SARSA RL for Edge Connectivity Management in Vehicular Edge Networks

Jannatul Ferdous, Mubashir Murshed
Department of Computer Science
Brock University, Canada
{jferdous, mmurshed}@brocku.ca

Rodolfo I. Meneguette
ICMC
University of São Paulo, Brazil
meneguette@icmc.usp.br

Robson E. De Grande
Department of Computer Science
Brock University, Canada
rdegrande@brocku.ca

***Abstract*—Vehicular network connectivity within Intelligent Transport Systems (ITS) is essential for enabling seamless data and resource sharing, including transmitting critical safety messages, traffic management information, entertainment, and comfort services. This connectivity enhances the user experience by supporting complex interactions between vehicles and infrastructure in dynamic network environments. Edge connectivity management has recently gained attention for maintaining connection stability while managing complex models effectively. In this context, connectivity refers to vehicles' ability to maintain a stable and robust link with network resources and other vehicles for optimal data exchange. In this paper, we propose an edge connectivity management approach, the Edge Connectivity Estimation Model ECEM, aimed at ensuring connection stability and strength. We design and implement the SARSA Reinforcement Learning (RL) algorithm to assess and estimate the overall connection reliability, determining the optimal vehicular edge - a selective combination of vehicles within groups - to ensure superior connection strength for data and resource sharing, even in high-mobility scenarios. This estimation process helps identify the most suitable edge to meet the data-sharing requirements for each vehicle. Our approach considers multiple parameters, including mobility, application parameters, and network density. Extensive realistic simulations have demonstrated that our proposed approach outperforms existing methods by reducing packet loss and delay while increasing throughput.**

***Index Terms*—Edge, Connectivity, SARSA, Data and Resource Sharing, High Mobility, Ultra-dense Network**

I. INTRODUCTION

Intelligent Transport Systems (ITS) are rapidly transforming the landscape of modern transportation, driven by enhanced connected vehicles [1]. These vehicles generate vast amounts of data, which they seamlessly share with surrounding infrastructure and other devices, creating a highly interconnected ecosystem [2]. The recent advancements in the automotive industry have given rise to intelligent vehicles incorporating cutting-edge technologies, significantly enhancing the overall driving experience. These developments mark the beginning of a new era in vehicular networks, where road safety, traffic management, and passenger comfort are being elevated to unprecedented levels [1]. With the continuous evolution of ITS, we are witnessing a profound shift towards smarter, safer, and more efficient transportation systems that cater to the needs of both drivers and the broader community.

This work is partially funded by NSERC Discovery grants.

The development of 5G technologies and IEEE 802.11p dedicated short-range communication (DSRC) provides a new era of wireless communication among vehicles and infrastructure [3] [4]. These advancements are revolutionizing how data is shared, enabling rapid and efficient communication even in highly mobile and dense environments. With the advancement of 5G and DSRC, vehicles can exchange vast amounts of data, ensuring high reliability, increased bandwidth, and minimal latency. This technological leap is not only enhancing the effectiveness of ITS but also paving the way for more responsive and resilient communication networks. As a result, we are moving towards a future where real-time data exchange supports safer and more efficient roadways, enabling the seamless integration of connected and autonomous vehicles.

Numerous studies have delved into various facets of vehicular network connectivity, such as route management, routing efficiency, and route optimization [5] [6] [7]. Some research has focused on the formation of clusters to maintain stable and reliable communication between vehicles and infrastructure [8] [9] [10], while others have sought to enhance service delivery by optimizing network performance and reducing collision risks [11] [12] [13]. In addition, machine and deep learning algorithms have been utilized to predict network behaviour and manage connectivity in dynamic and evolving environments [14] [15] [16]. While these strategies are crucial for improving the efficiency and robustness of vehicular networks, there remains a pressing need for better connectivity management, particularly for highly mobile and dense network scenarios. Moreover, edge connectivity management comes to attention for its outperformed performance in enhanced data and resource sharing, allowing networks to adapt more effectively to varying conditions and demands [17]. By incorporating the edge strategy, the overall connectivity in Intelligent Transport Systems (ITS) can be significantly enhanced, leading to safer, more reliable, and highly optimized vehicular communication networks.

In vehicular networks, maintaining and managing connectivity efficiently is crucial, especially for the dynamic nature of the environment [18]. Connectivity is facilitated through data exchanges within the environment, among vehicles, and between vehicles and infrastructure. However, ensuring consistent and reliable connections is challenging in highly mobile settings, where intermittent connectivity can disrupt services that rely on real-time data exchange. This work proposes an intelligent connectivity management approach leveraging the State–Action–Reward–State–Action (SARSA) Reinforcement Learning (RL) algorithm. We design SARSA RL in our approach as the vehicular network environment to optimize connectivity in vehicular networks by incorporating edge connectivity management to enhance overall network performance. We consider a scenario where multiple groups of vehicles, also referred to as clusters, define a series of network edges where vehicles share data and resources among themselves and towers [19]. Our proposed approach, ECEM, identifies the most suitable group of vehicles to act as the edge for data and resource sharing for each vehicle based on connectivity parameters. Multiple edges are possible in the network scenario. Vehicles within a group migrate to the edge, providing optimal connectivity and improving data and resource exchange efficiency. Our work aims to estimate and optimize connectivity strength among vehicles within a defined network edge in dynamic vehicular environments. To achieve this, we consider several connectivity parameters, including application, signal, mobility, and density, impacting connection stability, managing complex scenarios involving numerous vehicles, and adapting to evolving connectivity trends in urban settings. Our approach is designed to ensure robust and reliable connectivity, ultimately contributing to the effectiveness of data and resource sharing in ITS in highly mobile and unpredictable environments.

The structure of this paper is organized as follows. Section II offers a comprehensive review of previous research on connectivity estimation and modelling. Section III introduces our proposed approach for connectivity management. Section IV details the performance analysis and comparative results analyses. Finally, Section V concludes the paper and outlines potential directions for future research.

II. Related Works

Adopting SDVN modelling enables vehicular connectivity to adapt effectively to dynamic environments [20]. Self-learning theorems enable SDVN networks to adapt to changing environments, while Markov Decision Processes (MDP) introduce stochastic elements into connectivity models [21]. These learning-based approaches focus on optimizing connectivity across various parameters and may involve improving routing algorithms or maximizing service without network congestion. Overall, these models aim to enhance the efficiency and dependability of SDVN-based vehicular communication frameworks.

SDN enhances network performance, especially in urban SDVN where a fuzzy-based routing scheme segments regions based on criteria like mixed distribution and Valid Distance [7]. A central controller with initial routing values set by fuzzy logic prioritizes packet forwarding within segments, while Reinforcement Learning (RL) algorithms dynamically update routing table values, optimizing connectivity and stability. Utilizing UAVs as communication relays faces challenges like limited energy and coverage, addressed by a Deep Reinforcement Learning (DRL) framework [22] optimizing UAV control to enhance connectivity.

The Vehicular Mobility Management (VMM) model [23] regulates vehicle navigational parameters to foster robust communication links, ensuring sustained vehicle connectivity and enabling multi-hop paths. Quality of Service (QoS) is assessed by considering parameters like throughput and end-to-end data delivery delay, with an upstream Roadside Unit (RSU) regulating vehicle speeds to establish stable chains for continuous links between source and destination nodes. Graph theory, including Laplacian-based and adjacency exponent methods, plays a crucial role in VANET routing design [24], facilitating precise simulations of network behaviour and evaluating vehicle connectivity within fixed communication ranges. V2V mobility model analyzes highway communication, focusing on the impact of mobility-dependent metrics [25]. This model integrates fine-grained mobility patterns and lane-changing decisions with the AODV routing protocol in the RNN network. A study on the probability of link connectivity among vehicles has been conducted to enhance the accuracy of connectivity estimation, as detailed in [26]. This model is particularly suitable for vehicular networks on highways, considering vehicular headway dissemination while accommodating varying traffic conditions. This framework establishes a correlation between connectivity and the headway distance between vehicles, considering the characteristics of the corresponding communication channel in various traffic scenarios.

A modified Ad hoc On-demand Distance Vector (AODV) clustering algorithm has been used to analyze vehicle speed, energy usage, and link maintaining time to choose the best and most stable path for data transmission [5]. This model considers the intensity and high speed of the vehicle and performs data transmission and clustering. It optimizes the regular AODV routing protocol by predicting the link holding time of the node.

MDP-based solutions aid VANET in ensuring vehicle safety by disseminating alert messages during emergencies, detailing accident location, severity, and time [13]. Another MDP-based model has been used to estimate and represent the connectivity level in VN [21]. It maps resources and contents to estimate the connectivity level. It finds the suitable vehicular candidate in a VC scenario where vehicular access spreads the service delivery and resources. Vehicles individually supervise their recent connections and improve their MDP action of transition and reward matrices in an entirely distributed fashion. Region-based Connectivity Model (FMDP) [19] classifies regions by making clusters and updating them to find better connectivity. However, this model can handle limited states, actions, and transitions.

Our study finds that previous works have faced challenges in maintaining stable connectivity. High vehicle mobility presents challenges, leading to intermittent connectivity and compromising network safety. Cellular communication deployed in certain areas allows vehicles to join and leave at will, complicating efforts to maintain stable connectivity. In the FMDP Model, vehicles lack long-term communication prediction due to the model's complexity stemming from numerous states and actions. Our work addresses this deficiency by proposing a reinforcement learning-based model for computationally tractable, predictive, and adaptive system development. Training this model over extended periods can yield precise estimates, while adaptive learning enables real-time network adaptation to enhance stability.

III. Connectivity Management Model

Vehicular network connectivity is vital for seamlessly exchanging critical data and resources, particularly in environments characterized by high vehicle mobility and dense network populations. Ensuring reliable data transmission in such scenarios requires a robust connectivity model. Our proposed approach, ECEM, introduces an edge connectivity management model that utilizes key connectivity parameters to ensure consistent and dependable data transfer. ECEM operates by evaluating multiple groups of vehicles within the network to identify the optimal edge for establishing connections. This evaluation is based on a thorough analysis of connectivity parameters, enabling ECEM to select the most suitable set of vehicles as the edge among multiple groups for data and resource sharing. By implementing this strategy, ECEM ensures that the vehicular network remains resilient and capable of meeting the dynamic demands of high-speed mobility and dense networks. Our proposed approach leverages the SARSA RL algorithm, which dynamically adjusts connectivity based on real-time network conditions. SARSA RL employs a set of connectivity parameters, continuously refining the edge selection process to adapt to the ever-changing network environment.

In our scenario, a set of vehicles $V = \{v_1, v_2, ..., v_j\}$ communicates with network infrastructures, such as RSUs and 5G towers, utilizing IEEE 802.11p (DSRC) and 5G network technologies, represented as $T = \{t_1, t_2, ..., t_m\}$. A back-end controller (BNC) ensures seamless communication between 5G and DSRC devices, enabling efficient message exchange among the vehicles v_j and the network infrastructures t_m. Beacon messages containing connectivity parameters and SARSA RL data are exchanged periodically among the vehicles v_j and with the infrastructures t_m. The operation of ECEM occurs in the BNC for determining the optimal edge E_c for v_j among available sets of vehicles $c_i \in C$, facilitating efficient data and resource sharing across the network.

A. Connectivity Parameters

We consider a comprehensive set of connectivity parameters (CPs), encompassing factors from the application layer, signal strength, and mobility, to accurately estimate the connection strength between vehicles when forming a cluster. These parameters are essential for determining the reliability and efficiency of connections for data and resource sharing [25].

1) End to End Data Delivery Delay: We consider end-to-end data delivery delay as CP for measuring the time a packet travels across the network from its source to its destination. Lower data delivery delay helps regulate the speeds of incoming vehicles with interconnected, stable links [23]. These paths have a higher likelihood of improved connectivity. We systematically capture and log the content data sets throughout the simulation period. This data delivery delay has been measured for all the vehicles in the cluster using Equation (1).

$$ddd_{c_i} = \frac{\sum_{j=1}^{n} ddd_{v_j}}{n} \tag{1}$$

Here, ddd_{ci} is the average end-to-end data delivery delay for all the vehicles of the group c_i, ddd_{v_j} is the end-to-end data delivery delay for an individual vehicle v_j and n is the number of vehicles in the group c_i.

2) Throughput: Throughput is another CP, defined as the amount of data a node receives successfully over a specific route during the analysis period. Higher throughput determines the possibility of the end-to-end path and improved communication performance among the communicating nodes [23]. It is calculated by the total number of bits received by any vehicle within a given time frame, as outlined in Equation (2).

$$Th_i^{\theta} = \frac{\sum_{j \neq i} pkt_{r_s}^{l}}{T_{\theta}} \tag{2}$$

Here, pkt^l is the length of the received packet, r_s represents all the senders of the packets that arrived at v_j, and T_θ is the period in which the throughput was observed.

3) Inter-Vehicle Distance: We use inter-vehicle distance as a CP to represent the Euclidean distance between two vehicles. Inter-vehicle distance directly impacts the connectivity between two vehicles [26] [27] [28]. Each vehicle v_j travels across different road segments and records its coordinates (x_i, y_i). These coordinates are then used to calculate the distance $d_{i,j}$ from its previous position (x_i', y_i'). A lower distance represents better connectivity.

4) Signal Quality: Signal quality is a critical factor in ensuring reliable and efficient connectivity among vehicles when defining groups of vehicles. High signal quality translates to stronger, more stable connections, essential for maintaining uninterrupted communication and data transfer in a vehicular network. In our proposed approach, we have considered the average values of the following signal parameters SQ, Signal-to-Interference-plus-Noise Ratio (SINR), Received Signal Strength Indication (RSSI), Reference Signal Received Power (RSRP), and Reference Signal Received Quality (RSRQ) as CP. These signals indicate stronger coverage with higher throughput and lower interference [29]. Signal quality determines the reliability and efficiency of the network.

5) Vehicular Speed: We consider vehicular speed as a CP. As v_j moves across different road segments, variations in speed can cause fluctuations in signal parameters [25]. $VS(v_j)$ denotes the estimated speed of vehicle j. Vehicles travelling at lower speeds are more likely to remain within a group, facilitating more effective data and resource sharing compared to those at higher speeds.

6) Density: We consider vehicle density VD as a connectivity parameter (CP). Vehicle density refers to the total number of vehicles simultaneously travelling per unit area within a given network scenario. It significantly influences the performance of VANET systems. When the number of vehicles is consistently high, inter-vehicle spacing decreases, and the likelihood of collisions increases if there is a fixed communication infrastructure in place. On the other hand, if node density is very low, inter-vehicle spacing can be quite extensive. Therefore, achieving a moderate vehicle density is essential to maintaining stable VANET communication [25]. Density is measured as the number of vehicles per unit area (typically in square kilometres) and can be calculated using equation $VD = \frac{n}{A}$ where n represents the number of vehicles in Area A.

7) Vehicle Arrival Rate: Vehicle arrival rate is another CP that indicates how the rate of new vehicle arrivals impacts connectivity. An increased arrival rate generally leads to a higher vehicle density, which typically enhances connectivity across roadways [25]. While vehicle density measures the number of vehicles in a specific area, vehicle arrival rate tracks the change in the number of vehicles entering the network over time. To determine the vehicle arrival rate, we monitor the number of new vehicles joining a group of vehicles within a given time t. The vehicle arrival rate in group c_i is calculated using the equation $\text{var}_{c_i} = \frac{n}{t}$, where n represents the number of vehicles entering the group during period t.

8) Data Delivery Rate: The data delivery rate is considered CP, which reflects the amount of data successfully transmitted from a source to a destination within a specific time frame. It indicates the speed at which data moves between locations. This rate provides valuable insight into the data transmission performance over a group during a given interval, considering both successful and failed transmissions [25]. We measure the data delivery rate using the formula $ddr_{c_i} = \frac{n}{t}$, where ddr_{c_i} represents the data delivery rate for group c_i, n is the total number of bits transmitted from the group, and t is the time period over which the transmission occurs.

B. ECEM Functioning

We use SARSA reinforcement learning (RL) to manage edge connectivity and make informed decisions. In our proposed approach, SARSA RL identifies the most suitable edge for data and resource sharing from a set of clusters [19]. SARSA RL is a model-free online learning technique that updates Q-values based on actions taken under the current policy [30]. When the agent is in state s_k, it selects an action a_k according to policy π and receives a reward r_{k+1}, transitioning to the next state s_{k+1}. The agent then selects action a_{k+1} in state s_{k+1} following the same policy. SARSA maintains these state-action transitions as tuples $(s_k, a_k, r_{k+1}, s_{k+1}, a_{k+1})$, which are used to update Q-values with a learning rate α and a discount factor γ. We define state-action pairs based on vehicular communication requirements.

1) State-Action: We define each group c as a state s_k. The action a_k involves the transition of a vehicle v_j from one group c to another. Taking an action results in a change in the vehicle's state, meaning it migrates to another group of vehicles, which is represented as an edge transition. The available groups $c \in C$ in the network is the next state s_{k+1}, reflecting its new position in the network - existing groups of vehicles.

2) Reward: The reward r_{k+1} is calculated when an action a_k is performed for transition. We consider the average throughput of the corresponding group of vehicles has been used as the reward $R_{Th_i^\theta}$ in our proposed approach as in Equation (3).

$$R_{Th_i^\theta} = \overline{Th_i^\theta} \tag{3}$$

3) Policy: In our proposed approach, we employ an ϵ-greedy policy to effectively balance exploration and exploitation, tailored to the needs of vehicular networks [31]. At each time step k, we dynamically calculate ϵ_k based on the average of control parameters (CPs) over a time interval that includes the available groups of vehicles. Initially, we randomly select an action at time k, with the probability of exploration determined by ϵ_k. As the process continues, we shift towards selecting the action that yields the highest reward, using the probability allocated to exploitation.

4) Q-value Update: We consider the estimated connectivity $\mathcal{ES}$ as the Q-value, a scalar value derived from all the CPs associated with the factors discussed in Sub-section III-A. For simplicity, we compute $\mathcal{ES}_{c_i}$ for each group c_i using Equation 4, where each CP is treated as a weighted positive integer.

We used min-max normalization to scale the data, ensuring all variables were transformed to a common range [32]. This technique rescales the data to a fixed range, typically between 0 and 1, by subtracting the minimum value and dividing by the range (the difference between the maximum and minimum values). By doing so, we preserve the relationships and distribution of the data while making it easier to compare and analyze different metrics on a standardized scale. This approach is beneficial when dealing with diverse datasets where the metrics may have varying units or ranges.

Here, higher values indicate better connectivity for data and resource sharing. $\mathcal{ES}$ reflects the overall performance of a connection, with a higher $\mathcal{ES}$ signifying stronger connectivity among vehicles within their group. Therefore, a higher Q-value indicates that a group of vehicles is more suitable for maintaining a stable connection. Since we use the average throughput as the reward, this directly measures the performance of data and resource sharing, influencing decision-making.

$$\begin{aligned}\mathcal{ES}_{c_i} =& \frac{(1 - ddd_{c_i}) + Th_i^\theta + (1 - d_{i,j}) + (1 - VSc_i)}{n} \\ &+ \frac{SQ + VD_{c_i} + var_{c_i} + ddr_{c_i}}{n}\end{aligned} \tag{4}$$

Initially, when a vehicle v_j enters the network, it joins the group c_i and composes an edge with the highest estimated connectivity $\mathcal{ES}_{c_i}$. The initial state, action, and reward are determined based on this first group. As time progresses, the Q-value is continuously updated by performing actions within a state and observing the corresponding rewards. At each time step k, the beacon messages exchanged among v_j and between v_j and t_m carry SARSA RL-related information. Our proposed approach uses this information within a back-end controller (BNC) to make edge selection decisions. The BNC updates the Q-value for each v_j for a neighbour in range group c_i using Equation (5). When the Q-value for a particular v_j reaches its maximum value within a group c_i, that group is selected as the edge E_c for v_j. This process is repeated for every vehicle v_j within the BNC, enabling vehicles to migrate between groups (edges) and find the optimal edge for data and resource sharing. The continuous updates and edge selection ensure that each v_j maintains the best possible connectivity within the network.

$$\mathcal{ES} \leftarrow \mathcal{ES}_{E_c} + \alpha(R_{Th_i^\theta} + \gamma\mathcal{ES}_{ngbr} - \mathcal{ES}_{cur}) \tag{5}$$

The Q-value $\mathcal{ES}_{E_c}$ represents the Q-value at the time of the last migration to edge E_c, while $\mathcal{ES}_{cur}$ is the current Q-value for the present group c_i or edge E_c. Additionally, $\mathcal{ES}_{ngbr}$ denotes the Q-value of neighbouring groups within the range. The update of the Q-value is performed each time k. The Algorithm 1 describes the operation of our proposed approach ECEM.

ALGORITHM 1: ECEM for Adaptive Learning

Data: ddd_{c_i}, Th_i^θ, (x_i, y_i), SQ, $VS(v_j)$, VD, var$_{c_i}$, ddr_{c_i}
Result: E_c

$InitializeCondition$;
while $c \neq \varnothing$ **do**
  $CP \leftarrow calculateCP()$;
  $\mathcal{ES} \leftarrow determineConn()$;
  $a_k \leftarrow assignAction()$;
  $R_{Th_i^\theta} \leftarrow assignReward()$;
  $\epsilon_k \leftarrow determinePolicy()$;
  $Q-value \leftarrow assign\ \mathcal{ES}$;
  set α, γ;
  $\mathcal{ES} \leftarrow \mathcal{ES}_{E_c}$ + α ($R_{Th_i^\theta}$ + γ $\mathcal{ES}_{ngbr}$ - $\mathcal{ES}_{cur}$) **if** $argmax_{c_i}(\mathcal{ES})$ **then**
    $E_c \leftarrow determindeEdge$;
    execute migration from c_i to another E_c;
    $\mathcal{ES}_{E_c} \leftarrow argmax_{c_i}(\mathcal{ES})$;
  end
end

IV. Performance Analysis and Results

A sequence of simulations has been executed utilizing Veins, OMNet++, SUMO, and Simu5G to evaluate the suggested **ECEM** strategy for ensuring connection stability in vehicular networks. Our simulation setup utilizes the Cologne, Germany map, encompassing urban and highway environments, depicted in Figure 1. This map is a valuable tool for simulating ultra-dense networks and scenarios characterized by high mobility and dynamic randomness, mirroring real-world challenges.

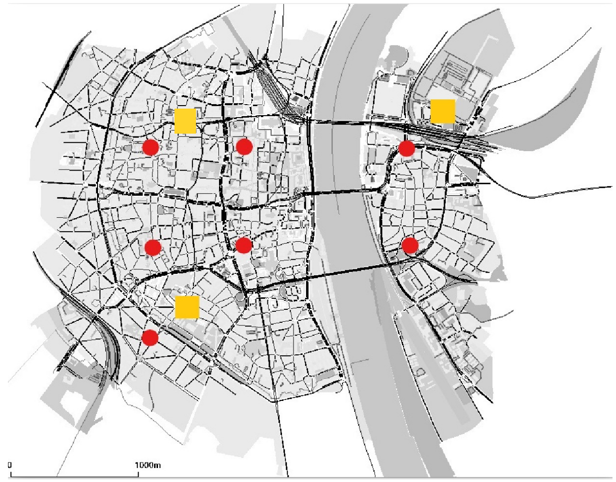


Figure 1: Map of Cologne, Germany in the simulation analysis.

Table I: Simulation Parameters.

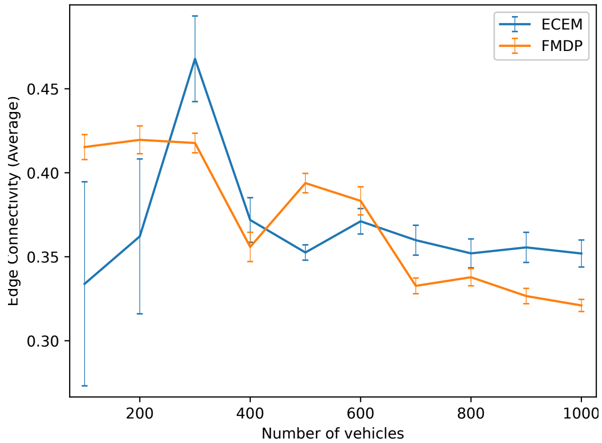
Parameter	Value Range
Cologne area	5532x3869m^2
Vehicle density	100 - 1000
Vehicle Speed	0 - 35m/s
RSU density	3 - 7
gNodeB density	2 - 3
RSU PHY model	IEEE 802.11p
gNodeB PHY model	LTE
Vehicle comm. range	400m
RSU comm. range	400m
gNodeB comm. range	14000m
Transmission power	30mW
α (Learning Rate)	0.5, 0.7
γ (Discount Factor)	0.5, 0.8

A. Parameters

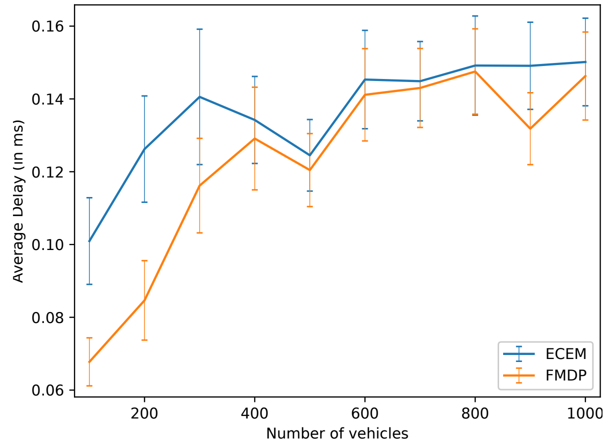
We assess the performance of our proposed approach using various parameter settings, as summarized in Table I. The performance of the groups (vehicular edges), in terms of connectivity, is influenced by various factors, such as vehicle density and speed. We randomly positioned 7 RSUs and 3 gNodeBs across the map, and this deployment has been reused for multiple iterations. Here, the red dots represent RSUs, while the yellow dots represent 5G towers.

B. Performance Metrics

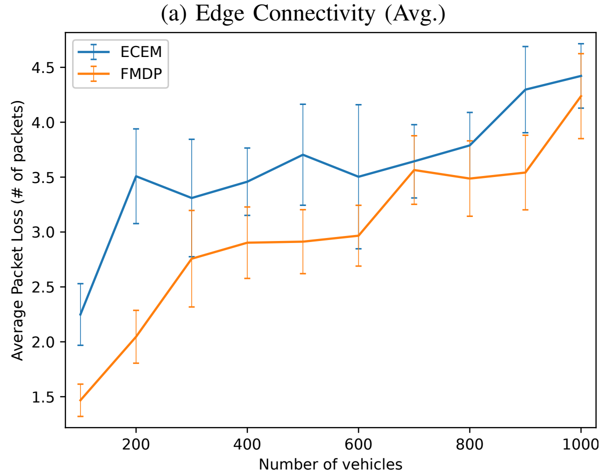
We evaluate the efficacy of our proposed model by employing a set of key metrics. These metrics serve as quantitative measures to assess and analyze performance, ensuring a comprehensive evaluation of the effectiveness and reliability of the proposed model. **Group Connectivity** indicates the effectiveness of inter-vehicle connections within a group. Enhanced connectivity implies robust links, facilitating seamless data sharing with minimal disruptions. Connectivity is quantified through diverse parameters outlined in Section III-A and derived from Equation 4. **Delay** corresponds to the time it takes for a packet to be transferred from an RSU/tower to a vehicle that belongs to the respective edge/group. This delay



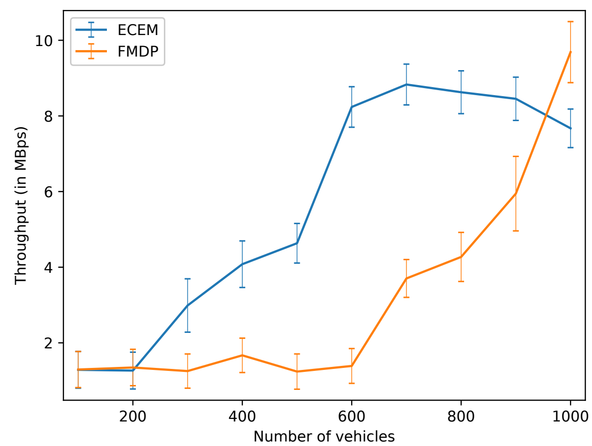
(a) Edge Connectivity (Avg.)



(b) Average Delay



(c) Average Packet Loss



(d) Throughput

Figure 2: Average Connectivity, Delay, Packet Loss, and Throughput Results from the **ECEM** Simulation with 5 RSUs and 2 gNodeBs.

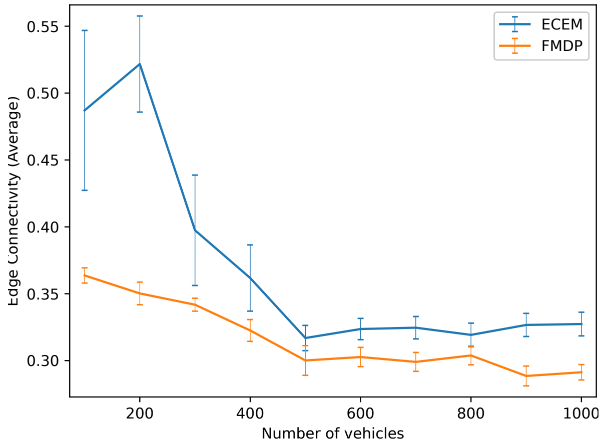
is measured in every transmission within a cycle where the model estimates connectivity and updates a group. **Packets Loss** is calculated based on the number of messages sent and received successfully among all nodes (vehicles and RSUs). The metric accounts for the number of packets lost during the transmissions within an estimation and group update cycle. An average is calculated among all cycles across the simulation. The average is ϕ, where $\phi = n/iteration$. Here, n is the total number of lost packets within a simulation, and $iteration$ is the number of cycles during the observed time (the simulation duration). **Throughput** corresponds to the amount of data transmitted to a single node (vehicle). Finally, an average throughput is obtained from all individual readings in each cycle and across the simulation time. It is measured in MBps.

C. Results

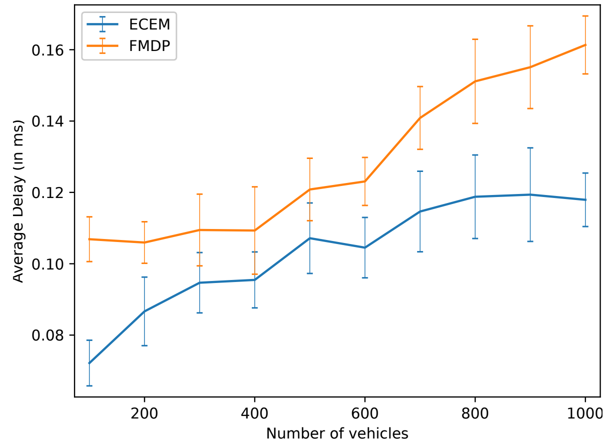
We evaluate our proposed approach across various vehicle densities ranging from 100 to 1000. The results are averages obtained from 30+ runs with different seeds, with 95% confidence intervals. The performance of ECEM is compared with a stochastic model, FMDP [19]. FMDP is a simple MDP-based naive connectivity estimation approach to maintain connectivity.

Categorizing vehicle groups establishes the degree of reliability. The performance evaluation of these groups involves analyzing metrics, such as group connectivity, packet delay, packet loss, and throughput, all of which contribute to assessing group/edge dependability. This analysis considers the deployment of 7 Roadside Units (RSUs) and 3 5G towers strategically placed in densely populated regions. Typically, adding RSUs has minimal impact on connectivity due to their ability to reach a larger number of vehicles and integrate them into the groups.

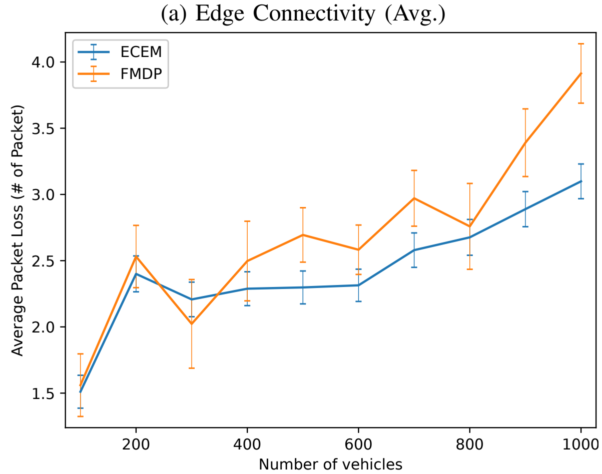
In the experiment depicted in Figure 2, we present the average results for group connectivity, delay, packet loss, and throughput across scenarios involving 100 to 1000 vehicles with 5 RSUs and 2 5G towers. In the ECEM scenario, connectivity ranges from 0.32 to 0.37, except where a spike occurs at a density of 300. This anomaly is due to the presence of groups with a minimal number of vehicles, some of which are out of range, preventing all vehicles from being considered. Consequently, scaling a smaller amount of data results in



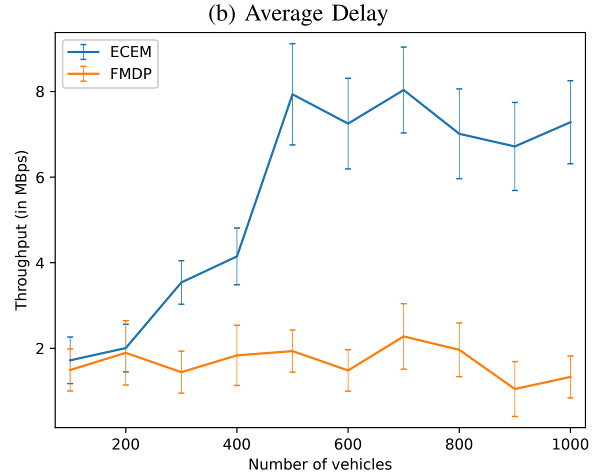
(a) Edge Connectivity (Avg.)



(b) Average Delay



(c) Average Packet Loss



(d) Throughput

Figure 3: Simulation Results of **ECEM** with 7 RSUs and 3 gNodeBs.

higher connectivity values. Figures 2b and 2c show that both average delay and packet loss increase with vehicle density. The average delay ranges from 0.1 to 0.15 ms, while packet loss varies between 2.3 and 4.5. Throughput also increases with vehicle density, ranging from 1 to 4 for lower densities and around 7.8 to 8 for higher densities.

These graphs illustrate that the ECEM model surpasses the FMDP model in maintaining stable connectivity within groups of vehicles. For this scenario, the stochastic model FMDP initially gives better results than ECEM regarding average delay and packet loss. However, with the increasing density, it experiences overlapping intervals. For throughput, both the models produce similar results initially, however, gradually higher dense vehicles produce higher throughput. This happens because learning algorithms produce better results when applied with enough data for sufficient time. Learning-based approaches are designed to steer vehicles toward groups with optimal connectivity by employing algorithms that estimate connectivity considering 8 different factors. While there are marginal differences among the models regarding delay, packet loss, and throughput calculations, with occasional overlapping intervals, there is a discernible gradual increase as more vehicles are introduced into the scenario. These trends indicate that these models exhibit an upward trajectory, yielding higher values as the exchange of data packets escalates.

However, with more RSUs and towers, the evaluation metrics become more consistent. In the experiment illustrated in Figure 3, we present the averaged outcomes for group connectivity, delay, packet loss, and throughput across scenarios with 100 to 1000 vehicles, using 7 RSUs and 3 5G towers. In this ECEM scenario, connectivity ranges from 0.35 to 0.52 for lower-density vehicles and stabilizes around 0.34 to 0.35 for higher-density vehicles. While the slope of delay and packet loss is lower in ECEM than in FMDP, the slope for group connectivity and throughput is higher. The graphs show that the ECEM model outperforms the FMDP model in maintaining stable group/edge connectivity. Although there are slight variations between the models regarding delay, packet loss, and throughput, with some overlapping intervals, there is a noticeable gradual increase as more vehicles are introduced. In this scenario, more vehicles were discovered by more RSUs and 5G towers. Hence, more data has been considered for training purposes. For this reason, ECEM consistently outperforms FMDP in this setting. These patterns indicate an upward trend, resulting in higher values as data packet exchanges intensify.

V. Conclusion

This paper addresses the connectivity management challenges for highly mobile, ultra-dense vehicular networks. To tackle these challenges, we introduce an edge connectivity management approach, ECEM, using SARSA RL to determine optimal connectivity estimation for a vehicle to share data and resources. Our proposed ECEM demonstrates significant improvements in network connectivity by reducing packet loss and delay while increasing throughput, as evidenced by comprehensive performance analyses. In future work, we plan to explore edge formation mechanisms within this framework and investigate its performance across various scenarios to further enhance the robustness and scalability of our approach.

References

[1] P. Rani and R. Sharma, "Intelligent transportation system for internet of vehicles based vehicular networks for smart cities," *Computers and Electrical Engineering*, vol. 105, p. 108543, 2023.

[2] N. H. Hussein, C. T. Yaw, S. P. Koh, S. K. Tiong, and K. H. Chong, "A comprehensive survey on vehicular networking: Communications, applications, challenges, and upcoming research directions," *IEEE Access*, vol. 10, pp. 86 127–86 180, 2022.

[3] J. Cui, J. Chen, H. Zhong, J. Zhang, and L. Liu, "Reliable and efficient content sharing for 5g-enabled vehicular networks," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 2, pp. 1247–1259, 2020.

[4] M. N. Tahir, M. Katz, and U. Rashid, "Analysis of vanet wireless networking technologies in realistic environments," in *2021 IEEE radio and wireless symposium (RWS)*. IEEE, 2021, pp. 123–125.

[5] Z. Degan, G. Changle, Z. Ting, Z. Jie, and P. Mingjie, "A new algorithm of clustering aodv based on edge computing strategy in iov," *Wireless Networks*, vol. 27, pp. 2891–2908, 2021.

[6] A. Farhan, A. Waleed, Rehman, Z. Ur, S. P. Azmat, R. Seungmin, and M. Irfan, "Clustering algorithm for internet of vehicles (iov) based on dragonfly optimizer (cavdo)," *The Journal of Supercomputing*, vol. 74, pp. 4542–4567, 2018.

[7] L. Zhao, Z. Bi, M. Lin, A. Hawbani, J. Shi, and Y. Guan, "An intelligent fuzzy-based routing scheme for software-defined vehicular networks," *Computer Networks*, vol. 187, p. 107837, 2021.

[8] A. Nahar and D. Das, "Adaptive reinforcement routing in software defined vehicular networks," in *2020 International Wireless Communications and Mobile Computing (IWCMC)*, 2020, pp. 2118–2123.

[9] J. Cheng, G. Yuan, M. Zhou, S. Gao, Z. Huang, and C. Liu, "A connectivity-prediction-based dynamic clustering model for vanet in an urban scene," *IEEE Internet of Things Journal*, vol. 7, no. 9, pp. 8410–8418, 2020.

[10] A. K. Dutta, M. Elhoseny, V. Dahiya, and K. Shankar, "An efficient hierarchical clustering protocol for multihop internet of vehicles communication," *Transactions on Emerging Telecommunications Technologies*, vol. 31, no. 5, p. e3690, 2020, e3690 ETT-19-0204.R1.

[11] C. Qiu, F. R. Yu, F. Xu, H. Yao, and C. Zhao, "Blockchain-based distributed software-defined vehicular networks via deep q-learning," in *Proceedings of the 8th ACM Symposium on Design and Analysis of Intelligent Vehicular Networks and Applications*, 2018, p. 8–14.

[12] S. Goudarzi, M. H. Anisi, A. H. Abdullah, J. Lloret, S. A. Soleymani, and W. H. Hassan, "A hybrid intelligent model for network selection in the industrial internet of things," *Applied Soft Computing*, vol. 74, pp. 529–546, 2019.

[13] A. Naja, O. A. Oualhaj, M. Boulmalf, M. Essaaidi, and A. Kobbane, "Alert message dissemination using graph-based markov decision process model in vanets," in *ICC 2020 - 2020 IEEE International Conference on Communications (ICC)*, 2020, pp. 1–6.

[14] T. P. Le, N. A. Vien, and T. Chung, "A deep hierarchical reinforcement learning algorithm in partially observable markov decision processes," *IEEE Access*, vol. 6, pp. 49 089–49 102, 2018.

[15] Y.-R. Chen, A. Rezapour, W.-G. Tzeng, and S.-C. Tsai, "Rl-routing: An sdn routing algorithm based on deep reinforcement learning," *IEEE Transactions on Network Science and Engineering*, vol. 7, no. 4, pp. 3185–3199, 2020.

[16] W. Quan, M. Liu, N. Cheng, X. Zhang, D. Gao, and H. Zhang, "Cybertwin-driven adaptive transmission scheduling for software defined vehicular networks," *IEEE Transactions on Vehicular Technology*, pp. 1–1, 2022.

[17] T. Gong, L. Zhu, F. R. Yu, and T. Tang, "Edge intelligence in intelligent transportation systems: A survey," *IEEE Transactions on Intelligent Transportation Systems*, vol. 24, no. 9, pp. 8919–8944, 2023.

[18] A. Boukerche and R. E. De Grande, "Vehicular cloud computing: Architectures, applications, and mobility," *Computer Networks*, vol. 135, pp. 171–189, 2018.

[19] P. Yan, G. H. S. Carvalho, and R. E. De Grande, "Mdp-based region-oriented connectivity estimation in vehicular fog computing for sdvn," in *Proceedings of the 20th ACM International Symposium on Mobility Management and Wireless Access*, 2022, p. 111–118.

[20] K. S. Atwal, A. Guleria, and M. Bassiouni, "Sdn-based mobility management and qos support for vehicular ad-hoc networks," in *2018 International Conference on Computing, Networking and Communications (ICNC)*, 2018, pp. 659–664.

[21] A. Saad and R. E. De Grande, "Mdp-based vehicular network connectivity model for vcc management," in *2020 IEEE/ACM 24th International Symposium on Distributed Simulation and Real Time Applications (DS-RT)*, 2020, pp. 1–8.

[22] O. S. Oubbati, M. Atiquzzaman, A. Baz, H. Alhakami, and J. Ben-Othman, "Dispatch of uavs for urban vehicular networks: A deep reinforcement learning approach," *IEEE Transactions on Vehicular Technology*, vol. 70, no. 12, pp. 13 174–13 189, 2021.

[23] M. Khabbaz, "Modelling and analysis of a novel vehicular mobility management scheme to enhance connectivity in vehicular environments," *IEEE Access*, vol. 7, pp. 120 282–120 296, 2019.

[24] S. Elaraby and S. M. Abuelenin, "Connectivity analysis of directed highway vehicular ad hoc networks using graph theory," *International Journal of Communication Systems*, vol. 34, no. 5, p. e4745, 2021.

[25] J. Naskath, B. Paramasivan, and H. Aldabbas, "A study on modeling vehicles mobility with mlc for enhancing vehicle-to-vehicle connectivity in vanet," *Journal of Ambient Intelligence and Humanized Computing*, 08 2021.

[26] S. M. Abuelenin and S. Elaraby, "A generalized framework for connectivity analysis in vehicle-to-vehicle communications," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 6, pp. 5894–5898, 2022.

[27] A. N. Hassan, O. Kaiwartya, A. H. Abdullah, D. K. Sheet, and R. S. Raw, "Inter vehicle distance based connectivity aware routing in vehicular adhoc networks," *Wireless Personal Communications*, vol. 98, pp. 33–54, 01 2018.

[28] A. Y. Abuelenin, Sherif M.and Abul-Magd, *Studying Connectivity Probability and Connection Duration in Freeway VANETs*. Cham: Springer International Publishing, 2020, pp. 27–38. [Online]. Available: https://doi.org/10.1007/978-3-030-22773-9_3

[29] K. Vasudeva, O. Ozdemir, S. R. Chandar, F. Erden, and I. Guvenc, "Vehicular lte connectivity analysis in urban and rural environments using usrp measurements," *Array*, vol. 8, p. 100045, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2590005620300308

[30] S. Zhang, T. Wu, M. Pan, C. Zhang, and Y. Yu, "A-sarsa: A predictive container auto-scaling algorithm based on reinforcement learning," in *2020 IEEE International Conference on Web Services (ICWS)*, 2020, pp. 489–497.

[31] M. Murshed, G. H. S. Carvalho, and R. E. de Grande, "Adaptive user-centric virtual cell handover decision-making in 5g vehicular networks," in *ICC 2023 - IEEE International Conference on Communications*, 2023, pp. 3983–3988.

[32] A. R. Gad, A. A. Nashat, and T. M. Barkat, "Intrusion detection system using machine learning for vehicular ad hoc networks based on ton-iot dataset," *IEEE Access*, vol. 9, pp. 142 206–142 217, 2021.