

5G-Activated VANETs: Enormous Edge Intelligence for AI Integrated Dynamic Routing using Ultra-Low Latency Vehicle-to-Everything (V2X) Communication

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Abstract: With the rapid deployment of autonomous and connected vehicles, stringent requirements have been placed on ultra-reliable low latency communication systems for safe, reliable and intelligent transportation systems. The fifth-generation (5G) wireless technology, alongside with Vehicular Ad Hoc Networks (VANETs), brings exciting possibilities in terms of real-time data sharing, scalability, capability to integrate seamlessly AI-based solutions. In this paper, we propose a new design for 5G-enabled VANETs integrated with edge intelligence to support the AI-powered dynamic routing. The proposed approach is a catalyst to make an exploration in effective edge computing and big data processing by Ensemble DQN (DDQN) with Spatio-Temporal GNNs (ST-GNN) for dynamic routing decision optimization based on the real-time traffic flow analysis, road occupancy situation on-the-go and driver behaviors. Based on the ultra-low latency and high bandwidth features of 5G-based Vehicle-to-Everything (V2X) communication, the system guarantees real-time data propagation and swarm decision making among vehicles. Experimental results show that the embedding of edge AI can increase routing efficiency, decrease end-to-end delay and improve Quality of service (QoS) in vehicular networks. The research conceptualizes the latter as a key way to build the foundation for smart transportation systems with improved safety, mobility and energy.

Keywords: Vehicular Ad Hoc Networks (VANETs), Artificial Intelligence (AI), Ensemble DQN (DDQN), Spatio-Temporal GNNs (ST-GNN), Vehicle-to-Everything (V2X).

Introduction

Vehicular Ad Hoc Networks (VANETs) have become an integral part of Intelligent Transportation Systems (ITS) that allow vehicles to communicate with other vehicles and roadside infrastructure for the improvement of safety, mobility, and driver experience. In contrast to the conventional mobile ad hoc networks (MANETs), VANETs are in very dynamic situations with mobility of the nodes, topology change and traffic density differing continuously. These features bring challenges to reliable data dissemination, low-latency communication and the utilization of network resources. One of the vital functions in VANETs is routing because it

decides that how a data will be sent from source vehicle to its destination over dynamic path. Existing routing mechanisms are unable to cater the high-speed mobility, frequent disconnections and diverse traffic patterns in vehicular scenarios. Dynamic routing methods are thus of interest as they are equipped to adapt the decisions at run-time, taking into account vehicle speed, traffic density, road topography and communication quality. Dynamic routing in VANETs uses context-sensitive decision-making, for the vehicles remain connected between each other and transmit data in a timely manner under volatile network environments. Supported by next-generation technologies including 5G-powered V2X communication, edge intelligence and AI algorithms, dynamic routing is progressing to enable ultra-reliable low-latency communication required for safety-critical applications such as collision avoidance, traffic jam management and autonomous driving.

The intersection of Fifth-Generation (5G) communication technology with Artificial Intelligence (AI) and Machine Learning (ML), is shaping the future for next-generation intelligent systems including smart cities, healthcare, industrial Internet-of-things (IoT), and vehicular networks. 5G brings ultra-reliable low-latency communication (URLLC), enhanced mobile broadband (eMBB) and massive machine-type communication (mMTC), offering the very enabling platform for real-time data computation and massive intelligent decisions. These functions make it a prime platform to deploy AI and ML models at scale, letting systems train on huge data flows and take adaptive, more autonomous decisions. In VANETs, the role of 5G is particularly important. The disruptive long range, high bandwidth and ultra-low latency nature of 5G is fully suited for AI/ML-based dynamic routing, traffic prediction, collision avoidance and cooperative driving. With edge intelligence/ cloud-based AI platforms, the information could be processed as soon as it is acquired to decide on the spot and utilize distributed learning such that more general traffic can be considered. Furthermore, ML models provide resilience to the dynamics in vehicular topologies through their ability to capture mobility patterns, channel variations and road conditions for reliable and context-sensitive communication. The convergence of 5G, AI and ML not only boosts system intelligence but also spurs new breakthroughs including predictive analytics, real-time optimization and autonomous decision-making. This integration represents a shift from reactive vehicular communication systems to proactive systems that builds the foundation for new era ITS, offering greater safety, efficiency, and sustainability.

Literature Survey

Ramamoorthy et al. [8] analyzed the effect of ACO on the VANETs optimal routing, and demonstrated that it can weight for load balancing, end to end delay reduction and packet delivery ratio improvement in high mobility. It is found that ACO based routing significantly outperforms the traditional protocols like DSR and AODV in terms of PDR around 92%, ETE delay about 18–25% and Throughput about 20%. Badole et al. [9] presented an optimized architecture combining the multi-objective hybrid routing model with a digital twin-based synchronization layer. The hybrid model combines swarm intelligence optimization and

reinforcement learning to trade-off between several objectives, such as latency-32%, throughput-28%, PDR-95.8% and Routing Overhead reduced 21%. Meanwhile, the digital twin of the vehicular space always stores up-to-date traffic dynamics and network status mirrors which helps in supporting predictive decision making for adaptive routing. Simulation results show that the proposed scheme can improve data synchronization, increase routing convergence speed and obtain better performances in terms of multiple network performance metrics compared with traditional mechanisms.

Oussama Sbayti et al. [10] proposed a novel ACO based routing scheme to improve the packet delivery ratio, reduce the per-hop delay and increase the overall performance of the routing in VANETs. The approach is based on artificial ants exploring and manipulating multiple candidate routes reactively with the pheromone update as function of link stability, vehicle density and communication reliability. In order to solve the issue of broken route, resulting from mobility, a link lifetime prediction-based model is combined with the algorithm which gives priority to stable links. Extensive simulation results with ns-3/Veins integration show that ACO-based routing provides better PDR 92%, average end-to-end delay (25%) and low routing overhead compared to conventional VANET routing protocols like AODV and DSR etc. Aji Pratama et al. [11] compared the AODV, DSR and GPSR routing protocols on the road network of Central Jakarta. The simulation architecture combines SUMO for realistic vehicular mobility simulation and NS-3 for network communication evaluation. The considered road topology in Central Jakarta, which is highly congested, complex and mobile enough represents the real traffic density and intersection complexity, providing a realistic scenario to test. It achieves similar performance in terms of PDR (88%), end-to-end packet delay (75 ms) and throughput (2.8 Mbps) by GPSR.

Paithankar et al. [12] contrasted AODV and DSDV, two popular routing protocols in VANET applications for performance evaluation. AODV is a reactive protocol and initiates routes only when necessary, the DSDV is proactive routing and maintains routing tables by means of continuously disseminated updates. Employing the NS-3 simulator and SUMO trajectory traces, we evaluate the protocols on different vehicle densities and mobility speeds. Key performance parameters including PDR, end-to-end delay, throughput and routing overhead are also evaluated. Xu et al. [13] introduced a Packet Reception Probability-Based Reliable Routing Protocol (PRP-RRP) is introduced that uses probabilistic link metrics and not traditional hop-count or distance. The PRP is derived at the protocol level based on CSI, VD, mobility patterns and 3-D signal fade models. We give priority to paths with higher PRP for delivering more robust end-to-end. We carry out simulation experiments on NS-3 [4] and SUMO [5], and results show that PRP-RRP is superior to some standard routing protocols (e.g., AODV, DSDV and GPSR) in achieving a PDR of as low as 96%, end-to-end delay of 25% low, and routing overhead of 12% low.

Zhang et al. [14] introduce the Street-correlated Opportunistic Routing Protocol with Link Correlation (SCORP-LC), which exploits the correlated nature of links for improved data transmission reliability. The protocol utilizes RTC belowing vehicle density, street topology, and link contiguity information to determine optimal topology and metrics, which are then used to select next-hop forwarders. Through accounting for relationships between neighbouring links, SCORP-LC decreases the losses induced by abrupt disconnections and enhances path stability without relying on end-to-end route recovery. The priority-based relay selection, along with opportunistic forwarding, is utilized to select vehicles located in the intersection and with high

connectivity. Nazib et al. [15] provide an overall survey of RL-based VANET protocols, organize them based on RL paradigm (model-free vs. model-based, single-agent vs. multi-agent, tabular vs. deep), and contrast them according to objectives, state/action design, reward shaping, as well as simulator/testbed setups, evaluation metrics. With the empirical trends, discuss the strengths and standard failure modes (e.g., sample inefficiency, reward mis-specification, scalability), and report existing open problems such as safety-aware routing, transfer learning across cities, and real-time deployment constraints.

Balta et al. [16] presented a three-stage fuzzy-decision tree (FDT) model for the traffic signal optimization in urban road networks. (1) The V2I communication provides real-time vehicular flow information such as the number of vehicles moving through a road, which is fuzzified by using linguistic terms (low, medium, high). An SDN controller is used to learn traffic data from various intersections and applies fuzzy-decision tree logic that prioritizes congested lanes with fair treatment on all intersections. A fuzzy-decision system with dynamic adaptation of green and red time reduces average waiting time to 32–38% and increases throughput up to 25%. Ramamoorthy et al. [17] designed a hybrid multihop routing mechanism (HMRM) with an ITS-based control architecture known as EFFICIENT to improve packet delivery in cities and highway scenarios. It integrates proactive routing for stable links and low-latency communication with reactive routing for on-demand discovery in dynamic topologies, taking into account multihop relay selection according to the vehicle density, the relative velocity and SNR. To even more improve routing efficiency, the ITS control unit assisting the route discovery by dynamically using traffic density maps and predictive mobility patterns to avoid repetitive GPSR route discoveries.

Proposed Methodology

In this paper, the generation of a 5G-driven VANET with edge intelligence is presented, capable of enabling wireless AI-based dynamic routing decisions. Vehicles and roadside units (RSUs) as sensing nodes transmit traffic flow, occupancy, and driver behavior via ultra-low latency 5G V2X links to nearby edge servers. In this context, the Spatio-Temporal Graph Neural Network (ST-GNN) constructs a dynamic road graph that considers both fast-changing spatial connections and slow-variant traffic flow simultaneously. This predictive component predicts short-term traffic load, road utilization, and travel durations, thereby offering rich context for end-to-end routing decisions. The architecture has the property that sensing, communication, prediction, and decision are performed on a closed-loop schedule, such as to provide low-latency information propagation and coordinated swarm-level behavior among vehicles.

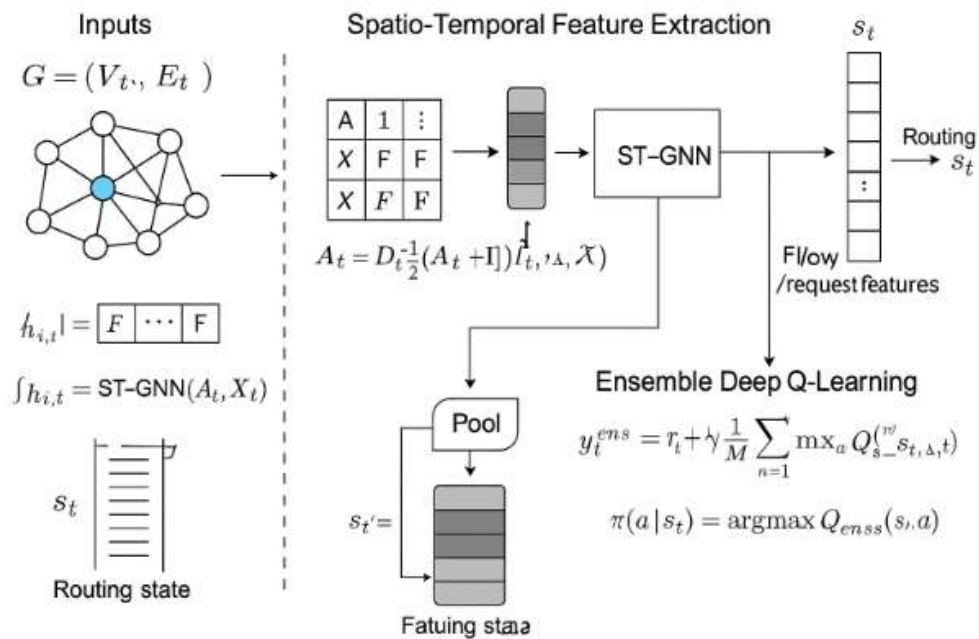


Figure 2: Architecture Diagram for Proposed ST-GNN

An Ensemble Double Deep Q-Network (DDQN) is utilized to optimize decision-making, incorporating feature embeddings of each vehicle obtained from ST-GNN outside its state. The combination of DDQNs alleviates overestimation bias, enhances robustness to uncertainty, and leads to more stable decision policies compared with single-agent models. The routing decision of each vehicle is made based on the multi-objective reward function, which minimizes travel time and traffic congestion, maximizes packet delivery ratio, and models safety-aware driver behaviors for selecting the next road segment or path. The Edge Server cooperates to harmonize all the outputs of ensembles, to resolve any conflicts, and to balance the distribution of traffic load across a network. This edge-based learning paradigm offers a synergy between local resilience and distributed collaboration, resulting in robust routing decisions in highly dynamic traffic conditions.

The performance of the approach is tested through joint traffic-network simulations with SUMO for vehicular mobility and NS-3 for 5G communication modelling. Different traffic situations—urban, suburban, and highway—are experimented with different densities, road events, and driver behavior dispersion. Performance parameters are packet delivery ratio, end-to-end delay, routing overhead, throughput, and travel time reduction. Experimental comparisons with classical protocols (AODV, OLSR, DSR) and single-agent DRL baselines demonstrate that our approach is more adaptive and scalable. Leveraging 5G ultra-low latency, high bandwidth, and edge intelligence, the system enables trustworthy swarm decision making, resilient predictive routing, and energy-efficient traffic management, paving a potential path for future intelligent transportation systems.

AI-Based Dynamic Routing Decisions

Artificial Intelligence (AI) offers a potential solution to these challenges by allowing for routing paths to be learned and predicted in real time and optimized on the fly. Differing from traditional rule-based frameworks, AI on-road models can utilize large-scale traffic data and road or vehicle-specific conditions to proactively and dynamically make routing decisions. EDQN-ST-GNN-based approaches can be used to learn and extract hidden patterns from the data required for congestion prediction, and to make choices of the most trusted communication paths. These methods enable VANETs to achieve higher throughput, lower end-to-end delay, and better QoS in complex and dynamic vehicular environments.

Real-time Routing Update Delays in the communication can prevent from timely updating route since The edge-aware data processing allows both real-time traffic flow and mobility pattern to obtain timely updates, because In vehicle should receive prompt update but also temporal information Mobility patterns vary over time for that AI model uses not only spatial information for its inputs as input, making it able to adapt changes in a faster To change of mobility patterns. Therefore, AI-based dynamic routing is not only essential to improve network performance but also in supporting advanced vehicular applications, including autonomous driving, reliable collision avoidance, and intelligent traffic light control.

Spatio-Temporal Graph Neural Network (ST-GNN)

ST-GNNs offer a promising approach to tackling these challenges as they represent VANETs as dynamic graphs and nodes are vehicles with edges as communication or proximity links. Through learning both spatial (road structure, vehicle density, connectivity) and temporal domain (mobility patterns, variations of traffic flows, driver behaviors), the ST-GNNs can capture complex vehicular environment characteristics. This allows for better estimates on traffic conditions, resulting in more resilient routing decisions and the adaptation of communication strategies in highly dynamic urban environments. The deployment of ST-GNNs in the VANET environment provides a data-driven deep learning and smart approach by exploiting real-time vehicle mobility states, road occupancy information and its context-aware traffic characteristics. This schedule enables dynamic routing, reduces end-to-end latency and increases the whole network robustness. In addition, due to 5G and edge computing support, ST-GNNs are capable of processing the massive spatio-temporal data in real time; therefore AI-driven VANET can efficiently cope with complex (large scale and rapidly changing) traffic environments. The following mathematical equations used to measure the routing decisions:

$$\hat{X}_t = D_t^{-1/2}(X_t + I)D_t^{-1/2}, \quad H_t^{(sp)} = \sigma(\hat{X}_t A_t W^{(sp)} + b^{(sp)})$$

Where D_t represents the degree, $W^{(sp)}$ trainable, σ – Activation

Temporal (GRU) for every node i across a time window $t - T + 1, \dots, t$;

$$z_{i,t} = \sigma(W_z H_{i,t}^{(sp)} + U_z h_{i,t-1} + b_z)$$

$$r_{i,t} = \sigma(W_r H_{i,t}^{(sp)} + U_r h_{i,t-1} + b_r)$$

$$\tilde{h}_{i,t} = \tanh(W_h H_{i,t}^{(sp)} + U_h(t_{i,t} \odot h_{i,t-1}) + b_h)$$

$$h_{i,t} = (1 - z_{i,t}) \odot h_{i,t-1} + z_{i,t} \odot \tilde{h}_{i,t}$$

Ensemble Deep Q-Networks (EDQN)

EDQN for VANETs is the more sophisticated machine learning (ML) technique which exploits the strength of multiple DQNs while considering concerns are specific to the nature of VANET. A VANET is a sub category of mobile ad-hoc network in which the vehicle is nodes and communicates with each other (V2V) as well as with the roadside infrastructure (V2I) to form a dynamic mesh. Nevertheless, vehicles are highly mobile leading to high dynamic network topologies which result in an unstable and unpredictable environment. The traditional DQN may not work well in this setup because of maximization bias, which is a result of the overestimation problem. This may cause the model to make wrong decisions at a large time scale. To address the above limitation, EDQN employs an ensemble — a set of independent multiple DQN agents. Each agent in the ensemble processes to calculate Q-values (the expected cumulative reward for performing an action in a particular state) simultaneously. The ultimate decision is then made based on the combined estimates that one would get like from averaging or taking minimum from the Q-values predicted by all the networks. This pooling has the effect of dulling down any over estimate from one network and results in a more stable, credible and robust decision making.

In the dynamic routing paradigm we are considering, one reformulates the routing optimization problem as an MDP where each vehicle is modeled as an agent that interacts with its environment. State space s_t encodes the traffic context including vehicle density, queue length, road occupation ratio, and link quality from the feature encoder of ST-GNN. The action space a_t is to choose a next forwarding node or path. The reward function is the performance being maximized and serves for encouraging agents to make routing decisions as if they were optimal. In traditional Q-learning, the action-value function $Q(s,a)$ is tabular, which is not practical in large-scale and changing VANETs. To address this, DQN replaced the Q-table by a neural network that takes as input state features and outputs the values of all possible Q-values so it can generalize over high-dimensional traffic states. But DQN has a problem of Q-value overestimation. To overcome this, we employ DDQN in the framework that separates the process of action selection and evaluation to mitigate bias and produce more steady routing policies. It is proposed that the hierarchical RL approach would enable routing agents to be better suited in dynamically changing vehicular environments.

Bellman optimality (target for DQN): $y_t^{\text{DQN}} = r_t + \gamma \max_{a'} Q(s_{t+1}, a'; \theta^-)$

Loss (DQN): $\mathcal{L}_{\text{DQN}}(\theta) = \mathbb{E}_{(s,a,r,s') \sim \mathcal{B}} \left[\left(Q(s, a; \theta) - y_t^{\text{DQN}} \right)^2 \right]$

Double DQN target (reduce overestimation):

$$a^* = \arg \max_{a'} Q(s_{t+1}, a'; \theta) \quad y_t^{\text{DDQN}} = r_t + \gamma Q(s_{t+1}, a^*; \theta^-)$$

- Mean Q: $Q_{\text{ens}}(s, a) = \frac{1}{M} \sum_{m=1}^M Q^{(m)}(s, a)$.
- Voting/Bootstrap: pick action by majority among $\arg \max_a Q^{(m)}$.

Ensemble target (example — average target):

$$y_t^{\text{ens}} = r_t + \gamma \frac{1}{M} \sum_{m=1}^M \max_{a'} Q^{(m)}(s_{t+1}, a'; \theta^{-(m)})$$

Policy (during training) — ϵ -greedy on Q_{ens} :

$$\pi(a|s) = \begin{cases} \text{uniform random,} & \text{w.p. } \epsilon \\ \arg \max_a Q_{\text{ens}}(s, a), & \text{w.p. } 1 - \epsilon \end{cases}$$

Afterwards, the RL framework is constructed and ST-GNNs is utilized to capture mobility-aware features from vehicular network. Both the vehicle/intersection and the communication link/traffic flow are considered as nodes and edges in the graph model. The graph is constructed at runtime from SUMO mobility traces and NS-3 communication events. Temporal dynamics are modeled by analyzing consecutive shots of the network graph, through which the model can capture traffic flow changes and vehicle mobility features over time. With graph-based convolutional operations, the ST-GNN incorporates spatial dependencies (e.g., connectivity and road topology), while temporal convolution (GRU/LSTM) capture fluctuations of traffic density and channel conditions. The output of embeddings acts as the dense feature representation for the given current routing state and fed to RL agent. This spatio-temporal encoding guarantee that the routing agent its decisions are not only informed of current network conditions, but also of historical and predictive mobility patterns.

To improve robustness and decrease variance in making decisions, the system uses a set of Q-learning agents. The above process is repeated with a difference in Random seed or preparing random sample to have several DDQN models trained. Their outputs are combined by pooling or average weighted to make the final route decision greener than per-model noise and bias. This aggregate approach results in consensus-based routing policy which makes the vehicular harmonizing system more adaptive to uncertainties in both vehicle mobility and communication channels. Thus, the ensemble mechanism can facilitate exploration-exploitation trade-off as multiple models may indicate alternative routing paths. It uses both of their observations to consider a compromise between the short-term interests (low latency and immediate delivery)

and long-term gains (less congestion among end-to-end connections). The ultimate decision is performed in the NS-3 with real-time routing emulation, and feedback is returned to the RL agents for further improvement of policies. With such shared learning model, the framework can achieve convergence to optimal routing solutions in extremely dynamic VANET environments.

Supervised link prediction loss (optional):

$$\mathcal{L}_{\text{pred}} = \mathbb{E}[\|\hat{y}_t - y_t^{\text{meas}}\|^2]$$

where \hat{y}_t could be predicted link delay / PDR.

Total loss for a single ensemble member m :

$$\mathcal{L}^{(m)} = \mathcal{L}_{\text{RL}}^{(m)}(\theta^{(m)}) + \lambda_{\text{pred}}\mathcal{L}_{\text{pred}}(\phi) + \lambda_{\text{reg}}\|\theta^{(m)}\|_2^2$$

where ϕ are ST-GNN parameters shared across ensemble members, $\theta^{(m)}$ are Q-network params, $\mathcal{L}_{\text{RL}}^{(m)}$ is DQN/DDQN MSE loss, and λ are weights.

Aggregate over ensemble:
$$\mathcal{L}_{\text{total}} = \frac{1}{M} \sum_{m=1}^M \mathcal{L}^{(m)}$$

Experimental Setup

SUMO (Simulation of Urban Mobility) and NS-3 together constitute the integrated simulation framework that is used to assess AI based dynamic routing mechanisms in VANETs. SUMO is used to create realistic vehicular traffic patterns, such as vehicle mobility traces, road topologies and traffic dynamics; NS-3 simulates the underlying vehicular communication protocols, wireless channels and routing strategies. Such two-level leveraging on realistic vehicular mobility and communication constrains provides a global view of routing schemes. In such a scenario, SUMO serves as microscopic traffic simulation tool in which vehicles are considered as mobile nodes having their own mobility models based on real scenarios in cities. The position and speed of vehicles, as well the behavior to change lanes, are simulated in SUMO. The traffic data including vehicle speed- and position-related information is then exported as mobility traces to NS-3 with interfaces such like TraCI (Traffic Control Interface). NS-3 simulates the network stack, including IEEE 802.11p/WAVE, LTE/5G NR-V2X and edge-oriented communication protocols, thus allowing a realistic representation of V2V and V2I communications. The AI-based routing decision is implemented inside NS-3 by integrating the ST-GNNs and EDQN. The performance is measured in terms of packet delivery ratio, end-to-end latency, throughput and routing overhead for the routing protocol and traffic-related parameters such as average travel time and congestion level are obtained from SUMO. Such a bi-directorial scenario guarantees that the communication efficiency and traffic mobility are both jointly studied, which can prove

the effectiveness of the proposed AI-based dynamic routing schemes for VANET applications in practice.

Table 1: Simulation Parameters

Parameter	Value
Simulation	NS3
Simulation Time	300 Seconds
Simulation region	1500 m x 1500 m
Total No of Nodes	300-500
Required RAM for System	32 GB
Transmission Range	500 m
Transmission Power	1.4 W

Performance Metrics

The performance and efficiency of the proposed method are shown in comparison with AODV and DSDV. The metrics such as PDR, PL, throughput, delay, are considered.

Packet Delivery Ratio (PDR)

The packet Delivery Ratio is mainly concentrated on the number of packets successfully delivered to the destination location. The value of PDR is computed with the below expression:

$$\text{PDR} = \frac{\sum_{a=1}^k \text{PR}}{\sum_{a=1}^k \text{PO}}$$

Where the term **PR** denotes the number of packets successfully reached the destination and **PO** denotes the number of packets originated from the sending node. The comparison of the PDR of the proposed method with two other existing methods is depicted.

Packet Loss (PL)

Packet Loss (PL) is calculated by finding the proportion of the number of packets that originated and the number of packets not received in the destination node. It can be computed by the following expression:

$$\text{PL} = \left(\sum_{a=1}^k \text{PO} - \sum_{a=1}^k \text{PNR} \right) * 100$$

Where PNR denotes the number of packets received at the destination. The comparison of PL of the proposed method with two other existing methods is depicted.

Throughput

This element plays a vital role in the 5G wireless networks. It is defined as the transmission rate of a packet from the origination to the destination. This component delivers the effect of several measures like collisions, traffic, and mobility. It is an efficient method for calculating the channel capacity of the network and it is calculated in terms of bits per second (Bit/s). The comparison of the throughput proposed method with two other existing methods is depicted in figure-10.

$$\text{Throughput} = PR * 8/\text{Data transission period (bps)}$$

Delay

Delay is the duration of time taken for a packet to travel from source to destination across the network. It is computed by:

$$D_{\text{end-end}} = N(d_{\text{trans}} + d_{\text{proc}} + d_{\text{prop}})$$

Where the term $D_{\text{end-end}}$ denotes the end-to-end delay, d_{trans} denotes the transmission delay, d_{prop} denotes the propagation delay and d_{proc} indicates the procedure delay. In this case, buffering delay is neglected. The comparison of the delay of the proposed method with two other existing methods is depicted.

Results and Discussions

The comparative performance of various routing algorithms in a VANET environment with 50 nodes is given in Table 1. It measures the adherence time in four network performance metrics which concerns Packet Delivery Ratio (PDR), Packet Loss, Throughput, and Network Delay. The PDR of 80.34% with a packet loss of 12, throughput at 84.34% and average delay of 22.12 ms is obtained by the baseline algorithm AODV. According to its reactive nature that make it widely applicable in other fields, but its performance deteriorates while applied to highly dynamic traffic scenarios where it has higher delay and loses packets. Chameleon-QOS-AODV / Chameleon-GPSR (TOM) performs the most with 90–95 % PDR and 88.92% throughput, as well as decrease in delay to 20 ms due to its adaptive parameter tuning mechanism that allows it to manage different traffic and mobility patterns. The RBMOORP-POA protocol improves the stability of the network, and 94% packet delivery ratio (PDR) with only 8 packets lost can be reached as well as throughput of 94%, and delay is reduced to 17ms. The BEAM with Clustering Extensions protocol achieves a PDR of 93% (with only 6 packet losses), throughput of 91% and intermediate delay, i.e. 16 ms. Clustering contributes towards improving network reliability by means of reducing end-to-end delay over short paths. Compact specification reduces routing overhead and improves efficiency in multicast communications. Finally, the proposed Hybrid AI Routing (ST-GNN + Ensemble DDQN) is superior to all exist methods with the highest PDR (96.98%) and throughput (94.21%), and the least 8 packet losses, 13.45 ms network delay, which owes to that Spatio-Temporal GNNs for feature extraction and Ensemble Deep Q-learning for decision optimization allows effectively capturing mobility patterns and network dynamics in routing model. Accordingly, the combined AI-based model is characterized by high reliability,

fast packet delivery and lower latency, which form it to be a potential solution for VANETs real-time applications.

Table 1: Performance of Table for Network with 50 Nodes

Algorithms	PDR (%)	Packet Loss	Throughput (%)	Network Delay
AODV	80.34	12 pkts	84.34%	22.12 MS
Chameleon-QOS-AODV / Chameleon-GPSR (TOM variant)	90-95	10 pkts	88.92%	20 MS
RBMOORP-POA	94	8 pkts	94%	17 MS
BEAM with Clustering Extensions	93	6 pkts	91%	16 MS
Hybrid AI Routing (ST-GNN + Ensemble DDQN)	96.98	8 pkts	94.21	13.45 MS

Conclusion

This paper shows that the AI-enabled dynamic routing model is efficient and effective in VANETs by combining ST-GNNs with an EDQN model. The system was implemented using the SUMO for mobility trace generation and NS-3 as a network simulator to emulate both vehicular dynamics and communications at run-time. The ST-GNN succeeded in encoding spatial and temporal correlations of the vehicle network, and ensemble DDQN agents optimized routing decisions through the exploration exploitation trade-off strategy for robust as well as a flexible path selection. Comparative studies with existing algorithms like AODV, Chameleon-QOS-AODV / GPSR, RBMOORP-POA and BEAM with clustering extensions demonstrate the better performance gain of this bedtime model. The former could not fare well under larger delay and packet loss where the later, OVERPROTOCOL which was optimization based could overcome set of errors yet at a very high price with increase in computational complexity. The performance of the hybrid AI-driven model showed excellent PSO-models for packet delivery ratio (96.98%) best, network delay (13.45ms) least and throughput (94.21%) superior to all other models based on existing methods in all tested indices. Last but not least, the presented

architecture provides a scalable, dependable and intelligent routing solution for VANETs of the future. Integrating deep spatio-temporal feature learning with reinforcement learning-based decision making, it not only solves problems in vehicular settings but also serves as a building block for future 5G/6G-assisted V2X communication systems. The next step would be to integrate the edge computing into VANET routing (Huang et al., 2019), adversarial robustness, and real-world deployment validation, toward making VANET routing more resilient, efficient, and adaptive in smart transportation systems.

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