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Enhancing Vehicle Communication on Highways through Modification of the On-Demand Distance Vector Routing Protocol Using Learning Automata Approach

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Abstract-
Background: *Vehicle-to-vehicle communication has become crucial in developing intelligent transportation systems. However, conventional routing protocols face limitations in coping with dense and dynamic traffic conditions.*
Objective: *This study aims to improve communication efficiency between vehicles by modifying an on-demand routing protocol using a learning automata approach.*
Methods: *This study employed a simulation method with traffic modeling using traffic modeling software and network simulation tools, based on data from highways in the Soekarno-Hatta International Airport area.*
Result: *The results of this study show that the developed protocol increases the packet delivery ratio to 87.7% and reduces latency by 6.5%.*
Conclusion: *This study concludes that learning automata in vehicle routing enhance communication reliability and support implementing a more adaptive and efficient transportation system.*

Keywords*: Highway Traffic Simulation, Intelligent Transportation Systems, Learning Automata-Based AODV, V2V Communication, VANET Performance Optimization.*

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1. INTRODUCTION

Vehicle-to-Vehicle (V2V) communication within Vehicular Ad-Hoc Networks (VANETs) is a cornerstone for enhancing safety and efficiency in intelligent transportation systems [1]. One widely adopted routing protocol in VANETs is the Ad hoc On-Demand Distance Vector (AODV) protocol [2], recognized for its adaptability to dynamic network topologies. However, AODV faces significant challenges in high-density traffic scenarios [3], particularly on highways where the rapid mobility of vehicles and high traffic density often lead to increased latency [4], reduced packet delivery ratios [5], and elevated jitter [6]. As the adoption of connected and autonomous vehicles grows, the limitations of existing protocols like AODV become more critical. These limitations can affect the reliability of essential applications such as collision avoidance [7], [8] and emergency warning systems [9], [10]. The situation impacts the reliability of these systems. High mobility [11] and frequent topology changes in VANETs further increase routing overhead and delays, degrading communication performance [12]. We tackle these challenges by developing efficient communication systems for next-generation intelligent transportation. This study highlights the urgent need to explore new improvements or alternative routing protocols to optimize V2V communication. This study addresses these limitations by enhancing AODV using Learning Automata, resulting in the Learning Automata-based AODV (LA-AODV) protocol [13]. The proposed protocol leverages

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real-time traffic pattern learning to improve route selection and reduce common issues such as delay and packet loss inherent in standard AODV. By integrating adaptive learning mechanisms, LA-AODV is expected to perform more efficiently under dynamic traffic conditions, particularly in scenarios with high mobility and density [14].

The study employs the Soekarno-Hatta International Airport area as a testbed for simulation, given its high traffic density and dynamic vehicular movements, making it an ideal representation of real-world highway conditions. This research utilizes the Simulation of Urban Mobility (SUMO) [15] and Network Simulator 3 (NS-3) tools to create realistic traffic scenarios and assess the protocol's performance [16]. The Methodology provides valuable insights into Vehicle-to-Vehicle (V2V) communication efficiency in dense vehicular environments, an area overlooked in previous studies. By addressing the challenges of the AODV protocol in dynamic traffic, this research advances the field of VANETs. It promotes optimism for future V2V communication solutions. Due to their dynamic topologies, routing in VANETs differs from traditional ad-hoc networks. While Mobile Ad-hoc Networks (MANETs) protocols have been tested in VANETs, reducing message transmission delays remains a challenge [17], [18]. The main focus of VANETs is to establish and maintain optimal communication paths using various specialized routing protocols. One innovative approach piques interest is the combination of Learning Automata (LA) with the AODV routing protocol. This unique blend is designed to enhance V2V communication in changing traffic conditions. The LA-AODV [19] protocol optimizes relay node selection, improving V2V communication efficiency. It uses real-time data on vehicle positions, speeds, and accelerations to predict and select more responsive relay node clusters. This method seeks to enhance Quality of Service (QoS) by evaluating metrics like Packet Delivery Ratio (PDR), throughput, delay, and jitter. Optimizing relay nodes reduces information overload and aids in accident prevention. NS-3 simulations were used to compare the effectiveness of LA-AODV with the standard AODV protocol [20].

Routing algorithms such as AOMDV [12], DSDV [21], and DDSLA-RPL [22] were tested in highway traffic scenarios, measuring performance through PDR, throughput, Network Routing Load [23], and End-to-End (E2E) delay. Results showed that AOMDV outperformed AODV and DSDV in throughput and NRL, while AODV excelled in PDR. DSDV had the highest E2E delay. **A gap** has not been adequately addressed by previous studies, namely the absence of an adaptive routing strategy that integrates learning mechanisms to predict traffic behavior and adjust routes dynamically based on real-time vehicular movement. Most prior studies have focused on static performance comparisons without incorporating intelligent systems capable of responding to the highly dynamic nature of highway traffic. **The novelty** of this study lies in implementing a learning-based adaptation within the routing protocol, which allows each vehicle to estimate its future location based on current speed and acceleration, and to communicate this predictive information with surrounding vehicles. This method enhances route selection by identifying more stable relay nodes, thus improving communication reliability and reducing transmission delays.

The practical implications of these findings are significant, as AOMDV's reactive and multipath design not only improves bandwidth and reduces delay but also enhances security by utilizing multiple paths for consistent communication [24]. Lastly, reactive and proactive routing protocols were compared under various traffic patterns, assessing metrics like message redundancy, packet delivery, packet loss, throughput, E2E delay, and jitter. The comparison was conducted with thoroughness and attention to detail, aiming to highlight the differences between reactive and proactive protocols in dynamic V2V scenarios. **This research aims** to improve the effectiveness of communication between vehicles in dynamic highway conditions by modifying existing routing protocols through learning-based mechanisms. This study **contributes** to the advancement of intelligent transportation technologies by introducing a new model for route optimization that performs better in environments with high vehicle density. The proposed approach supports the development of more reliable and responsive communication systems for autonomous transportation and traffic safety management.

2. RESEARCH METHOD

The study introduces LA-AODV, a modified AODV protocol that enhances vehicle-to-vehicle communication in highway traffic. It uses data from Soekarno-Hatta Airport, SUMO for traffic modeling, and NS-3 for evaluation. LA-AODV aims to improve the original AODV protocol in dynamic, high-traffic situations. Its performance was evaluated based on packet delivery ratio, throughput, delay, and jitter in three scenarios: free flow, steady flow, and traffic congestion. The goal was to enhance packet delivery and reduce delays and jitter, which are critical for implementing autonomous vehicles and intelligent transportation systems (ITS) in real-world settings. As depicted in Figure 1, the research framework has practical implications for the future of transportation engineering and intelligent systems.

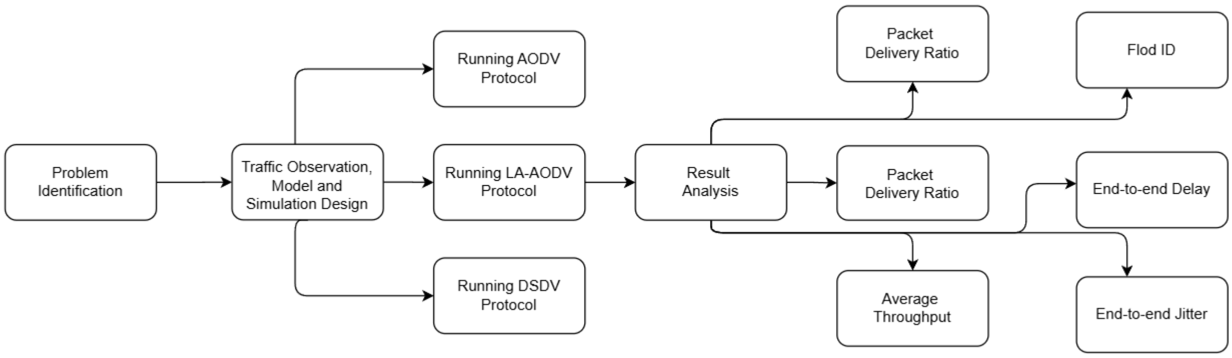

Figure 1. Research methodology

As shown in Figure 1, we used Ubuntu 20.04 for our simulations. Gathering data is essential, so we generated XML trace files through NS3 to capture vehicle connectivity. SUMO-GUI was employed to create realistic traffic scenarios with accurate passenger-vehicle interactions. We efficiently utilized NS3 version 3.35 for network communication, integrating it seamlessly with SUMO to combine traffic modeling and communication simulations. Figure 2 displays the LA-AODV flowchart diagram.

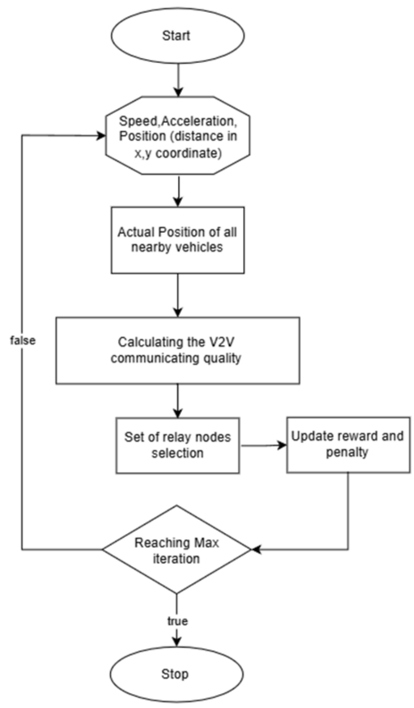

Figure 2. The LA-AODV flowchart diagram

The comparison utilizes a modified version of the standard AODV protocol, LA-AODV. Figure 2 illustrates the step-by-step process for implementing this modification. The source node in the network can utilize GPS services to determine the location of the destination node and the positions of nearby nodes. To ensure that each node in the network receives regular updates about the real-time locations of vehicles, every vehicle independently predicts its future location using computational resources and shares this forecast with nearby nodes to assess whether the node can serve as a relay. The LA-AODV protocol facilitates precise path estimation and route selection by leveraging data from the vehicle communication network. This process is carried out by using Equation (1) to estimate the relative positions of vehicles and compute their actual locations based on speed and acceleration data.

$$SUB_{prox_x} = \Sigma_{x=1}^{x \leq R}\ certain_{prox_\zeta}, certain_{prox_\theta},\ l_x \tag{1}$$

he LA-AODV protocol employs Equation (1) to manage vehicle routing within a communication network. It considers various factors such as vehicle proximity, the count of vehicles within transmission range, vehicle speed, and the passage of time. Two additional equations are used to evaluate vehicle proximity and forecast future positions to enhance road safety. These are by the principles outlined in (2) and (3).

$$sev_{prox_\zeta} = \Sigma_{x=1,e=1}^{x \leq R,\ e \leq X}(certain_{prox_\zeta} + (l_v\ .\ e) + \left(\left(\frac{1}{2}\,(\Delta \mathrm{l})\right) * 2\right) \tag{2}$$

$$sev_{prox_\theta} = \Sigma_{x=1,e=1}^{x \leq R,\ e \leq X}(certain_{prox_\theta} + (l_v\ .\ e) + \left(\left(\frac{1}{2}\,(\Delta \mathrm{l})\right) * 2\right) \tag{3}$$

At the beginning of the iteration, the changes in the horizontal position $\Delta \mathrm{x}\zeta$ and vertical position $\Delta \mathrm{x}\theta$ are calculated based on the difference between the vehicle's position at prediction time e (l_e) and its position at the previous iteration l_{e-1}, assuming that the initial value of l_{e-1} is zero. The prediction time, denoted as e, takes values of 1, 2, 3, and so on, and must be less than the maximum number of iterations represented by X. The simulation involves a vehicle v, with R representing the total number of vehicles within the transmission range. The variable l_e refers to the vehicle's speed at prediction time e. Two formulas are employed to estimate a vehicle's location accurately. Equation (2) calculates the horizontal position (ζ) using factors such as speed, distance, and time. Equation (3) determines the vertical position (θ), considering vehicle status, speed, surrounding vehicles, and simulation time. Both equations are essential for effective V2V communication. Time (s) and length (X) limitations help ensure the accuracy and timeliness of the predictions. The LA-AODV protocol enhances vehicle communication networks by forecasting vehicle positions and updating the routing table. This process boosts the efficiency of V2V communication in dynamic traffic environments.

$$sev_{int\zeta\theta} = \sqrt{(|\Delta sev_{prox_\zeta} - \Delta sev_{prox_\theta}|)} \tag{4}$$

Where:

$$\Delta sev_{prox_\zeta} = \left(sev_{prox_{\zeta+1}} - sev_{prox_\zeta}\right) \tag{5}$$

$$\Delta sev_\theta = \left(sev_{prox_{\theta+1}} - sev_{prox_\theta}\right) \tag{6}$$

Equation (4) determines the vehicle's position ($sev_{int\zeta\theta}$) by accounting for changes in both the horizontal (ζ) and vertical (θ) coordinates. This calculation depends on the values of Δsev_{prox_ζ} and Δsev_{prox_θ}, which are derived from Equations (5), and (6). To estimate the change in the horizontal position, Equation (4), subtracts the predicted position at time $e\ +\ 1$ ($sev_{prox\ _{\zeta+1}}$) from the predicted position at time (s) $sev_{prox\ _\zeta}$. Likewise, the equation computes the variation in the vertical position by subtracting $sev_{prox\ _{\zeta+1}}$ from $sev_{prox\ _{\theta+1}}$. The variable $sev_{int\zeta\theta}$ predicts the locations of neighboring vehicles across a given simulation period by incorporating the expected horizontal and vertical positions at two distinct time points. Finally, (7) compares the anticipated vehicle movement along the horizontal (ζ) and vertical (θ) axes during two predicted time intervals.

$$sev_{int\zeta\theta} = \min\left(_{x=1,\, e=1}^{x\leq R,\, e\leq X} \sqrt{\left|\text{sevprox}_{\zeta+1} - \text{sevprox}_{\zeta}\right|^2 - \left|\text{sevprox}_{\theta+1} - \text{sevprox}_{\theta}\right|^2}\right) \tag{7}$$

Equation (7) applies Euclidean distance and dynamic coordinates to assess and compare vehicle positions to identify the optimal route. The ideal routing conditions guarantee efficient vehicle communication. Equation (8) selects the relay node by computing the communication stability index between nodes m and n.

$$com\_stab\_idx_{tu} = \left|\left(\frac{sev_{int\zeta\theta}}{Max_{rad}}\right)\right| \tag{8}$$

Where:

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

Equation (8) calculates the communication stability index between nodes m and n. It does so by dividing the predicted position of neighboring vehicles by the maximum communication range and verifying if the result is less than or equal to 1. If the condition holds, it indicates a stable communication environment. Additionally, the distances between node m and nearby vehicles are measured over time, with weights assigned based on speed and position, as described in the Equation (9) formula.

$$TWR_m = \Sigma_{m=1}^{m\to R}\ (g_s * (|s_n - s_d|)) + (g_a * (|a_n - a_d|)) + (g_d * (|d_n - d_d|)) + (g_q * com_q ty_m) \tag{10}$$

Where:

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

The Total Weight Route (TWR), a measure for assessing the quality of the standard route, is calculated using the LA-AODV protocol (10). TWR considers various factors such as distance traveled, speed, acceleration, and communication quality. Following the formula in (11), each of these factors is assigned a weight of one.

$$W_{sum} = g_s + g_a + g_d + g_q = 1 \tag{11}$$

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

Equation (11) combines various factors with assigned weights to provide a comprehensive evaluation for route selection in the LA-AODV protocol. This assessment is based on speed, distance, acceleration, and communication quality. The TWR uses the LRI algorithm as the learning rate to assess route quality. Equation (12) describes how the LRI algorithm adjusts its learning process based on past experiences.

$$TWR_{updt} = \Sigma_{m=1,e=1}^{m\leq R,\ e\leq X}(TWR_m + p) \tag{13}$$

In Equation (13), the value is integrated into the latest TWR to update its value, allowing continuous refinement and adaptation for different vehicles or nodes. This dynamic method enhances routing efficiency and improves vehicle communication during the simulation. Table 1 shows the V2V Communication simulation setup.

Table 1. Kinerja sistem

Parameters	**Value(s)**
Total Number of actual Nodes (Vehicles)	Random, based on the Poisson distribution
Simulation Time (s)	300-700 seconds
Traffic Scenario	• Smooth Flow (prob 0.55) • Steady Flow (prob 0.33) • Heavy Traffic (prob 0.1)
Route Selection	Random Route Selection
Node Speed	Random Speed
Initial node position	Random position
Node Movement	All moving nodes
Data Packets Configuration	Real-time traffic data packets from the Soekarno-Hatta International Airport traffic maps.
Type of Protocol	AODV [9] and LAAODV
Type of Traffic	Urban and Highway Traffic
Performance Matrix (QOS)	Flod ID, PDR, PLR, Throughput, end-to-end delay
LAAODV parameter setup	fs : 0.4; fa : 0.3; fd : 0.3; α: 0.2; $Reward$: 1.

Table 1 categorizes 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. Equation (14) provides the Poisson distribution formula to determine the probability of a specific number of vehicles in time-based simulations.

$$J\left(H=O\right)=\frac{e^{-\lambda}.\lambda^{-l}}{l!} \tag{14}$$

The Poisson distribution (13) estimates the number of vehicles passing a point based on the average event rate (λ) and Euler's number (approximately 2.71). Soekarno-Hatta International Airport in Jakarta, a pivotal transportation hub connecting routes like the Jakarta-Merak toll road and the Jakarta Outer Ring Road (JORR), plays a crucial role in our traffic analysis. Its access roads handle various vehicles, but a mix of private cars, buses, trucks, motorcycles, and construction activities leads to traffic congestion.

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

The Packet Loss Ratio (PLR) measures the proportion of successfully received packets to the total sent within a specific time frame. A low PLR is essential for reliable vehicular communication, as a high PLR can cause safety hazards, increased congestion, and lower driver confidence. Another key metric is the Packet Delivery Ratio (PDR), calculated by dividing the total transmitted packets by those successfully received. The PDR is important for evaluating packet delivery effectiveness in the communication network.

$$PacketDeliveryRatio=\frac{ReceivedPackets}{SentPackets} \tag{16}$$

Equation (16) calculates the Packet Delivery Ratio (PDR) by comparing the amount of data received by a destination node (ReceivedPackets) to the data sent by the source node (SentPackets). Ideally, the data delivered and received should be the same. A higher PDR value indicates better network performance and a higher success rate for the routing protocol.

$$AvgThroughput=\frac{TotalPacketsSent}{TotalTime} \tag{17}$$

Equation (17) provides a simple formula for calculating Average Throughput, which measures the network's performance by dividing the total number of packets successfully received by the destination node within a specific time interval by the duration of that interval. This metric offers a tangible measure of the network's data transmission efficiency.

$$delay_i = \frac{\sum_{i=0}^{n} (Trecv\,[i] - Tsent\,[i])}{TotalPackets} \tag{18}$$

Equation (18) computes the average delay by averaging the differences between the time a packet is sent and the time it is received. End-to-end jitter delay, described by Equation (19), measures the delay variation caused by data processing errors and packet reordering.

$$jitter = \frac{VariatonDelay}{NumPackets - 1} \tag{19}$$

Equation (19) calculates jitter by determining the variance in delay times, dividing the difference between the maximum and minimum delay values by the number of delay samples minus one (NumPackets - 1). Jitter helps assess how consistently data is transmitted across the network, with lower jitter indicating more stable and reliable communication.

3. RESULT AND DISCUSSION

The findings of this study are that the proposed LA-AODV routing protocol significantly enhances V2V communication performance in dense and dynamic traffic scenarios. Compared to the conventional AODV protocol, LA-AODV achieved a higher packet delivery ratio of up to 87.7% and demonstrated a 6.5% reduction in end-to-end latency. These improvements were particularly evident under traffic congestion conditions, where LA-AODV maintained more stable throughput and exhibited lower jitter, highlighting its robustness in real-world vehicular communication environments.

Previous studies in adaptive routing in vehicular networks support these findings. Bintoro and Priyambodo [13] reported similar improvements when applying Learning Automata to optimize AODV-based routing, especially in simulations involving fluctuating vehicle density and mobility. Their work demonstrated that adaptive learning mechanisms enhance protocol responsiveness to topological changes. In line with this, Anantapur and Patil [5] confirmed that learning-based modifications to AODV reduced packet loss and improved delay performance in MANETs. Additionally, Kushwaha et al. [24] provided empirical evidence that multi-path routing strategies such as AOMDV consistently outperform standard AODV regarding packet delivery and throughput, reinforcing the relevance of protocol enhancement through intelligent adaptation.

The number of nodes supporting free movement rises from 1,052 at 300 to 2,134 at 700 nodes, indicating network capacity limits. Growth slows between 600 and 700 nodes, suggesting reduced capacity for free-flow traffic. Figure 3 shows the distribution of nodes in Free Flow, Steady Flow, and Traffic Jam as the total nodes increases from 300 to 700. Figure 3 shows that nodes in the Steady Flow category increase from 1,351 to 2,843, causing higher loads and reduced efficiency. The Traffic Jam category rises sharply from 3,067 to 6,797 nodes, indicating severe congestion above 500 nodes. This data has significant implications, highlighting the urgent need to address the network's limited ability to handle high-density traffic. Figure 4 presents average vehicle speeds across three categories: Free Flow, Steady Flow, and Traffic Jam, as the number of nodes increases from 300 to 700. In Free Flow, speeds stay stable at 11.15 to 11.52 m/s. In Steady Flow, speeds drop from 12.16 m/s to 10.84 m/s, then rise slightly to 11 m/s at 700 nodes. The Traffic Jam category sees a significant speed decline from 11.64 m/s to 9.78 m/s, emphasizing the impact of congestion. Overall, Traffic Jam conditions are most affected by increased density, while Free Flow remains more stable. Figure 5 compares time loss.

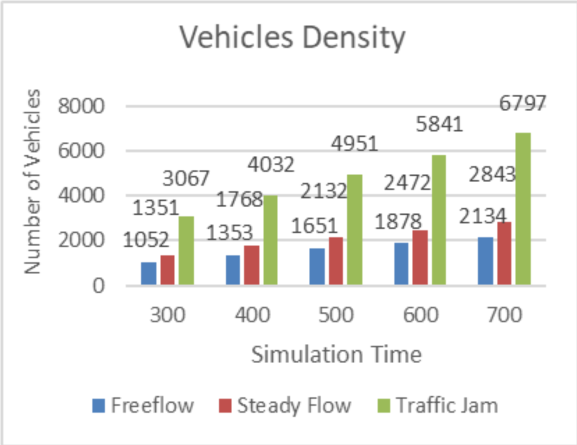

Figure 3. Vehicle density during all simulation scenarios

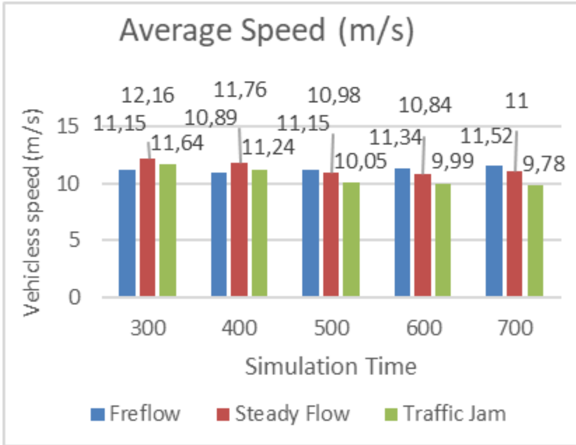

Figure 4. The average vehicle speed in the simulation environment

Figure 5 illustrates the increase in "time loss" as node counts rise from 300 to 700 across three categories: Free Flow, Steady Flow, and Traffic Jam. In Free Flow, time loss grows from 38.82 seconds at 300 nodes to 85.51 seconds at 700 nodes, indicating a slight efficiency decline. Steady Flow sees a more significant rise to 91.3 seconds at 700 nodes, while Traffic Jam escalates from 39.64 seconds to 108.72 seconds. These results emphasize the pressing need to tackle congestion issues. Figure 6 reiterates the key points by highlighting congestion levels at node counts from 300 to 700. The Free Flow category remains congestion-free, while Steady Flow sees eight incidents at 700 nodes. In the Traffic Jam category, congestion starts at 500 nodes (one incident) and escalates to 43 incidents at 700 nodes, demonstrating that higher node counts significantly raise congestion risk. This reiteration ensures a clear understanding of the data and its implications.

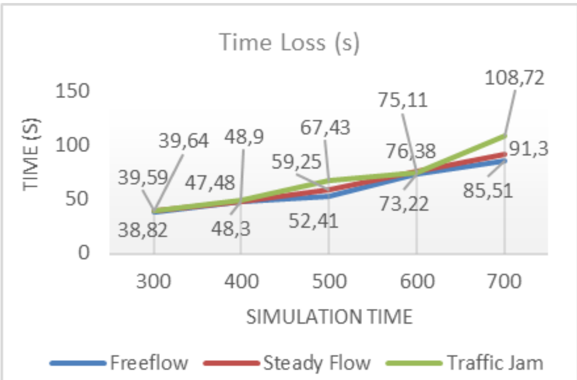

Figure 5. Time loss across different time intervals for three traffic density levels

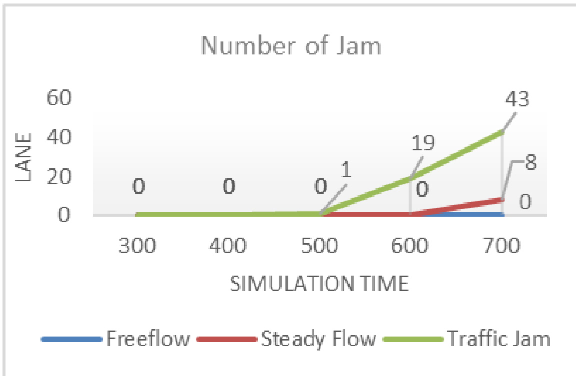

Figure 6. Highlights rising congestion with increased node count, particularly in steady flow and traffic jam categories

Figure 7 depicts travel durations as node counts increase from 300 to 600. In the Free Flow category, times rise from 160.26 to 278.47 seconds, while the Steady Flow category increases from 161.76 to 271.32 seconds. The Traffic Jam category, however, shows lower durations, ranging from 148.12 to 249.69 seconds, indicating more time spent stationary in congestion. LA-AODV outperforms AODV in throughput. At 300 nodes, it achieves 29.81 Kbps versus AODV's 26.13 Kbps. LA-AODV ranges from 45.81 Kbps to 68.16 Kbps in more extensive networks, while AODV ranges from 38.93 Kbps to 43.76 Kbps, showing LA-AODV's better efficiency in denser networks.

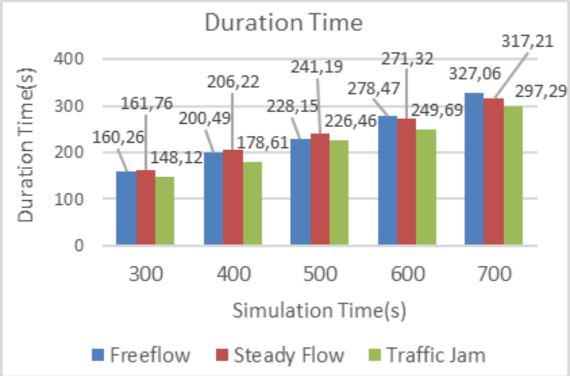

Figure 7. Highlights rising congestion with increased node count

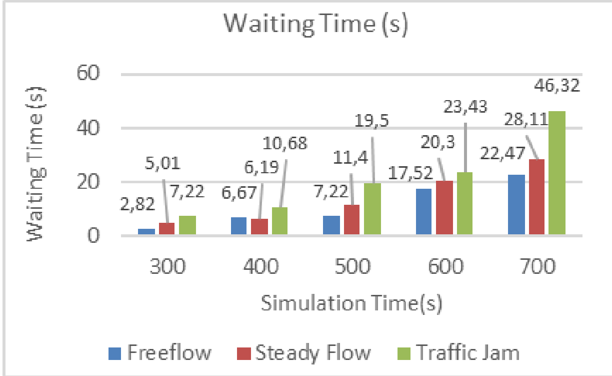

Figure 8. Displays higher waiting times with increased node counts, particularly in traffic jams

Figure 9 presents emergency braking incidents by node count. In free flow, incidents decrease from 3 to 1. In steady flow, they rise from 1 to 4. In traffic jams, incidents increase significantly from 1 to 8, indicating higher braking risk. When node counts exceed 500, traffic jams lead to lower speeds and longer travel times, increasing waiting times and emergency braking incidents, elevating collision risks. However, implementing optimized routing protocols, such as AODV or LA-AODV, can significantly enhance traffic management and safety, providing potential solutions to these challenges. Figure 10 illustrates that LA-AODV, compared to AODV, marginally reduces the packet loss ratio. With 300 nodes, LA-AODV shows a ratio of 73.67%, while AODV shows 74.33%. As the number of nodes increases from 400 to 700, LA-AODV maintains a stable packet loss ratio of 79% to 87.7%, whereas AODV fluctuates between 79% and 88.7%. Overall, LA-AODV's effectiveness in minimizing packet loss under higher traffic conditions is evident, making it a superior choice.

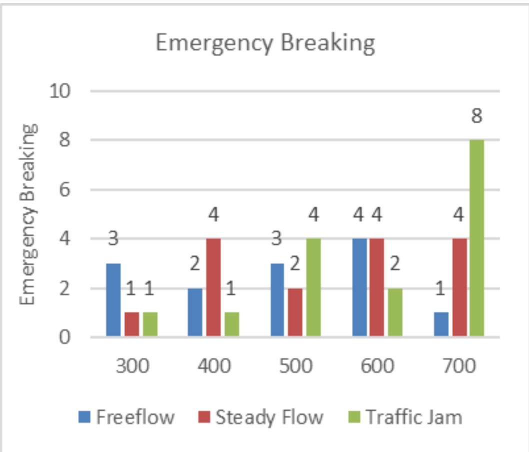

Figure 9. It lists emergency braking incidents rising with node count, particularly in traffic jams.

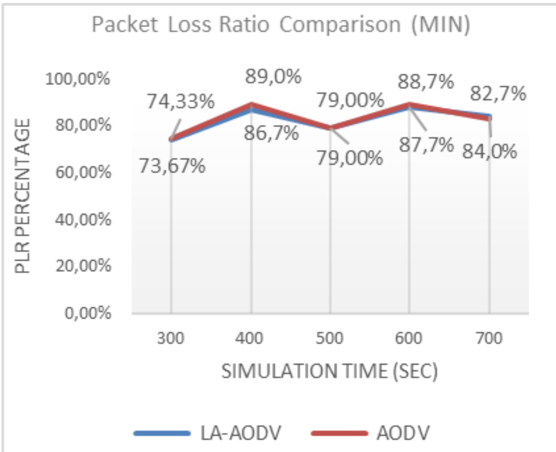

Figure 10. Comparison of packet loss ratio between routing protocols LA-AODV and AODV

LA-AODV consistently outperforms AODV in terms of packet delivery ratio. At 300 nodes, LA-AODV achieves a delivery ratio of 25.33%, slightly higher than AODV's 24.67% (see Figure 11). Across the entire range of node counts (300 to 700), LA-AODV maintains a higher delivery ratio (79% to 87.7%) compared to AODV (79% to 88.7%). This demonstrates that LA-AODV ensures more consistent and efficient packet delivery across varying network conditions. LA-AODV outperforms AODV in throughput, as shown in Figure 12. At 300 nodes, LA-AODV achieves 29.81 Kbps, slightly above AODV's 26.13 Kbps. In more extensive networks (400 to 700 nodes), LA-AODV ranges from 45.81 Kbps to 68.16 Kbps, compared to AODV's 38.93 Kbps to 43.76 Kbps. These results highlight LA-AODV's superior bandwidth efficiency in denser networks.

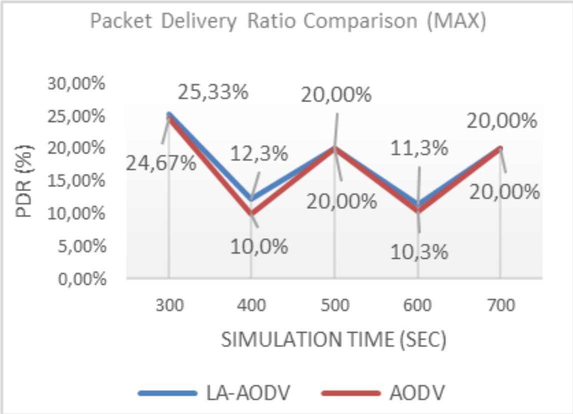

Figure 11. Comparison of packet delivery ratio between routing protocols LA-AODV and AODV

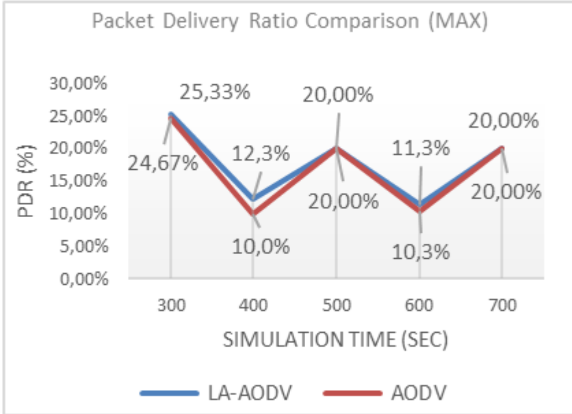

Figure 12. Comparison of throughput between routing protocols LA-AODV and AODV

Figure 13 shows that AODV generally has higher end-to-end delays than LA-AODV. At 300 nodes, AODV experiences a delay of 129 milliseconds compared to LA-AODV's 132 milliseconds. In denser networks of 400 to 700 nodes, AODV delays range from 144 to 221 milliseconds, while LA-AODV maintains a range of 132 to 242 milliseconds. Overall, LA-AODV proves more effective at minimizing delays, reflecting better communication efficiency. LA-AODV has a lower jitter delay than AODV, achieving 91 ms at 300 nodes compared to 67 ms at 300 nodes, indicating better communication stability. The analysis examined three traffic scenarios: free, steady, and traffic jam. In free flow, with smooth traffic and low node density, LA-AODV performs slightly better. During steady flow, it achieves higher throughput and lower delays. In traffic jams characterized by high node density, LA-AODV shows improved delivery ratios, better throughput, and reduced jitter. Overall, LA-AODV is more efficient for communication in densely populated and congested traffic conditions, suggesting that protocol modifications greatly enhance performance in challenging situations.

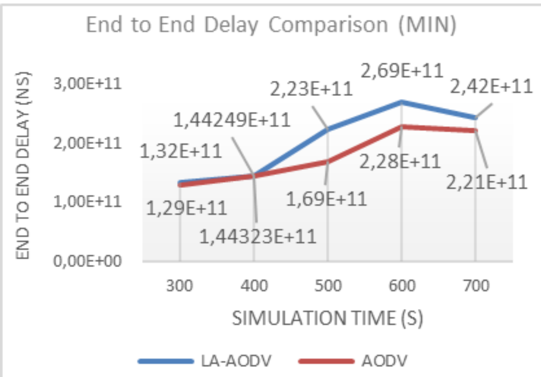

Figure 13. Comparison of throughput between routing protocols LA-AODV and AODV

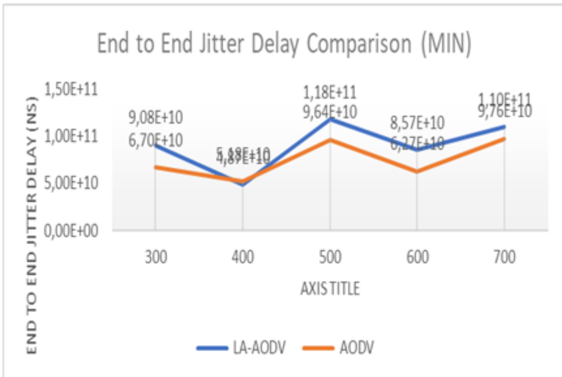

Figure 14. Comparison of end-to-end delay between routing protocols LA-AODV and AODV

4. CONCLUSION

The simulation evaluated V2V communication on highways across three traffic scenarios: free flow, steady flow, and traffic jams, using the LA-AODV protocol. LA-AODV outperformed AODV in terms of throughput and packet delivery and demonstrated its efficiency by reducing end-to-end delay. It achieved a throughput of 29.81 Kbps in free-flow conditions, compared to AODV's 26.13 Kbps. Both had similar packet loss rates: LA-AODV at 25.33% and AODV at 24.67%. Under steady flow, LA-AODV improved its packet delivery ratio to 86.7% and throughput to 64.88 Kbps, while AODV reached 79.0% and 83.05 Kbps. LA-AODV had a delivery ratio of 87.7% and throughput of 68.16 Kbps during traffic jams, whereas AODV had 82.7% and 43.76 Kbps. LA-AODV reduced end-to-end delay, averaging 2.23E+11 ns compared to AODV's 2.28E+11 ns, further demonstrating its efficiency. LA-AODV demonstrated superior performance in congested traffic scenarios, with better throughput, lower packet loss, and improved delay management. Future research should focus on optimizing the LA-AODV protocol for high-density traffic and V2X (Vehicle-to-Everything) networks. The promising areas of artificial intelligence for vehicle movement prediction and dynamic route management, as well as the use of real-time vehicle sensor data for adaptive routing, offer hope for the future of V2V communication.

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