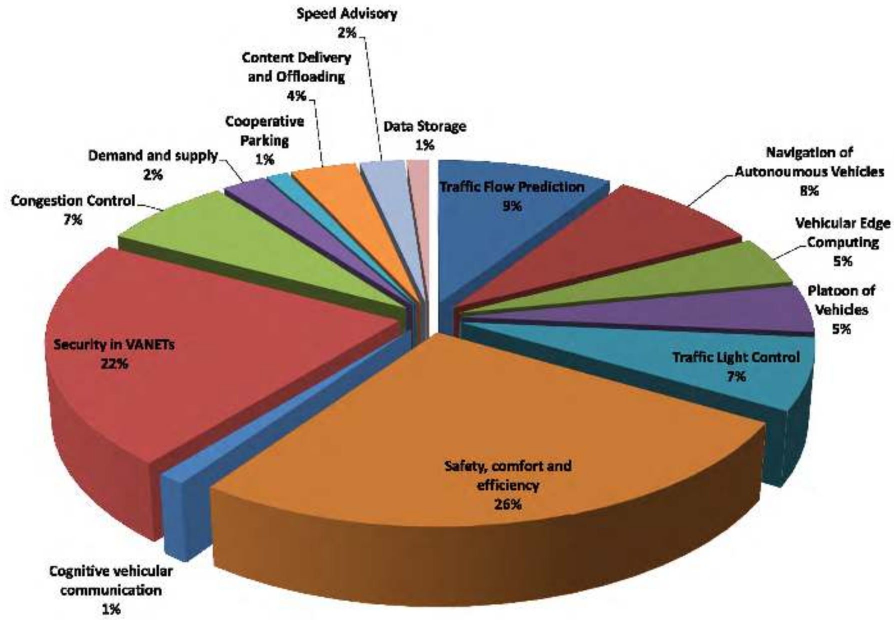

FIGURE 7. Overall representation of AI applied to V2X applications.

that Deep learning and Swarm Intelligence are two popular and widely used techniques. Traditionally, Fuzzy logic was considered the most popular AI technique for scientific research. Figure 6 shows the yearly (2009 to 2018) trend of AI applied to V2X in terms of percentage. The computation resources, storage resources, and the advancements in AI algorithms have established a firm path of AI based research for V2X enabled by the 5G paradigm. It should be noted that Figure 5 and Figure 6 are based on the research articles referenced in this survey paper.

Yet, there are issues that require attention in this context. Let us start with traffic flow prediction which is still a challenging task in terms of modeling and optimization. AI predicts and reproduces the macroscopic traffic flow from the previous records. However, some AI approaches and simulations are time consuming. For example, heuristic optimization algorithms such as GA are often deployed to accelerate the process but the convergence speed of those algorithms is still a big question. One of the major difficulties that RL is facing for the control of traffic signal timing is the complexity of the signal timing design that increases exponentially with the number of traffic flow state/control actions. Figure 5 represents the research contribution in terms of the specific techniques of AI employed in the V2X paradigm, and Figure 7 shows the overall representation of AI applied to V2X applications in this survey.

In VANETs, the practical implementation of ML based congestion control techniques require RSUs that should be equipped with GPUs. These RSUs would have to perform larger calculations and operations for ML algorithms. The deployment of Edge computation facilities is also a requirement for AI driven V2X applications. Decision of the agent's fairness policy is a big question in the domain of Reinforcement Learning. How much fairness should be considered appropriate? For example a fair TLC system would ensure that all vehicles are given same priority while traversing the intersection. However, this fairness will cause a conflict with the optimization of certain traffic metrics. These optimization metrics can be the minimum delay or maximum throughput. A future challenge is to obtain a balance between fairness and optimization, that can be achieved by the appropriate reward function and utilizing other AI techniques.

The TLC systems, whose reward functions assign penalty for each halted vehicle, can cause rapid switching of traffic lights. This rapid variation results in the form of vehicles that are always accelerating and decelerating. Although this problem has been addressed by employing DQN that uses a reward function that balances multiple objectives, including the penalization of rapid decelerations (Emergency brakes). However, DQN agents may not be able to work due to the loss of information while conversion from continuous traffic scenario to sparse position matrix. This may be attributed to failure of the convolution filters of the DQN agent to trigger for the vehicles whose information is missing in the matrix.

A. OPEN ISSUES

Consumers trust building is also very important in AI-driven vehicular safety. An average human mind would not understand how multi-layer neural network is making decisions based on the things that they do not know. AI algorithms should be developed and taught by ensuring that their solutions would not cause other problems especially beyond the areas for which they are considered. Finally, the user

TABLE 7. The following abbreviations are used in this manuscript.

Abbreviation	Term	Abbreviation	Term
AI	Artificial Intelligence	LIDAR	Light Detection And Ranging
AIS	Autonomous Intersection Management	LLE	Local Linear Embedding
ABS	Anti-lock Braking System	LSTM	Long Short Term Memory Network
ADAS	Advanced Driver-Assistance Systems	LTE	Long Term Evolution
ADP	Adaptive Dynamic Programing	MA	Macro Action
ACO	Ant Colony Optimization	MEC	Mobile Edge Computing
API	Application Programming Interface	MDP	Markov Decision Process
AR-HUD	Augmented Reality Head up display	ML	Machine Learning
ARIMA	Autoregressive Integrated Moving Average	ML-CC	Machine Learning based Congestion Control
ANN	Artificial Neural Network	MNCS	Movidius Neural Computing Stick
AWS	Amazon Web Services	MIDP	Maximum Interaction Defensive Policy
AV	Autonomous Vehicle	NAV	Navigating Autonomous Vehicle
AVE	Autonomous Vehicle Edge Computing	NC-CC	Network Coding Congestion Control
BSM	Basic Safety Message	NHTSA	National Highway Traffic and Safety Association
CA	Collision Avoidance	NOOP	Near Optimal Online motion Planning
CABS	Context Awareness Beacon Scheduling	OBU	On Board Unit
CACC	Cooperative Adaptive Cruise Control	OEMs	Original Equipment Manufacturers
CAM	Common Awareness Messages	OL-SVR	OnLine SVR
CAV	Connected and Automated Vehicle	PAAS	Platform As A Service
CCTV	Closed-Circuit TeleVision	PSO	Particle Swarm Optimization
CDM	Continuous Decision Making	PSAO	Planning, Scheduling, And Optimization
CH	Cluster Head	PeMS	Performance Measurement System
CNN	Convolutional Neural Network	PCA	Principal Component Analysis
CR	Cognitive Radio	PEV	Plug-in Electric Vehicle
C-V2X	Cellular V2X	PHC	Policy Hill Climbing
CV2X	Cellular V2X	PI	Platform Independence
CSO	Cat Swarm Optimization	PRT	Poisson Regression Trees
DCP	Decentralized Cooperative Planning	RF	Random Forest
DHRL	Deep Hierarchical Reinforcement Learning	RNA	Random Network Access
DNN	Deep Neural Networks	RNN	Recurrent Neural Network
DMA	Dynamic Manoeuvre Adaptation	RL	Reinforcement Learning
DRQN	Deep Recurrent Q Network	RSI	Road Side Infrastructure
DQTSCA	Deep Q-network Traffic Signal Control Agent	RSU	Road Side Units
DOS	Denial Of Service	SAAS	Software As A Service
D-FPAV	Distributed-Fair Power Adjustment for Vehicular environment	SAETLP	Stacked Auto Encoder based Traffic Light Prediction
DIFRA	Distributed Intelligent Fair Rate Adaptation	SI	Swarm Intelligence
DL	Deep Learning	SVD	Singular Value Decomposition
DSRC	Dedicated Short Range Communication	SVR	Support Vector Regression
DSX	Data Science Experience	SBW	Steer By Wire
EDL	Embedded Deep Learning	TCS	Traction Control System
ETSI	European Telecommunications Standards Institute	TDMA	Time Division Multiple Access
ESP	Electronic Stability Program	TST	Traffic Signal Timing
EV	Electric Vehicle	TL	Traffic Light
FREDY	Fair beacon Rate greEDY	UAV	Unmanned Aerial Vehicle
FILR	Frame Information Loss Rate	V2I	Vehicle-To-Infrastructure
FSTS	Fuzzy Short Time-Series	V2G	Vehicle-To-Grid
GA	Genetic Algorithms	V2P	Vehicle-To-Passenger
GBO	Game-Based Offloading	V2V	Vehicle-To-Vehicle
GLOSA	Green Light Optimal Speed Advisory	V2X	Vehicle-to-Everything
GPU	Graphical Processing Units	V2R	Vehicle-To-Roadside Infrastructure
IAAS	Infrastructure As A Service	VANET	Vehicular Ad hoc NEtwork
IDS	Intrusion Detection System	VEC	Vehicular Edge Computing
IRG	Inter-Reception gap	WEKA	Waikato Environment for Knowledge Analysis
ITS	Intelligent Transportation Systems	3DQN	Double-Deuling-DQN
K-NN	K Nearest Neigborhood	5G	Fifth Generation

acceptance of the AI deployment in V2X must be tested, based on comfort, safety, and interaction with other participants in the real conditions.

Another major area of concern is the privacy enhancement while monitoring the fleet of vehicles. Although anomalies and attacks in VANETs should be detected by the ML algorithms, expert knowledge and appropriate rules should be defined which can increase the accuracy of detection. Offloading with MEC service has greater potential to aid autonomous driving in terms of real-time safety oriented tasks, sensory data analysis, identification of appropriate navigation paths, and the prediction of congested intersections etc.

Finally, as stated by the 5th Generation Automotive Association (5GAA) [130], price of developing DSRC based system is much expensive than C-V2X driven solutions for V2X. Currently, neither of these systems has been described as an authorized V2X communication system. It may be likely that future vehicles would be equipped with V2X devices that may have implementation of both of them. AI can also provide an intelligent way in understanding and decoding data transfer using these two systems for V2X.

VII. CONCLUSION

This article presents a comparative survey on the related AI algorithms applied to the Vehicle-to-Everything paradigm. We have presented various AI techniques. AI-driven algorithms for V2X applications have shown improved performance over traditional algorithms. In general, all optimization problems face uncertainty in the intensions of the surrounding participants. Different branches of AI can help each other to bring out an optimum solution that would not cause or generate problems in the domain they are not intended for. The AI algorithms in most cases require higher computational resources. These resources may not require to be inside the vehicle. Thanks to V2X, MEC and VEC technology, the computation burden of AI can be offloaded to the edge computation servers in the nearby road side infrastructure. The future V2X applications will get great benefits from the emerging field of edge computing. Table 7 presents list of abbreviations which are used in this manuscript.

APPENDIX

See Table 7.

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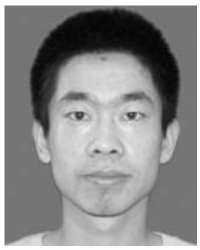

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