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Jakarta, 24 September 2024

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Performance Optimization of V2V Communication Reactive Routing Protocol Through Simulation Analysis

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***Abstract* — This study was conducted to explore and find the optimum parameters related to the Quality of Service (QoS) in Vehicle-to-Vehicle (V2V) communication within Vehicular Ad Hoc Networks (VANETs) by optimizing the Learning Automata-based Ad Hoc On-Demand Distance Vector protocol (LA-AODV). The study compared three variants of LA-AODV (LA-AODV(A), LA-AODV(B), and LA-AODV(C)) with the standard AODV. The simulation result evaluated their performance based on crucial QoS metrics such as FLOD ID, Packet Loss Ratio (PLR), Packet Delivery Ratio (PDR), Average Throughput, End-to-End Delay, and End-to-End Jitter. The results indicated that LA-AODV(B) consistently outperformed the other variants, particularly in FLOD ID. The improvements of 9.14%, 40.29%, and 22.79% in 50, 100, and 200-trial scenarios compared to LA-AODV(A) were significant. However, LA-AODV(C) showed suboptimal performance in the exact scenarios. Nevertheless, practical parameter tuning of LA-AODV(C) led to a remarkable improvement in protocol performance, with a 74% reduction in FLOD ID compared to AODV in various simulation scenarios. Parameter tuning is crucial for consistent efficiency in V2V communication, as LA-AODV's adaptability under different traffic conditions provides valuable insights. Our focus is on evaluating LA-AODV's performance in realistic scenarios. While we plan to compare it with established methods in the future, our current research allows us to understand its effectiveness in real-world V2V communication compared to standard AODV. We aim to expand our scope by comparing LA-AODV with other established methods in future studies.**

Keywords: V2V communication, Learning automata, AODV routing protocol, NS3, VANET.

I. Introduction

Vehicular Ad Hoc Networks (VANETs) revolutionize vehicle communication, using self-organizing networks that rely on vehicle cooperation [1]. AODV is a widely used routing protocol in VANETs [2]. but it faces limitations like suboptimal relay node selection [3], high control message overhead [4], and challenges in adapting to dynamic mobility patterns [5]. AODV generates high control overhead due to frequent RREQ and RREP messages, leading to increased latency and energy consumption, as well as challenges with scalability and handling link failures. LA-AODV, while improving Quality of Service (QoS), introduces algorithmic complexity and depends on precise parameter tuning, resulting in longer convergence times in dynamic scenarios and less compatibility with hybrid networks [6][7]. The protocol also produces many control messages, which increase overhead and can cause network congestion and slower performance [8][9]. Adapting to dynamic mobility patterns further affects AODV's efficiency in varying vehicular conditions [10]. Efficient protocols that adapt to mobility patterns and select relay nodes with minimal control messages can improve VANET performance [11]. In recent years, many researchers are exploring new routing protocols to enhance performance and reliability in VANETs.

Researchers have developed the Learning Automata-based Ad Hoc On-Demand Distance Vector (LA-AODV) protocol [12] to address these challenges. LA-AODV optimizes relay node selection, reduces control message overhead, and adapts to changing network conditions using Learning Automata. It enhances real-time responsiveness in bandwidth-limited scenarios [13] and is highly adaptable to dynamic vehicle mobility patterns, ensuring efficient communication [14]. Additionally, LA-AODV improves connectivity during network partitioning, scalability in dense traffic, and mitigates congestion. The protocol supports diverse QoS metrics [15], providing low latency, high throughput, and reliable packet delivery in V2V communication[16].

The study aims to optimize LA-AODV by comparing three variants with the standard AODV protocol to identify the most effective one. It will focus on tuning LA-AODV parameters to enhance QoS in V2V communication within VANETs and evaluate its adaptability to varying traffic conditions. The findings will provide valuable insights for optimizing parameters, selecting the best variant, and improving LA-AODV's performance in real-world traffic, advancing efficient and reliable V2V communication.

Over the years, numerous studies have focused on identifying and addressing the challenges of the AODV

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routing protocol in V2V communication, particularly concerning QoS and channel availability [17], [18].

Researchers have proposed several methods to improve AODV performance. For instance, implementing Prediction Node Trends on AODV can predict a packet's destination and reduce hop count [3], The Mobility and Detection AODV (MDA-AODV) adjusts routing paths based on node mobility [19], Additionally, Flooding-awareness-AODV [20] efficiently manages the broadcast storm problem, enhancing packet delivery ratio and reducing average delay compared to standard AODV.

Researchers have also explored various strategies, such as a Cluster-based communication approach with learning automata-assisted prediction [21] and the use of learning automata for channel reservation [22] to ensure optimal channel availability for V2V communication in VANET. These approaches address handoff calls within the VANET environment. Additionally, multipath routing strategies, including Particle Swarm Optimization [23], leap-frog algorithm [24], and adaptive prediction models [25]. incorporate reinforcement learning [26] to provide reliable and efficient routing paths for V2V communications [27].

This research, while acknowledging that some studies may not directly target VANET or network scenarios, outlines strategies to enhance the AODV routing protocol and improve V2V communications by optimizing the LA-AODV protocol, identifying key factors for optimal QoS, determining the most effective LA-AODV variant for specific needs, and assessing the protocol's adaptability to various traffic conditions, ultimately leading to safer and more efficient vehicular networks.

II. Research Methods

The process of simulating the V2V communication protocol comprises several phases. Initially, configuration settings are modified to define the traffic map, followed by the establishment of mobility scenarios to observe how vehicles move within the simulated traffic environment. The specific steps of simulation and comparison are detailed in Figure 1.

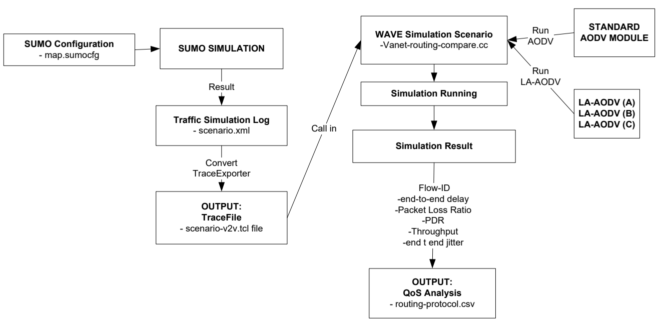

Fig. 1. Research Procedure for the Comparison between LA-AODV and AODV Through SUMO and NS3 Simulation

In Figure 1, once the mobility scenarios are set up, AODV and LA-AODV simulations are conducted across all scenarios for up to 200 seconds. The simulations generate continuous data to evaluate various LA-AODV protocol performances compared to standard AODV-supporting V2V communication in dynamic traffic environments. The collected data includes PDR, throughput, average end-to-end delay, end-to-end jitter, and packet loss ratio for each scenario and iteration. After completing the simulation, the results are carefully analyzed in Figure 1. The purpose is to evaluate how the LA-AODV protocol enhances the QoS of V2V communication in dynamic traffic situations. In the final stage, the simulation results are thoroughly examined and interpreted. The findings' strengths, weaknesses, and implications on the QoS for V2V communication are discussed. This simulation provides a deeper understanding of the compared routing protocols (AODV and various LA-AODV with parameter tune) that support V2V communication in dynamic traffic environments. In order to conduct a helpful comparison between AODV and LA-AODV, it is essential to implement the Learning Automata method into AODV, which will result in the creation of LA-AODV, allowing for a more comprehensive evaluation of the two protocols.

The comparison requires a modified version of the standard AODV protocol known as LA-AODV. The network's source node detects the locations of its neighbors and utilizes GPS services to determine the destination node's location using A-GPS[28]. A-GPS enhances performance in urban areas or environments with poor satellite visibility by utilizing cellular networks to improve the speed and accuracy of location data. Each vehicle independently predicts its future location using computational capabilities and broadcasts this prediction to neighboring nodes. This ensures that every node in the network periodically receives updates on actual vehicle locations, a critical step in determining each node's potential as a relay. The LA-AODV protocol ensures accurate estimation of vehicle parts and routing decision-making that leverages information within the vehicle communication network. This is achieved by predicting the relative positions of vehicles and determining their actual positions using speed and acceleration parameters, as outlined in Equation (1).

$$\text{INITpos}_c = \sum_{k=1}^{k\leq N} \text{actual}_{pos_x},\ \text{actual}_{pos_y}, v \tag{1}$$

The LA-AODV protocol accurately routes and positions vehicles in a communication network achieved through Equation (1), which considers various parameters, including the initial x and y positions of vehicle c (*INIT 〖pos〗_c*), to determine vehicle proximity. The LA-AODV protocol uses different variables such as vehicle speed (*vi*), the number of vehicles within transmission range (*N*), and a specific node or vehicle as a reference (*c*). Two equations are employed to evaluate vehicle proximity and predict future positions within the communication network by integrating these factors.

These equations aim to improve road safety by considering vehicle speed, the number of vehicles in transmission range, and elapsed time for informed routing decisions. They align with the principles outlined in Equations 2 and 3.

$$INITpos_x = \sum_{k=1,t=1}^{k\leq N, t\leq M} (actual_{pos_x} + (v_t.t) + \left(\left(\frac{1}{2}(\Delta v)\right)*2\right) \tag{2}$$

$$INITpos_y = \sum_{k=1,t=1}^{k\leq N, t\leq M} (actual_{pos_y} + (v_t.t) + \left(\left(\frac{1}{2}(\Delta v)\right)*2\right) \tag{3}$$

Where :

Δvx=(v_t-v_t-1) at the begginning of iteration vt-1=0, *Δvy=(v_t-v_t-1)* at the begginning of iteration v_t-1=0

And :

t : Prediction time, where t = 1,2, and t < M,

M : Maximum Iteration and K, Vehicle k,

N : Total number of vehicles within the range,

v_t : Vehicle speed at time t.

Equation 2 predicts a vehicle's x-axis position at time (t) based on speed, distance, and time, while Equation 3 predicts the y-axis position considering additional factors. Both equations are crucial for accurate inter-vehicle communication and routing decisions. The LA-AODV protocol predicts the positions of vehicles and improves the efficiency of communication in the vehicle network. The vehicles exchange data with each other to determine their minimum predicted positions. This data is then used to update the routing table and determine the status of vehicles with minimum distance and speed using Equation 4.

$$\text{pred\_acc}_{xy} = \sqrt{(|\Delta\text{pred\_pos}_x - \Delta\text{pred}_{\text{pos}_y}|)} \tag{4}$$

Where:

$$\Delta pred\_pos_x = (pred\_pos_{x+1} - pred\_pos_x) \tag{5}$$

$$\Delta pred\_pos_y = (pred\_pos_{y+1} - pred\_pos_y) \tag{6}$$

Equation 4 computes the prediction of the vehicle's position ($pred\_acc_{xy}$), taking into account changes along the x and y axes. This calculation method utilizes the values of $\Delta pred\_pos_x$ and $\Delta pred\_pos_y$, obtained from Equation (5) and Equation (6). In Equation (4), the change in the predicted position along the x-axis is actively determined by subtracting the expected position at time t+1 ($pred\_pos_{x+1}$) from the actual predicted position of the vehicle at time (t) ($pred\_pos_x$). Similarly, Equation (4) calculates the movement along the y-axis, where the predicted position along the y-axis is based on subtracting $pred\_pos_{y+1}$ from $pred\_pos_x$, as described in Equation (6). The variable $pred\_acc_{xy}$ predicts the positions of surrounding vehicles during a specific simulation time period, considering the expected x and y coordinates at two points.

Equation 7 uses the Euclidean Distance formula to determine the minimum value, comparing the optimal movement changes of vehicles along the x and y axes for each vehicle during two prediction time intervals.

$$pred_{acc_{xy}} = MIN\left(\sum_{k=1,t=1}^{k\leq N,t\leq M} \sqrt{\begin{matrix} (\left|predpos_{x+1} - pred_{pos_x}\right|)^2 - \\ (\left|predpos_{y+1} - pred_{pos_y}\right|)^2 \end{matrix}} \right) \tag{7}$$

Equation 7 predicts and compares vehicle positions for optimal routing using dynamic coordinates and Euclidean distance. The most efficient routing conditions ensure inter-vehicle communication responsiveness. The communication stability index between nodes k and j is calculated using Equation 8 to select the relay node.

$$\text{comm\_stability\_index}_{kj} = \left|\left(\frac{\text{pred}_{\text{acc}_{xy}}}{\text{Max}_{\text{rad}}}\right)\right| \tag{8}$$

Where :

$$comm\_stability\_index_{kj} = \left\{\left(\begin{matrix} stable,\ if \leq 1 \\ unstable,\ if > 1 \end{matrix}\right)\right\} \tag{9}$$

Equation 8 in the LA-AODV protocol introduces the communication stability index $comm\_stability\_index_{kj}$. This metric is crucial in assessing the communication stability between nodes, specifically nodes k and j. To calculate this index, the total predicted positions from neighbor vehicles (*represented by* $pred_{acc_{xy}}$) , are divided by the maximum communication radius. (Max_{rad}), This encompasses an area of 50 grids in width and length, set at 2500 grid units. When the value $comm\_stability\_index_{kj}$, ≤1 indicating that the communication environment between nodes "k" and "j" is stable. Conversely, if the index value is greater than 1, it suggests that the communication conditions tend to be unstable. After evaluating the communication quality between node "k" and its neighboring vehicles, based on the distance between them during two prediction time intervals 't' and '$t+1$', the next step is to assign weights to each vehicle. Weights for each vehicle are calculated based on factors like speed, acceleration, position, and node 'k' communication quality (Equation. 9). This helps make optimal decisions about relay node selection.

$$TWR_k = \sum_{k=1}^{k\ to\ N} \left(\begin{matrix} ((f_s*(|s_n - s_d|)) + (f_a*(|a_n - a_d|) \\ +(f_d*(|d_n - d_d|) + (f_q*(comm\_quality_k)) \end{matrix} \right) \tag{9}$$

Where $0.6 \geq TWR = 1, Optimal, and$ $TWR \leq 0.59, suboptimal.$

The LA-AODV protocol utilizes Equation 9 to compute the Total Weight Route (TWR), a parameter used to assess the quality of the standard route. TWR takes into account several variables, such as speed, distance, acceleration, and communication quality, each assigned a weight equivalent to 1, as per the formulation described in Equation (10).

$$W_{total} = f_s + f_a + f_d + f_q = 1 \tag{10}$$

Equation 10 amalgamates various factors by assigning specific weights to each parameter, creating a balanced evaluation of all these parameters. The LA-AODV protocol employs this mechanism to ensure that speed, distance, acceleration, and communication quality are all optimally taken into account when selecting the best route. This approach results in an effective routing mechanism for vehicle communication. The TWR provides a comprehensive assessment of the overall route quality. After deciding on the LA method, it applies the LRI algorithm as the learning rate (α). The source node then informs its neighbors that it is the relay node. The LRI algorithm rewards or penalizes each decision, as outlined in Equation (11).

$$a_{t+1} = \left\{ \begin{matrix} Q(t),\ a_{selected} = 1,\ reward \\ Q(t), +1, a_{ignore} = 0,\ punishment \end{matrix} \right\} \tag{11}$$

In Equation 11, the LRI algorithm adapts its learning by assessing (α) based on past experiences. Rewards set the learning rate to 1, while penalties reduce it to 0. The fine-tune variable value of the algorithm's learning rate is related to its decision-making ability. Equation (12) elucidates the addition of the 'a' value to the latest TWR in the predicted iteration (t+1).

$$TWR_{update} = \sum_{k=1,\ t=1}^{k\leq N, t\leq M} (TWR_k + a) \tag{12}$$

Equation 12 updates the TWR value, allowing continuous adjustment and refinement for various vehicles or modes using the learning rate α. The TWR value adapts to changes in network conditions and routing decisions, resulting in dynamic and responsive routing decisions during the simulation. This process contributes to improving the performance of inter-vehicle communication and routing. The value of α plays a crucial role in shaping the TWR value and routing decisions throughout the maximum simulation (M).

A. The Simulation Environment

We evaluated our V2V communication model using SUMO-GUI and NS3 v3.35. SUMO-GUI generated a traffic system with various scenarios to test the communication system in complex environments, while NS3 v3.35 simulated network communication in conjunction with SUMO. These tools enabled a comprehensive evaluation of our communication model, enhancing efficiency and safety in road transportation.

B. Simulation Setup

In this simulation, the authors evaluated various traffic scenarios across different time intervals. These scenarios involved network instability, data density, and communication delays. Table 1 presents the simulation parameter configurations utilized in this research.

TABLE. 1. COMMUNICATION SIMULATION PARAMETER SETUP

No	Parameter	Value(s)
1	Total number of Nodes	20, 30, and 40 Nodes
2	Simulation time (s)	50, 100, and 200 Second
3	Route Selection	Random route selection
4	Type of Protocol	AODV dan LA-AODV
5	Type of traffic	Passenger cars only, Left-hand drive.

Table 1 outlines real-world vehicle scenarios using various parameters. Performance evaluation was done with different simulation time intervals and node counts. The authors ran three traffic scenario simulations to assess the LA-AODV protocol's performance in V2V communication. They used parameter tuning to enhance QoS and protocol effectiveness. Performance was measured using Flow ID, PLR, PDR, Average Throughput, End-to-end Delay, and End-to-end Jitter.

TABLE. 2. V2V SIMULATION LA-AODV PARAMETER TUNNING

Parameter Tunning			
Variables	**LA-AODV(A)**	**LA-AODV (B)**	**LA-AODV (C)**
fs	0.3	0.4	0.3
fa	0.3	0.4	0.4
fd	0.4	0.2	0.3
TWRmax	20	30	10
TWRmin	10	15	5
Imax	15	20	10
Imin	5	7.5	2.5
alpha	0.6	0.8	0.4
reward	1	1	1
Selected_node	5	5	5

Table 2 shows that communication efficiency from each vehicle is influenced by factors including speed factor (fs), acceleration factor (fa), distance factor (fd), total weighted ratio maximum (TWRmax), total weighted ratio minimum (TWRmin), maximum intensity (Imax), minimum intensity (Imin), Alpha, reward, and selected_node. Alpha, the learning rate, and the reward, a value of (1) for favorable decisions, are two key elements in the communication system. They play a crucial role in the system's learning and decision-making processes.

C. Quality of Services Performances Matrix

The study compares various LA-AODV routing models with AODV, using important Quality of Service (QoS) metrics such as FLOD ID, Packet Delivery Ratio (PDR), Packet Loss Ratio (PLR), Average Throughput, End-to-End Delay, and End-to-End Jitter for assessing the performance and capabilities of LA-AODV in meeting QoS standards for V2V communication.

III. RESULT AND DISCUSSION

Simulation metric analysis will provide insights into the extent of LA-AODV's superiority over AODV in network performance. These metrics will encompass the following performance parameters. The comparative results for Flod ID are illustrated in Figure 2.

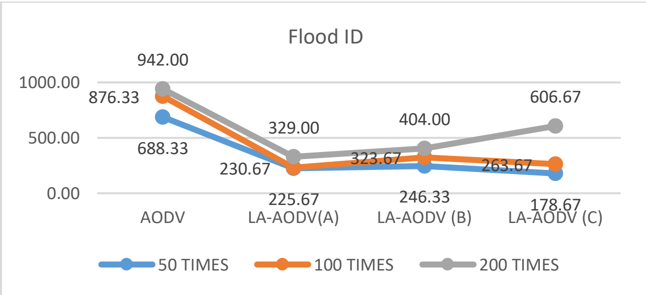

Fig. 2. Comparison of Flod ID routing protocols LA-AODV and AODV

The results showed in Fig. 3 that LA-AODV(B) performed better than the other two protocols in terms of FLOD ID, with an increase of approximately 9.14% in the 50-trial scenario, a significant increase of approximately 40.29% in the 100-trial scenario, and an increase of around 22.79% in the 200-trial scenario, compared to LA-AODV(A).

However, LA-AODV(C) consistently performed worse than the other two protocols, with a decrease of around 20.85% in the 50-trial scenario, an increase of about 14.31% in the 100-trial scenario, and a significant increase of about 84.80% in the 200-trial scenario. The comparison between LA-AODV(C) and LA-AODV(B) showed a decrease of about 27.54% in the 50-trial scenario and a decrease of about 50.16% in the 200-trial scenario. LA-AODV(C) performed better than AODV in the 50-trial scenario, with a 74% reduction in FLOD ID. However, in the 100-trial scenario, LA-AODV(B) showed a 65% increase in FLOD ID compared to AODV. In the 200-trial scenario, LA-AODV(A) and LA-AODV(B) both had a decrease in FLOD ID, while LA-AODV(C) had a slight increase. LA-AODV has a higher Packet Loss Ratio (PLR) than AODV in some testing situations. See Figure 3 for comparative PLR data.

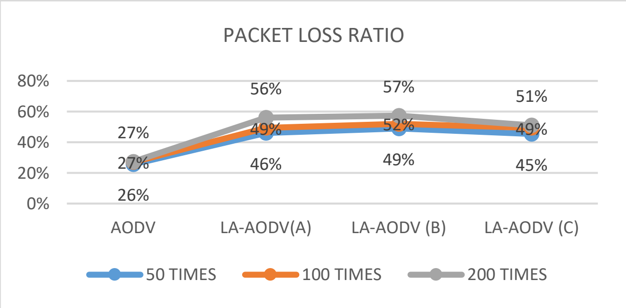

Fig. 3 Comparison of Packet Loss Ratio routing protocols LA-AODV and AODV

The analysis of PLR in Fig. 3 shows that different scenarios (50, 100, and 200 times) have shown significant variations in the performance of LA-AODV protocols compared to AODV. In scenario 50, LA-AODV(B) had the highest increase of 88.46%, while LA-AODV(A) and LA-AODV(C) saw increases of 76.92% and 73.08%, respectively. Different LA-AODV variants have significantly different values for various parameters. In scenario 100, LA-AODV(B) had a higher Packet Loss Rate (PLR), and the *Imax and Imin* parameters were significant. In scenario 200, LA-AODV(B) continued to perform worse than AODV, and LA-AODV(C) increased TWRmin. Proper parameter tuning is essential for improving the protocol's performance. The AODV protocol may be more efficient in packet delivery, while some LA-AODV variants may face challenges in specific scenarios. Comparative results for Packet Delivery Ratio are illustrated in Figure 4.

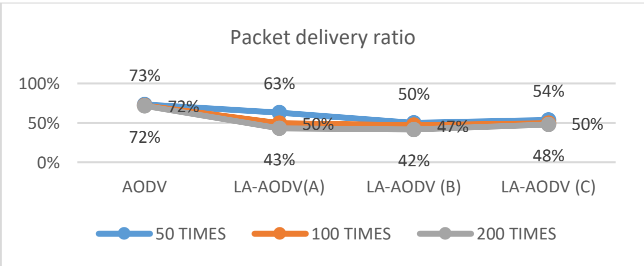

Fig. 4 Comparison of Packet Delivery Ratio routing protocols LA-AODV and AODV

The analysis result in Fig.5 revealed significant performance variations between protocols in scenarios 50, 100, and 200. LA-AODV(B) had lower PDR than AODV, highlighting the complexity of selecting tuning parameters for LA-AODV and its impact on handling traffic variations. Lower PDR can lead to unreliable V2V communication, especially in fluctuating traffic.

Comparative results for Average Throughput are depicted in Figure 5.

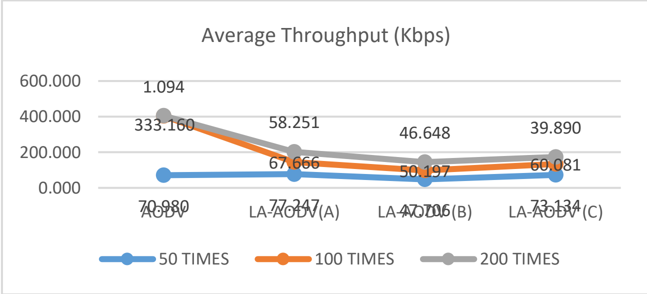

Fig. 5. Comparison of Average Throughput (Kbps) routing protocols LA-AODV and AODV

Fig.5 show compares the Average Throughput (Kbps) in three scenarios for AODV and its variants (LA-AODV(A), LA-AODV(B), and LA-AODV(C)). In the 50-scenario, LA-AODV(A) had the highest throughput at 77.247 Kbps, followed by AODV (70.980 Kbps). In scenario 100, LA-AODV(A) maintained its lead with an average throughput of 67.666 Kbps, while AODV outperformed all variants with 333.160 Kbps. In scenario 200, AODV had the highest throughput at 1.094 Kbps, surpassing all LA-AODV variants. AODV exhibits very high End-to-End Delay in some scenarios. Comparative results for End-to-End Delay are depicted in Figure 6.

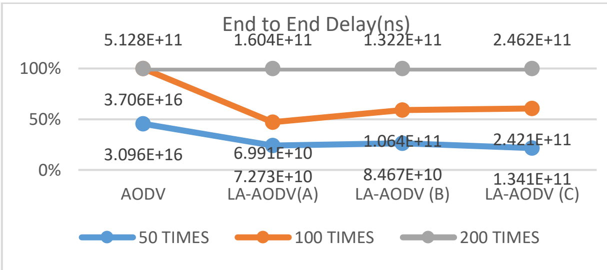

Fig. 6. Comparison of End-to-End Delay(ns) routing protocols LA-AODV and AODV

In Figure 6, during the 50-time scenario, LA-AODV(A) demonstrated the lowest end-to-end delay, outperforming AODV and other LA-AODV variants. Critical parameters such as *TWRmax and TWRmin* significantly influenced protocol performance. In the 100-time scenario, LA-AODV(A) maintained superiority, while AODV outperformed all LA-AODV variants with the lowest delay. In the 200-time scenario, all LA-AODV variants showed reduced delay compared to AODV. Parameter optimization is crucial for consistent LA-AODV performance across traffic scenarios. Low jitter delay can support reliability and consistency in communication networks. Comparative results for End-to-End Jitter Delay are depicted in Figure 7.

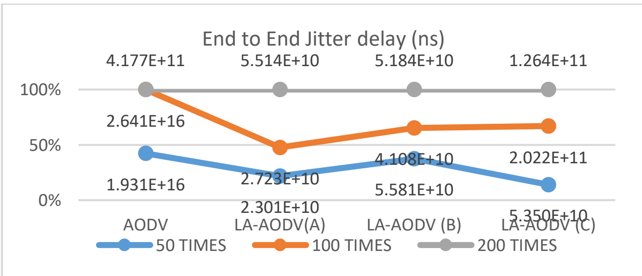

Fig. 7. Comparison of End to End Jitter Delay(ns) routing protocols LA-AODV and AODV.

The End-to-End Jitter Delay (ns) in Figure 7 was analyzed for scenarios of 50, 100, and 200 times. LA-AODV(A) had the lowest Jitter Delay at 2.301E+10 ns in the 50-time scenario. In the 100-time scenario, LA-AODV(A) continued to lead with 2.723E+10 ns, while LA-AODV(B) and LA-AODV(C) showed significant variations. In the 200-time scenario, LA-AODV(A) again demonstrated the lowest Jitter Delay. LA-AODV variants outperformed AODV despite its high Jitter Delay.

IV. Conclusion

Our study compared LA-AODV variants (A, B, and C) with the standard AODV protocol in V2V communication, highlighting the crucial role of parameter tuning in enhancing QoS. Notably, LA-AODV(B) exhibited superior performance with a remarkable 40.29% improvement in the 100-trial scenario, while LA-AODV(C) consistently demonstrated suboptimal results. Through precise parameter tuning, LA-AODV(C) achieved a substantial 74% reduction in FLOD ID. The research aims to comprehensively assess the performance of LA-AODV in specific, realistic scenarios, with the future goal of comparing it with alternative methods.

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