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Performance Optimization of Vehicle-to-vehicle Communication through Reactive Routing Protocol Analysis

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Abstract: The study focuses on improving the Quality of Service (QoS) in Vehicle-to-Vehicle (V2V) communication within Vehicular Ad Hoc Networks (VANETs) by enhancing the Learning Automata-based Ad Hoc On-Demand Distance Vector (LA-AODV) routing protocol. Unlike the standard AODV, which is a reactive routing protocol, and previous configurations of LA-AODV, this research introduces a fine-tuning strategy for the learning automata parameters. This strategy allows the parameters to dynamically adapt to changing network conditions to reduce routing overhead and enhance transmission stability. Three modified versions of LA-AODV referred to as setups A, B, and C, are evaluated against the standard AODV and earlier LA-AODV configurations. The performance of each setup is measured using key QoS metrics: flood ID, packet loss ratio (PLR), packet delivery ratio (PDR), average throughput, end-to-end delay, and jitter. These metrics are crucial in evaluating the efficiency, reliability, and performance of V2V communication systems within VANETs. The results demonstrate that the LA-AODV variants significantly reduce flood ID counts, which represent the number of times a packet is broadcasted, compared to AODV, with setups A and B achieving reductions of 10.24% and 28.74%, respectively, at 200 transmissions, indicating enhanced scalability. Additionally, LA-AODV setup A provides 5.4% higher throughput in high-density scenarios. The modified versions also significantly decrease delay and jitter, achieving reductions of over 99.99% and 99.93%, respectively, at 50 transmissions. These findings underscore the adaptive capabilities of the proposed LA-AODV modifications, providing reassurance about the robustness of the system. They also highlight the importance of parameter optimization in maintaining reliable V2V communication. Future work will benchmark LA-AODV against other state-of-the-art protocols to validate its effectiveness further.

Index Terms: AODV, LA-AODV, Parameter Tuning, Quality of Service, V2V Communication.

1. Introduction

V2V communication is a cornerstone of modern transportation systems, especially with the increasing adoption of autonomous vehicles and intelligent transport technologies [1]. Effective V2V communication in dynamic traffic environments depends heavily on robust and adaptive routing protocols [2]. One commonly used protocol is the Ad Hoc On-Demand Distance Vector (AODV), which, despite its widespread use, faces several challenges in highly dynamic network topologies. These challenges include slow data transfer rates [3], increased end-to-end delays [4], reduced throughput [5], and congestion issues [6], primarily due to the protocol's limited adaptability to rapidly changing network structures [7, 8].

In response to these limitations, the Learning Automata-based Ad Hoc On-Demand Distance Vector (LA-AODV) protocol has emerged as a promising alternative [9]. LA-AODV enhances routing performance by leveraging real-time vehicle data (e.g., location, acceleration, and speed) to predict and select optimal relay nodes. This intelligent relay node selection contributes to improved link stability, scalability under high traffic loads, and congestion mitigation during network disruptions. Additionally, the protocol supports critical Quality of Service (QoS) metrics, including low latency, high throughput, and reliable packet delivery.

However, while LA-AODV shows significant potential, its performance depends on several adjustable parameters, such as data update frequency, relay node selection logic, and other dynamic adjustment mechanisms [10]. Incorrect configurations can impair the protocol's ability to respond to rapidly shifting traffic conditions, highlighting the need for parameter optimization.

This research identifies the optimal configuration of LA-AODV parameters to enhance V2V communication quality within Vehicular Ad Hoc Networks (VANETs). Although LA-AODV has already demonstrated advantages over traditional AODV, there is a critical need to determine which parameter setups yield the most reliable performance under varying conditions. The study compares six variations of LA-AODV configurations against standard AODV to determine their effectiveness in improving QoS across different traffic scenarios. To clearly outline the novelty and value of this work, the main contributions of this paper are as follows:

- Propose a comprehensive evaluation of six parameter configurations of the LA-AODV protocol under various VANET traffic conditions.
- Identify and analyze the impact of parameter tuning on key QoS metrics, such as latency, throughput, jitter, and packet delivery ratio.
- Demonstrate the LA-AODV protocol's adaptability compared to traditional AODV, particularly in high-mobility and high-density network scenarios.
- Recommend the most effective configuration of LA-AODV for optimizing V2V communication reliability and scalability in real-world deployments.

2. Literature Review

Extensive experiments have demonstrated that the benefits of the AODV routing protocol outweigh its drawbacks. By adjusting the default settings[11], AODV can be optimized to determine appropriate V2V communication ranges, minimize delays in intra-vehicle communication, and incorporate real-world measurements. Understanding the impact of route request parameters, such as RREQ_RETRIES and MAX_RREQ_TIMEOUT, on AODV compared to OLSR is essential. In mobile node scenarios, AODV achieves an average Packet Delivery Ratio (PDR) of 84.6%, outperforming OLSR. It also shows higher throughput and lower packet loss rates (10.4% compared to OLSR's 19.50%). However, AODV has longer delays (0.1722ms) compared to OLSR (0.022ms). Despite these differences and varying simulation environments such VANET[12] and MANET[13], AODV is well-suited for mobile node scenarios, though extensive experiments are necessary to further improve its performance in V2V communication systems[14]. Extensive experiments have demonstrated that the benefits of the AODV routing protocol outweigh its drawbacks. By adjusting the default settings, AODV can be optimized to determine appropriate V2V communication ranges, minimize delays in intra-vehicle communication, and incorporate real-world measurements.

LA-AODV improves QoS by selecting relay nodes in real-time based on vehicle speed, distance, and position. Simulations at Bulaksumur region in Yogyakarta show that LA-AODV outperforms AODV with Packet Delivery Ratios of 95%-99% and Throughputs of 36.90-56.50 Kbps, while reducing Packet Loss Ratios to 1%-4%. Though LA-AODV has slightly higher delays, it optimizes routing, reduces communication overhead, and enhances network resource use[9]. Despite a slightly longer delay, LA-AODV optimizes routing, minimizes communication overhead, and maximizes network resource utilization. These insights can help improve V2V communication protocols for better efficiency in dynamic traffic conditions.

Recent study evaluates QoS in LA-AODV for V2V communication, comparing it with AODV in various traffic scenarios using NS3 and SUMO. Results show LA-AODV significantly outperforms AODV in smooth traffic, with a 38.27% higher PDR, 85.26% lower PLR, and a 56.62% increase in average throughput. In steady flow traffic, both protocols perform similarly with high PDRs and low PLRs. In heavy traffic, AODV has a slightly higher PDR (97.60%) than LA-AODV (96.87%), but LA-AODV achieves a 17.24% higher average throughput. These insights can help improve

V2V communication protocols for better efficiency in dynamic traffic conditions[15].

Prediction-based routing protocols in VANETs optimize relay node cluster selection and power consumption during packet exchanges, reducing transmission delay and improving network performance with over 200 nodes. They mitigate node interference in dense environments, achieving higher packet delivery, reduced control overhead, enhanced throughput, decreased interference, and shorter end-to-end delays.[16, 17]. The choice of techniques should depend on the specific network characteristics, considering the limitations of fuzzy clustering[18], C-means[19], and K-means[20]. Further research has also investigated the application of Particle Swarm Optimization (PSO) [21], and basic learning automata[22, 23]to improve the process of learning V2V communication inside the VANET. DP-AODV dynamically adjusts power levels[24], while FLOW-AODV employs machine learning to intelligently choose relay nodes, optimizing QoS parameters and communication efficiency[25]. These protocols demonstrate how adaptive and intelligent systems can enhance V2V communication in VANETs by developing more robust and efficient routing protocols that adapt to dynamic conditions and achieve better QoS and network performance."

3. Proposed LA-AODV Methods

The V2V communication protocol simulation is a multi-phase process. Modifying configuration parameters first defines the traffic map. Next, mobility scenarios are established to represent the movement of cars in the traffic simulation visually. Fig. 1 outlines each step of the comparison and simulation.

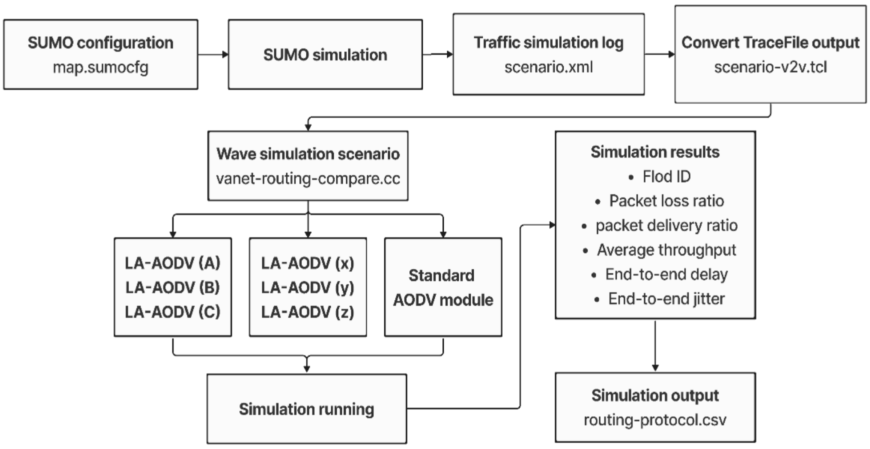

Fig.1. Research procedure for comparison between LA-AODV and AODV through SUMO and NS3 simulation

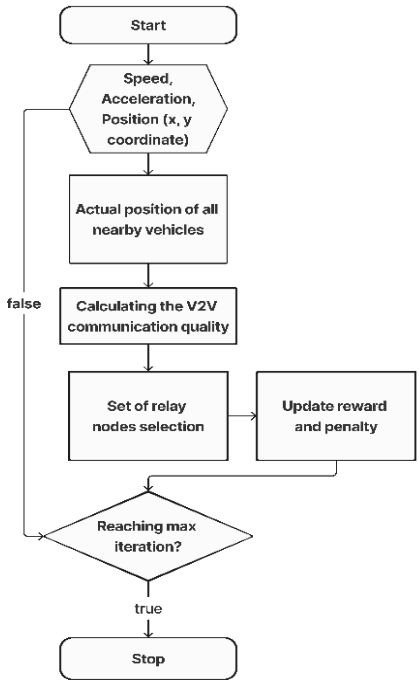

Fig.2. The modified version of AODV, known as LA-AODV

We conducted simulations to compare the performance of AODV and LA-AODV protocols in V2V communication under dynamic traffic conditions. The simulations ran for 200 seconds for each scenario. They collected data on packet delivery ratio (PDR), packet loss ratio (PLR), average throughput, average end-to-end delay, and end-to-end jitter. The goal was to evaluate how LA-AODV impacts the quality of V2V communication in different traffic scenarios and understand how different routing methods support V2V communication under dynamic traffic environments. Applying the Learning Automata approach to AODV resulted in the creation of LA-AODV, enabling a more comprehensive comparison between the two protocols. The final analysis will summarize the advantages and disadvantages of the study and discuss how LA-AODV affects the quality of V2V communication.

The comparison requires a modified version of the standard AODV protocol known as LA-AODV. Fig. 2 demonstrates the step-by-step procedure for this modification. The source node of the network can use GPS services to determine the locations of both the destination node and its surrounding nodes. To ensure that every node in the network receives periodic updates about actual vehicle locations, each vehicle independently predicts its future location using computing power and communicates this prediction to surrounding nodes to determine whether the node can act as a relay. The LA-AODV protocol ensures accurate path estimation and route selection using data from the vehicle communication network. The process is achieved by employing equation (1) to estimate the relative positions of vehicles and calculate their actual positions based on speed and acceleration data.

$$SET_{point_x} = \Sigma_{x=1}^{x\leq J}\, certain_{point_\alpha}, certain_{point_\beta}, z_x \quad (1)$$

Equation (1) allows LA-AODV to dynamically select relay nodes by incorporating both current and predicted network conditions. Specifically, it evaluates:

- Vehicle proximity, using distance and signal strength to ensure reliable communication links.
- Number of vehicles within transmission range, as an indicator of potential congestion or broadcast collisions.
- Vehicle speed and elapsed time, to predict route stability and reduce frequent route breakages due to high mobility.

Two additional sub-equations (not shown here) are used to calculate **current proximity** and **predict future location**, which are then fed into equation (1) as input parameters. By predicting node mobility trends, LA-AODV aims to minimize link failures, improve packet delivery success rates, and enhance road safety by maintaining stable and efficient communication paths. They align with the ideas in equations 2 and 3.

$$fut_{point_\alpha} = \Sigma_{x=1,t=1}^{x\leq J, t\leq L}(certain_{point_\alpha} + (z_x \,.\, t) + \left(\left(\frac{1}{2}(\Delta z)\right) * 2\right) \quad (2)$$

$$fut_{point_\alpha} = \Sigma_{x=1,t=1}^{x\leq J, t\leq L}(certain_{point_\beta} + (z_x \,.\, t) + \left(\left(\frac{1}{2}(\Delta z)\right) * 2\right) \quad (3)$$

Where:

$$\Delta c = (c_t - c_{t-1}) \text{ at the begginning of iteration } c_{t-1} = 0$$

And:

t: Prediction time, where t = 1, 2, 3, … and $t < L$,
L: Maximum Iteration,
x: Vehicle x,
J: Total number of vehicles within the transmission range,
z_t: Vehicle speed at time t.

These two equations (2) and (3) define a kinematic prediction model that proactively estimates future vehicle positions by considering speed, acceleration, and time. The equation (2) and equation (3) allow the LA-AODV protocol to predict positions across multiple vehicles and time steps, enhancing performance compared to relying on outdated locations. The model supports more brilliant relay node selection, reducing route breakages and improving communication efficiency while ensuring low latency and adaptability in dynamic VANETs. The LA-AODV protocol improves vehicle communication networks by predicting positions through vehicle communication and updating the route table. This process enhances V2V communication efficiency in dynamic traffic conditions.

$$fut_{eff_{\alpha\beta}} = \sqrt{(|\Delta fut_{point_\alpha} - \Delta fut_{point_\beta}|)} \quad (4)$$

Where:

$$\Delta fut_{point\,\alpha} = (fut_{point\,\alpha+1} - fut_{point\,\alpha}) \tag{5}$$

$$\Delta fut_{point_\beta} = (fut_{point\,\beta+1} - fut_{point\,\beta}) \tag{6}$$

Equation (4) calculates the position of the vehicle ($fut_{eff\,\alpha\beta}$), accounting for variations in the horizontal (α) and vertical (β) points. The values of $\Delta fut_{point\,\alpha}$ and Δfut_{point_β}, calculated using equations (5) and (6), are used in this calculation method. By deducting the expected position at time t + 1 ($fut_{point\,\alpha+1}$) from the actual predicted location of the vehicle at time (t) ($fut_{point\,\alpha}$) equation (4) actively determines the change in the predicted position down the horizontal points (α). Like equation (6), equation (4) calculates movement along the vertical points. The predicted position along the vertical points is calculated by deducting $fut_{point\,\beta+1}$ from $fut_{point\,\beta}$. The variable $fut_{eff\,\alpha\beta}$ makes predictions about the locations of surrounding cars over a given simulation time interval by considering the expected horizontal and vertical points at two different locations. Equation (7) compares the ideal vehicle movement changes along the horizontal (α) and vertical (β) points for each vehicle during two predicted time intervals.

$$fut_{eff\,\alpha\beta} = MIN\left(\begin{smallmatrix} x \le J, t \le K \\ x=1, t=1 \end{smallmatrix} \sqrt{\begin{matrix} (\left|fut_{point\,\alpha+1} - fut_{point\,\alpha}\right|)^2 - \\ (\left|fut_{point\,\beta+1} - fut_{point\,\beta}\right|)^2 \end{matrix}} \right) \tag{7}$$

Equation (7) uses Euclidean distance and dynamic coordinates to estimate and compare vehicle positions for the best route. The most effective routing circumstances ensure responsive vehicle communication. Equation (8) is used to determine the relay node by calculating the communication stability index between nodes q and r.

$$com\_stab\_idx_{xy} = \left|\left(\frac{fut_{point_{\alpha\beta}}}{Max_{rad}}\right)\right| \tag{8}$$

Where:

$$com\_stab\_idx_{xy} = \left\{\left(\frac{stab, if \le 1}{unstab, if > 1}\right)\right\} \tag{9}$$

The LA-AODV protocol introduces the communication stability index in equation (8), which is crucial for evaluating communication stability between nodes. The index is determined by dividing the total positions from surrounding vehicles by the maximum communication radius. When the index is less than or equal to 1, it indicates stable communication, while a value higher than 1 suggests an unstable environment. Equation (9) determines vehicle weights based on factors like position, speed, acceleration, and communication quality, aiding in selecting an effective relay node.

$$TWR_x = \Sigma_{x=1}^{x \to J} \left(e_s * (|s_n - s_d|)\right) + \left(e_a * (|a_n - a_d|)\right) + \left(e_d * (|d_n - d_d|)\right) + \left(e_q * com\_qty_x\right) \tag{10}$$

Where:

$$0.6 \ge TWR = 1, Optimal, and\ TWR \le 0.59, suboptimal.$$

The Total Weight Route (TWR), a metric used to evaluate the standard route's quality, is calculated by the LA-AODV protocol using equation (10). TWR considers multiple factors, including distance travelled, speed, acceleration, and communication quality. According to the formula given in equation (11), each of these variables is given a weight equal to one.

$$W_{sum} = e_s + e_a + e_d + e_q = 1 \tag{11}$$

$$i_{t+1} = \left\{ \begin{matrix} Q(t), i_{selected} = 1, reward \\ Q(t), +1, i_{ignore} = 0, penalize \end{matrix} \right\} \tag{12}$$

Equation (11) combines factors with defined weights to create a balanced assessment for route selection based on speed, distance, acceleration, and communication quality in the LA-AODV protocol. The TWR uses the LRI algorithm as the learning rate to evaluate route quality. Equation (12) explains how the LRI algorithm adjusts its learning based on previous experiences. Equation (13) incorporates the I value into the most recent TWR to renew the TWR value, enabling constant fine-tuning and adaptation for different vehicles or nodes. This dynamic approach improves routing efficiency and inter-vehicle communication during simulation.

$$TWR_{renew} = \Sigma_{x=1,t=1}^{x \le J, t \le L}(TWR_x + i) \tag{13}$$

3.1. Simulation Environment and setup

Our V2V communication model was tested with NS3 v3.35 and SUMO-GUI. To evaluate the communication system in challenging circumstances, SUMO-GUI developed a traffic system with multiple scenarios. We paired SUMO with NS3 v3.35 to simulate network connection. With the support of these tools, we could conduct a comprehensive assessment of our communication model and improve road transportation efficiency and safety. The study tested multiple traffic scenarios across different time intervals in this simulation. Data density, communication delays, and network instability were present in these scenarios. The simulation parameter settings used in this study are shown in Table 1.

Table 1. V2V communication simulation parameter setup

No	Parameter	Value(s)
1	Total number of actual Nodes	20, 30, and 40 Nodes
2	Simulation time (s)	50, 100, and 200 Second
3	Route Selection	Random route selection
4	Node Speed	Random speed
5	Initial node position	Random position
6	Node Movement	All moving nodes
7	Network Map Configuration	Customized Network Map
8	Type of Protocol	AODV dan LA-AODV
9	Type of traffic	Passenger cars only, Left-hand drive.

In Table 1, we have presented various scenarios for actual vehicle construction with different parameters. We conducted a performance assessment using node counts of 20, 30, and 40 and simulation time intervals of 50, 100, and 200 seconds. The LA-AODV protocol's performance in V2V communication was evaluated through three traffic scenario simulations. To enhance the Quality of Service (QoS) and the efficiency of the AODV protocol in V2V communication, each scenario with parameter tuning represents a unique configuration of learning automata. We used metrics such as flood ID, packet loss ratio, packet delivery ratio, average throughput, end-to-end delay, and end-to-end jitter to measure the average protocol efficiency for each parameter and assess performance. The study provides comparisons across several parameter-tuning scenarios. We tested two distinct scenarios for LA-AODV. The first scenario, LA-AODV (A, B, C), involved parameters explicitly simulated for this study, while the second scenario, LA-AODV (x, y, z), utilized parameters derived from previous research[9]. All the parameter values used in the simulations are detailed in Table 2.

Table 2. V2V simulation LA-AODV parameter setup

Parameter Tunning						
Variables	**LA-AODV (A)**	**LA-AODV (B)**	**LA-AODV (C)**	**LA-AODV (x)** [9]	**LA-AODV (y)** [9]	**LA-AODV (z)** [9]
fs	0,4	0,3	0,4	0,3	0,4	0,3
fa	0,3	0,4	0,2	0,3	0,4	0,4
fd	0,3	0,3	0,4	0,4	0,2	0,3
TWRmax	15	30	45	20	30	10
TWRmin	10	20	30	10	15	5
Imax	15	19	24	15	20	10
Imin	6,5	9	11,5	5	7,5	2,5
alpha	0,6	0,8	1	0,6	0,8	0,4
reward	1	1	1	1	1	1
Selected_node	5	5	5	5	5	5

Table 2 presents a comprehensive set of factors that influence the communication capabilities of each vehicle. These factors encompass speed *(fs*), acceleration (*fa*), and distance (*fd*) priorities, along with the total weighted ratio maximum (*TWRmax*), total weighted ratio minimum (*TWRmin*), maximum intensity (Imax), minimum intensity (*Imin*), Alpha, Reward, and selected_node. Notably, the speed, acceleration, and distance priorities (*fs, fa, and fd*) play a vital role in determining the behavior of each vehicle. Additionally, the selection of relay nodes is governed by TWRmax and *TWRmin*, with *TWRmax* holding a higher probability of selection. Imax and Imin regulate the levels of rewards or sanctions, while Alpha symbolizes the learning rate. Furthermore, the reward value (1) is assigned for making astute choices, and the variable selected_node denotes the number of nodes chosen as relay nodes during each learning iteration. The primary objective of our comparative analysis is to significantly enhance our understanding of how fine-tuning these parameters impacts the performance of the LA-AODV protocol across a diverse range of simulated scenarios.

3.2. Quality of Services Performance Matrix

By analyzing several LA-AODV routing models alongside AODV using Quality of Service (QoS) measures such as Flow ID, Packet Delivery Ratio (PDR), Packet Loss Ratio (PLR), Throughput, Delay, and Jitter, the study evaluates the performance of the models. These metrics assess the performance and capacity of LA-AODV routing based on the Quality of Service requirements for Vehicle-to-Vehicle (V2V) communication. The Packet Loss Ratio (PLR), defined by equation (14), measures the percentage of all transmitted packets within the communication network that were not delivered successfully.

$$PacketLossRatio = \frac{LostPackets}{SentPackets} \tag{14}$$

The PLR is an essential metric defined by equation (14), which quantifies the proportion of packets successfully received relative to the total number of packets sent within a specific time frame. This metric underscores the critical nature of maintaining a low PLR to ensure the safety and efficiency of vehicular communication systems. A high PLR can introduce safety risks, traffic congestion, and a reduction in driver confidence, thereby underscoring the fundamental need for dependable V2V communication protocols. Equation (15) formally outlines the calculation for the Packet Delivery Ratio (PDR), another crucial metric in vehicular communication systems. It is defined as the total number of packets transmitted within a given time unit divided by the number of packets successfully received [22]. PDR plays a significant role in evaluating the effectiveness of packet delivery within the communication system.

$$PacketDeliveryRatio = \frac{ReceivedPackets}{SentPackets} \tag{15}$$

Equation (15) is used to calculate the Packet Delivery Ratio (PDR) by comparing the amount of data received by a destination node (ReceivedPackets) with the amount of data sent by a source node (SentPackets). An ideal scenario is achieved when the amount of data delivered and received is equal. A higher PDR value signifies better network performance and a higher success rate of the employed routing protocol. Equation (16), a practical and straightforward formula, is utilized to determine the Average Throughput. This metric, which involves dividing the total number of packets successfully received by the destination device within a specific time interval by the duration of the interval, provides a clear and tangible measure of network performance.

$$AvgThroughput = \frac{TotalPacketsSent}{TotalTime} \tag{16}$$

Average throughput (16) is a key metric in network performance evaluation, directly assesses the efficiency of data transfer. It does so by dividing the total number of packets successfully received by the destination device over a specific period. Lower values suggest slower rates, while higher values indicate more efficient transfer. The average end-to-end delay, on the other hand, depicts the average time taken for packets to reach their destinations. Equation (17) is used to calculate the average delay for all packets that successfully arrive at their destinations.

$$delay_i = \frac{\sum_{i=0}^{n}(Trecv[i] - Tsent[i])}{TotalPackets} \tag{17}$$

The average delay for each packet is calculated using equation (17), which averages the differences between the times a packet is sent and received. equation (18) describes the end-to-end jitter delay resulting from errors in data processing and packet rearrangement.

$$jitter = \frac{VariatonDelay}{NumPackets-1} \tag{18}$$

The network's variance in delay time can be calculated using the equation (18). By dividing the difference between the maximum and minimum delay values by the number of delay samples less one ($NumPackets - 1$), it may be calculated. Jitter is used to evaluate how consistently data is transmitted across a network.

4. Result and Discussion

Analyzing simulation metrics will provide insights into the performance difference between LA-AODV and AODV in terms of network performance. It's crucial to understand the impact of LA-AODV on Flod-id values, which vary depending on testing circumstances. Therefore, it's important to consider different testing scenarios and the roles played by each variant in network traffic management. Fig. 3 displays the comparison results for flood id.

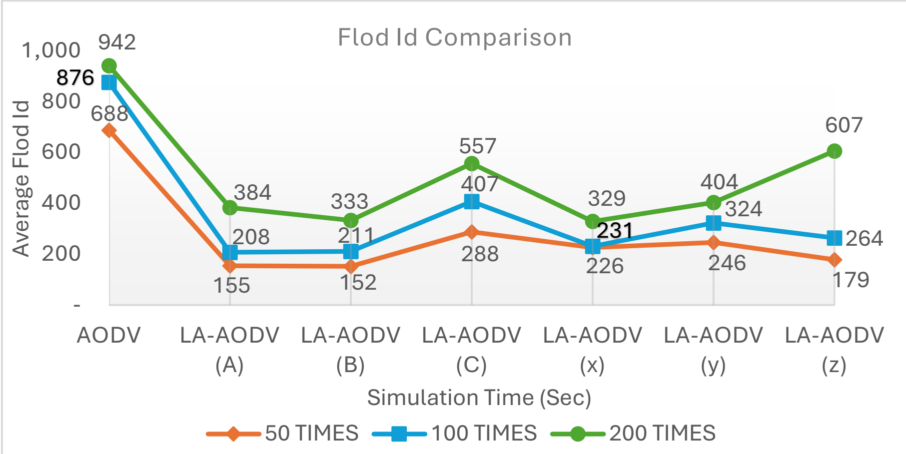

Fig.3. Comparison of flod id routing protocols LA-AODV and AODV

Fig. 3 shows that the flood ID count of AODV increases as the scenario time progresses, from 688 at 50 times to 942 at 200 times. In contrast, all LA-AODV variants demonstrate significantly lower flood-id counts. Surprisingly, LA-AODV (A) and (B) show the most notable improvements, increasing from 155 and 152 at 50 times to 383 and 333 at 200 times, respectively. Other variants, such as LA-AODV (C), (x), (y), and (z), also maintain lower flood-id counts than AODV, with varying performance. The decrease in flood-id counts in LA-AODV (A) and (B), specifically by 10.24% and 28.74% at 200 times compared to AODV, indicates lower network overhead, potentially leading to improved network performance with reduced latency and increased throughput. Additionally, the scalability of these protocols suggests they are better suited for more extensive networks or high-communication scenarios. The result signifies more efficient utilization of network resources, which are particularly valuable in resource-constrained environments. In some testing scenarios, LA-AODV outperforms AODV regarding packet loss ratio (PLR), indicating that certain LA-AODV variations might be more susceptible to packet loss and should be carefully considered for network scenarios and use cases. For comparable PLR statistics, refer to Fig. 4.

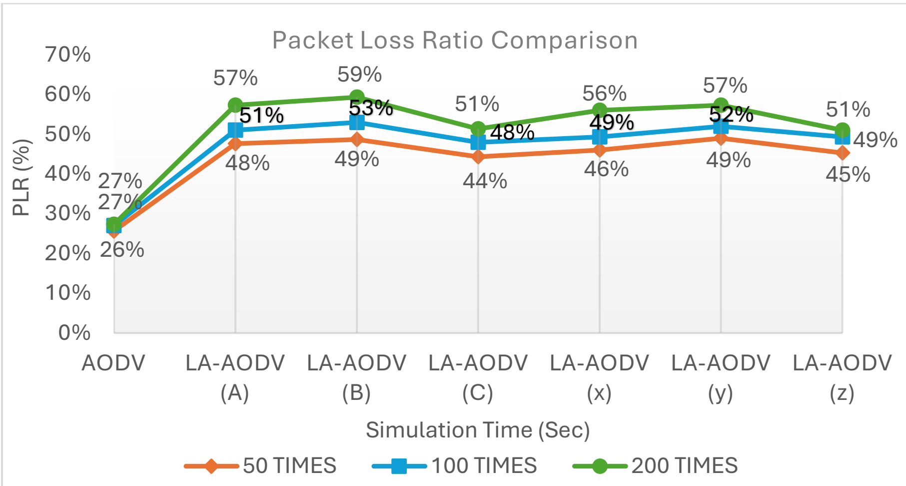

Fig.4. Comparison of packet loss ratio routing protocols LA-AODV and AODV

The packet loss ratio (PLR) for AODV and various LA-AODV protocol variants (A, B, C, x, y, z) was compared in three scenarios—50, 100, and 200 times, with AODV consistently showing a lower PLR (26% to 27%) than all LA-AODV variants. The PLR of LA-AODV variants increased as scenarios progressed, with LA-AODV (B) exhibiting the highest PLR (59%) at 200 times. The simulation proves that AODV's superior performance in managing packet loss. Additionally, AODV showed a higher packet delivery ratio (PDR) than several LA-AODV variants across different scenarios, suggesting its effectiveness in delivering packets. Fig. 5 provides a comparison of the results for the packet delivery ratio.

Fig.5. data shows that AODV outperforms all LA-AODV variants in packet delivery ratio (PDR) across different scenarios. AODV maintains a stable PDR of around 72-73%, highlighting its reliability. LA-AODV variants demonstrate varied performance, with LA-AODV (C) and (z) performing relatively better. LA-AODV (B) shows the lowest

performance, especially at 100 times, with a PDR of 46%. The results suggest that AODV offers better stability in PDR, making it a reliable choice for applications requiring consistent packet delivery. This reassures the audience about the performance of AODV in maintaining a stable PDR, even across different scenarios. Further development is needed for LA-AODV variants, especially (B). LA-AODV performs better in lower throughput scenarios, suggesting potential for improved performance in certain situations, especially in scenarios involving extensive networks.

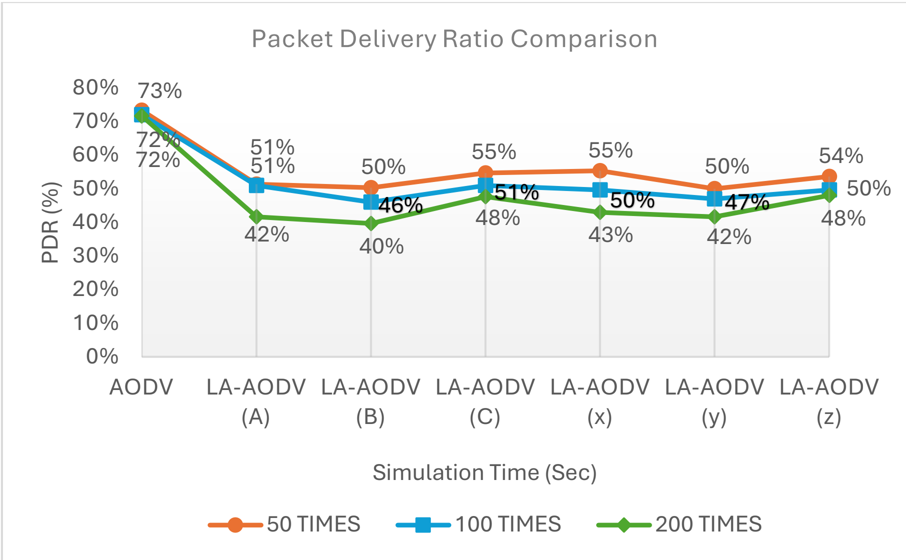

Fig.5. Comparison of packet delivery ratio routing protocols LA-AODV and AODV

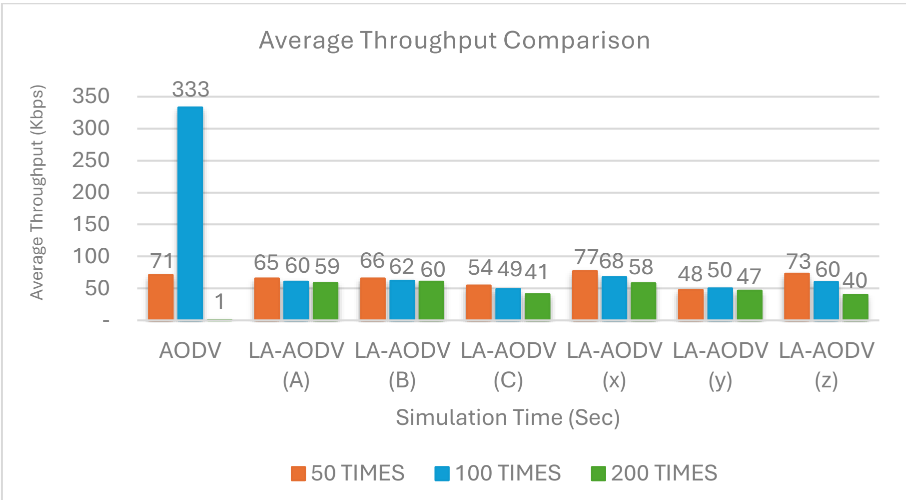

Fig.6. Comparison of average throughput routing protocols LA-AODV and AODV

In Fig. 6, AODV and its LA-AODV variants are compared in 50, 100, and 200 scenarios. AODV performs best in the 100 times scenario and is less stable in the 200 times scenario. In the 200 times scenario, all LA-AODV variants show higher throughputs. Notably, for medium-scale networks (50 times), AODV, LA-AODV (x), and (z) are found to be suitable, offering practical options for network engineers. For large-scale networks (100 times), AODV is preferred. For very large-scale networks (200 times), LA-AODV (A) is recommended due to its higher throughput. The stability of LA-AODV in lower throughput scenarios suggests that modifications to AODV can improve performance. For comparable end-to-end delay statistics, reporting the average throughput along with standard deviations or 95% confidence intervals would enhance the scientific rigor of the analysis and provide better insight into the consistency and reliability of the results across multiple simulation runs. Different LA-AODV versions may perform better than AODV in terms of end-to-end delay. For comparable end-to-end delay statistics, refer to Fig. 7.

The data in Fig. 7 shows that LA-AODV variants consistently have lower delay values across all scenarios (50, 100, and 200 times) compared to AODV. The result significantly higher delays for AODV. The data suggests that LA-AODV has the potential to significantly reduce end-to-end delay, offering a key advantage over AODV, especially for applications requiring rapid response times. LA-AODV may be an adequate substitute for regular AODV in reducing jitter delay, an essential measure in communication networks. Including standard deviations or confidence intervals for delay measurements would strengthen the validity of these findings and clarify the variability observed between simulation runs. Fig. 8 presents the comparison results for end-to-end jitter.

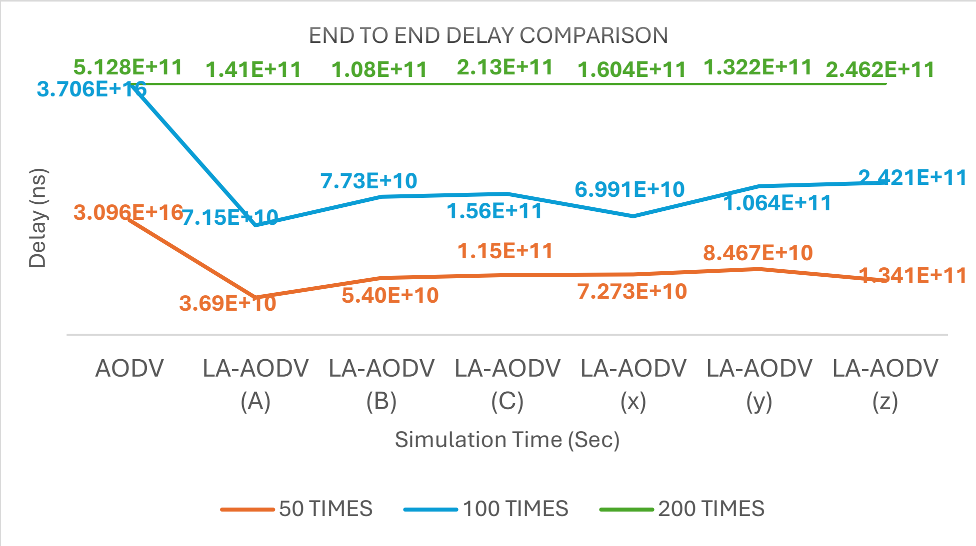

Fig.7. Comparison of End-To-End delay routing protocols LA-AODV and AODV

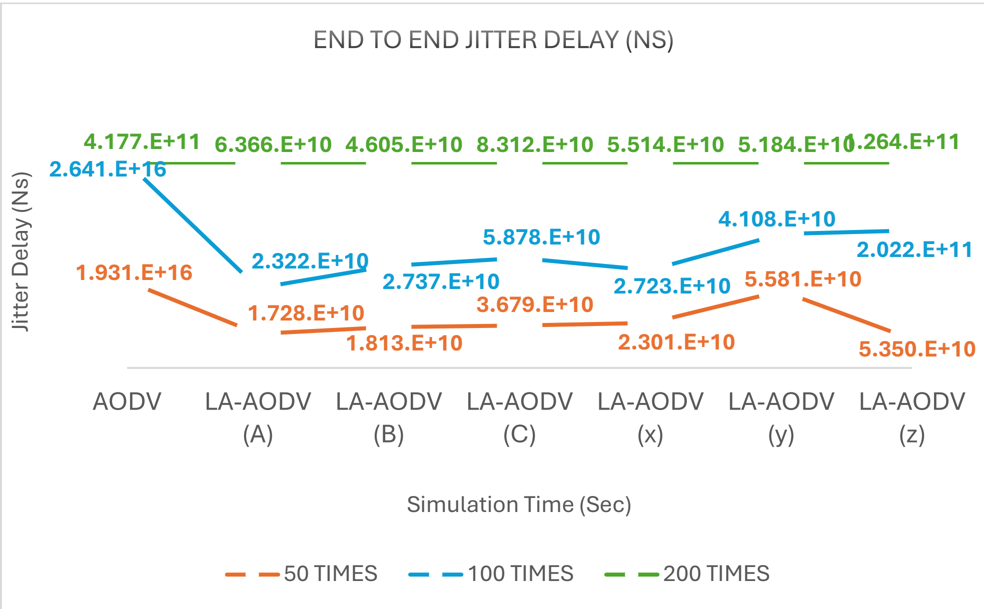

Fig.8. Comparison of End-To-End delay routing protocols LA-AODV and AODV

The results from Fig. 8 show that the AODV protocol has consistently high jitter delay values in all scenarios, while all variants of LA-AODV demonstrate significantly lower jitter delay values. Specifically, LA-AODV (A) performs the best, especially for V2V communication. The LA-AODV variants' variations highlight algorithm alterations' impact on jitter delay. Overall, LA-AODV shows promise in improving network service quality by reducing packet delay variation. However, choosing the appropriate variant based on the specific application and usage scenario is essential.

The proposed LA-AODV variants demonstrate improved throughput and end-to-end delay performance across different network sizes, highlighting their potential for enhancing Quality of Service (QoS) in vehicular networks. However, it's essential to consider several limitations to ensure the protocol's applicability in real-world scenarios. Firstly, the scalability of LA-AODV under extreme traffic conditions—such as high node density and network congestion—has not been extensively evaluated. These conditions may introduce significant routing overhead that could degrade performance. Secondly, the current simulation setup assumes ideal node behavior and does not account for critical factors like node failures, intermittent connectivity, or mobility-induced disconnections. Such issues are common in real vehicular environments and could affect the protocol's reliability and effectiveness.

In addition to QoS considerations, the robustness of V2V communication must address vulnerabilities like packet loss from interference, malicious node behavior, and rapid topology changes. While LLA-AODV improves route stability and reduces delays, these benefits haven't been thoroughly tested. Thus, future research should focus on stress-testing its protocol under high loads and evaluating its fault tolerance, security, and adaptability in dynamic, failure-prone environments.

5. Conclusions

The study provides a detailed comparison between LA-AODV and AODV routing protocols, highlighting significant performance differences. LA-AODV variants, particularly LA-AODV (A) and (B), show substantial reductions in flood-id counts, with improvements of 10.24% and 28.74%, respectively, at 200 times, indicating reduced network overhead and better scalability. However, AODV consistently exhibits lower packet loss ratios (PLR), with LA-AODV (B) showing a 118.52% increase in PLR compared to AODV. Regarding packet delivery ratio (PDR), AODV remains more reliable, maintaining around 72-73%, while LA-AODV (B) shows a 36.99% decrease in performance. AODV achieves the highest average throughput in medium-scale scenarios. However, LA-AODV (A) performs more stably in more extensive networks, showing a 5.4% higher throughput at 200 times compared to AODV's significant drop. LA-AODV variants also reduce end-to-end and jitter delays, with reductions exceeding 99.99% and 99.93% at 50 times scenarios, respectively, compared to AODV. The findings suggest that while AODV remains a reliable and efficient protocol for scenarios requiring low packet loss and high packet delivery ratios, LA-AODV variants significantly improve network overhead, end-to-end delay, and jitter delay. Specifically, LA-AODV (A) and (B) are promising for large, dynamic networks due to their reduced control overhead and improved scalability.

The conclusion can be strengthened by suggesting specific future directions, such as optimizing LA-AODV variants to reduce packet loss and improve delivery. Tailoring these protocols to particular use cases and network conditions could enhance their effectiveness. Additionally, future research might explore integrating LA-AODV with machine learning for predictive routing or adapting it for 6G vehicular networks. The 6G would help LA-AODV compete better with AODV in various scenarios. Overall, the study highlights the potential benefits of LA-AODV variants, instilling optimism about the future of networking and the importance of choosing protocols based on the specific needs of network environments.

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