Smart Vehicular Communication: A Survey

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Abstract **- Vehicular communication has received widespread recognition from Industry and Research due to their strong potential to provide effective commutation facility by improving safety on roads and traffic efficiency. In this paper, an all-inclusive survey of recent works related to smart Vehicular communication and implementation of various Machine learning techniques for road type prediction and levels of traffic congestion are examined. Some important features such as estimation of Vehicular channel modeling alongside with resource allocation, intelligent wireless resource management are studied and various methodologies such as Finite-State Markov Chain (FSMC), Deep- Q-Network (DQN) algorithm are analyzed. Several performance parameters are examined for Device-to-Device (D2D) based network such as Instance resource allocation schemes, design criterion for network selection. We aim to discover the challenges faced by the modern vehicular communication system.**

Keywords - Vehicular communication, Machine Learning (ML), Traffic congestion, Road Side Unit (RSU), Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I), Vehicle-to-Everything (V2X)

I. INTRODUCTION

As the connectivity among Vehicles are increasing, it is important for the development of Intelligent vehicular systems. The emerging Vehicular communication are expected to facilitate a variety of services such as, improving safety on roads, optimizing traffic efficiency in particular from Autonomous cars to wide range of Internet access on vehicles, which plays a vital role in making our commutation convenient and safer.

Allowing vehicles to exchange information with other vehicles or Infrastructure ie. V2V and V2I is hard due to complex Communication environment, fig.1 shows the essential components of a vehicular communication system. It's very challenging for an efficient Vehicular communication to provide high mobility, as it has to satisfy various requirements, especially lower latency and higher reliability for sharing of safety-related information.

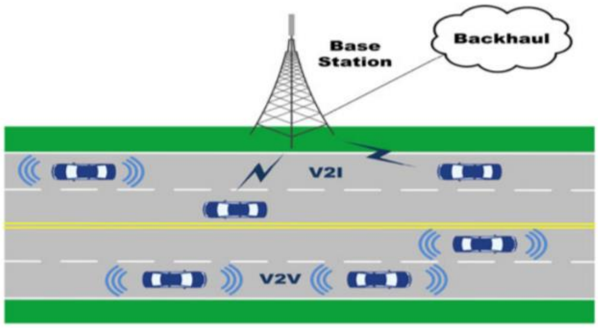

Fig. 1 Basic components of Vehicular communication system

Gradually vehicle users are increasing, customer's demand automobile manufacturers to build contemporary vehicles which are smart, provide effective fuel economy without giving up on safety and performance.

Long Term Evolution (LTE) is the main aspect of Vehicle to Infrastructure (V2I) communication. LTE is a wireless broadband technology which delivers data at high rate and provides low latency for Mobile users. Goal of LTE in V2I is to deliver judgmental calculations on LTE proficiency and to provide certain LTE services or requests. Fig. 2 shows the structure of Vehicular communication Network.

While developing intelligent vehicular system, wide variety of techniques from Artificial Intelligence is used, right from Clustering algorithms, Neural networks to Machine learning ideas and algorithms are applied to address decision making data and the problems of wireless resource management in vehicular networks.

Fig. 2 An informative structure of Vehicular networks

II. LITERATURE SURVEY

Brief literature of papers which emphasizes on the key features of smart and intelligent Vehicular communication is as follows.

[4] Gives, methods for Vehicular channel modeling and for nodes of D2D vehicular networks, a resource allocation estimation using Heuristic allocation schemes. For devices in proximity, D2D communication enables direct transmission without the need for routing through a Base station. [2] Also mentions how sparse scattering is exhibited by V2I and V2V channels for vehicular communications. In [5] Wireless communications are implemented by applying Mobile ad-hoc network (MANET) principles, the design of event-driven safety messages for manually driven vehicles and periodic beacon messages for cooperative driving of Autonomous Vehicles (AV) are also mentioned. Vehicular Ad-hoc Network (VANET) [6] provides lot of secure services like, road condition warnings, accident alerts, etc.; deep reinforcement learning agent has been implemented at Road Side Unit (RSU), it's found that DQN algorithm is optimal for the deployment of RSU.

NN_RT & TC Neural network [2] has been built for predicting different type of roads along with traffic congestion levels; it retrieves ideal controlling parameters of different type of roads. [7] Discusses, intelligent wireless resource management using reinforcement learning, Virtual resource allocation, and Distributed resource management. [1] Usage of filtering algorithm also known as K-means clustering algorithm, its theoretical and practical demonstration is noted.

[3] Tells us about two things, firstly, capacity and market penetration: a soaring penetration rate is attained by LTE as it gives high downlink as well as uplink size (up to 300 and 75 Mbs, and up to 1 Gbs for LTE-A). Secondly, Transport modes and channels: certain uplink/ downlink transport channels have an upshot on the slow up and size in relation to maximum number of vehicles per cell. [8] Tells how, Mobile and wireless networks driven by Deep learning emphasis on Deep learning Apps, which are constructed from the mobile data collected when they were in the network, they might also include network prediction.

III. METHODOLOGY

After examining good range of papers, we have recognized that the following methodologies must be adopted appropriately, while we are designing Intelligent vehicular network for safe commutation.

A. VEHICULAR CHANNEL

Vehicular communication takes place through special channels known as Vehicular channels [4] which has propagation characteristics primarily different from other various types of Wireless network systems. Vehicular channels demonstrate rapid temporal variability and inherent non-stationarity of channel statistics, due to their exclusive physical environment dynamics.
essential parameters of Vehicular channels, need to be properly defined and understood, Wireless signals propagate through different paths, each paths with different propagation delays, attenuations, and phase shift consequences. These multipath components then gets added up at the receiver, leading to fading effect.

1) Wireless Channel Characterization

To simplify fading channel categorization and to ease the theoretical performance analysis, Finite-state Markov chain (FSMC) is used, where a set of finite channel states are used to approximate fading and varied according to a set of Markov transition probabilities.

2) V2X Channel Modeling

This can be done in three ways,

- *Deterministic Model*: channel propagation is characterized in a completely deterministic way.
- *Geometry-Based Stochastic Model*: this approach arbitrarily creates the geometry (scatters) of the propagation environment as per certain stochastic distributions along with simplified ray tracing.
- *Non-Geometric Stochastic Model*: without assuming any underlying geometry, vehicular channels will be modeled by a stochastic approach

B. ESTIMATION of VEHICULAR CHANNEL

In wireless communication systems, efficient and precise estimation of channel is a vital component because design of receiver is right away affected, e.g., channel equalization, decoding, demodulation, etc., and other affected ones are radio resource management for performance optimization and interference mitigation ; for vehicular communications, Sparse scattering is generally exhibited by V2I and V2V channels.

C. RESOURCE ALLOCATION

An important role is played by Resource allocation in optimizing resource utilization and diminishing interference for vehicular communications. System performance can be enhanced by a substantial greater bandwidth which includes an mm Wave band of 30–300 GHz, because of its significant potential; it is desirable for vehicular communications.

D. GENERAL VEHICULAR NETWORKS

1) Vehicular Network Applications

Sharing information and aiding multiple cooperative applications are the main focus of the design of communication networks in the moving Vehicles.

- *Safety applications*: by sharing safety-related information, safety services can be provided. The occurrence of traffic related accidents can be noticeably reduced, and the commuters' life, property and health can be successfully protected. Fig. 3 shows the vehicles sharing event-driven safety information
- *Non-safety applications*: by sharing information among moving vehicles, value-added services can be provided for instance, infotainment support and traffic management can be equipped, to increase the comfort of the commuters.

2) Vehicular Network Characteristics

These characteristics are classified into two categories:

- *Detrimental characteristics*: These characteristics cause challenges to communication over vehicular networks, including tough delay constraints, complex communication environment and high mobility.
- *Beneficial characteristics*: Wireless communications in vehicular networks are benefited from the following characteristics such as, prediction of driving route and weak energy constraint.

3) Manually Driving Vehicular Networks (MDVNET)

High mobility has an incomparable impact on the manually driven vehicular networks.

- *Technologies for MDVNETs*: Many contemporary vehicles are equipped with cellular, Wi-Fi, etc., which enhances safety and vehicular experience.
- *Routing Protocols*: The prior motive of routing protocols in wireless communications is to scale down the communication time while using merest network resources.
- *Hand-off Strategies*: They intend to provide a faultless communication for vehicles in MDVNETs while reducing, hand-off latency, packet loss and financial cost.

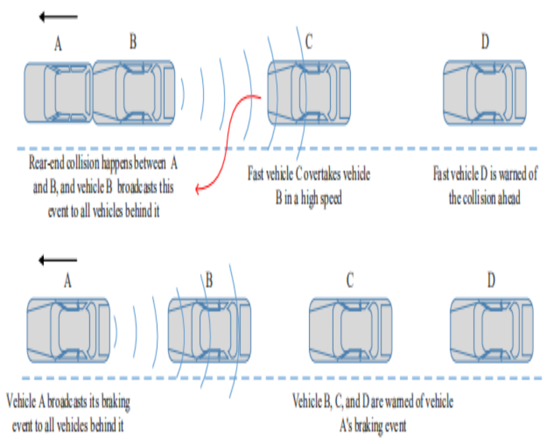

Fig. 3 Examples of vehicles sharing event-driven safety information

E. MARKOV DECISION PROCESS MODEL(MDP)

At Road side units (RSU), a deep reinforcement learning agent is implemented which engages itself with the automobile environments [6]. DQN algorithm is optimal for deployment at the RSU. At every time frame, the agent chooses an action and accordingly the RSU will acquire a safety message. Changes in the environment are observed by the agent and a reward is obtained.

1) Input from the Environment

Agent notices the automobile environments at the beginning of every time frame and obtains parameters that describe system state.

2) Rewards and Costs

During every time-frame, agent chooses an action, notices the effect on its environment. Road Side Unit obtains a scalar value referring to either reward or amount related to the action that is chosen.

3) MDP Resolution

The system state definitions, RSU's actions and reward/costs provide MDP where its transition probability kernel might not be known. Henceforth, MDP's resolution requires Reinforcement learning techniques to boost RSU's rewards.

F. PREDICTING ROADWAY TYPE AND TRAFFIC CONGESTION LEVEL

1) Selecting Features

Different type of roadways and traffic-congestion levels are observable in vehicle speeds [2]. Statistics obtained enable us to describe driving patterns including 16 parameter groups. Fuel usages along with emissions are adversely affected by the 9 groups of parameters. A fivefold cross validation method is used here to determine a more sensible estimate of generalization.

2) Neural Network for predicting different type of roads

NN_RT&TC is developed to predict different type of roads and traffic congestion levels. It has 14 inputs, 20 hidden nodes along with 11 output nodes .It uses the algorithm of backward propagation. Fig. 4 shows the general architecture of NN_RT&TC

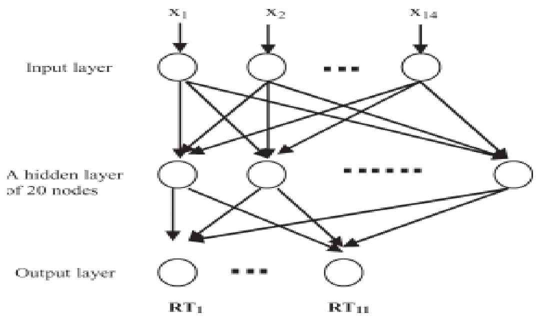

Fig. 4 Architecture of NN_RT&TC

- UMD_IPC: in a PSAT simulation environment, UMD_IPC that includes NN_RT&TC has been implemented in an Intelligent Vehicle power controller. It includes a knowledge base which is obtained by the machine-learning algorithm. It obtains the current vehicle state and predicts types of roadways and traffic congestion level.

G. MACHINE LEARNING(ML)

ML has been used to solve conventionally challenging and a range of problems in Vehicular networks [7] providing data driven approach. Its categorization methods are:

1) Supervised Learning

It learns from labeled data sets, with adequate data, error rate bound is reduced to minimum, it is further classified into:

- *Classification algorithms* like, Bayesian networks, KNN, Decision-Trees, Neural Networks and SVM having discrete value and assigning a class label to incoming sample.
- *Regression*: They predict continuous value for each sample, network throughput and channel parameters. Logistic, Support vector (SVR), and Gaussian process are few of the algorithms including regression.

2) Unsupervised Learning

Their representations include unlabeled data. Dirichlet process, k-means, hierarchical and spectrum clustering are included under few clustering algorithms.

3) Reinforcement Learning

Tentative search within the environment is done. Q function is used to solve the MDP problem. Vehicular networks are applicable by this learning for managing the temporal variations up to wireless environments.

4) Deep Learning

It corresponds to multiple neuron layers as a sigmoid function, its bottom being the input layer and the top layer consisting of corresponding outputs.

H. FILTERING ALGORITHM

Kd-tree is a binary tree used for storing multidimensional data points known as query's or centers [1]. The cells in kd-tree usually have high aspect ratios. As the filtering algorithm consists of many stages, time spent in each stage is analyzed.

Fig. 5 shows the analysis process of a Filtering algorithm. This includes lemma 3 which states that for a random vector drawn with mean, it would have been associated a cluster within certain distance along with theorem 1 that deals with the number of nodes visited even though there is cluster distribution with separation and a set of candidate centers.

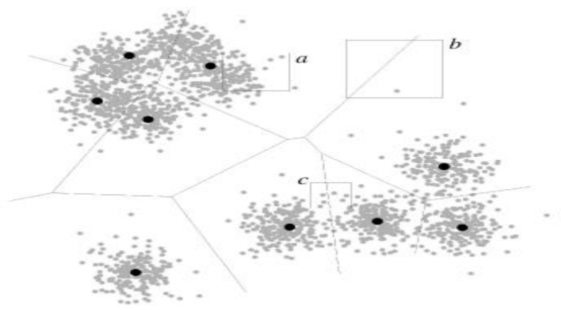

Fig. 5 Filtering algorithm analysis

I. NATIVE V2V SUPPORT

In LTE [3] Vehicle to vehicle communications are not supported natively. Hence, to distribute messages among vehicles, infrastructure nodes must be engaged.

But, in LTE-A, to facilitate direct Device to Device (D2D) communications, research is ongoing. Terminals in closeness may communicate uncontrollably and send resources in D2D mode.

- *Packet scheduling and QOS Support*:

  The uplink channel is particularly the key for the design plan of the scheduler; this is done to increase the efficiency, which is a tailback in closely occupied networks. In downlink, the attempt is to deliver effective and consistent transmission or broadcast that exists alongside the conservative uni-cast mode.

J. CENTRAL STANDARDS of DEEP LEARNING (DL)

The major task of Deep Neural Networks (DNN) [8] is estimation of complex functions of simple and prebuilt processes of units (neuron nodes). This given function could be of any kind, for example, mapping of images in addition to the label (sorting or classifying), calculating stock price from previously obtained data.

Neural network architecture bears a resemblance to the discrete processing of the brain.

IV. PERFORMANCE ANALYSIS

Analysis of overall performance based on key parameters such as design criteria, modeling vehicular channels, network congestion is as follows:

Popularity and demands of exploiting mm Wave bands [4] for high data rate exchange between vehicles have increased significantly. However, modeling of vehicular channels and channel measurement at mm Wave frequencies are very limited for D2D networks due to its remarkable signaling overhead to obtain CSI (Channel state information) at the central controller. To assure the consistent and timely distribution of two types of beacon messages in HDVNETs [5] a new beacon scheduling algorithm has been projected.

Security attack either on communication channel or tampering of sensor considerably impacts the safety driving. Design principle for network selection among mm Wave and other wireless communication technologies is challenging.

Allocation issue among computing resources and storage of each vehicle are complicated. DQN algorithm [6] execute better than LRT (Least residual time), RVS (Random vehicle selection), and GPC (greedy power conservation) algorithms with reference to service requests that are not complete. It performs better than RVS and LRT with reference to battery life. It provides an enhanced battery life when compared to GPC. RSU's batteries are preserved for an extended amount of time when DQN operates the RSU.

Fig. 6 shows the analysis of battery lifetime with reference to DQN and other algorithms, in some situation GPC performs better than DQN with reference to battery life only when the traffic are not heavy or when the average request size is vast enough to handle vehicles in low energy consumption zones. In both conditions, QoS levels are degraded in GPC algorithm. [2] UMD_IPC is implemented and applied to 11 PSAT drive cycles, subsequently its performance outcomes are compared to DP controller and Taurus controllers.

UMD_IPC provides 2% more savings on fuel utilization based on 6 drive cycles. It also provides better fuel-efficiency when compared to the present conventional strategies in all drive cycles, and in some of them it provides an ideal performance.

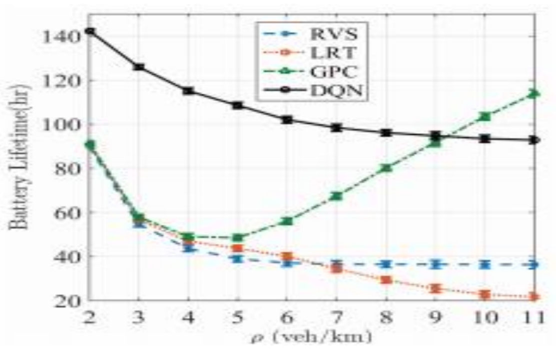

Fig. 6 Battery lifetime of DQN with reference to other algorithms

Due to the strict and diverse quality of service in traditional wireless communications system [7] various challenges were unnoticeable. Some of preliminary examples are as follows,

1).TRAFFIC FLOW PREDICTION

Combined sources of data are used as inputs, which includes real time as well as historical data. Poisson regression trees (PRT) are used to produce the predicted outputs and accuracy.

2) STORING LOCAL DATA IN VEHICULAR NETWORKS

When Vehicles are in moving state, the connectivity and its position are constantly varying. There is a need for storing some data like camera sensor and road status being region specific which are used for the estimation and particulars about local traffic that benefit for user behavior.

3) NETWORK CONGESTION CONTROL

By the usage of k-means clustering algorithm the communication and congestion of vehicles are designed.
The measure of the squared-error distortion [1] is done to solve the problem of minimizing the squared distance in distinction to each data point to its nearest center.
K-means cannot increase distortions. Distortions in any clustering algorithms can be improved by running k-means algorithm. Its performance analysis is done by empirical and synthetic analysis.

I.EMPIRICAL ANALYSIS

Here the testing and performance measurement are done which includes data generated synthetically and in real world applications. Various algorithms are taken for comparison. The algorithm running time is measured in two ways, which includes the CPU time and the number of nodes (quantity).

II.SYNTHETIC ANALYSIS

Three experiments were performed to conclude the variation in the running time as a function of dimension, cluster separation, and data set size.

V. CONCLUSION

Our paper provides a comparative study on vehicular communications and its implementation using various ML techniques. Consistent and competent vehicular communication systems will fetch significant benefits to society and people, at the same time they also present incomparable challenges due to its distinct characteristics. An extensive variety of research works attempting to ease such challenges have been reviewed.

Due to complex communication environment, challenges faced by vehicular communications are abundant. Various research works regarding these challenges are carried out. An artificial agent [6] has been set up as the Road side unit, which learns a scheduling policy obtained using high-dimensional continuous inputs that uses deep reinforcement learning.

DQN algorithm can be used to provide a better overall performance and it extends the battery life of the Road Side Unit. An UMD_IPC power controller [2] that uses NN_RT&TC has been conducted in the PSAT environment. It has been designed for 11 different types of roadways along with traffic congestion levels. It saves more fuel and provides a better overall performance. Further, reinforcement learning is used in intelligent wireless resource management [7] including Load balancing and vertical control, Distributed Resource management and Virtual Resource allocation.

Lloyd's k-means clustering algorithm is a Filtering algorithm [1], applicative efficiency of this algorithm includes theoretical and practical demonstration. Analysis of LTE [3] indicates the main features of the procedures and results which are in demand.

For the safe commute, by both manually-driven-vehicles and Autonomous vehicles (AV) we desperately need the Vehicles to communicate. After surveying various papers, we are now aware that, various concepts and technologies from multiple disciplines must be perfectly blended to provide a perspective for the implementation of an Intelligent Vehicular communication system**.**

VI. REFERENCES

[1] T. Kanungo, D. Mount, N. Netanyahu, C. Piatko, R. Silverman, A. Wu, " An efficient K -means clustering algorithm: Analysis and implementation ", IEEE Trans. Pattern Anal. Mach. Intell., vol. 24, no. 7, pp. 881-892, Jul. 2000.

[2] P. Jungme, C. Zhihang, L. Kiliaris, M. L. Kuang, M. A. Masrur, A. M. Phillips, Y. L. Murphey, "Intelligent vehicle power control based on machine learning of optimal control parameters and prediction of road type and traffic congestion", IEEE Trans. Veh. Technol., vol. 58, no. 9, pp. 4741-4756, Nov. 2009

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

[4] L. Liang, H. Peng, G. Y. Li, and X. Shen, “Vehicular communications: A physical layer perspective,” IEEE Trans. Veh. Technol., vol. 66, no. 12, pp. 10647–10659, Dec. 2017

[5] H. Peng, L. Liang, X. Shen, and G. Y. Li, “Vehicular communications: A network layer perspective,” IEEE Trans. Veh. Technol., vol. 68, no. 2, pp. 1064–1078, Feb. 2019.

[6] R. Atallah, C. Assi, M. Khabbaz, "Deep reinforcement learning-based scheduling for roadside communication networks", Proc. 15th Int. Symp. Model. Optim. Mobile Ad Hoc Wireless Netw. (WiOpt), pp. 1-8, May 2017.

[7] H. Ye, L. Liang, G. Y. Li, J. Kim, L. Lu, M. Wu, "Machine learning for vehicular networks", IEEE Veh. Technol. Mag., vol. 13, no. 2, pp. 94-101, Jun 2018

[8] C. Zhang, P. Patras, and H. Haddadi, “Deep learning in mobile and wireless networking: A survey,” arXiv preprint arXiv: 1803.04311, 2018.