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Data Security Enhancement in 4G Vehicular Networks Based on Reinforcement Learning for Satellite Edge Computing

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Abstract

The vehicular network provides the dedicated short-range communication (DSRC) with IEEE 802.11p standard. The VANET model comprises of cellular vehicle-to-everything communication with wireless communication technology. Vehicular Edge Computing exhibits the promising technology to provide promising Intelligent Transport System Services. Smart application and urban computing. Satellite edge computing model is adopted in vehicular networks to provide services to the VANET communication for the management of computational resources for the end-users to provide access to low latency services for maximal execution of service. The satellite edge computing model implemented with the 4G vehicular communication network model subjected to data security issues. This paper presented a Route Computation Deep Learning Model (RCDL) to improve security in VANET communication with 4G technology. The RCDL model uses the route establishment model with the optimal route selection. The compute route is transmitted with the cryptographic scheme model for the selection of optimal route identified from the satellite edge computing model. The proposed RCDL scheme uses the deep learning-based reinforcement learning scheme for the attack prevention in the VANET environment employed with the 4G technology communication model. The simulation results expressed that proposed RCDL model achieves the

	higher PDR value of 98% which is ~6% higher than the existing model. The estimation of end-to-end delay is minimal for the RCDL scheme and improves the VANET communication. ***Keywords: VANET, 4G technology, Deep Learning, Route Establishment, Route Selection***

1. Introduction

Vehicular Adhoc Networks (VANETs) is considered as the emerging ad hoc communication network for the Wireless Local Area Network (WLAN). The communication with Vehicle Units (VU) are segmented for communication with the Roadside Units (RSUs) or vehicles performed with wireless communication. The VU users are acquired with the Internet service connection offered through wireless communication [1]. The VU are emerged with improved mobility, dynamic changes in the topology of network to establish unstable connections. However, those constraints are imposed with the vehicle transmission range interference model for the larger source unit in the target vehicle for packet transmission between vehicles to reach the destination route for the target vehicle [2].

Generally, the wireless technology in VANETs is called Wireless Access in Vehicle Environment (WAVE) provides communication between vehicles and RSUs. The WAVE architecture describes the exchange of security messages [3], while the WAVE communication ensures passenger safety through the updated traffic and vehicle information. The application ensures the safety of both the pedestrian and the driver and improves traffic flow and efficiency. There are several VANETs, including OBUs, TA and RSUs, where RSU helps in hosts an application for the purpose of communicating with other devices and it assist the OBU to mount on VU to collect information on the vehicle, including speed, location and fuel [4]. These data are then transmitted via the wireless network to the nearby vehicles. Each RSU connected to each other also has a wired network connection to TA. In addition, TA is responsible for maintaining the authentication in VANETs [5].

Security of VANET ensures that the messages transmitted by the attackers are not injected or altered. In addition, within a short time, the driver must accurately inform the traffic conditions. Because of its distinctive characteristics, VANETs are more sensitive to attacks [6]. Security challenges need to be properly addressed; otherwise, many constraints are created for VANETs to ensure safe communication. In VANET Security, the requirements to have the system aligned with the relevant network operation must be mentioned. The failure on meeting the requirements often leads to attacks. The security requirements is thus divided into confidentiality, accessibility, data completeness, authenticity and non-respect [7].

So far, date, several routing protocols for different purposes have been developed. In certain protocols, vehicle density is detected for the optimal routing path selection [8]. The problem is the occurrence of such detection. The data is transmitted between the vehicles after finding the density information, which leads to an increase in overhead control. Moreover, converging takes longer time for the rapidly changing density of vehicles. This leads to real-time information processing for the inaccurate data to perform effective routing [9]. Finally, it is observed that vehicle information is acquired form the subsequent road to achieve optimal problem to achieve routing protocol with per-hop calculation.

Machine learning model uses the VANET route selection with the RSUs unit to prevent traffic and vehicle movement. The risk of vehicles in its communication range can be estimated. This ensures that the packet is crossed via correct predictions of appropriate path for data transmission. The machine study model forecasts the condition based on past and current vehicle states in real time [10]. Such a forecast provides information on the efficient routing protocol. Normally, VANETs are mainly affected by chartered and multiple charted security attacks in wireless sensor networks. The message transmitted may be blocked, forged, or overloaded with malicious devices revealing the attacker's customer information. This leads to a privacy disclosure issue, and VANETs ensure privacy and security concerns only through proper authentication. However, because of the mobile and distributed nature of VANETs, the authentication systems are typically vulnerable to various security challenges. Moreover, these mechanisms are designed to ensure data privacy without routing metrics. The measurements are unfortunately not provided by the security mechanism because the Quality of

Services (QoS) for the user is difficult and differing [11]. An enhanced authentication method is therefore necessary to protect the message during message transmission and message transmission. Based on consideration of different application high effective and minimal cost construction model is required for the VANET environment. The VANET model comprises of the 4G technology for the application of government, car manufacture and academic gain attention of interest. However, with the effective VANET deployment comprises of the components, key to establish the effective routing within the path form source to destination in the urban scenario.

In this paper developed a RCDL model for the data security in the VANET communication environment with the 4G technology. The optimal route in the network is computed based on the route established with the RCDL model. To increases the data security deep learning model is measured for the VANET 4G communication. The proposed RCDL scheme uses the cryptographic scheme for the estimation of the optimal path in the network. The simulation results expressed that proposed RCDL model achieves the higher PDR value of 98% which is ~6% higher than the existing model. The estimation of end-to-end delay is minimal for the RCDL scheme and improves the VANET communication.

This paper is organized as follows: Section 2 provides the related works on the VANET security and section 3 provides the proposed RCDL scheme methodology. The results obtained are presented in Section 4 and overall conclusion is presented in Section 5.

2. Related Works

In [12] utilized an Adhoc On-request Distance Vector (AODV) steering in view of Q-learning fluffy imperative calculation. The convention uses a smooth rationale for assessing whether remote associations are great by considering a few measurements, in particular the transmission capacity, connect quality and the overall development of the vehicle. This proposed convention is assessed utilizing the course demand messages (RREQ) and hi messages to gain proficiency with the best course by assessing every Remote Connection. At the point when position data are not free, the convention can derive vehicle development considering neighbour data. In the PFQ-AODV the lower layers are likewise autonomous.

In [13] evaluated a subterranean insect province optimization-based calculation called Time-Insects. Time-Subterranean insects accept that traffic is doled out whenever during the day an amount of pheromone or traffic. In light of these traffic appraisals, the streets of the vehicle are chosen involving an imaginative calculation in time. These outcomes are ideal worldwide rush hour gridlock framework after a few emphases. AI recognizes and forestalls bottlenecks.

In [14] evaluated the exhibition of Het-Net that comprises of different remote V2V correspondence advances. The application layer handoff technique empowers the assortment and forward impact advance notice of Het-Net correspondence information. The review shows that Het-Net enhances V2V interchanges. However, the review confines that the application execution in rush hour gridlock information assortment has been compromised because of the utilization of Het-Nets. Since not at all like vehicle wellbeing applications, it does not need lower inactivity.

In [15] acquainted an AI Calculation with process and produce steering measurements to work on the impact of vehicle information, specifically, Backing Vector Machine (SVM). This technique reviews the logical and handling strategies for test vehicle information and furthermore examines the conceivable use of AI calculations in VANET steering.

In [16] proposed QoS information spread working with productive information scattering and QoS dispersal utilizing a superior Kruskal calculation in progressive VANET. This approach builds the most un-extending trees in each street fragment with Kruskal calculation where the vehicle was grouped by the intra-bunch QoS strategy, utilizing the c-mean grouping technique. The group head for each spreading over tree is to gather information from the leaf hubs and scatter the information to other organizer hubs, as well as the other way around.

The incorporated directing framework with a versatility expectation is proposed in [17] for VANET upheld by an organization regulator in view of computerized reasoning and controlled by programming. Specifically, a high-level fake brain network innovation can permit the SDN regulator to play out a definite forecast of portability. The RSUs and BSs can then gauge the fruitful likelihood of transmission and normal deferral of the solicitation for a vehicle, in view of the versatility expectation. The gauge depends on a stochastic metropolitan traffic model that follows the uniform course of Poisson when the vehicle shows up. The SDN regulator gathers RSU and BS network data which is viewed as switches. The SDN regulator computes ideal steering ways for turns based on worldwide organization data. The RSUs and BS will choose further on the directing autonomously, to limit the general time spent in vehicle administration, while the source vehicle and target truck are situated on a similar switch inclusion region.

In [18] presented a procedure in view of the TESLA; this strategy is utilized to plan and confirm TESLA utilizing the coordinated variety control approach Petri model. Afterward, scientists viewed that the two variables had as dissected: first, security productivity and second, fruitful assault rate. In [19] introduced another procedure utilizing the Circular Bend Advanced Mark Calculation (ECDSA) for the verification of the message. It can likewise guarantee that VANETs are validated Highlight Point (P2P) as a feature of a system. P2P can further develop calculation productivity and cut-off message delay by joining P2P with ECDSA and VANET. In [20] proposed another technique for grouping the basic security message, as well as a versatile strategy for validating the ECDSA message and Merkle tree. The fostered a solid correspondence over cloud and its related information transmission. A gathering of vehicles arranged in VANETs is utilized in this way to deal with make a protected and dynamic VC. It considers secure combination and trade of information in all vehicle assets, and any cloud client can deal with their information safely after the framing in [21] presented the VANET framework convention PW-CPPA-GkA to guarantee the shielding of the secret word-based validation and gathering keys. There are a few elements in this strategy, for example, yield, client info and secret key changes. This convention is created without bilinear blend and elliptic bend technique makes the tasks stable.

VANETs supply many uses from security to infotainment. The utilization of assets, loss of packs, and equity are normal execution measures for infotainment applications, which are generally expected by street security applications to diminish transmission time and to accomplish high unwavering quality. In specific correspondence situations, different QoS measurements might be counterproductive for each other, for instance thickly associated engine vehicles, which can, by channel clog and obstruction, increment the parcel misfortune proportion. The best QoS directing determination with various QoS limits ought to be considered with various traffic data to meet heterogeneous applications.

3. 4G Vehicular Communication with Satellite Edge Computing

The satellite edge computing model comprises of the data collection from the 4G vehicular communication system. The 4G vehicular system establishment of cluster-based communication model. The vehicular communication comprises of the road segments those are cluster and identifies the traffic density based on the vehicle speed. With increase in density of vehicle and traffic congestion to improve average speed of vehicles. The implements Route Computation Deep Learning Model (RCDL) to estimate the location of vehicles.

Consider the current location L for the incorporated vehicles$\{L = L_1, L_2, \ldots\ldots, L_n\}$ between the adjacent RSUs defined as $\{\theta = d_1, d_2, \ldots\ldots, d_n\}$, the present route in the 4G vehicular communication is denoted as $R = R_1, R_2, \ldots\ldots, R_n$and the vehicle density is states as $D = k_1, k_2, \ldots\ldots, k_n$. The transition state from one state to other state is computed as in equation (1)

$$\delta_{ij}: x \to R \tag{1}$$

where,

$$R\ ranges\ from\ 1 \le i \le n, 1 \le j \le n$$

δ_{ij}stated as stochasitc function whichprovides the possible routes that operates based on parameter $x = (L, \theta, D)$. The distance between the vehicle and RSU is estimated, where the current location of the vehicle and vehicle density is found in order to attain the optimal routes for future vehicles. With measurement of total number of vehicles in one region, the vehicle density is estimated on all VUs, which is accessible over entire VANETs at a particular instant. This is estimated using Equation (2),

$$D = \frac{\sum_{i=1}^{n} NV_i}{\sum_{i=1}^{n} n_i} \tag{2}$$

where,
NV_i- total VU in the region i and
n_i– number of total vehicles in time t.

The developed RCDL model perform communication with the coverage range of 150m those are predefines. The own vehicle density is evaluated based on the vehicle cluster or region with the proper mapping function as in equation (3)

$$\begin{bmatrix} \delta_{11} & \delta_{12} & \ldots\delta_{1n} \\ \delta_{21} & \delta_{22} & \cdots\delta_{2n} \\ \vdots & \vdots & \ddots \; \vdots \\ \delta_{n1}\delta_{n2} & \cdots & \delta_{nn} \end{bmatrix} \tag{3}$$

The developed RCDL model estimates the Transition Probability Matrix (TPM) matrix values. The TPM model values are elected to estimate the best routes in the disseminate data. The identification of best route focused on estimation of minimum parametric weight.

3.1 RCDL for Secure Data Routing with Deep Learning Model

RCDL model comprises of the two phases such as Route Establishment (REP) and Route Selection Phase (RSP). The model estimates the optimal route with optimization of route through selection.

3.1.1 Route Establishment Phase

In first stage, the packets are transmitted through vehicular unit with specific packages such as vehicle location, density, current and neighbourhood distance. The information between intermediate nodes is computed based on position of nodes, density of network and delay within region.

Algorithm 1: Secure RCDL Route establishment
Input: Vehicle Location, Distance, Density, present route, delay, and position Output: Established Route in Network Step 1: Initialize the parameters for computation Step 2: Estimate RCDL for optimal establishment of route through input parameters Step 3: If route is optimal collision is eliminated Step 4: Route Establishment

3.1.2Optimal Route Establishment

The unit packet of vehicle comprises of the estimation of RSUs vehicle distance, position, end-to-end delay, and density of vehicle. The RCDL model optimal routes are established based on award, transition function based on threshold path with estimation of distance between sources to destination. Based on destination node weights are constantly updated based on weights $\psi \in [0, 1]$, with the reward function denoted as ψ. The constant function is utilized to determine each path reliability those value closer to 1 as represented as ψ. However, the path optimized is achieved with the optimal path closer to zero. To achieve the effectiveness value is lies between $\varphi \in [0, 1]$ to minimize cumulative weight.

3.1.3 Route Selection Phase

Based on the routing established through the initial stage optimal neighbourhoods are elected for the routing list node. Particularly, with the routing model each vehicle's maximal parametric value in neighbouring for the transmission system based on vehicle density for the packet routing. The complete process is classified based on different time interval with vehicle density and intensity. The vehicle speed and density are evaluated with the traffic based on interval with traffic density for the routing at specific time interval.

3.1.3.1 Route Selection Phase Using RCDL

Based on the previous observations the RCDL route finds the optimal routing paths. The RCDL that predicts the next TPM is used to compute optimal routes efficiently. This can be considered a supervised problem of learning. The supervised learning task in this present study considers a sample and a labelling space i.e. X and Y, respectively. The supervised learning task in the present study is RCDL (A), which is a function mapping value in X to the labels the values in Y. The mapping function is to map with sample set (xi) and true labels (yi) belonging to X×Y. The mapping produces precise labels for the new sample set, which are obtained via a distribution like the data.

3.2 Deep Reinforcement Learning

With RCDL model mapping strategy model is forecasted with the optimal roads those are mapped directly. The interacted RCDL perform iteration within the vehicle environment based on segments of road and time with time-slots in to sub-segments. Initially, every time slots are computed based on the current state (s_{t-1}) elected based on fixed action. The selection of action (a_t), the vehicular environment between (s_{t-1}) to (s_t). The received agent is performed with reward (r_t) or penalty (p_t) to compute significantly based on state (S) and action (A), with mapping function (π) defined as RCDL (π: S $\rightarrow$ A). The algorithm to perform optimal route selection is presented.

Algorithm 2: Optimal route selection
Step 1: Initially, compute the time t, operator using TPM and observation based on optimal routes to predict the iteration with the routing strategy with the R(t) (reward or penalty). Step 2: The TPM value is computed based on the present state with the reward function TPM(t) denoted as r(t) = - u(t)/O(t),it uses the link for maximal utilization u(t) to perform the effective routing strategy model. The optimal route for strategy is represented as R(t) in TPM with the O(t) Step 3: The optimal route based on routing strategy is predicted based on optimal routes with the increases reward function.

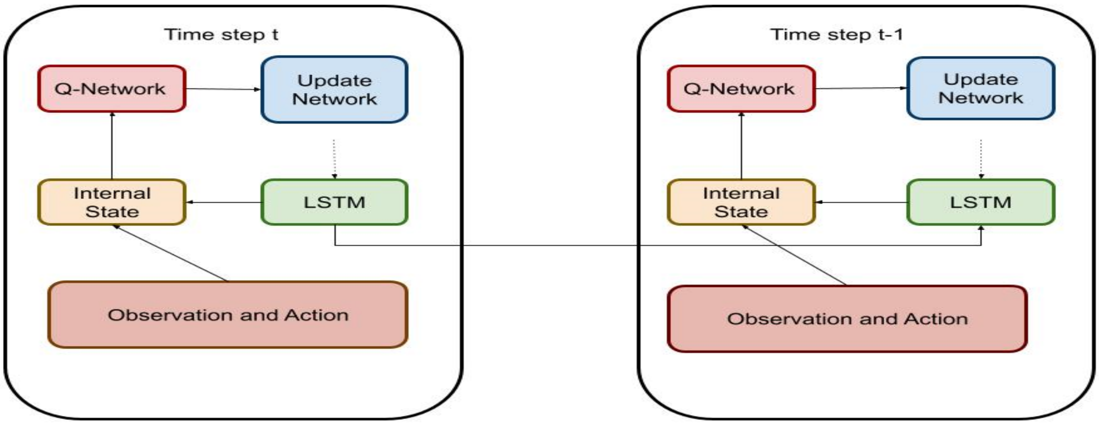

Figure 1. Architecture of Edge Computing 4G Technology

The proposed RCDL scheme uses the LSTM model based 4G communication model the data transmission in the VANET communication. The figure 1 provides the architecture model implemented with the proposed RCDL scheme.

4. Results and Discussion

Using the simulation tool NS-2 (version 2,35), the performance of the proposed method is evaluated. The simulation takes place in an area of between 1000m×1000m. VanetMobiSim simulates the movement of vehicles and their behaviour with regards to the urban environment. RSUs are randomly distributed here, with speeds ranging from 5 to 30 m/s for each vehicle. The transmission power is varied in order to meet the range, where the maximum transmission range is 250 m. The packets are

512 bytes in size and are transmitted from the source node via CBR. The simulation parameters are represented in Table 1. The RCDL routing is evaluated against control overhead, Packet Delivery Ratio (PDR) and end-to-end delay time.

Table 1. Parameters Used for Simulation

Parameters	Values
Topology of Network (meters)	1000 × 1000
Communication range	250 m
Lanes of each direction	3
Radio Model	Two-ray-ground model
RSU coverage ratio	[50 - 90]% in multiples of 10
Speed of Vehicle	5-30 m/s
Transport layer	UDP
Vehicle Number	450
Application	CBR
MAC	802.11p
CBR rate	1 Mbps
Packet Size of CBR	512 bytes
Vehicle beacon interval	1 second
Time for simulation	400 seconds

The proposed method is compared with Heuristic Q-Learning (HQL), Collaborative Learning Automata Routing (CLAR) (Kumar et al. 2015) and Support Vector Machine (SVM) (Sangare et al. 2008). The RCDL is compared with the existing methods such as CLAR, HQL and SVM for PDR testing. A ratio between the RSU coverage and total area is defined by the RSU coverage ratio. The capability of transmission and destination position is determined by the RCDL, based on RSU data. The result of Table 2 and Figure 2 shows that the coverage area for transmission is significantly improved. This shows that the network performance increases in all four methods with the growing coverage range of RSU. This results in higher PDR than existing methods being achieved by the proposed process. The proposed method achieves an improvement of an average of 5% over the previous CLAR since the RCDL retains information on connectivity between the units by means of announcement messages.

Table 2. Comparison of PDR (%)

RSU coverage ratio	PDR			
	HQL	**SVM**	**CLAR**	**RCDL**
50	63	74	77	98
60	67	78	80	97
70	71	81	83	98
80	76	85	87	99
90	79	88	89	98

The comparison between the PDR and low and high-density vehicles is shown in Table 3 and Figure 2. The method proposed is 6.5% higher than the CLAR method already in use. Other methods appear unstable, as their design is based on distributed architecture and increases their density. The result shows that RSUs improve the PDR to 23% as compared to existing methods by deploying control messages

Figure 3. Comparison of PDR with Vehicle Density

Vehicle Density	PDR			
	HQL	**SVM**	**CLAR**	**RCDL**
High	64	71	79	98
Low	67	76	83	97

The results of the final delay are shown in Table4 and Figure 3. The result shows that the delays in the forwarding of packets between RSUs are highly affected by RSU coverage. Reducing the total area for transmission reduces the associated delays considerably. The results show that in the proposed method RSU information resolution is stable compared to the existing methods.

Table 4. Comparison of End-to-End Delay

RSU coverage ratio	End-to-End Delay			
	HQL	SVM	CLAR	RCDL
50	103	97	93	47
60	99	91	86	49
70	96	88	81	53
80	90	83	77	56
90	88	79	75	52

Table 5. Comparison of End-To-End Delay (S) With Vehicle Density

Vehicle Density	End-to-End Delay (s)			
	HQL	SVM	CLAR	RCDL
High	103	97	93	56
Low	88	79	74	47

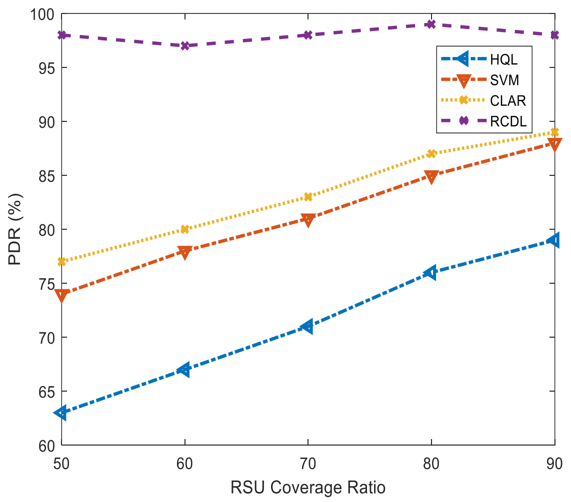

Figure 2. Comparison of PDR

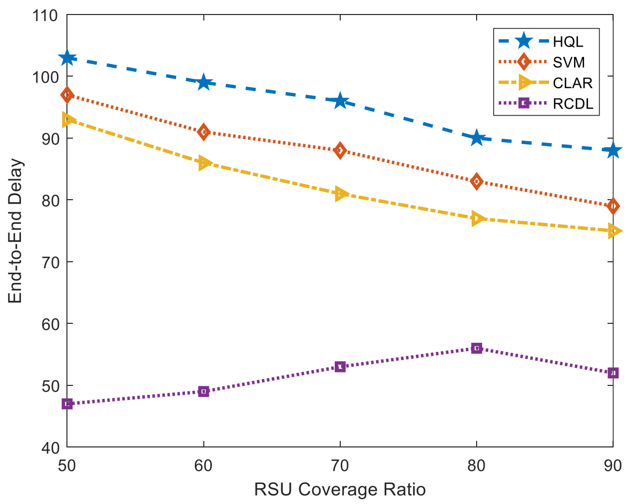

Figure 3. Comparison of End-to-End Delay

Table 6 and Figure 4 shows comparative results for control overhead in VANETs between the existing and the proposed method. The control overhead determines the information for the RCDL training of the reporting units of the vehicle to the RSUs. Table 6 or Figure 4 results show the method proposed to reduce overhead controls as compared to the methods already in place. The overhead is increasing in relation to the total number of RSUs, as the network density is increasing. However, the RCDL shows a reduced overhead control compared to existing methods with a coverage ratio of 90%, for both the proposed and existing protocols.

Table 6. Control Overhead (per min)

RSU coverage ratio	**Control Overhead (per min)**			
	HQL	**SVM**	**CLAR**	**RCDL**
50	4201	3876	3581	2987
60	4189	3813	3482	2860
70	4058	3795	3394	2821
80	3983	3724	3295	2794
90	3962	3693	3261	2741

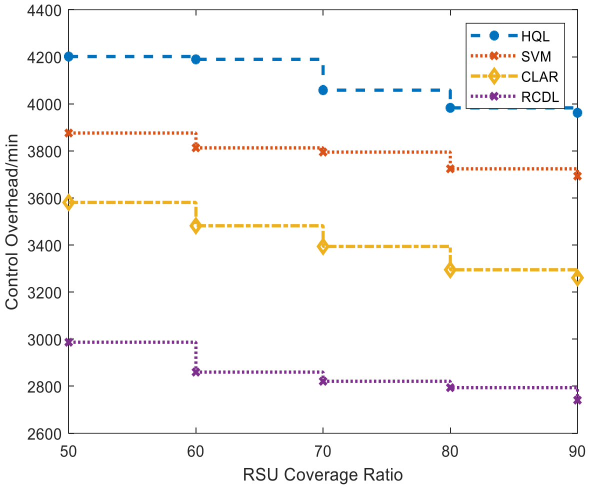

Figure 4. Comparison of Control Overhead

The approach to RCDL machine learning selects the chance of high success rates. In the proposed method it has been more accurate to compare the existing methods and collect information, i.e. vehicle density, direction and speed. In addition to the existing methods, the data transmission takes place in reliable way. Lastly, the RCDL route results in a higher PDR with a smaller delay and an overhead control that enhances the transmission of the data. In comparison with other urban environments the simulation results show that RCDL routing in VANETs has a higher scale. The table 7 provides the network connectivity measured based on average distance.

Table 7. Measurement of Network Connectivity

Average Distance	**Transmission range**			
	200m	**150m**	**100m**	**50m**
5	1	1	1	1
10	0.98	0.96	0.95	0.93
15	0.97	0.99	0.98	0.97
20	0.96	0.95	0.96	0.92
25	0.95	0.94	0.94	0.87
30	0.89	0.93	0.93	0.85
35	0	0.92	0.92	0.83
40	0	0	0.88	0.79
45	0	0	0	0

Table 8. Measurement of CDF for 300 Vehicle

Connection probability	CDF		
	CDSLS	**RCDL**	**ANN**
0.1	0.02	0.2	0.15
0.2	0.03	0.12	0.16
0.3	0.05	0.11	0.18
0.4	0.06	0.09	0.19
0.5	0.08	0.09	0.13
0.6	0.1	0.1	0.14
0.7	0.07	0.1	0.12
0.8	0.07	0.12	0.11
0.9	0.07	0.09	0.17
1	0.08	0.1	0.19

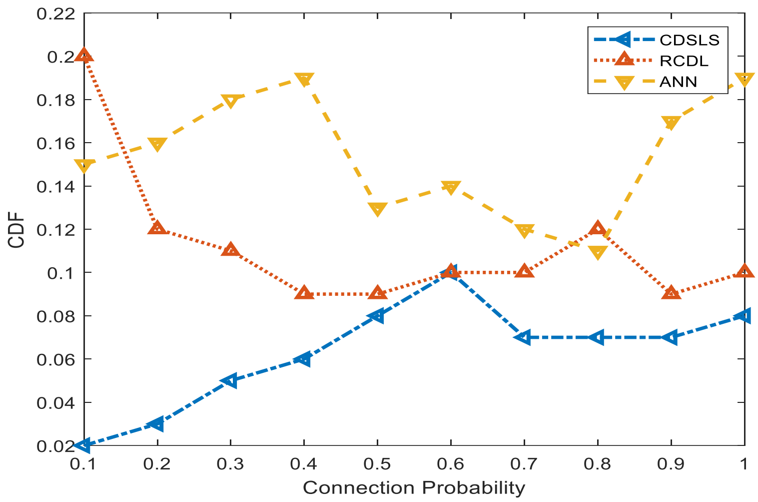

Figure 5. Comparison of CDF

Table 8 shows the measurement of CDF over Successful connection probability with 300 VANET vehicle nodes also illustrated in figure 5. The result shows with increasing connection probability, the CDF reaches the maximal value i.e., unity and on other hand, the reduced probability has worsened the CDF between the proposed and existing methods. The comparative result shows that proposed CDSLS has optimal CDF than RCDL and existing ANN.

Table 9. Comparison of Latency

Velocity	Average latency		
	CDSLS	RCDL	ANN
10	3.2	4.9	7
15	5.5	6.3	11.78
20	8.2	8.4	16.92
25	9.3	10.8	21.95
30	11.8	13.9	26.94
35	13.9	16.73	28.03
40	16.8	18.9	31.05

Table 9 shows the measurement of average latency by varying the VANET vehicle node velocity. The result shows that with increased vehicle velocity, the proposed CDSLS achieves reduced average latency than proposed RCDL and existing ANN. With increasing velocity, it is observed that the average latency tends to increase affecting the entire performance of packet delivery.

Table 10. Comparison of Delay and Hop Count

Node Density	**Average end-to-end delay**			**Probability of hop counts**		
	RCDL	**CDSLS**	**ANN**	**RCDL**	**CDSLS**	**ANN**
75	0.4	1.1	1.5	12.5	15.5	16.8
100	0.3	0.8	1.3	11.8	15.2	15.4
125	0.3	0.8	1.3	10.7	14.7	14.8
150	0.4	0.7	1.5	9.6	14.2	13.7
175	0.4	0.6	1.2	9.6	13.7	12.8
200	0.2	0.6	1.1	8.3	13.4	11.6
225	0.1	0.8	0.9	7.2	12.6	11.2
250	0.3	0.9	0.9	6.7	11.7	10.8
275	0.4	0.9	1.1	6.1	10.3	10.1
300	0.4	0.7	0.8	5.6	9.6	9.8

The figure 6 provides the comparison of end-to-end delay measured for the proposed RCDL with the existing CDSLS and ANN model. Also the figure 7 illustrated the probability of hop count for the RCDL with th conventional techniques.

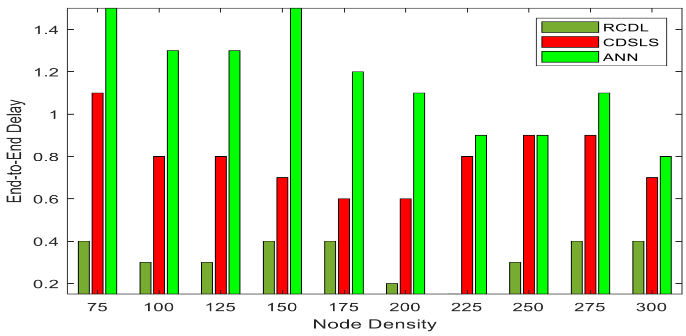

Figure 6. Comparison of End-to-End Delay

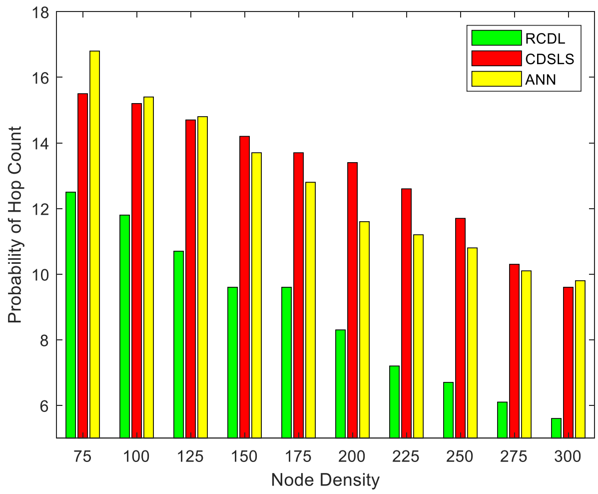

Figure 7. Comparison of hop count

Table 10 shows the measurement of average end-to-end delay by varying the VANET vehicle node density. The result shows that with reduced node density, the proposed CDSLS achieves reduced average end-to-end delay than proposed RCDL and existing ANN. With increasing node density, it is observed that the average end-to-end delay tends to increase affecting the entire performance of packet delivery. Also, table 10shows the measurement of Hop counts by varying the VANET vehicle node density. The result shows that with increasing vehicle density, the probability of hop counts reduces to unity and with further more increase in vehicle density, the study has observed further more drops in hop fount probability. This successful reduced in hop count is prominently due to 100 increased vehicle density that avoids the growth of packet collision and link breakage, which avoids losing in link connectivity. The result shows that proposed CDSLS achieves reduced probability of hop counts than RCDL and ANN

5. Conclusion

The research focus on road selection with high traffic density to increase the packet transmission during the route establishment. It reduces the transmission delays and monitors traffic density automatically with increased precision. This is achieved by splitting the entire region into several clusters and optimizing the way through the various input parameters such as the density and location of the VU. In addition, this method identifies the vehicle density and selects the best path. The simulation results show the efficiency with regard to PDR, speed of vehicle, density of vehicles, transmission range and the total number of APs and network delay. The proposed RCDL scheme exhibits the effective secure data transmission between the VANET communications enabled with the 4G technology. The proposed RCDL scheme achieves the ~6% higher than existing schemes.

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