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Optimizing connected vehicle routing protocol for smart transportation systems

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Abstract

The significant growth in integrating connected vehicles into intelligent transportation networks has underscored the importance of Vehicle-to-Vehicle (V2V) communication in optimizing route efficiency, reducing traffic congestion, and enhancing road safety. However, routing protocols such as AODV face substantial challenges in dynamic automotive environments characterized by high mobility and rapid topology changes, leading to issues like packet loss, delays, and network congestion. Reactive protocols like AODV often suffer from route discovery delays, while proactive protocols like DSDV, although reducing latency, increase bandwidth consumption, making them less effective in highly dynamic contexts. This study introduces the Learning Automata Ad Hoc On-Demand (LA-AODV) routing protocol, designed to improve relay node selection and V2V communication efficiency. The proposed method leverages real-time vehicle data to predict and select optimal relay nodes under dynamic traffic conditions, thereby enhancing packet delivery ratio, throughput, and reducing latency and routing overhead. The results demonstrate that LA-AODV significantly outperforms AODV and DSDV across various traffic scenarios, with an increase in packet delivery ratio up to 4% in high traffic conditions, throughput reaching 125 units, and a reduction in end-to-end delay within the range of 2E+10 to 6E+14. These improvements highlight LA-AODV's superior efficiency in handling packet loss and latency, making it a suitable protocol for data-intensive and safety-critical applications that demand reliable and efficient data transmission. This study contributes by developing the LA-AODV protocol, which significantly enhances V2V communication performance in dynamic traffic scenarios and provides a robust simulation model replicating real-world conditions, potentially reducing traffic accidents.

1. Introduction

Incorporating connected vehicles into intelligent transportation networks has significantly increased in recent years. Vehicle-to-vehicle (V2V) communication is a game-changer in our efforts to maximize route efficiency, reduce traffic congestion, and improve road safety [1]. By allowing vehicles to exchange crucial data such as position, speed, and traffic conditions, V2V communication is revolutionizing the way we plan and execute urban transportation. This distributed communication also brings hope for more flexible and dynamic urban areas as the necessity for roadside infrastructure decreases [2]. V2V communication allows vehicles to communicate in real-time, enabling them to respond to changing traffic conditions. This supports intelligent transportation applications, such as collision avoidance systems and real-time traffic monitoring. By reducing the likelihood of accidents and allowing for faster reactions to potential threats, V2V communication empowers drivers and makes driving safer. Additionally, V2V systems help minimize traffic congestion by optimizing vehicle speed and route selection [3].

The background of this study focuses on the challenges faced by V2V communication protocols in connected vehicles, especially in dynamic automotive environments. V2V communications use three main routing methods: hybrid, proactive, and reactive. Reactive protocols like AODV minimize overhead but have route discovery delays, while proactive protocols like DSDV maintain routing information continuously[4]. Hybrid protocols like ZRP combine the benefits of both proactive and reactive routing[5]. Routing protocols such as AODV face major challenges in the automotive context due to its dynamic nature, characterized by high mobility and rapid topology changes. These protocols find it difficult to handle packet loss, delays, and network congestion in such situations [6], [7]. In the same context, while proactive routing reduces delays, DSDV consumes more bandwidth and is less effective in highly dynamic contexts [8]. Critical services, such as real-time traffic diversion or emergency braking notifications, can be hampered by these inefficiencies, leading to delays that compromise public safety. Consequently, optimizing routing protocols for V2V communications is critical to improving the overall efficacy of intelligent transportation systems. The result also enhances the performance and reliability of connected vehicle networks, directly reducing traffic accidents [9].

This study focuses on optimizing relay node selection in V2V communication for connected vehicles. Efficient V2V protocols enhance network performance and reliability, directly reducing traffic accidents. The study presents the LA-AODV routing protocol, which improves relay node selection and enhances V2V communication by utilizing real-time vehicle data. The protocol minimizes communication delay, improves packet delivery ratio, and reduces routing overhead, leading to a more stable network, reduced data congestion, and diminished communication delays[10]. Additionally, the proposed approach enhances traffic safety by decreasing the likelihood of accidents and improving the reliability and efficiency of vehicular communication systems in dynamic and complex traffic conditions. Another study introduces DDSLA-RPL [11], utilizing learning automata to adjust parameter weights, enhancing network service quality and extending node lifespan. While DDSLA-RP exhibits precision and adaptability, it requires improvement in various situations, and the selection of techniques should consider the specific characteristics of the network, weighing the limitations of fuzzy clustering, C-means, and K-means [12]. Another research applying the PSO [13], leap-frog algorithm [14], and basic learning automata [15] to ensure channel availability for V2V communication in VANET.

In contrast, LAAODV has effectively addressed communication enhancements in dynamically changing traffic situations. DP-AODV[16] and FLOW-AODV [17] serve as routing protocols for vehicular communication networks. DP-AODV dynamically adjusts power, and FLOW-AODV utilizes machine learning to select relay nodes intelligently, optimizing QoS parameters and communication efficiency. Several studies have focused on enhancing the quality of service (QoS) in various contexts using relay nodes modification [18], such as in V2V communication within VANET [19]. The AODV routing protocol requires modifications to exploit real-time information on vehicle location, acceleration, and velocity to choose a group of responsive relay nodes [20]. These modifications are necessary to implement AODV for V2V communication, especially in dynamic traffic scenarios[21].

As a contribution, the research introduces the LA-AODV protocol, which improves relay node selection and V2V communication in connected vehicles by using real-time vehicle data, enhancing efficiency and reducing delays in dynamic environments. The study aimed to improve V2V communication in dynamic traffic scenarios by optimizing relay node selection and reducing information overload. Simulations using NS3 compared the effectiveness of the LA-AODV approach with standard AODV in managing traffic. The integration of learning automata with the AODV routing protocol shows promise in enhancing QoS parameters for V2V communication in connected vehicles, thus contributing to better communication performance, reduced delays, and improved safety by preventing accidents in dynamic traffic conditions.

The research paper presents the Introduction in Section 1, the Research Method in Section 2, and the Results and Discussion, including a comparison of AODV, LA-AODV, and DSDV, in Section 3. Finally, the Conclusion is presented in Section 4.

2. Research Method

The research method comprises several vital phases. Initially, the study identifies critical issues in contemporary vehicle communication systems. Figure 1 depicts the research method for simulation.

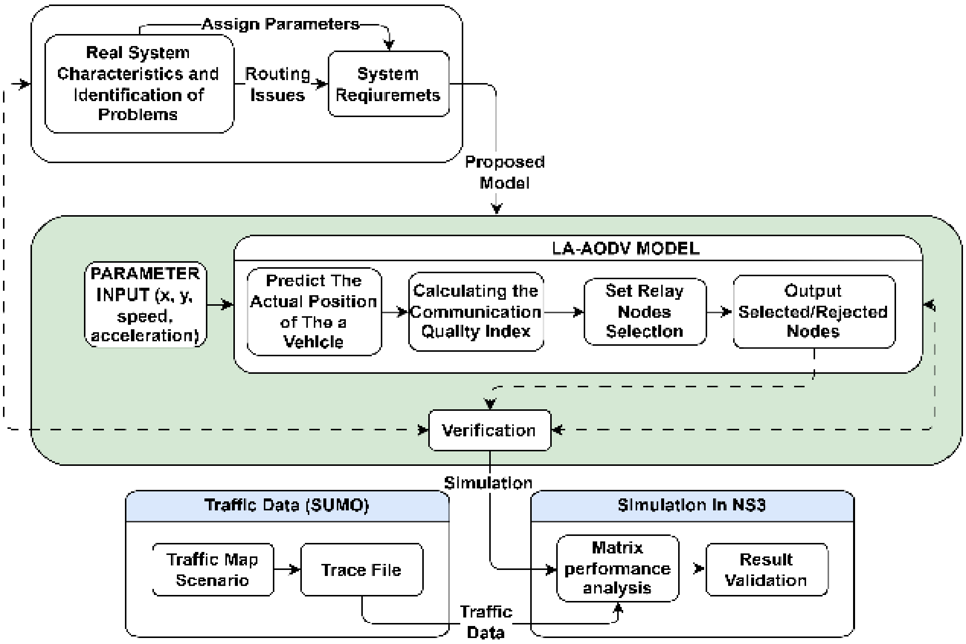

Figure 1. Research Method Protocol LAAODV

Figure 1 depicts the LA-AODV protocol, a crucial element in V2V communication between vehicles. This protocol involves measuring vehicle parameters, calculating communication quality, and selecting relay nodes to ensure stable communication. In Equation 1, $INITpos_k$ represents the initial position of vehicle *k*, calculated by integrating its actual position along the *x* and *y* axes ($actual_{pos_x}$ and $actual_{pos_y}$), along with the vehicle's speed (v_i). *N* denotes the total number of vehicles within the communication radius, and *k* represents the specific vehicle being considered. The protocol's adaptability is demonstrated by its ability to dynamically update reward and incentive values, optimizing relay node selection for more efficient communication. It ensures accurate vehicle location estimation and effective decision-making for route selection based on real-time data. By predicting the vehicle's relative position and determining its actual position using parameters such as speed and acceleration, as described in Equation 1, the protocol adapts to dynamic traffic conditions, improving performance in connected vehicle networks.

$$INITpos_k = \sum_{k=1}^{k\leq N} actual_{pos_x}, actual_{pos_y}, v_i \tag{1}$$

The LAAODV protocol accurately positions vehicles in a communication network using vehicle speed, positions, and the number of nearby vehicles. It helps reduce the risk of road accidents by making appropriate route decisions based on these factors. Therefore, it can help reduce the risk of road accidents as outlined in Equation 2 and Equation 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:

- $\Delta_{vx} = (v_t - v_t - 1)$ at the beginning of iteration $v_t - 1 = 0$
- $\Delta_{vx} = (v_t - v_t - 1)$ at the beginning of iteration $v_t - 1 = 0$

And:

t : Prediction time, where *t* = 1,2,3, and t < M; M: Maximum Iteration; *k*: Vehicle *k*,
N : Total number of vehicles within the transmission range; v_t : Vehicle speed at time *t*.

Equation 2 predicts a vehicle's position on the x-axis at a specific time, and equation 3 forecasts the vehicle's position on the y-axis, considering various factors. These Equations 2 and Equation 3 are used in the LAAODV protocol to enhance the efficiency of the vehicle communication network by predicting vehicle positions. This data, crucial for updating the routing table, determines the vehicle status using the minimum distance and speed as presented in Equation 4.

$$pred_{acc_{xy}} = \sqrt{\left(\left|\Delta pred_{pos_x} - \Delta pred_{pos_y}\right|\right)} \tag{4}$$

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 predicts the vehicle's position based on changes along the x- and y-axes, using values from Equations 5 and Equation 6. Equation 5 calculates the predicted position change along the x-axis, while Equation 6 does the same for the y-axis. The variable predicts the position of surrounding vehicles during a specific time simulation period using expected *x* and *y* coordinates. Equation 7 uses the Euclidean distance formula to determine the optimal movement changes of vehicles along the x- and y-axes for each vehicle during two prediction time intervals.

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

Equation 7 predicts and compares vehicle positions to make accurate routing decisions. It calculates changes in coordinates and assesses euclidean distance to identify efficient routing conditions for vehicle communication. After determining the expected positions, communication reliability with the next node is evaluated before selecting a relay node. The importance of this evaluation is underscored by the fact that Equation 8 computes the communication stability index between nodes *k* and *j*, a crucial step in our process.

$$comm_{stability_{index_{kj}}} = \left|\left(\frac{pred_{acc_{xy}} =}{Max_{rad}}\right)\right| \quad (8)$$

Where

$$comm\_stability\_index_{kj} = \left\{\left(\frac{stable, if \leq 1}{unstable, if > 1}\right)\right\}$$

Equation 8 is a fundamental concept in our discussion, as it introduces the communication stability index, a key element in evaluating node communication stability, particularly *k* and *j*. This index is determined by dividing the total predicted position of neighboring vehicles by the maximum communication range. A value of _kj ≤ 1 indicates stable communication between nodes "k" and "j," while a value exceeding 1 signifies an unstable scenario. Once the communication quality between node "k" and its neighboring vehicles are assessed, the next step is to assign weights to each vehicle based on speed, acceleration, vehicle position, and calculated communication quality, as defined in Equation 9.

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

Where:

0.6≥TWR=1, Optimal, and TWR≤0.59, suboptimal

LA-AODV employs Equation 9 to calculate the Total Weight Route (TWR), a measure used to evaluate the standard route. TWR considers several factors such as speed, distance, acceleration, and communication quality, each assigned an equal weighting factor of 1 as specified by Equation 10.

$$W_{total} = f_s + f_a + f_d + f_q = 1 \quad (10)$$

Equation 10 in the LA-AODV protocol uses speed, distance, acceleration, and communication quality weights to find the best route. After the final decision state, the FSA engine activates the Learning Rate (α), and source nodes share info with relay nodes. The LRI algorithm, a significant element, is used as a learning rate (α) for reward/punishment in each decision in Equation 11.

$$a_{t+1} = \begin{Bmatrix} Q(t), a_{selected} = 1, reward \\ Q(t), +1, a_{ignore} = 0, punishment\end{Bmatrix} \quad (11)$$

The LRI algorithm adjusts the learning rate (α) in Equation 11 based on past experiences. The reward sets the learning rate to 1, while the penalty reduces it to 0. Equation 12 explains the addition of the 'a' value to the latest TWR in the predicted iteration (t+1).

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

Equation 13 updates TWR values continuously, adapting to changing network conditions and routing decisions. Adaptability improves communication and routing performance of V2V connections during the simulation period (M), with the *α* value being crucial.

2.1 Research Framework

The study addresses challenges in communication systems, including network instability, data congestion, and communication delays. We created a simulation to replicate real-world scenarios with accuracy. Figure 2 shows the research design of the research.

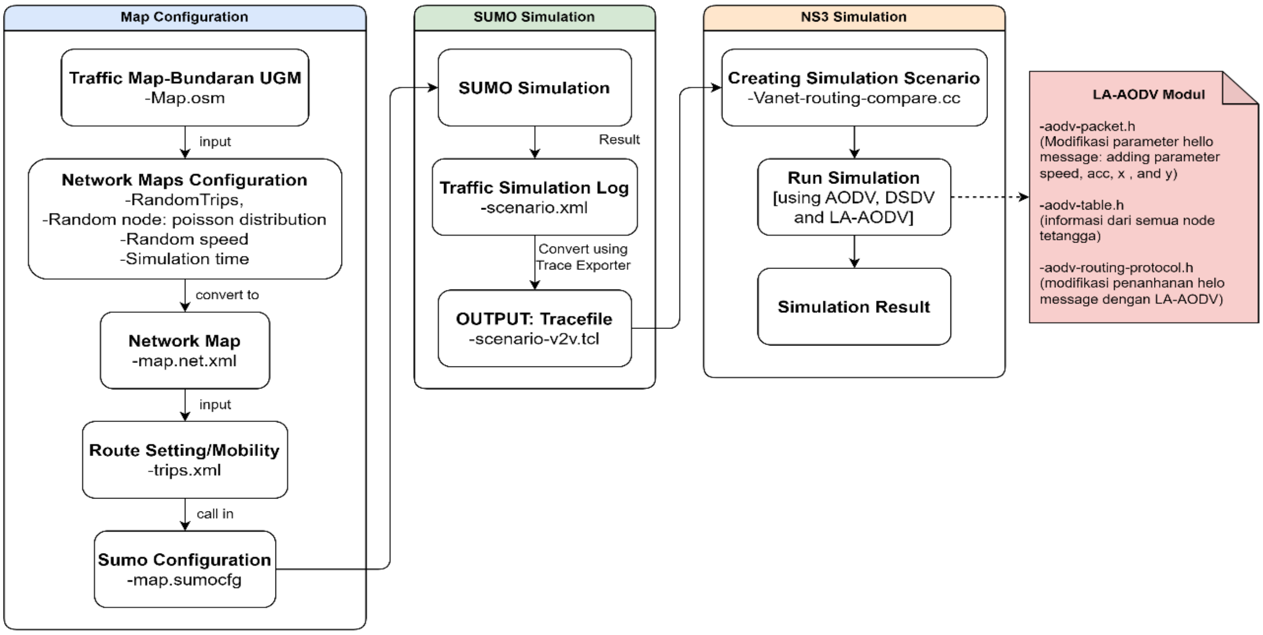

Figure 2. Research Framework

Figure 2 shows a simulation workflow of three main stages: Map Configuration, SUMO Simulation, and NS3 Simulation, focusing on the LA-AODV Module. The process begins with configuring a traffic map (Map. osm), which is then transformed into a network map (map.net.xml) using random trips and node distributions. This network map and route settings (trips.xml) are used in SUMO configuration (map. sumocfg). The SUMO simulation produces a traffic log (scenario.xml), which is then converted into a trace file (scenario-v2v.tcl) for the NS3 simulation. The NS3 simulation integrates AODV, DSDV, and LA-AODV protocols to generate the final simulation results. The LA-AODV module is responsible for adjusting specific parameters and protocols to enhance simulation accuracy.

2.2 The Simulation Environment

Our research uses V2V communication evaluated with SUMO and NS3 v3.35. SUMO models traffic systems, aiding in understanding vehicle and pedestrian movement, while NS3 simulates network configurations to identify issues and find solutions. Integrating SUMO and NS3 allows us to model vehicle movement and assess V2V communication effectiveness accurately. Table 1 shows the V2V Communication simulation setup.

Table 1. V2V Communication Simulation Parameter Setup

No	Parameters	Value(s)
1	Total Numbers of actual Nodes (Vehicles)	Random, based on poisson distribution
2	Simulation Time (s)	300-1000 seconds
3	Traffic Scenario	• Smooth Flow (prob 0.55) • Steady Flow (prob 0.33) • Heavy Traffic (prob 0.1) **Based on Poisson Distribution*
4	Route Selection	Random Route Selection
5	Node Speed	Random Speed
6	Initial node position	Random position
7	Node Movement	All moving nodes
8	Data Packets Configuration	Real-time traffic data packets from the Buluksumur traffic maps.
9	Type of Protocol	AODV, DSDV and LAAODV

10	Type of Traffic	Passengers cars only, Left-hand drive
11	Performance Matrix (QOS)	Flod Id, PDR, PLR, Throughput, end to end delay
12	LAAODV parameter setup	*fs* : 0.4; *fa* : 0.3; *fd* : 0.3; *α*: 0.2; *Reward*: 1;

Table 1 categorized real-world vehicle simulations into three traffic scenarios: smooth flow, steady flow, and heavy traffic. To evaluate the LAAODV protocol, we used metrics such as Packet Delivery Ratio, delay, throughput, packet loss, and jitter. Vehicle communication efficiency relies on speed, acceleration, and distance. We employed the Poisson distribution formula, shown in Equation 13, to calculate the probability of vehicles appearing in different traffic scenarios [22].

$$P(X = I) = \frac{e^{-\lambda}.\lambda^{-i}}{i!} \tag{13}$$

The Poisson distribution, as shown in Equation 14, tracks the number of vehicles passing through a specific point based on the average event rate λ. It involves the Euler number (approx. 2.71) and can predict the likelihood of multiple vehicle occurrences.

2.3 Simulation and Data Analysis

Simulations are used to compare and assess the effectiveness of the AODV, DSDV, and LA-AODV routing protocols in dynamic vehicular networks. The methodology section provides more information on this process. The evaluation process is systematic, starting from traffic monitoring and problem detection and ending with each protocol being executed in a simulated environment. Performance metrics, including Flood ID, Packet Loss Ratio, Packet Delivery Ratio (PDR), Average Throughput, and End-to-End Delay, are analyzed to evaluate the efficiency of each protocol. The steps involved in the simulation and data analysis are shown in Figure 3, which also serves as a visual representation of the methodology framework.

Figure 3 demonstrates the methodology for evaluating and comparing LA-AODV, AODV, and DSDV routing protocols for V2V communication in intelligent transportation systems. It starts with problem identification, observation of traffic patterns, and simulation model design. The model takes into account factors like vehicle speed and network topology. After simulating the protocols, the results are analyzed based on packet delivery ratio, packet loss ratio, average throughput, and end-to-end delay. This thorough analysis compares the protocols' effectiveness in V2V communication, providing a solid basis for research findings. The diagram visually represents the entire process, illustrating the workflow used to assess and improve vehicular communication protocols.

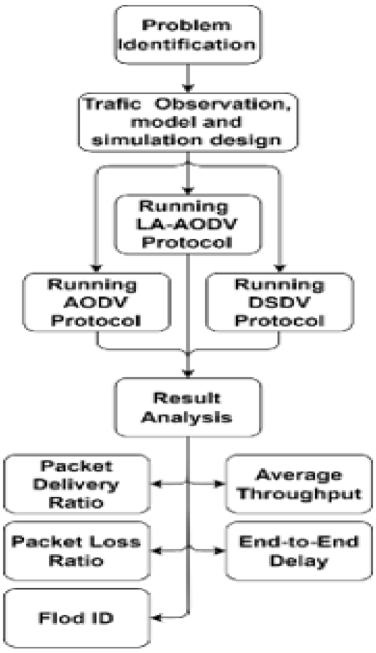

Figure 3. Methodology to Evaluating and Comparing Routing Protocol LAAODV, AODV and DSDV

2.4 Result and Analysis

Using analytical metrics, the Result Analysis will assess how effective the recently developed DSDV, AODV, and LAAODV routing model is in comparison to the earlier AODV and DSDV routing technique. Flood ID, PDR, PLR, Throughput, and Delay are among the metrics that will be examined in order to assess LAAODV capabilities and establish the level of V2V communication quality. Packet Delivery Ratio (PDR) is defined as the ratio of packets successfully received to the total number of packets transmitted within a given time interval [23].

$$PDR = \frac{DataObtained}{DataTransmitted} \tag{14}$$

Equation 14 calculates the PDR value by taking the amount of data obtained at the destination node ($DataObtained$) and dividing it by the amount of data transmitted from the source node ($DataTransmitted$). The ideal ratio occurs when the data obtained matches the data transmitted. A higher PDR ratio signifies improved network performance and indicates a more successful routing protocol. Next, Packet Loss Ration (PLR) is Defined in Equation 15.

$$PLR = \frac{LostPackets}{SentPackets} \tag{15}$$

Packet Loss Rate (PLR) is a metric used to assess the proportion of packets that fail to reach their destination relative to the total number of packets transmitted within a communication network [24]. PLR is calculated using the formula Loss Packet/Sent Packet, as shown in Equation 15. Maintaining a low PLR is crucial for ensuring secure and efficient V2V communication. A high PLR can lead to safety hazards, increased traffic congestion, and a decline in driver confidence, highlighting the need for reliable V2V communication protocols. Besides PLR, throughput is another key performance metric in network communications. Throughput quantifies the rate at which data is effectively transmitted and received across the network, offering a thorough assessment of the network's capacity and operational efficiency [25].

$$AVG_{Througput} = \frac{\text{Number of packets transmitted}}{\text{Total transmission time}} \tag{16}$$

Analyzing throughput in conjunction with PLR is essential for a complete evaluation of the communication system's overall performance and dependability. Equation 16 determines the average throughput, a key indicator of network performance. This is calculated by dividing the number of packets transmitted by the total transmission time. Elevated throughput values signify more efficient data transfer, whereas reduced values suggest slower transmission rates. Average end-to-end delay (AVG_{Delayk}) denotes the average duration required for packets to arrive at their destination [26]. Equation 17 computes this average delay for all packets that successfully reach their endpoint.

$$AVG_{Delayk} = \sum_{k=0}^{n} \frac{t_{obtained}[\mathrm{k}] - t_{transmitted}[\mathrm{k}]}{\text{packet\_measure}} \tag{17}$$

Equation 17 computes the average delay encountered by each packet in reaching its destination. This is done by summing the differences between the reception time at node *k* ($t_{obtained}[\mathrm{k}]$) and the transmission time from the same node ($t_{transmitted}[\mathrm{k}]$), then calculating the average delay (AVG_{Delayk}) for all packets that were successfully delivered (packet_measure). The result is divided by the total number of these packets (n).

3. Results and Discussion

The research analyzes the QoS performance of AODV, LA-AODV, and DSDV protocols in V2V communication, focusing on metrics like PLR, PDR, throughput, and delay. Simulations over 300 to 1000 seconds under various traffic conditions assess protocol behavior and the impact of traffic density and mobility. Figures 4 and 5 show performance results and comparisons with other studies.

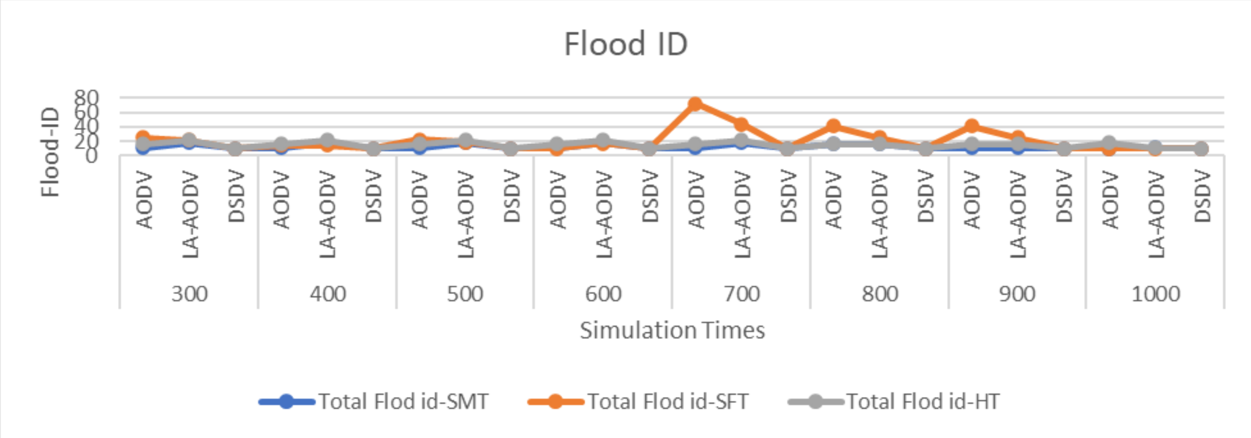

Figure 4. Comparison of Flood ID between AODV, LAAODV and DSDV Across the 300 – 1000 Second

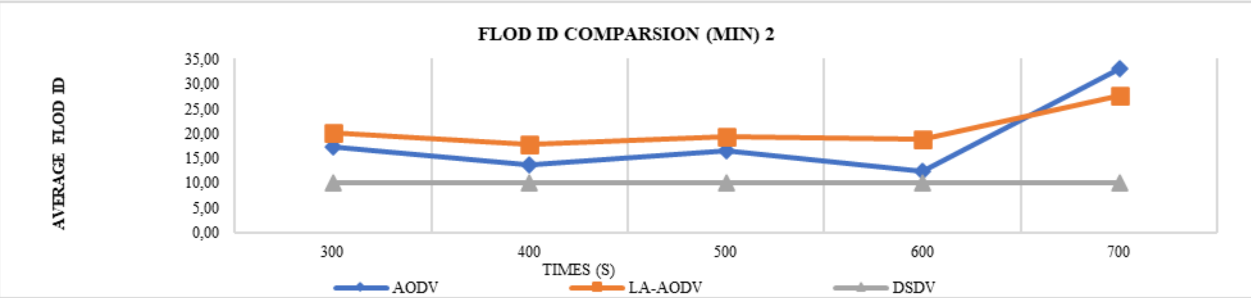

Figure 5. Comparison of Flood ID between AODV, LA-AODV, and DSDV Across the 300-700 Second, Based On Syahputra et.al. [10]

The comparisons in Figures 4 and 5 reveal that LA-AODV outperforms AODV and DSDV in V2V communication under various traffic conditions. LA-AODV shows consistently lower Flood ID values, indicating more efficient control message dissemination, reduced network overhead, and fewer retransmissions due to its proactive design that anticipates routing changes. In contrast, AODV's reactive approach results in inconsistent Flood ID values because of inefficiencies in on-demand route discovery. While DSDV is stable, it struggles with dynamic traffic due to its static routing table. LA-AODV, however, is well-suited for high-mobility scenarios and offers reliable performance. With its scalability and improved network performance, LA-AODV is better suited for large-scale, high-mobility networks, showcasing great potential. Additionally, Figure 5 from another study supports LA-AODV's effectiveness in reducing overhead and ensuring reliable communication among connected vehicles. Next, we will analyze the PLR for V2V communication, which is vital for data integrity and reliability. We will compare the PLR of AODV, DSDV, and LA-AODV with results illustrated in Figure 6 and findings from another study in Figure 7.

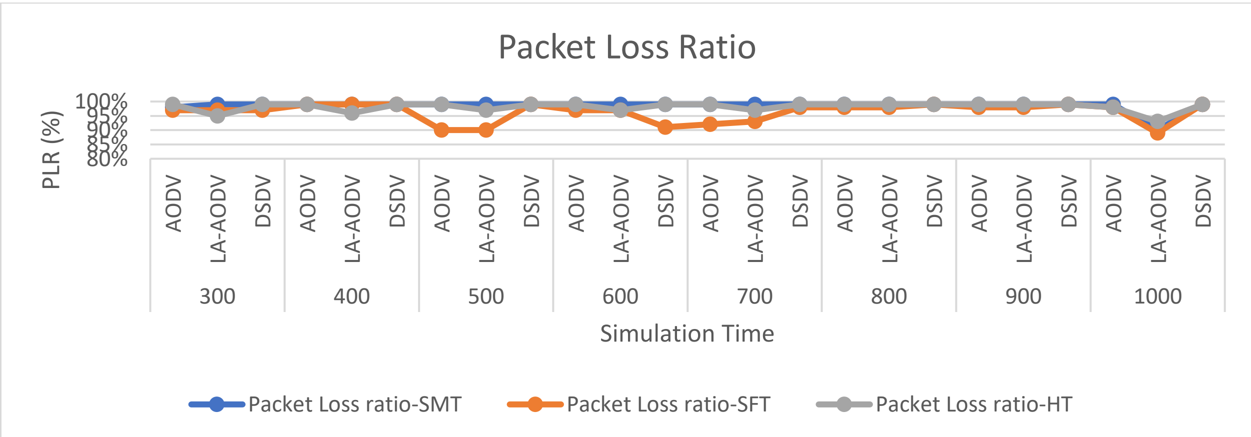

Figure 6. Comparison of PLR between AODV, LA-AODV, and DSDV Across the 300-1000 Second

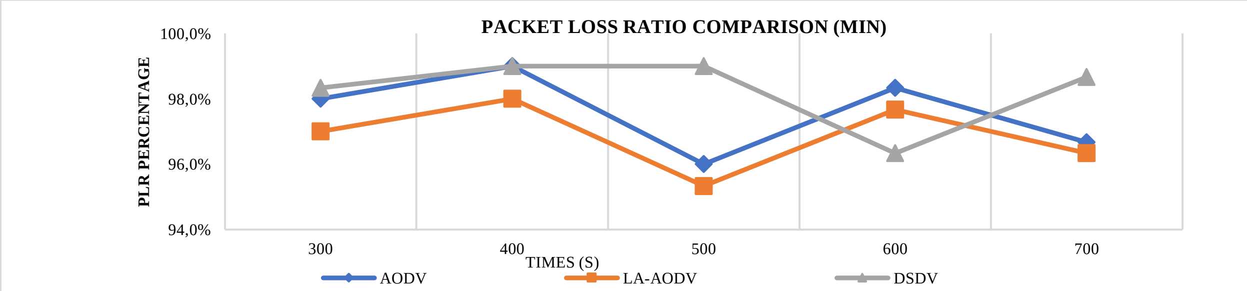

Figure 7. Comparison of PLR between AODV, LA-AODV, and DSDV Across the 300-700 Second, Based On Another Study [10]

The comparisons of Packet Loss Ratio (PLR) data from Figures 6 and 7 highlight the superior performance of LA-AODV in vehicle-to-vehicle (V2V) communication within connected vehicles. In Figure 6, covering 300 to 1000 seconds of simulation, LA-AODV maintains a near-perfect packet delivery ratio (PDR) of around 99%. AODV shows slight degradation, with PDR values fluctuating between 97% and 99%, while DSDV has the lowest and most variable PDR, dropping to 90% in more extended simulations. Figure 7 reinforces these results, showing LA-AODV achieving a PDR of 98% to 99% during 300 to 700 seconds. AODV reaches a maximum of 98%, and DSDV shows 95% to 97%. These findings indicate that LA-AODV provides more reliable communication under dynamic conditions, while AODV and DSDV face challenges due to their routing strategies. Next, Figure 8 will evaluate the Packet Delivery Ratio (PDR), followed by Figure 9 from previous study.

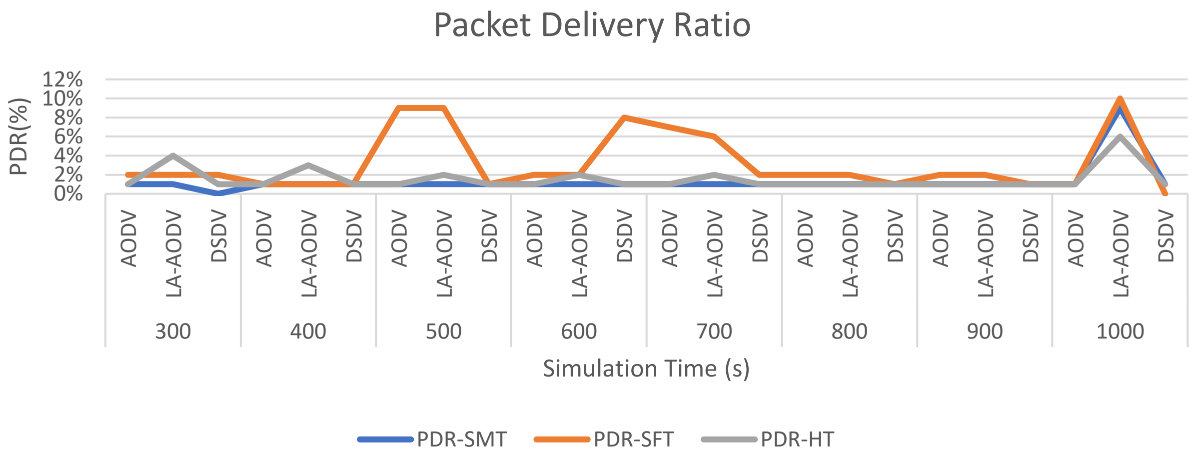

Figure 8. Comparison of PDR between AODV, LA-AODV, and DSDV Across the 300-1000 Second

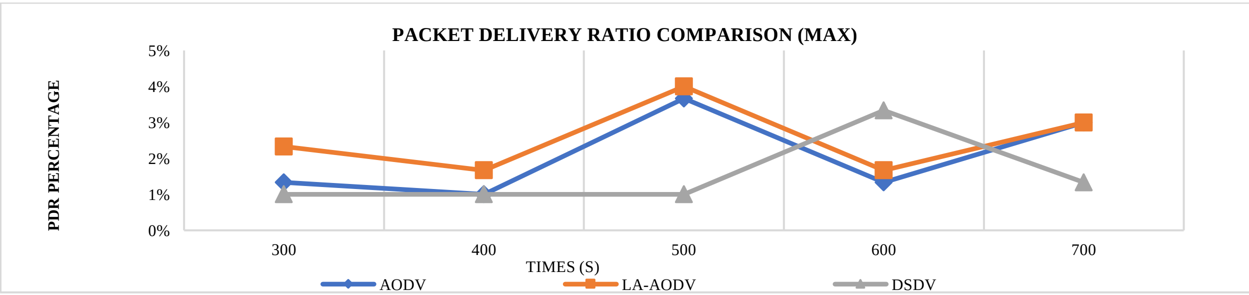

Figure 9. Comparison of PDR between AODV, LA-AODV, and DSDV Across the 300-700 Second, Based On Another Study [10]

The comparison of Packet Delivery Ratio (PDR) data in Figures 8 and 9 shows that LA-AODV consistently outperforms AODV and DSDV in vehicle-to-vehicle (V2V) communication among connected vehicles, regardless of traffic conditions. In Figure 8, which covers simulation periods of 300 to 1000 seconds under Smooth Traffic (SMT), Steady Flow Traffic (SFT), and High-Traffic (HT) scenarios, LA-AODV maintains a stable PDR around 1%, while AODV and DSDV show lower and more variable PDRs ranging from 0% to 9%. Figure 9, from a separate study with a 300—

to 700-second simulation period, also demonstrates LA-AODV's superior performance, yielding PDR values between 1% and 4%. In contrast, AODV and DSDV present significantly lower PDR levels. These findings indicate that LA-AODV ensures more efficient and reliable packet delivery in connected vehicle networks across various traffic conditions.

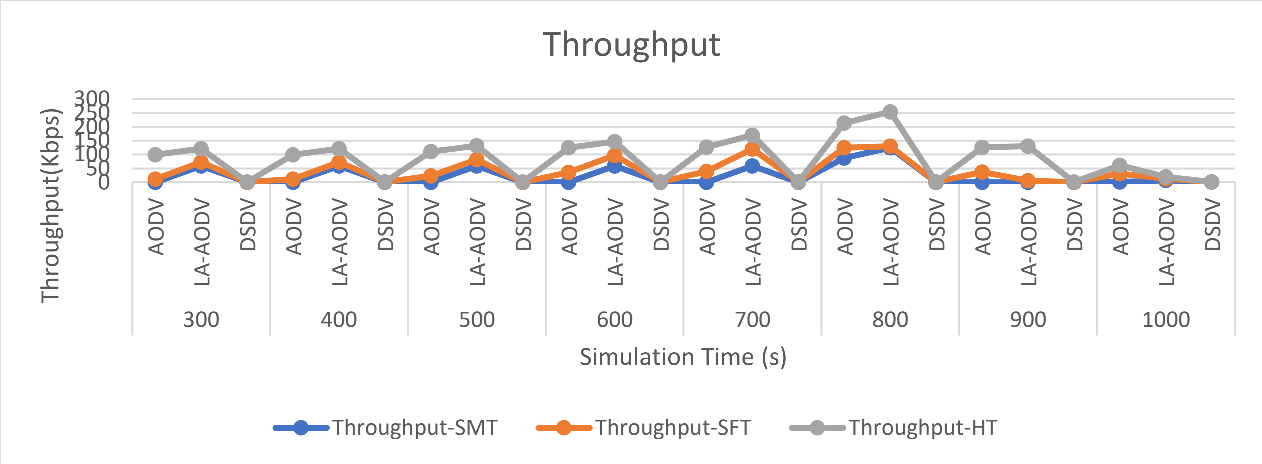

Figure 10. Comparison of Throughput between AODV, LA-AODV, and DSDV Across the 300-1000 Second

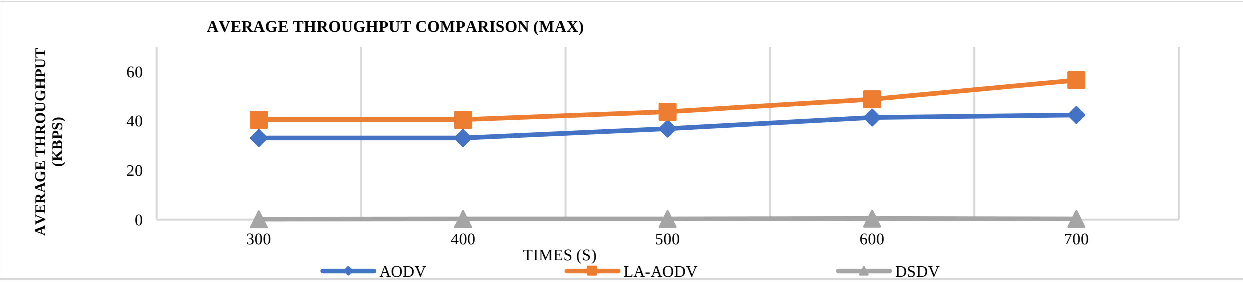

Figure 11. Comparison of Throughput between AODV, LA-AODV, and DSDV Across the 300-700 Second, Based On Another Study [10]

The throughput data in Figures 10 and 11 show that LA-AODV consistently outperforms AODV and DSDV across different simulation times and traffic conditions. In Figure 10, LA-AODV achieves throughput values of 59.12 Kbps at 300, 500, and 600 seconds and 124.53 Kbps at 700 seconds, while DSDV drops as low as 0.04 Kbps. Figure 11 reveals that LA-AODV reaches 40.54 Kbps at 300 seconds, 43.76 Kbps at 500 seconds, and 56.50 Kbps at 700 seconds. Although AODV peaks at 4136 Kbps at 600 seconds, its performance is inconsistent, and DSDV ranges from 0.20 Kbps to 0.44 Kbps. These results demonstrate that LA-AODV provides superior and stable throughput, making it ideal for vehicle-to-vehicle (V2V) communication. Figures 11 and 12 will assess End-to-End Delay to evaluate latency performance further.

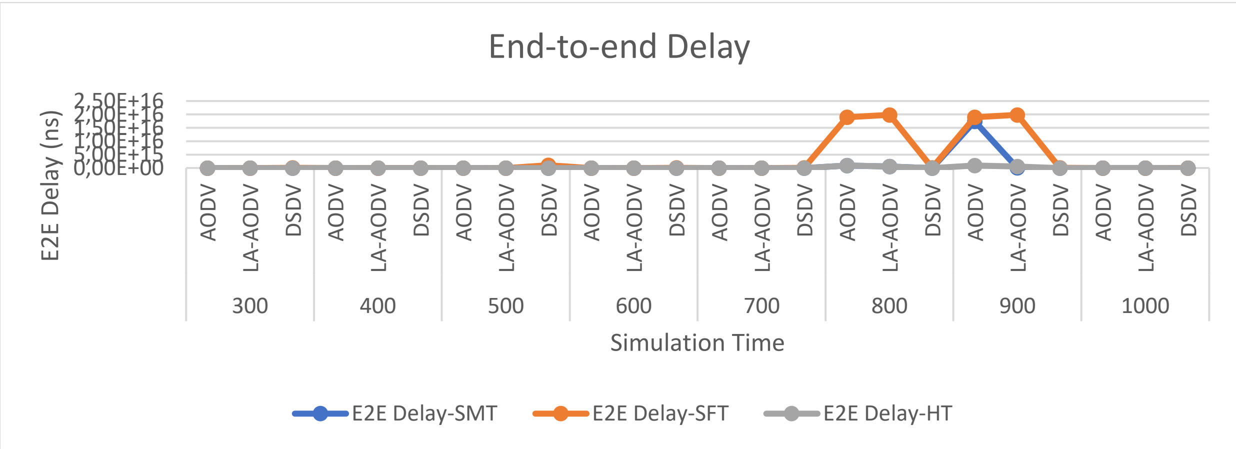

Figure 12. Comparison of End-to-end Delay between AODV, LA-AODV, and DSDV across the 300-1000 second

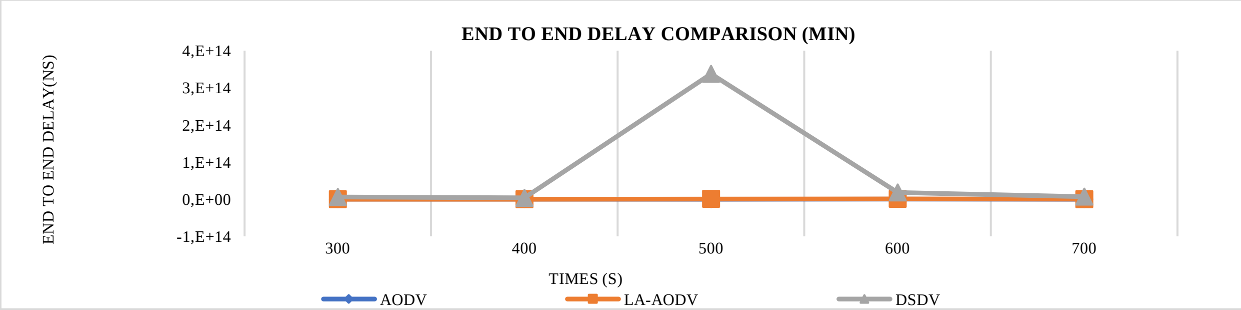

Figure 13. Comparison of End-to-end Delay between AODV, LA-AODV, and DSDV Across the 300-700 Second, Based On Another Study [10]

Figure 12 shows that LA-AODV consistently outperforms AODV and DSDV in terms of latency across different traffic scenarios, including Smooth Traffic (SMT), Steady Flow Traffic (SFT), and High Traffic (HT), where it records lower delays than the other two protocols. This demonstrates LA-AODV's efficiency in reducing latency, thus improving overall network performance for V2V communication. In contrast, Figure 13 from another study shows that AODV has lower delays compared to DSDV and LA-AODV, with delay values of 7.40E+10 ns at 300s, 2.00E+11 ns at 500s, and 1.64E+11 ns at 700s. While AODV is faster, it is less suitable for latency-sensitive applications, and LA-AODV offers a better balance of reduced latency and reliable performance across varied traffic conditions.

4. Conclusion

This study highlights the significant improvements in the LA-AODV routing protocol for enhancing vehicle-to-vehicle communication in connected vehicles. LA-AODV achieves notable advancements, including a 4% increase in high-traffic packet delivery ratio, a throughput improvement of up to 125 units, and a reduction in end-to-end latency. The protocol excels at reducing latency and packet loss, with a packet loss rate of 95-97% in high traffic, making it ideal for data-intensive and safety-critical applications. While it generally outperforms AODV and DSDV, AODV may still be favored in some cases due to its lower control message overhead. LA-AODV's remarkable adaptability in fluctuating traffic conditions is a testament to its reliability for diverse V2V scenarios. Future research should focus on optimizing LA-AODV for scalability, energy management, and enhanced security and privacy.

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