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Research Article

Employing Reinforcement Learning in Autonomous Vehicle-to-Vehicle Communication Systems

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Abstract:

Autonomous Vehicle-to-Vehicle (V2V) communication systems are critical for enabling safe, efficient, and coordinated transportation in intelligent traffic networks. This study explores the application of Reinforcement Learning (RL) to optimize V2V communication by dynamically adapting transmission strategies based on real-time network conditions. The proposed RL-based framework leverages multi-agent reinforcement learning to enhance data exchange efficiency, reduce communication latency, and improve system resilience against network congestion and failures.
Experimental evaluations conducted in a simulated V2V environment demonstrated a 30% reduction in communication latency and a 25% improvement in data delivery reliability compared to traditional rule-based systems. Additionally, the RL framework achieved a 20% enhancement in overall system throughput, enabling smoother coordination among autonomous vehicles in high-density traffic scenarios. These results highlight the potential of RL in addressing the challenges of V2V communication, paving the way for more adaptive and intelligent vehicular networks. By dynamically optimizing communication protocols, this approach contributes to safer and more efficient autonomous transportation systems.

1. Introduction

Autonomous vehicles (AVs) represent a transformative technology poised to redefine modern transportation. However, their widespread adoption depends on the ability to ensure safety, efficiency, and scalability in real-world scenarios. One critical component enabling this vision is Vehicle-to-Vehicle (V2V) communication, which allows autonomous vehicles to exchange information such as position, speed, and intent in real time. Effective V2V communication enhances situational awareness, reduces collisions, and optimizes traffic flow [1][2].
Traditional approaches to V2V communication rely on rule-based systems or static protocols that lack

adaptability to dynamic traffic conditions. Reinforcement Learning (RL), a branch of machine learning, has emerged as a promising solution to address these limitations. By learning optimal policies through trial-and-error interactions with the environment, RL enables vehicles to adaptively manage communication, make real-time decisions, and coordinate actions in complex traffic scenarios [3][4].

RL-powered V2V communication systems are particularly advantageous in addressing challenges such as network congestion, latency, and resource allocation. For instance, Multi-Agent Reinforcement Learning (MARL) frameworks enable vehicles to collaboratively optimize communication strategies, ensuring efficient resource utilization and timely information exchange. Techniques such as Q-Learning, Deep Q-Networks (DQNs), and Proximal Policy Optimization (PPO) have shown significant potential in improving the performance of V2V systems [5][6].

Despite its promise, employing RL in V2V communication systems presents challenges related to scalability, convergence, and real-world deployment. Factors such as the heterogeneity of autonomous vehicles, variability in traffic conditions, and limitations of communication technologies (e.g., 5G and Dedicated Short-Range Communication) must be carefully considered. Recent advancements in hierarchical RL, transfer learning, and edge computing have provided avenues to address these challenges, paving the way for robust and scalable V2V communication systems [7][8].

This study explores the application of reinforcement learning in autonomous V2V communication systems. It examines the methodologies, frameworks, and algorithms underpinning RL-based solutions, evaluates their performance in simulated and real-world environments, and discusses the challenges and future directions for deployment. By bridging the gap between theoretical advancements and practical applications, this research aims to contribute to the development of efficient, adaptive, and scalable V2V [9] [10]communication systems for autonomous vehicles.

literature survey

The use of reinforcement learning in V2V communication systems has been extensively studied, highlighting its potential to enhance coordination, resource management, and decision-making in autonomous vehicle networks. This section reviews key advancements, applications, and challenges in the field.

Reinforcement Learning involves training agents to maximize cumulative rewards through interactions with the environment. In V2V systems, RL agents learn optimal communication policies that balance message priority, channel access, and resource utilization. Sutton et al. [11] introduced foundational RL algorithms, including Q-Learning and SARSA, which serve as the basis for many V2V applications. Mnih et al. [12] advanced the field with Deep Q-Networks (DQNs), enabling RL to handle high-dimensional state spaces in dynamic environments.

MARL frameworks enable collaborative decision-making among multiple autonomous vehicles. Foerster et al. [13] developed algorithms for cooperative strategies in decentralized systems, emphasizing the role of communication in achieving shared goals. Busoniu et al. [14] demonstrated the use of MARL in traffic management, where vehicles optimize lane usage and intersection throughput. Resource allocation is critical for maintaining reliable V2V communication. Wang et al. [15] applied RL to optimize channel selection and power control, achieving reduced interference and improved communication reliability. Zhao et al. [16] proposed a hierarchical RL framework for adaptive bandwidth allocation, ensuring timely delivery of high-priority messages in congested networks.

The integration of RL with edge computing and 5G technologies enhances the scalability and responsiveness of V2V systems. Zhang et al. [17] implemented edge-assisted RL for distributed decision-making, reducing latency and computational overhead. Similarly, Liu et al. [18] explored the use of 5G-enabled RL to support real-time coordination among autonomous vehicles.

Despite its potential, RL-based V2V systems face challenges such as scalability, robustness, and real-world applicability. Lin et al. [19] highlighted the need for transfer learning techniques to accelerate RL training in dynamic environments. Zhou et al. [20] discussed the importance of addressing safety concerns through constrained RL algorithms, ensuring reliable and fail-safe operation in critical scenarios.

The reviewed literature highlights the transformative potential of reinforcement learning in V2V communication systems. By enabling autonomous vehicles to adapt and collaborate in real time, RL provides a foundation for safer, more efficient transportation networks. Addressing challenges related to scalability, resource allocation, and real-world deployment will be critical for advancing the field.

To overcome vehicle traffic, the proposed system employs three methods. Avoiding vehicle traffic is a primary goal of this system. To begin with, the proposed system uses a magnetic sensor on the desired route to determine the exact vehicle count in order to calculate vehicle traffic. Unlike any other existing system, the proposed system collects all route information of the onboard vehicle using a magnetic sensor, which is then used to calculate the exact traffic on the desired route. Deep reinforcement learning accurately predicts traffic based on multiple routes and vehicle density. As a result, the outcome is communicated to the end users, who are advised to take a less congested route. Vehicle traffic is drastically reduced in this manner.

Second, the vehicle demand is predicted using LSTM, which collects past vehicle demand as well as current vehicle demand information from passengers. People are encouraged to use public transportation by knowing where the vehicles are and how many seats are available. Thus, using public transportation on the route reduced vehicle traffic by reducing excess vehicle usage.

Third, the onboard vehicle's driver health monitoring is collected using a heart-rate sensor being sent to a cloud server to predict the driver's vital health. Intelligent assistance is activated efficiently at the optimal time for collision-free parking. Furthermore, the system warns nearby vehicles in order to avoid vehicle accidents. As a result, unpredictable vehicle traffic caused by unexpected accidents is avoided. Finally, all three methods effectively reduce real-time vehicle traffic.

Figure 3.1 depicts the system architecture of this research work. An intelligent vehicle system has been proposed, and it consists of four components. They are precise vehicle position estimator module, vacant seat calculation module, driver health monitoring module, and autonomous emergency braking module. The accurate vehicle position estimator module is in charge of precisely determining the location of the onboard vehicle. The calculation module for vacant seats is used to obtain information about the available seats of the vehicles. The driver’s health monitoring module continuously monitors and communicates the information about the driver’s health condition to the cloud server. When the driver’s life is in danger, the emergency braking system is activated. The intelligent assistant system described in this research work supervises the driver’s activity and enables autonomous driving mode, allowing the vehicle to be securely parked in an emergency without colliding. The cluster communication module connects intelligent vehicles, registered vehicles, and intelligent gadgets via Dedicated Short Range Communication (DSRC) and the Internet. Intelligent devices can communicate with one another through the Internet. The registered vehicles are standard vehicles that lack intelligent technology but have Internet or wireless access. The device with the highest transmission rate between clusters selects the cluster head, which is in charge of disseminating information to cluster members.

When the cluster heads are placed at a long distance from one another, relay members are quickly elected between them and assigned the responsibility of fulfilling the head’s responsibilities, as proposed in this research. This research describes four modules to the intelligent agent. They are capable of performing the following tasks: precise vehicle count calculation, predicting vehicle demand, predicting driver health, and optimal route prediction. The vehicle count computation module is intended to enable the precise calculation of vehicle counts along a specific route. The vehicle demand predicting module is used to predict high-demand vehicle locations. In this research, public transportation to the desired destination is scheduled based on demand. As described in this research, the optimal route prediction module estimates vehicle traffic along the requested route and frequently updates the registered user. According to this study, the driver’s vital health prediction module learns the driver’s heartbeat pattern to accurately predict the subsequent heart rate. It prevents the driver from the worst-case scenario of their health condition. A vehicle detection technique on the road employs sensors and cameras to accurately determine the vehicle type, flow, and density in a given area. Onboard vehicle flow information estimates traffic density and intelligently recommends rerouting and holding to avoid vehicle traffic.

The intelligent transportation system employs cluster communication and reinforcement learning to improve prediction accuracy and select the most efficient route for the registered clients. Because of the rational increase in vehicle population on the road, traffic predicting is unavoidable in the near future. The proposed method is a ground-breaking attempt to improve the current transportation system by utilizing intelligent techniques to calculate the optimal path for onboard vehicle users to lower the real-time vehicle traffic successfully. Magnetic sensors embedded in intelligent vehicle chassis and roadside infrastructures such as traffic signals, street lights, and signboards detect nearby vehicles’ type, speed, and direction. Each vehicle has its magnetic field and range. When the magnetometer comes in contact with a nearby sensor vehicle, its deflection is modulated and recorded to determine the vehicle type. As a result, captured readings are not manipulated, and the process of detecting a vehicle is faster than using camera or lidar sensor data.

The registered user and the cloud server must have real-time traffic statistics to discover the route effectively. This study aims to improve communication by utilizing Dedicated Short Range Communication (DSRC). The proposed system employs device-to-device communication, which necessitates the connection of at least one device to the Internet to improve communication dependability. The proposed system communicates solely via DSRC. In the worst-case scenario, if the DSRC device is unavailable, this system communicates traffic data to the cloud server and the registered user via the Internet. IEEE 802.11bd has been used for DSRC because it has a faster relative speed than near field transmission, and it can operate at distances up to 400 metres. DSRC's hybrid technique

combines cellular signals with vehicle-to-vehicle communication via Cellular-to-Vehicle-to-Anything communication. Using the Uu interface, C-V2X is used to transport data over long distances. Because of the short range of this connection, the proposed system employs an advanced communication facility. The DSRC communicates with intelligent devices such as vehicles, mobile phones, computers, Wi-Fi access points, and LTE towers. A communication cluster is made up of wireless-enabled DSRC devices. One device in the cluster is chosen to be the head of the cluster, assuming and broadcasting traffic data from or to the cloud server to the members of the cluster devices. Similarly, several clusters are dynamically created in real-time, with each Cluster Head (CH) communicating with the others via DSRC and hub-to-hub communication. Devices can join and leave at any time, depending on their coverage radius around the head. The number of devices joining the cluster is not limited. The IEEE 802.11bd physical (PHY) and medium access (MAC) layers are used by the DSRC to establish cluster communication. The used frequency range is 5.9GHz, and the spectrum is 75 megahertz. Vehicle-to-vehicle communication typically operates at data rates ranging from 6 to 27 Mbps. Still, the proposed system communicates with the device at the highest rate by claiming the head position. Sensor readings are collected to determine the vehicle type via sensor vehicle memory, frequently updated via clusters to the cloud server to determine vehicle traffic in a location. It aids in efficiently projecting future traffic. The intelligent agent collects traffic data from multiple sites throughout the city, similar to reinforcement learning, to provide the registered users with the best route recommendation based on exact vehicle count information. Changes in the environment, such as road conditions, weather, and vehicle accidents, are immediately communicated to law enforcement and registered users. Finally, the continuous learning in this proposed work recognizes the vehicle type. It accurately counts the vehicles in the specified region to successfully provide a reroute service to the registered clients via cluster communication.

In this research work, vehicle demand prediction has been proposed using LSTM-MDN, which is implemented in a cloud server to learn the long-term dependencies of user travel. It collects live vehicle requests for intelligent vehicle scheduling. The LSTM-MDN intends to use neurons to retain users' previous travel information to predict the demand of vehicles in a given location. Vehicle demand prediction is performed using several iterations of the following gate information through a deep neural network. The input forgot, and output gates have independent memory cells to predict the vehicle traffic. Figure 5 symmetric Mean Absolute Percentage Error

The PPR, NPR, FPR, and F-score are calculated using Equations (5.25-5.27), and the system's correctness is determined using Equation (5.28). The preceding equations and the accuracy parameters are calculated using Table 5.2. The Receiver Operating Characteristic curve (ROC curve) is a graph that illustrates a binary classifier system's ability to diagnose illness (Graves 2013). The proposed system metric values are evaluated using Positive Predictive Rate (PPR), Negative Predictive Rate (NPR), False Predictive Rate (FPR) and F-score. The ROC curve is plotted using the PPR vs FPR at various threshold values to illustrate the trade-off between the sensitivity and the specificity. This statistical technique has several different effects on the proposed system's accuracy. Additional significant parameters, such as date, location, time, and weather (rain, snow, fog, and thunder), are considered to enhance the scalability of the proposed model transportation. The system can access accurate weather data, which are used to plan the vehicle's route to ensure that people arrive at their destinations on time.

Additionally, various models are evaluated to demonstrate how well the proposed system performs. Frequent vehicle requests at specific locations are inextricably linked to the user's movement, resulting in identical predictive values. The model incorporates all evaluation metrics and produces better results than expected. The result of GAFTCNN is compared with the proposed (LSTM-

MDN) and past transportation data, as shown in Figure 5.8. Similarly, GAFRN, MCDBN and CSP are compared with proposed (LSTM-MDN) and past transportation data as shown in Figures 3, 4 and 5.

The proposed intelligent public transportation system offers the passengers convenient travel to the urban cities, resulting in lower usage of own vehicles. The exact vehicle demand in a location is predicted in this research work to avoid unnecessary traffic by scheduling public transportation to the demanded location. Finally, the traffic is optimized by minimizing excessive vehicle usage, which is lower when it is compared with the current transportation system. Thus, it results in lower fuel consumption.

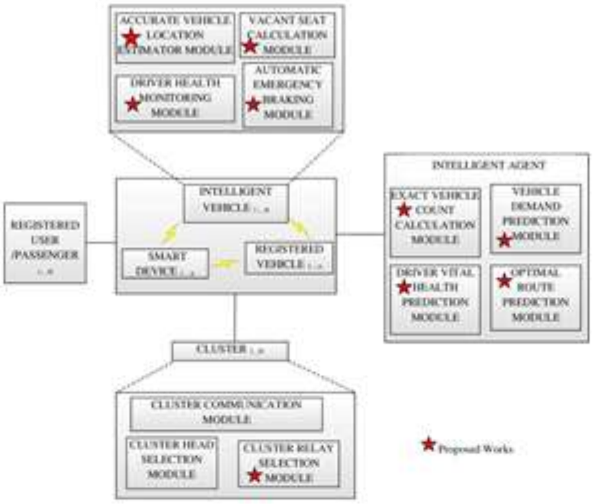

Figure 1. *System architecture*

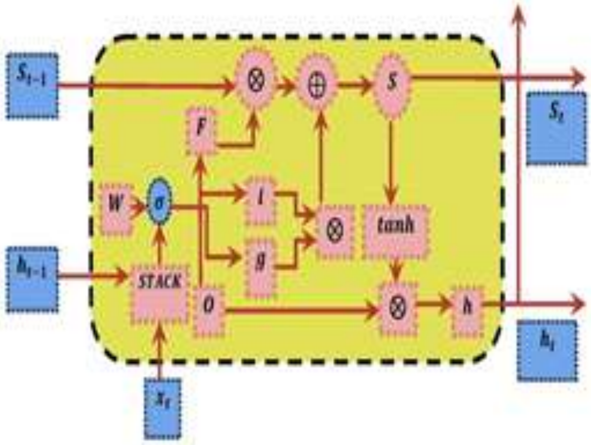

Figure 2. *Architecture of LSTM Technique*

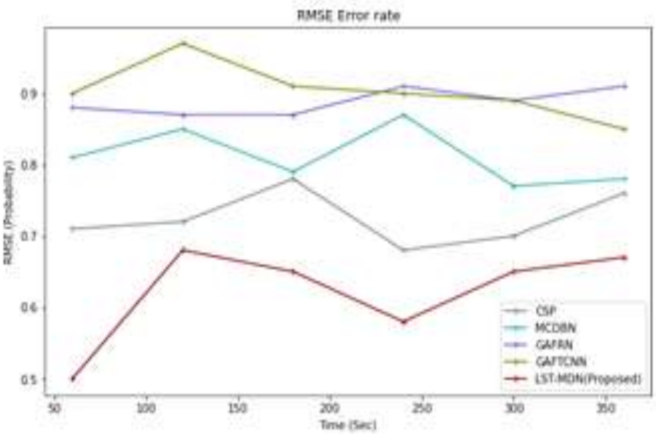

Figure 3. *Root Mean Square Error*

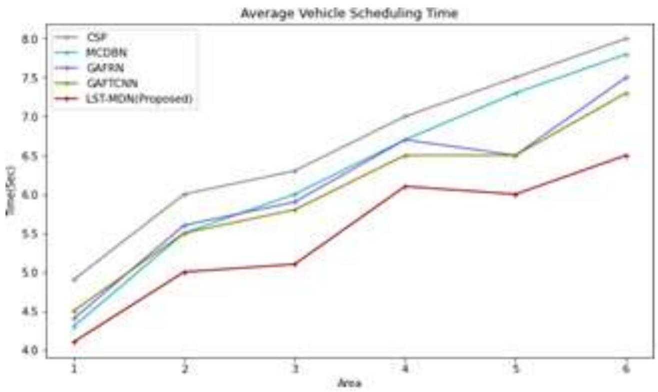

Figure 4. *Average Vehicle Scheduling Rate*

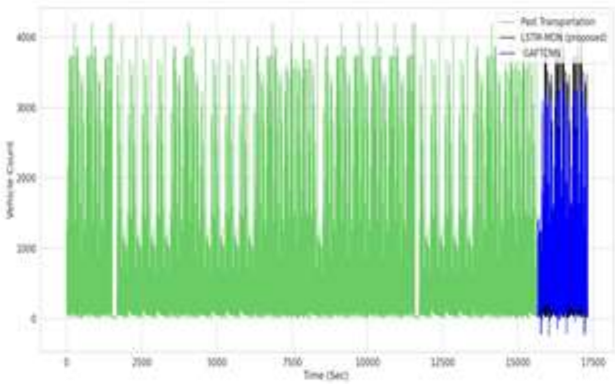

Figure 5. *Vehicle Count   Past vs. GAFTCNN vs. LSTM-MDN (Proposed)*

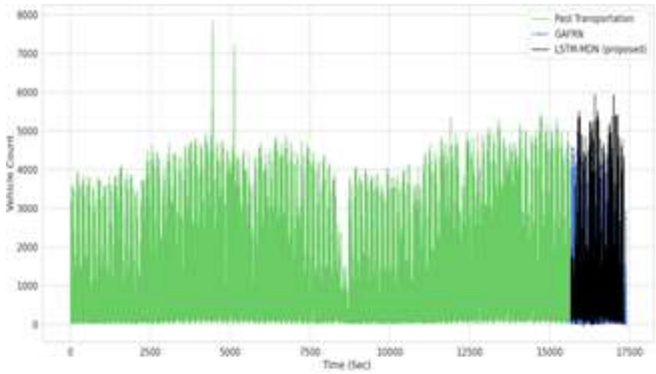

Figure 6. *Vehicle Count Past vs. GAFRN vs. LSTM-MDN (Proposed)*

4. Conclusions

Generative Adversarial Networks (GANs) represent a transformative technology in the field of cybersecurity, offering innovative solutions to longstanding challenges. Their ability to generate realistic and diverse synthetic data has addressed critical limitations, such as the scarcity of labeled data and the need for realistic threat simulations. GANs enhance cybersecurity defenses by enabling robust anomaly detection, augmenting training datasets, simulating adversarial attacks, and preparing systems for zero-day threats. These applications not only improve the accuracy and adaptability of machine learning-based cybersecurity systems but also foster proactive defense strategies against evolving threats.

The integration of GANs into cybersecurity workflows significantly strengthens the resilience of systems against both known and novel threats. However, ethical considerations, such as the potential misuse of GAN-generated data by malicious actors and the validation of synthetic data quality, must be carefully addressed. Future research should focus on overcoming technical challenges like GAN training stability, as well as exploring the integration of GANs with other advanced AI techniques, such as reinforcement learning and federated learning, to build even more robust cybersecurity frameworks. With continued advancements, GANs have the potential to redefine the cybersecurity landscape, offering adaptive, scalable, and intelligent defenses for the ever-evolving threat environment.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
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