An Efficient Routing Mechanism for IOT Using Deep Learning

Pranjal Maurya[1], Sangeeta Devi[2], Rajan Kumar Yadav[3], Munish Saran[4], Upendra Nath Tripathi[5]

[1,2,3,4,5] Department of Computer Science, Deen Dayal Upadhyaya Gorakhpur University, Gorakhpur, Uttar Pradesh, India

Abstract:
Combining WLAN with ad hoc networks, Vehicular Ad hoc Networks (VANETs) are a new and exciting area of study. VANETs consist of many different entities that must coordinate with one another and with other services in order to function properly. Routing problems and security breaches are only two of the common problems that plague VANETs. Existing literature has a number of solutions to these problems, but most of them don't address routing and security problems at the same time. In this paper, we identify the restrictions imposed by routing behavior, such as control overhead, convergence, and erroneous location, and we use those constraints to determine the best paths for ensuring that no vehicles or packets collide with one another. Intrusions on the security of routed packets or vehicle nodes necessitate a selected security mechanism to ensure the privacy of sent information. To reduce this additional control load, we create a routing system based on Deep Reinforcement Learning (DRL). The DRL speeds up convergence on dynamic vehicle density by optimizing the routing path. The DRL keeps a close eye on the transmission capacity and vehicles to analyze and anticipate routing behavior. As a result, V2I communication shortens the time it takes to transmit data by having the vehicles in close proximity transport the packets

Keywords: Machine Learning,Deep Reinforcement Learning,VANET, WAVE Architecture, IoT.
DOI: 10.24297/j.cims.2023.7.11

1. Introduction

VANETs are rapidly expanding their ad hoc network infrastructures via which cars are linked via wireless communication (Liang et al., 2018). In recent years, VANETs have been implemented to increase road safety, facilitate traffic flow, lessen congestion, and better direct drivers. On-board units (OBUs) and roadside units (RSUs) provide for effective two-way communication between cars and infrastructure in vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) systems. In addition, OBUs, RSUs, and TAs—the three building blocks of VANETs—are discussed in detail below. In VANETs, automobiles are able to talk to base station units (RSUs) thanks to a wireless technology standard called Wireless Access in Vehicle Environment (WAVE). WAVE communication promotes the safety of passengers by providing them with up-to-date information about traffic and vehicles, as described by the WAVE architecture [1]. The software enhances the efficiency and effectiveness of traffic operations while also protecting pedestrians. The OBU, TA, and RSU make up a VANET, with the RSU hosting an application for inter-device communication and the OBU being mounted on the VU to gather data about the vehicle (such as its speed, position, and fuel level). To reach adjacent automobiles, these details are broadcast across a wireless network. Every RSU in a group has a direct wired connection to TA as well as to each other RSU in the group. VANET authentication is also the responsibility of the TA [2].

To begin, road safety apps [3][4][5] are designed to help drivers avoid accidents and decrease the number of people killed in collisions. Due to the time-sensitive nature of these applications, traffic data should be provided without delay. All cars must have a high degree of dependability, as this feature is intrinsically linked to the danger light. Figure 1 demonstrates some of these uses, such as lane change assistance and collision warning.

There are further apps for traffic management and efficiency that aim to increase speeds and efficiency by installing adaptive lighting and delivering real-time data on traffic conditions in specific areas. Due to the importance of the information supplied to the drivers, most applications in this category have a high availability.

These programs primarily deal with speed management and collaborative navigational systems. Drivers can save time and fuel with the assistance of the Speed Management System [6]. When it comes to the regulation/contextual speed limit notice and the green light, this method offers the best speed advice to associated drivers. Vehicle navigation management via V2V and V2i communications is facilitated by the Cooperative Navigation System [7][8][9]. Infotainment applications are also classified as non-safety sectors that increase passenger comfort and make travels more appealing for drivers and passengers [10][11]. In order to give drivers access to relevant information at the correct time, these apps often need to be reliable, available, and connected.

Fig.1. Applications of VANETs

Multiple routing methods exist for assigning unique logical addresses to cars; however, existing routing protocols do not prevent the assignment of duplicate addresses within vehicle networks. There are several challenges that the VANET must overcome, including those related to its setup, population, number of cars, patterns of vehicle movement, random vehicle movement in and out of the network, and road dimensions smaller than transmission cover. Finding and keeping track of the best path for data packets to take between nodes is the primary focus of the routing algorithm. Since VANETs employ the unique routing protocols of MANETs, their operations are intricate due to the unpredictable behavior of mobile nodes. Topology-based routing techniques require a distinct identifier for each node in the network. Therefore, a protocol is needed to issue unique identifiers, but there is no assurance that there will be no overlapping assignments inside the network. Because of differences in network architecture, mobility model, traffic volume, rate of change, and road width, MANET algorithms are unsuitable for VANETs, and conventional routing protocols are not definitive enough to address these unique challenges. Routing table driven and routing process launched by the source on demand are the two primary methods used by most routing protocols for creating ad hoc intrinsic networks. Table-driven routing, also known as proactive routing protocols, keeps track of how to get from one network node to another. With these protocols in place, any node can reliably and regularly provide an updated map of the whole network. Proactive routing protocols offer the advantage of not having a low latency in real time, which results in wasted data pathways that minimize available bandwidth. This is because the destination route is stored in the background.

Higher VU mobility typically results in dynamic network topology changes, making the connection relatively stable in VANETs. However, the constraints are mostly caused by transmission and interference from vehicles. When the sending VU is far away from the receiving VU, the data packets between them must take more circuitous routes to reach their destination. However, there is no other vehicle in range until the nearby car enters the communication range. However, in cases when packets are transferred in this manner, the transmission latency is increased as a result of the packets' passage across the network. Delays may often be avoided by selecting densely populated stretches of route. This is typically taken into account while developing the routing protocol. Multiple routing protocols for a wide range of needs have been established. Some routing systems take into account the density of vehicles on the road while making their decision. This detection keeps happening, and that's the problem. Once the data on vehicle density has been gathered, it is shared with other cars. This results in a rise in bureaucratic micromanagement. Additionally, it takes more time to keep convergence while the vehicle density is shifting. Thus, machine learning models can help in VANET route selection. RSU uses machine learning to make predictions about upcoming vehicle movements and transportation data. Vehicle presence can be assessed within its range of communication. By making the right assumptions, this guarantees that the packet takes the shortest or most efficient route possible. Using data from the present and the past, the machine learning model makes forecasts about the future. The protocol includes these forecasts to ensure efficient navigation. The goal of this research is to track, examine, and forecast vehicle behavior in terms of capacity and accessibility using a model for DRL. RSU monitors DRL traffic data to optimize the network for higher throughput. The DRL estimates the time it will take to transmit data based on the current location of the vehicle. A real-time scouting unit (RSU) and the V2I routing protocol are used to locate the nearest vehicle-to-vehicle packages.

2. Related Work

Digitization has various fields including client relationship the executives, bioinformatics, picture preparing, man-made brainpower and illustrations. Information mining can assume a focal part towards the CRM, subsequently, information mining analysts communicated on CRM research and applying information mining strategies to critical administration of client relationship information for the client arranged system. In [12], authors implemented Q-learning fuzzy constraint-based Adhoc On-demand Distance Vector (AODV) routing. By considering multiple parameters, including bandwidth, link quality, and relative velocity of the vehicle, the protocol employs a smooth logic for determining whether or not wireless connections are satisfactory.

Time-Ants is an optimization technique developed by [13] that is based on the work of ant colonies. Time-Ants theorizes that a certain number of pheromones or traffic are allotted to each hour of the day. An advanced algorithm in real time decides which roads to go based on these traffic assessments. After further refinement, the resulting global transportation system is ideal. Bottlenecks may be avoided and detected with the use of machine learning.

Tang et al. in [14] propose a software-based AI-based network controller to provide a centralized routing system with mobility prediction for VANET. In particular, if the SDN controller has access to cutting-edge artificial neural network technology, it can accurately forecast mobility. Based on the mobility prediction, the RSUs and BSs may calculate the likeliness of a successful transmission and the typical latency of a vehicle request. Authors in [15], investigate the relay routing problem for car helpers. In this research, we created a relay routing algorithm for stationary VUs, which include the following steps: the periodic Hello Packet Exchange Mechanism; the updating of the applicant relay list; the evaluation of the quality of the communication connection; and the selection of the applicant relay list. To mitigate buffered packet loss over long distances and maintain a constant connection to RSUs, Marchang et al. in [16] designed a local route repair.

Akila and Iswarya's in [17] data replication method To control the flow of requests for access to VANET-related data like position, velocity, and fuel level. High-mobility cars cause VANET topologies to fluctuate, leading to frequent disconnections. Vehicles' ability to talk to one another and share information is hampered if and when connections are lost. In order to boost data access speeds, the distributed system makes advantage of data replication. Customers may now access internet services over VANETs thanks to the TA created by [18]. Therefore, it is crucial to ensure that the messages exchanged between TA and VANETs remain private and legitimate. For the purpose of tracking and monitoring VANET disorder, authors in [19] implemented an EAAP strategy to protect against malicious VU. In VANETs, bilinear pairing is formed by the use of TA to ensure that vehicles and RSUs remain anonymous.

In order to protect against eavesdropping, Zhang et al. in [20] presented a novel approach based on one-time authenticated asymmetric group key for building cryptographic mix zones. In order to ensure the safety of data sent over the cloud, Zhang et al. in [21] created a secure communication system. This method employs a fleet of automobiles connected by VANETs to form a resilient and adaptable virtual community. After the formation of the VC, all vehicle resources may integrate and exchange data safely, and any cloud user can process their data safely in the cloud. To assure the security of password-based authentication and group keys, Islam et al. in [22] have created the VANET system protocol PW-CPPA-GkA. Output, user input, and password updates are just a few of the capabilities of this system. The protocol's scalability comes from the elliptic curve approach, which was created without bilinear combination.

Security and entertainment are only two of the many uses for VANETs. Infotainment applications often demand road safety applications to decrease transmission time and attain high reliability, with common performance indicators including resource utilization, pack loss, and justice. Different quality of service measures may work against one another in some communication contexts, such as highly interconnected automobiles, which might raise the packet loss ratio due to channel congestion and interference. Different traffic data should be taken into account when making the appropriate QoS routing choices with varied QoS thresholds to accommodate a wide variety of applications.

3. Problem Statement

Multiple routing protocols for a variety of objectives have been created to this point. In certain procedures, the density of vehicles on the road is used to determine the most efficient route. The incidence of such detection is the issue. After locating the density data, the vehicles share the findings to improve their control from above. In addition, the time needed to converge increases when the vehicle density fluctuates at a high rate.

This causes problems with the routing protocol's efficiency by providing erroneous data in real time. Finally, it has been observed that because the routing protocol includes a per-hop computation, cars that get only information from their next or subsequent road segment lead to an optimal local issue.

For these reasons, route selection in VANETs can benefit from the application of machine learning models. The RSUs, with the aid of machine learning, can stop traffic and vehicle movement. Vehicles within its range of communication can have their potential danger assessed. In this way, the packet is guaranteed to be routed through the most efficient and least time-consuming path possible. Based on historical data and the present state of the vehicle, the machine learning model makes a prediction as to the outcome. An effective routing protocol may be determined from such a prediction.

As with other wireless sensor networks, chartered and multiple charted security threats are a major concern for VANETs. There is a risk that the sent communication will be intercepted, faked, or flooded with malicious software that reveals the victim's data to the attacker. This raises worries about privacy exposure, because VANETs can only guarantee security and privacy if users are authenticated. However, VANETs' dispersed and mobile nature makes their authentication methods susceptible to a number of security flaws. Additionally, these techniques are intended to protect sensitive information without the use of routing metrics, which are regrettably not supplied by the security mechanism due to the complexity and variability in user requirements for Quality of Service (QoS). As a result, the transmission and reception of the message require an improved authentication system.

4. Proposed Routing Protocol

As with other wireless sensor networks, chartered and multiple charted security threats are a major concern for VANETs. There is a risk that the sent communication will be intercepted, faked, or flooded with malicious software that reveals the victim's data to the attacker. This raises worries about privacy exposure, because VANETs can only guarantee security and privacy if users are authenticated. However, VANETs' dispersed and mobile nature makes their authentication methods susceptible to a number of security flaws. Additionally, these techniques are intended to protect sensitive information without the use of routing metrics, which are regrettably not supplied by the security mechanism due to the complexity and variability in user requirements for Quality of Service (QoS). As a result, the transmission and reception of the message require an improved authentication system. The re-routing takes place in a city setting. But with the help of DRLs, RSUs can provide superior traffic data and status updates. The suggested strategy does not rely on any sort of conventional routing protocol. DRL is used to forecast the growth or decline in traffic volumes, as well as the paths these vehicles will take on the roadways. When the DRL driver is contacted, the routes are chosen dynamically based on transmission capacity and success probability. The system is learned from the vehicle's velocity and motion relative to the surrounding RSU. Incoming RSU units trigger real-time data refreshment. In addition to wireless communication, the RSUs in the research area are connected together so that data from incoming vehicles may be shared. In doing so, information about the arrival, including its position and velocity, may be sent to nearby RSUs. GPS has a hard time pinpointing moving vehicles because of the Rapid motion is achieved by vehicles. It's challenging for a GPS to keep up with a moving car when data is sent in hop-by-hop packets. GPS locations raise serious privacy and safety concerns. The suggested approach utilizes deep strengthening learning to circumvent this problem. The suggested method is broken down into the Route Formation Stage (RFS) and Route Choice Stage (RCS) stages. Both the RFS and the RCS employ DRL to choose the best routes possible.

Route Formation Stage (RFS)

In the first phase, packets are routed through RFS to a nearby VU. The packets essentially contain information on the present location, proximity to the neighborhood, vehicle density, and travel path of the car in question. Information on the location, density of the network, and latency in a given area are all provided by the intermediate node. With the help of the intelligent system, the intermediate nodes may be chosen in such a way that the correct path is taken via the several hops until the final destination is reached.

Proposed Algorithm-1

Begin

Input: Current position, distance to nearby vehicles, vehicle density, route, delay, and intermediate position are inputs.

Output: The formation of a Route

First Step: To set the initial values.

Second Step: To construct the best possible path with DRL by picking good inputs.

Third Step: To assume optimum routes and collision avoidance,

Fourth Step: To form the route.

End

Route Choice Stage (RCS)

The DRL route determines the best possible routes based on historical data. The DRL's ability to foretell the next TPM is put to good use in the efficient computation of optimum paths. We have here a classic supervised learning problem. The DRL projects the best possible routes for the future based on the results of future TPMs and an effective mapping technique. The DRLs get knowledge of the TPM via the mapping approach and from observation. In DRL, the agent has repeated interactions with the vehicle's surroundings. Time slots (t) and sub segments of the route are further divided into smaller intervals of time. At each time slot (s), the agent first takes stock of the current state (c_s-1) before deciding which action to take from a predetermined pool. The traffic pattern shifts from (c_s-1) to (c_s) once you select the corresponding action (a_s). Then, depending on whether the deed was good or poor, the agent receives a reward (r_s) or punishment (p_s). This enhanced model for states and actions is referenced from Cheng et al. (2017), from which DRL learns the mapping.

Proposed Algorithm-2

Begin

First Step: At time t, the agent i.e. operator utilizes TPM and optimum routes of observations from previous iterations to anticipate the future routing strategy R(s) (reward or penalty). The current state is what is being referred to here.

Second Step: The observed TPM is utilized to alter the current state, denoted by TPM(s), and the reward is obtained, denoted by r(s) = − u(s)/O(s), where u(s) is considered the maximum use of the connection under the future routing method. We define the optimal use of the connection as R(s) for the current TPM(s) and O(s) with respect to D(s).

Third Step: DRL uses the state and action function to forecast future routing methods that maximize the expected reward, hence identifying the best routes.

End

5. Experimental Work And Discussion

The efficiency of the suggested approach is measured using the simulation program NS-2 (2.35). The simulated region is between a thousand and a thousand square meters in size. With the help of VanetMobiSim, we can model how cars and trucks operate in a metropolitan setting. Here, RSUs travel at varying rates, anything from 5 to 30 meters per second. The maximum range is 250 m, and the transmission power is adjusted accordingly. The packets have a fixed size of 512 bytes and are sent via CBR from the source node. Data speeds are affected by several factors towards the end of reception, such as the fading channel and the distance between the sending and receiving vehicles. Data connections and physical layers in a simulation can use the parametric setting. However, this parameter value has a smaller impact on the machine's learning and fewer routes are available for V2V communication with RSUs.

The suggested method is evaluated against popular machine learning technique: Collaborative Learning Automata Routing (CLAR) [23].

For PDR analysis, the DRL is compared to the CLAR and SVM currently in use. The RSU coverage ratio is the ratio of the RSU covered area to the total area. The DRL uses RSU information to calculate transmission capacity and final destination location.

Table 1 or Figure 2 demonstrates that the transmission coverage area has been much enhanced. This demonstrates that the network performance improves across all four metrics as the RSU coverage area expands. As a result, the suggested procedure achieves a greater PDR than does the status quo. Since the DRL keeps track of connectivity between the units via announcement messages, the suggested technique yields an average 5% improvement over the existing CLAR. Sending control signals between the RSU and vehicle units is more reliable than sending them between cars themselves.

Table 1. Comparison between Coverage Ratio and Packet Delivery Ratio

RSU Coverage Ratio	Packet Delivery Ratio		
	SVM	CLAR	DRL
30	81.27	83.71	86.8
40	84.63	85.9	89.53
50	88.54	91.22	93.91
60	92.45	94.75	96.01
70	94.05	97.81	98.11
80	95.78	98.83	99.12

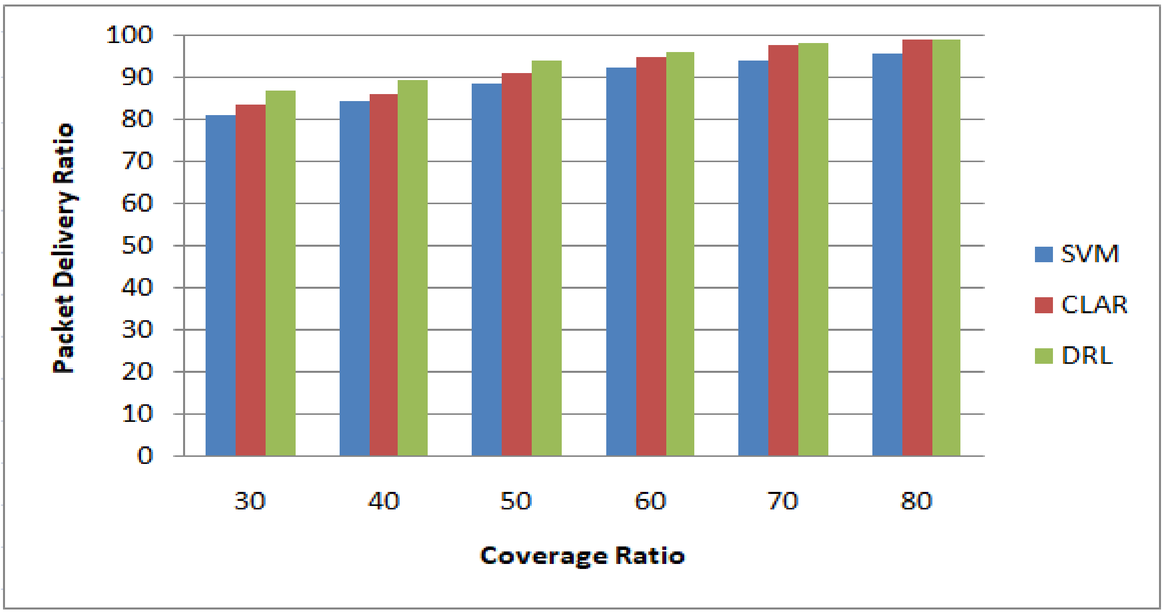

Fig.2. Comparison between Coverage Ratio and Packet Delivery Ratio

Table 2 and Figure 3 depict the differences and similarities between the PDR and low and high vehicle density. When compared to the current CLAR approach, the suggested method is 6.5% more expensive. The dispersed nature of their architecture makes alternative approaches look unreliable. The data demonstrates that as compared to conventional approaches, RSUs' use of command messages yields a 23% increase in PDR.

Table.2. Comparison between Packet Delivery Ration and Vehicle Density

Vehicle Density	PDR		
	SVM	CLAR	DRL
High	88.9	90.48	92.54
Low	81.01	88.58	90.22

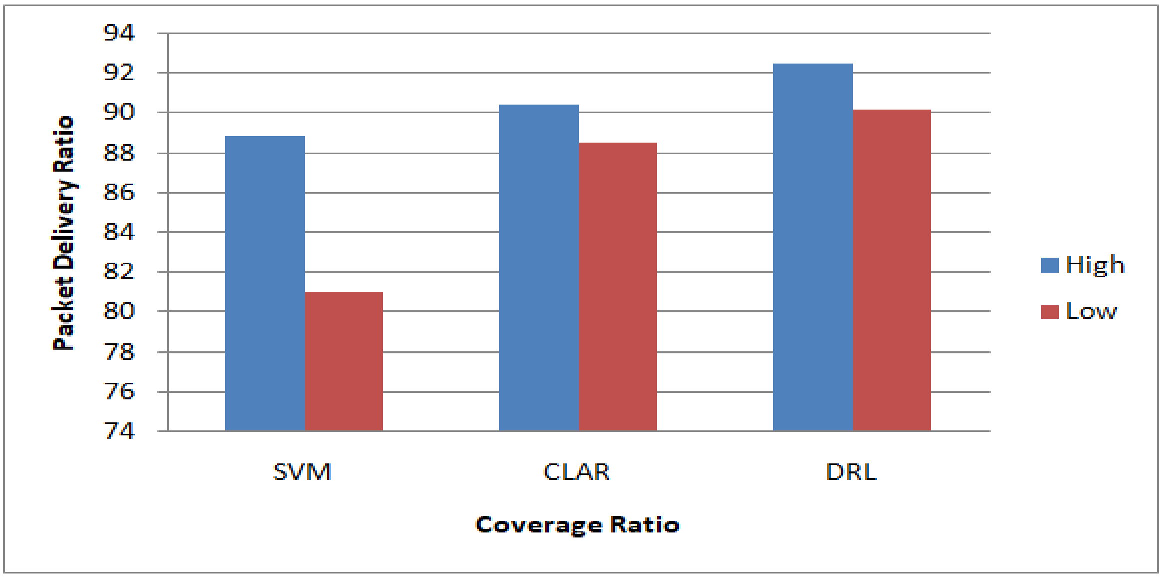

Fig.3. Comparison between Packet Delivery Ratio and Vehicle Density

Table 3 and Figure 4 display the final delay results, which show that RSU coverage has a significant impact on the delays experienced when forwarding packets from one RSU to another and that decreasing the total area for transmission significantly lessens the associated delays.

Table.3. Comparison between Coverage Ratio and End-to-End Delay

RSU coverage ratio	End-to-End delay		
	SVM	CLAR	DRL
30	14.61	5.43	5.11
40	14.31	5.21	4.46
50	13.98	5.92	4.17
60	13.82	4.67	3.98
70	13.66	3.98	2.61
80	12.63	3.84	2.15

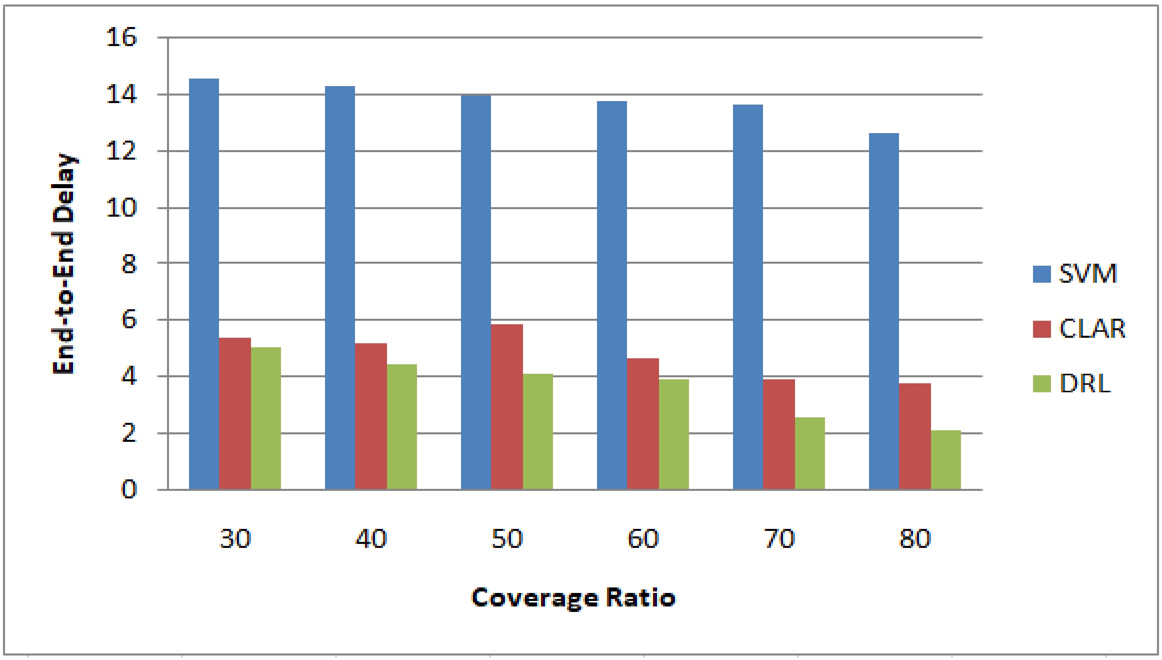

Fig.4. Comparison between Coverage Ratio and End-to-End Delay

Table 4 and Figure 5 depict the differences and similarities between the End-to-End Delay and low and high vehicle density.

Table.4. Comparison between End-to-End Delay and Vehicle Density

Vehicle Density	End-to-End delay		
	SVM	CLAR	DRL
High	11.58	3.48	2.64
Low	22.47	6.1	5.74

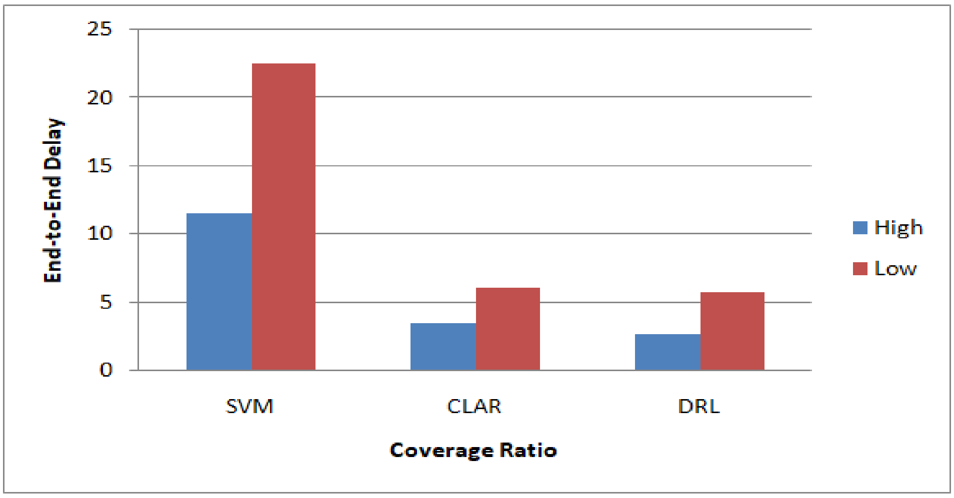

Fig.5. Comparison between End-to-End Delay and Vehicle Density

6. Conclusion And Future Work

In this paper, we look at the problem of addressing, resolving, and lowering the transmission stability. In order to maximize packet transmission throughout the route establishment process, this study focuses on the selection of roads with high traffic density. It improves the accuracy of automated transmission delay reduction and traffic density monitoring. To do this, we divide the entire area into a number of smaller clusters and optimize the path by means of several input factors, including population density and the position of the VU. In addition, the approach determines the traffic volume and chooses the most efficient route. Performance data for PDR, vehicle speed, vehicle density, transmission range, total number of APs, and network latency are all displayed in the simulation results. In order to reduce communication and computational costs in e-healthcare, i-transportation, and smart ecosystems, the proposed work may be expanded to include aspects such as anonymity qualities, mutual authentication, and intractability property. The proposed research idea may be further upon by including a trust-based intrusion detection system into a cooperative VANET. Faster computation in V2I communication in real-time applications is possible with the addition of a deep learning algorithm to the routing.

References

1. Nidhal, M, Ben-othman, J & Hamdi, M 2014, 'Survey on VANET security challenges and possible cryptographic solutions', Vehicular Communications, vol. 1, no. 2, pp. 53–66.
2. Vijayakumar, Azees, M, Kannan, A & Deborah, LJ 2016, 'Dual authentication and key management techniques for secure data transmission in vehicular ad hoc networks', IEEE Transactions on Intelligent Transportation Systems, vol. 17, no. 4, pp. 1015–1028.
3. Chen, H, Zhang, R, Zhai, W, Liang, X & Song, G 2018, 'Interference- free pilot design and channel estimation using ZCZ sequences for MIMO-OFDM-based C-V2X communications', China Communications, vol. 15, no. 7, pp. 47–54.
4. Srivastava, D., Sharma, V., & Soni, D. (2019, April). Optimization of CSMA (Carrier Sense Multiple Access) over AODV, DSR & WRP routing protocol. In 2019 4th international conference on internet of things: Smart innovation and usages (IoT-SIU) (pp. 1-4). IEEE.
5. Srivastava, D., Kumar, A., Mishra, A., Arya, V., Almomani, A., Hsu, C. H., & Santaniello, D. (2022). Performance Optimization of Multi-Hop Routing Protocols With Clustering-Based Hybrid Networking Architecture in Mobile Adhoc Cloud Networks. International

Journal of Cloud Applications and Computing (IJCAC), 12(1), 1-15. http://doi.org/10.4018/IJCAC.309932.

6. Neudecker, T, An, N, Gaugel, T & Mittag, J 2012, 'Feasibility of virtual traffic lights in non-line-of-sight environments', in Proceedings of the Ninth ACM International Workshop on Vehicular Inter- Networking, Systems, and Applications—VANET' 12, pp. 103–105, Lake District, UK.
7. Soni, D., Srivastava, D., Bhatt, A., Aggarwal, A., Kumar, S., & Shah, M. A. (2022). An Empirical Client Cloud Environment to Secure Data Communication with Alert Protocol. Mathematical Problems in Engineering.
8. Kaushik, SS 2013, 'Review of different aproaches for privacy', International Journal of Advanced Engineering and Technology, vol. 5, no. 2, pp. 356–363.
9. Tang, Y, Cheng, N, Wu, W, Wang, M, Dai, Y & Shen, X 2019, 'Delay-minimization routing for heterogeneous VANETs with machine learning based mobility prediction', IEEE Transactions on Vehicular Technology, vol. 68, no. 4, pp. 3967-3979.
10. Gonzalez-Martin, M, Sepulcre, M, Molina-Masegosa, R & Gozalvez, J 2019, 'Analytical models of the performance of C-V2X mode 4 vehicular communications', IEEE Transactions on Vehicular Technology, vol. 68, no. 2, pp. 1155–1166.
11. Molina-Masegosa, R & Gozalvez, J 2017, 'LTE-V for sidelink 5G V2X vehicular communications: a new 5G technology for short-range vehicle-to-everything communications', IEEE Vehicular Technology Magazine, vol. 12, no. 4, pp. 30–39.
12. Srivastava, D., Chui, K. T., Arya, V., Peñalvo, F. J., Kumar, P., & Singh, A. K. (2022). Analysis of Protein Structure for Drug Repurposing Using Computational Intelligence and ML Algorithm. International Journal of Software Science and Computational Intelligence (IJSSCI), 14(1), 1-11. http://doi.org/10.4018/IJSSCI.312562.
13. Srivastava, D., Soni, D., Sharma, V., Kumar, P., & Singh, A. K. (2022). An Artificial Intelligence Based Recommender System to analyze Drug Target Indication for Drug Repurposing using Linear Machine Learning Algorithm. Journal of Algebraic Statistics, 13(3), 790-797.
14. Tang, Y, Cheng, N, Wu, W, Wang, M, Dai, Y & Shen, X 2019, 'Delay-minimization routing for heterogeneous VANETs with machine learning based mobility prediction', IEEE Transactions on Vehicular Technology, vol. 68, no. 4, pp. 3967-3979.
15. Singh, A.K., Pamula, R., Jain, P.K. et al. An efficient vehicular-relay selection scheme for vehicular communication. Soft Comput 27, 3443–3459 (2023). https://doi.org/10.1007/s00500-021-06106-4

16. Marchang, Jims, Douglas, Roderick, Ghita, Bogdan, Lancaster, David and Sanders, Benjamin (2018). Dynamic neighbour aware power-controlled MAC for multi-hop ad hoc networks. Ad hoc Networks, 75-76, 119-134.
17. Akila & Iswarya, T 2011, ‘An efficient data replication method for data access applications in VANETs’, in Proceedings of the International Conference on Electronics, Communication and Computing Technologies (ICECCT), Pauls Nagar, India.
18. Vijayakumar, Azees, M, Kannan, A & Deborah, LJ 2016, ‘Dual authentication and key management techniques for secure data transmission in vehicular ad hoc networks’, IEEE Transactions on Intelligent Transportation Systems, vol. 17, no. 4, pp. 1015–1028.
19. Azees, M, Vijayakumar, P & Deboarh, LJ 2017, ‘EAAP: efficient anonymous authentication with conditional privacy preserving scheme for vehicular ad hoc networks’, IEEE Transactions on Intelligent Transportation Systems, vol. 18, no. 9, pp. 2467–2476.
20. Cui, Wei, L, Zhang, J, Xu, Y & Zhong, H 2019, ‘An efficient message- authentication scheme based on edge computing for vehicular ad hoc networks’, IEEE Transactions on Intelligent Transportation Systems, vol. 20, no. 5, pp. 1621–1632.
21. Zhang, L 2019, ‘Key management scheme for secure channel Establishment in fog computing’, IEEE Transactions on Cloud Computing, pp. 1
22. Islam, SKH, Obaidat, MS, Vijayakumar, P, Abdulhay, E, Li, F & Reddy, MKC 2018, ‘A robust and efficient password based conditional privacy preserving authentication and group-key agreement protocol for VANETs’, Future Generation Computer Systems, vol. 84, pp. 216–227.
23. Kumar, N, Misra, S & Obaidat, MS 2015, ‘Collaborative learning automata-based routing for rescue operations in dense urban regions using vehicular sensor networks’, IEEE Systems Journal, vol. 9, no. 3, pp. 1081-1090.