VEHICULAR NETWORKS: MULTI-NODE DEEP SELF LEARNING-ENABLED CHANNEL ACQUISITION

Abstract

Modern living has greatly benefited from intelligent transportation systems (ITS). This technology provides new services to reduce unfavourable occurrences like traffic or accidents and enhance traffic management. The significant classes of future-generation networks that quickly evolved for vehicles and road transmissions is the Vehicular Ad Hoc Network (VANET). It can assist in putting into action a wide range of applications relating to vehicles, traffic lights, traffic jams, drivers, passengers, ambulances, police, fire trucks, and even pedestrians.

The effectiveness of vehicle-to-everything (V2X) networks is significantly and directly impacted by channel allocation. Given the fluidity of vehicle surroundings, devising a hybrid method for efficient resource sharing is interesting. However, the conventional channel allocation strategies frequently have trouble adapting to the quickly varying network conditions and fall short of fully realizing the potential advantages of vehicle cooperation in decision-making.

In this research, we use multi-node deep reinforcement learning (MADRL) to present a unique method for dealing with the channel allocation issue in vehicular networks. Our approach uses deep reinforcement learning to give vehicles the ability to choose channels on their own with the help of real-time network circumstances and interactions with other nearby vehicles. We motivate the vehicles to cooperate and jointly optimize the channel assignment by structuring the

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channel allocation process as a cooperative multi-node learning problem. These results in improved network throughput, decreased latency, and improved system performance.

Keywords: vehicular ad hoc networks; node; Internet of Vehicles; mobile ad hoc networks.

I. INTRODUCTION

A low delay end-to-end routing method is required in metropolitan Vehicular Ad hoc Networks (VANETs) due to the high vehicular environment mobility and often changing network architecture. In this research, we propose a decentralized routing method based on Multi-Node Reinforcement Learning (MARL), which makes use of the inherent similarities between the routing problem in VANET and the MARL problem[9]. These wireless connections between network nodes—such as automobiles or equipment by the side of the road—are what the vehicular ad hoc network (VANET) wants to provide. Because of its possible function in Intelligent Transport System(ITS), this network has recently caught the interest of researchers[8]. Applications of the VANET include increasing passenger safety, maximizing traffic efficiency, approach to the Internet of Vehicles (IoV), gathering real-time data to operate traffic and road safety systems, automatically paying tolls, and entertainment apps. In the meantime, Mobile Edge Computing (MEC) is a potential strategy to enhance network performance and quality of service (QoS)[11]. Traffic safety and efficiency are greatly increased because to the ability to exchange information in real-time between vehicles and everything, and ubiquitous Internet access makes it possible to support new vehicular data services and applications [2].

Also, the cloud resource management now includes the resource allocator as a key element. In the cloud environment, the resources, services, and cloud applications are dispersed according to various goals. The cloud environment has a wealth of resources, including processing power, memory, and storage for user applications, all of which may be scaled up or down depending on demand. The main goal of resource allocation strategies is for the cloud resource provider to maximize resource consumption and increase revenue. The goal is to fulfil the user's expectations while spending as little money as possible[3]. Ad hoc vehicular networks' vehicular units broadcast and receive data that includes details on the telemetry of the connected vehicles. Since data transferred over the air is extremely susceptible to interference, a network outage might endanger the lives of drivers and anybody around. There is a substantial chance of car-to-car communication breakdown since a shared wireless medium lacks a significant infrastructure. Nodes or mobile units serve as hosts and routers in multi-hop communication, sending and receiving data from other nodes[12]. This can be done by allocating a channel using MARL, which is discussed in this paper.

II. LITERATURE SURVEY

One of the previous work has mentioned the effectiveness of vehicle-to-everything (V2X) networks is significantly and directly impacted by channel allocation. Given the fluidity of vehicle surroundings, developing a hybrid method for efficient resource sharing is interesting. In this study, they have used deep learning methods to forecast the movement patterns of automobiles. Then, in order to maximize the spectrum efficiency of all engaged vehicles, we suggest an architecture that combines distributed channel allocation with centralized decision-making [1].

The latter work has described about the multi-dimensional resource management for vehicular networks supported by unmanned aerial vehicles (UAVs). The macro eNodeB and UAV, both mounted with multi-access edge computing (MEC) servers, collectively make

association decisions and assign appropriate quantities of resources to vehicles in order to effectively provide on-demand resource access [2].

Sedeng Danba, Jingjing Bao, Guorong Han, Siri Guleng and Celimuge Wu, have discussed mainly about IoV systems and its enormous potential to enhance driving experiences to enable better transportation systems, Internet of Vehicles (IoV) technology has been drawing significant interest from both academics and industry. Although there are likely to be many intriguing Internet of Vehicles (IoV) applications, because of the mobility of vehicles and the complexity of road conditions, it is more difficult to develop an efficient IoV system than it is for traditional Internet of Things (IoT) applications. We focus on collaborative communications, collaborative computing, and collaborative machine learning methodologies to discuss the literature on allowing collaborative intelligence in IoV systems [3].

In the previous work ,utility-based resource allocation to the customers and how it is made possible by cloud computing. The mechanism for allocating resources must take greater resource utilization and the lowest possible cost per service to the client into account. These requirements for resource allocation presuppose that the problem of resource allocation is one of optimization. The allocator must have access to information about the status of the resources, anticipated client demand, and dynamic changes in the cloud in order to perform the optimum allocation. In this study, they've divided the parameters for the resource allocator into groups depending on the cost of allocation, resource consumption, execution time, and reliability [4].

In the previous work, the main issue with information transmission in VANETs is routing, and there are many different distribution methods, including unicast, broadcast, multicast, and geo-cast [5].

In the previous work, they provide a Sparse Code Multiple Access (SCMA)-based resource allocation approach for V2X communications. We formulate the problem of resource allocation to maximize the system throughput by studying the interference model in the V2X scenario. To address the issue, a resource allocation technique based on the clustering result as well as SINR and graph colour-based user clustering are described [6].

In the previous work they have mentioned about the Long-Term Evolution (LTE) standardization work that has begun under the Third Generation Partnership Project (3GPP), V2V has recently attracted a lot of attention. It is still difficult to allocate time-frequency resources efficiently and consistently across various vehicle user equipments (VUEs), especially in crowded urban areas. For an urban V2V communication situation, an innovative autonomous resource selection strategy is put forth in this work [7].

Jan Lansky, Amir Masoud Rahmani and Mehdi Hosseinzadeh according to their research study they state that the task of routing in these networks is difficult. Recently, the development of routing algorithms for VANET has heavily incorporated reinforcement learning (RL). In this research, they examine reinforcement learning, discuss its features, and investigate the application of this method for developing routing protocols in VANETs. In these networks, we suggest classifying RL-based routing algorithms. This work aids scholars

in comprehending the obstacles and potential in this field in order to create RL-based routing algorithms in VANET and enhance the current methods [8].

In the previous they have declared about the low delay that exists all the way through routing method which is required in metropolitan Vehicular Ad hoc Networks (VANETs) due to the high vehicular environment mobility and often changing network architecture. In this research, they have proposed a decentralized routing method based on Multi-Node Reinforcement Learning (MARL), which takes use of the inherent similarities between the routing problem in VANET and the MARL problem [9].

In the previous study,have proposed a study on how decision-making issues can be effectively resolved via Reinforcement Learning (RL). Large-scale wireless networks have enormous and complex state and action spaces, though. As a result, RL might not be able to identify the ideal plan of action in a timely manner. To solve this problem, Deep Reinforcement Learning (DRL), a combination of RL and DL, has been developed. To start off this examination, we briefly introduce the principles of RL and DRL before introducing vehicular networks [10].

In the previous study, have proposed an NP - hard (non-deterministic polynomial-time hardness) and non-convex optimization problem to optimize the energy consumption and completion delay while minimizing the computation cost, subject to limitations on computation capacity and energy availability. In order to obtain the best task offloading policies while considering dynamic computation requests and stochastic time-varying channel conditions, we formulate the problem as a Markov decision process (MDP) and suggest a multinode deep reinforcement learning (MADRL)-based scheme[11].

In the previous work they have proposed a paper about how reinforcement learning (RL) is a fantastic method for addressing this issue. To train a model and find the best route based on route stability and hop number, they suggest establishing a complicated goal space including geo-positioning data for cars, propagating signal strength, and environmental path loss with obstructions (city map, with buildings) [12].

III. PROBLEM STATEMENT

Modern transportation systems must include vehicular networks because they allow seamless connection between infrastructure and cars. To provide dependable data interchange, minimal latency, and enhanced network performance, effective channel allocation is crucial in these networks. Traditional channel allocation methods face substantial difficulties in dealing with the dynamic nature of vehicular environments, which is characterized by constantly changing network topologies, variable traffic densities, and a variety of mobility patterns.

Static frequency assignment and hand-crafted heuristics, which are common strategies for channel allocation in automotive networks, find it difficult to respond fast and efficiently to the changing circumstances. As a result, these strategies frequently result in inadequate resource use, increased interference, and decreased overall service quality. This study attempts to create an inventive Multi-Node Deep Reinforcement Learning (MADRL)-based system to address these problems.

IV. EXISTING SYSTEMS AND ITS FUNCTIONALITY

Many people are interested in the efficient resource distribution for vehicle networks[1]. Seamless data transfer in a highly dynamic setting with low-speed to high-speed cars in a shared environment, as well as significant variance in data services to allow delay-sensitive vehicular communication are the present significant obstacles. Other writers have conducted surveys on the multicast routing protocols used in VANET, but they have not looked into the factors that are considered by each one[5]. Therefore, in this article, we establish these parameters and offer various QoS, vehicle trajectory, scheduling method, and emergency application categories for the multicast routing protocol. Compared to the conventional Mobile Ad hoc Network (MANET), VANET frequently has data packet failures [9]. Ad hoc on-demand distance vector (AODV), Dynamic Source Routing (DSR), optimized link-state protocol (OLSR), and other MANET routing protocols, as a result, will perform significantly worse in VANET, especially in scenarios where vehicle communication is highly dynamic.

Specific characteristics of VANETs include shifting nodes, dynamic topology, and frequent disconnections. These characteristics for vehicular ad hoc networks are summarized in Table 1[8].

Table 1: Important Features of Vehicular ad Hoc Networks [8].

Dynamic mobility scenarios	The dynamic mobility scenarios for the moving nodes in this network range from low velocity (below 50 km/h) to high velocity (over 500 km/h). As a result, the lifespan of the found pathways between the nodes is decreased.
Dynamic topology	In a VANET, network topology is constantly changing, connection links have a short lifespan, and the network density fluctuates with time and place.
Frequent failure of links	The collapse of linkages between nodes is brought on by inadequate climate conditions, rapid node movement, and frequent topological changes.
Different quality of services (QoS) requirements	Varying data services on the VANET require varying levels of quality of service (QoS), including reliability, delay, and data rates.
Various network densities	Network densities fluctuate due to changes in traffic flow, making some areas—such as rural areas—have very low densities while others—such as city centres—have very high densities due to gridlock or heavy traffic.

In this work, we assume that the automobiles are nodes and analyse the multi-node problem of channel allocation among vehicles with different rates of mobility. License-holding primary users are regarded as high priority users, whilst secondary users without licenses are designated as medium priority users and low priority users [1].

Ad hoc vehicular networks' vehicular units broadcast and receive data that includes details on the telemetry of the connected vehicles. Since information transferred over the air is extremely susceptible to interference, a network outage might endanger the lives of drivers and anybody around. There is a substantial chance of car-to-car communication breakdown since a shared wireless medium lacks a significant infrastructure. Nodes or mobile units serve as hosts and routers in multi-hop communication, sending and receiving data from other nodes. As a result, nodes are selected depending on their connectedness, making the choice of routing algorithm in this kind of system a delicate matter that needs to be handled with care [12].

It is possible that in the near future, routing protocols designed for legacy networks won't be able to adequately support vehicular networks. As a result, fresh solutions must be created to address the routing issue in these intricate networks. The methods for enhancing the functionality of the methodology include:

- Picking the best possible path based on signal strength inbetween adjacent nodes and avoiding hosts with high path loss to prevent retransmissions.
- Utilizing a reward feature that evaluates the path loss between hosts, pick the route with the longest lifespan and,
- Analysing performance parameters like route lifetime, number of retransmissions, and so on.

Significance of artificial intelligence (AI) methods has been studied by authors in numerous VANETs-related domains. They have briefly presented three AI techniques in this work, including deep learning (particularly DRL), machine learning methods (specifically RL), and intelligent swarms [8]. Many authors have researched on various AI methods to analyse and make VANET more productive. They undergo a thorough inspection in six categories, including application, architecture, mobility management, resource and access technologies, and routing.

Despite numerous efforts, routing protocols are still weak and incomplete. Machine learning (ML) is a relatively new field that emerged from artificial intelligence. (AI) that consists of effective and potent methods [8]. They could be used to incorporate to address their varied problems, autonomous decision-making systems in vehicle ad hoc networks difficulties and problems, like routing. ML can create trained machines that are more intelligent without human intervention, based on prior experiences. Therefore, they do not require explicit programming.
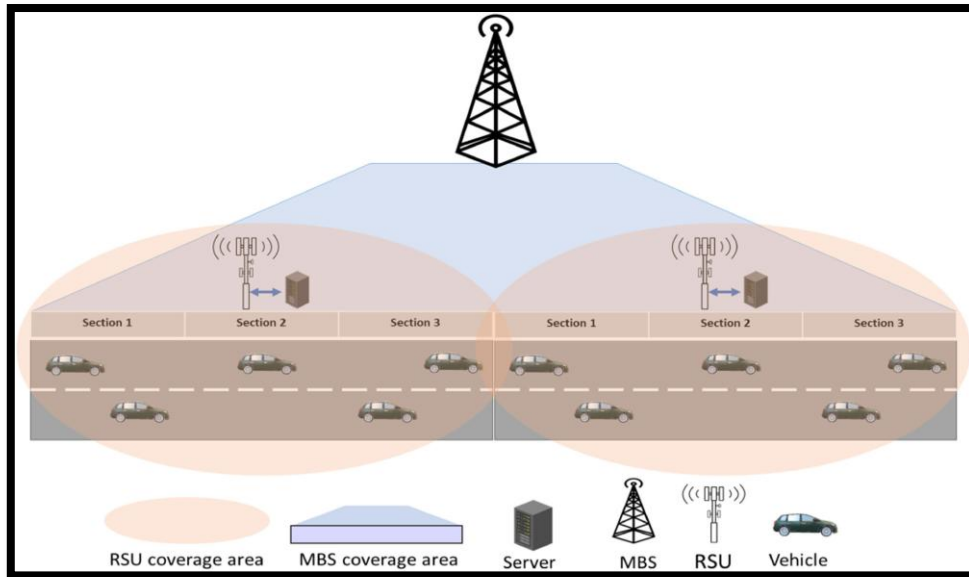
Figure 1: Model for the Vehicular Networks [8].

Reinforcement learning is currently being applied in vehicular networks as a developing technique to effectively address various issues and obstacles [10].

Network entities such as vehicles and base stations need to make local and autonomous decisions, such as spectrum access, data rate selection, transmission power control, and base station association, under unpredictably stochastic conditions in order to achieve the goals of various networks, such as, for example, throughput maximization and energy consumption minimization. But given the size and complexity of modern networks, the computational complexity of the techniques quickly becomes unmanageable. Deep reinforcement learning has therefore emerged as an alternate approach to address the problem.

1. **Deep Reinforcement Learning:** DL is utilized as an effective method to speed up the learning rate for RL algorithms in DRL, an advanced model of RL . Particularly, the experiences gained during the real-time learning process would be recorded and used to train the neural network.

   In the later section, is going to be utilized to help the node make instantaneous judgments that are as optimal as possible. It should be highlighted that, unlike DL methods, the neural network used in the DRL will undergo routine training based on fresh experiences gained through real-time interactions with the environment. Examples of RL and DRL algorithms are shown in Figure 2. For a finite number of discrete variables, the Q values can be written as a table.

   However, in order to express the Q-values for continuous state spaces, function approximators like DNNs are required. For instance, in DQL, a DNN transfers a collection of actions' Q-values from the continuous state space to those values. The Q-values of all possible actions must be anticipated. This forbids the usage of extraordinarily expansive or uninterrupted activity spaces.
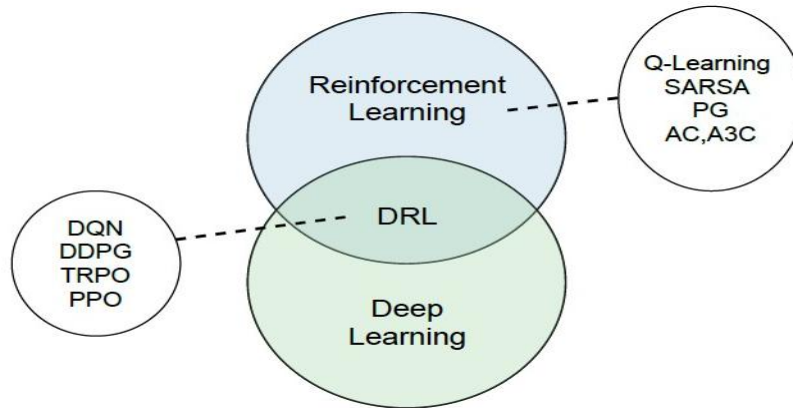
Figure 2: RL, DL and DRL

For instance, the Soft Actor-Critic (SAC) approach uses a second DNN to approximate the Boltzmann distribution over the predicted Q-values of available actions, while the critic DNN is trained to forecast the Q-values for a state action tuple.

Depending on the study or application setting, the actual implementation and specifics of the equations and algorithms utilized in MADRL for channel allocation in vehicular networks may change. Researchers may use various DQN iterations, investigate other deep RL algorithms like Multi-Node Actor-Critic (MAAC), or develop unique reward functions and network designs specifically designed to address the difficulties of vehicular networks.

V. CONCLUSION

Channel allocation for vehicular networks using Multi-Node Deep Reinforcement Learning (MADRL) has a lot of potential and offers a number of benefits. MADRL enables vehicles to make intelligent judgments in a dynamic and complicated environment by enabling the channel allocation process with cutting-edge AI algorithms. This improves communication performance, reduces interference, and boosts overall network efficiency.

We have shown throughout this study how well MADRL addresses the difficulties given by vehicular networks, including dynamic network topologies, variable traffic patterns, and communication limitations. Decentralized decision-making is made possible by the multi-node strategy, which improves the scalability and adaptability of large-scale networks. The results of this study show that in terms of throughput, latency, and fairness, MADRL-based channel allocation beats conventional approaches and even other AI-based alternatives. The potential for self-optimizing vehicle networks is demonstrated by the nodes' capacity to adjust their strategies over time and learn from interactions with the environment.

The handling of extreme network conditions, maintaining safety, and resolving the computational complexity associated with deep reinforcement learning algorithms remain problems, despite the positive outcomes. Further research is required into actual implementation as well as interactions with other Vehicular Networks components.

In conclusion, channel allocation in autonomous vehicle networks may be addressed using Multi-Node Deep Reinforcement Learning, which is a strong and practical method. It is

a strong candidate for further study and implementation in actual vehicular communication settings because to its capacity to learn from data, adjust to changing conditions, and outperform conventional approaches. We believe that MADRL will be essential in providing effective and dependable communication in vehicular networks as technology develops and computational resources become more widely accessible, helping to realize smarter and safer transportation systems.

REFERENCES

[1] Anitha Saravana Kumar, Student Member, Lian Zhao and Xavier Fernando, "Multi-Node Deep Reinforcement Learning-Empowered Channel Allocation inVehicular Networks," IEEE Transactions on Vehicular Technology, vol. 71, No.2, pp.1726-1736, February 2022.

[2] Haixia Peng and Xuemin Shen, "Multi-Node Reinforcement Learning Based Resource Management in MEC- and UAV-Assisted Vehicular Networks," IEEE Journal on Selected Areas in Communications, vol.39, No.1, pp.131-141, January 2021.

[3] Sedeng Danba, Jingjing Bao, Guorong Han, Siri Guleng and Celimuge Wu, "Toward Collaborative Intelligence in IoV Systems: Recent Advances and Open Issues," Sensors 2022, vol. 22(18), 6995, Published: 15 September 2022.

[4] Naika, Kavitha Soodab, KarunakarRai, "A study on Optimal Resource Allocation Policy in Cloud Environment," Research Article, Turkish Journal of Computer and Mathematics Education, vol.12, No.14, pp. 5438-5446, 2021.

[5] Ahmed Jawad Kadhim and Seyed Amin Hosseini Seno, "Recent Multicast Routing Protocols in VANET: Classification and Comparison," Journal of University of Babylon, Engineering Sciences, Vol. 26, No.5, pp.371-382, 2018.

[6] Wei wu, Linglin Kong and Tong Xue, "Resource Allocation Algorithm for V2X Communications Based on SCMA," International Conference in Communications, Signal Processing, and Systems-CSPS 2017, vol 463, pp.1997–2004, 2019.

[7] J. Yang, B. Pelletier and B. Champagne, "Enhanced autonomous resource selection for LTE-based V2V communication," 2016 IEEE Vehicular Networking Conference (VNC), pp. 1-6, doi: 10.1109/VNC.2016.7835937, Published: 2018.

[8] Jan Lansky, Amir Masoud Rahmani and Mehdi Hosseinzadeh, "Reinforcement Learning-Based Routing Protocols in Vehicular Ad Hoc Networks for Intelligent Transport System (ITS)," Mathematics 2022, vol.10(24), 4673, Published: 9 December 2022.

[9] C. Lu, Z. Wang, W. Ding, G. Li, S. Liu and L. Cheng, "MARVEL: Multi-node reinforcement learning for VANET delay minimization," IEEE, Published in China Communications, vol.18, No. 6, pp. 1-11, June 2021, doi: 10.23919/JCC.2021.06.001.

[10] Abdelkader Mekrache, Abbas Bradai, Emmanuel Moulay, Samir Dawaliby, "Deep reinforcement learning techniques for vehicular networks: Recent advances and future trends towards 6G," Vehicular Communications, Research Article, Vol 33, Issue C, January 2022.

[11] Yanlong Li, Lei Liang, Jielin Fu, Junyi Wang, "Multinode Reinforcement Learning for Task Offloading of Space/Aerial-Assisted Edge Computing", Security and Communication Networks, vol. 2022, Article ID 4193365, 10 pages, 2022.

[12] Lincoln Herbert Teixeira and Árpád Huszák, "Á. Reinforcement Learning Environment for Advanced Vehicular Ad Hoc Networks Communication Systems", Sensors (Basel), vol. 22(13), 4732, 2022 Jun 23; doi: 10.3390/s22134732.