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Smart AODV routing protocol strategies based on learning automata to improve V2V communication quality of service in VANET

Ketut Bayu Yogha Bintoro[*1], Tri Kuntoro Priyambodo[2], Yadie Prasetyo Sardjono[1]
Departement of Informatics Engineering, Faculty of Sciences, Technology and Design, Trilogi University, Jakarta, Indonesia[1]
Departement of Computer Science and Electronics, Faculty of Mathematics and Computer Sciences, Gadjah Mada University, Yogyakarta, Indonesia[2]

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*Corresponding author.
Ketut Bayu Yogha Bintoro
E-mail address:
ketutbayu@trilogi.ac.id

Abstract
The Adhoc On-Demand Distance Vector (AODV) protocol faces challenges in selecting the best relay nodes, which requires optimization to improve performance in Vehicular ad-hoc networks (VANETs). This study aims to enhance Vehicle-to-Vehicle (V2V) communication in VANETs by implementing the Learning Automata-Driven Ad-hoc On-Demand Distance Vector (LA-AODV) routing protocol. LA-AODV is designed to achieve higher packet delivery ratios and optimize data transfer rates, even under congested network conditions, by dynamically adjusting to changing network scenarios. The performance evaluation includes six key metrics analyzed under varying node densities and time intervals, comparing LA-AODV against the standard AODV protocol. Results indicate that LA-AODV consistently outperforms AODV, demonstrating improved efficiency in flood identifier management, reduced data loss, higher packet delivery ratios, better throughput, and reduced end-to-end delay and jitter. Specifically, under a 20-node scenario, LA-AODV exhibits lower flood ID scores (54 vs. 88), reduced packet loss (11% vs. 12%), higher PDR (88.0% vs. 87.0%), and superior throughput (85.34 Kbps vs. 47.26 Kbps). Additionally, LA-AODV achieves lower end-to-end delay (6.84E+09 ns vs. 3.76E+10 ns) and jitter (2.52E+09 ns vs. 2.15E+10 ns). These findings suggest that LA-AODV significantly enhances Quality of Service (QoS) in vehicular ad-hoc networks, positioning it as a promising solution for optimizing V2V communication performance.

1. Introduction
The study proposes a simulation-based approach to enhance Quality of Service (QoS) in V2V communication. The primary problem addressed in this research is the inefficiency of the AODV protocol in Vehicular ad-hoc networks (VANETs), particularly its challenges in managing network congestion, packet loss, high latency, and selecting optimal relay nodes. These issues significantly impair the reliability and efficiency of V2V (Vehicle-to-Vehicle) communication, a critical component of intelligent transportation systems. Given vehicular networks' dynamic and highly mobile nature, the standard AODV protocol must adapt to rapidly changing network conditions, resulting in suboptimal QoS. Therefore, there is a pressing need to optimize the AODV protocol to enhance data transfer rates, packet delivery ratios, and overall communication performance in VANETs. This research proposes implementing the LA-AODV protocol to address these challenges and improve V2V communication efficacy[1]-[2]. This study presents a new approach to enhance Quality of Service (QoS) in V2V communication. We propose a new routing protocol, Learning Automata-Driven AODV (LA-AODV), which dynamically adjusts route selection and parameters to optimize QoS metrics. Extensive simulations evaluate the protocol's effectiveness and compare it with traditional AODV regarding QoS improvement.

The background of this study focuses on V2V communication and the AODV routing protocol. V2V communication enables wireless communication between vehicles, facilitating crucial applications such as collision avoidance [3], cooperative driving [4], and traffic management [5]. However, the widely used AODV protocol in V2V communication faces significant challenges in ensuring reliable and efficient communication due to network congestion [6], mobility [7], and varying channel conditions [8]. Understanding these concepts provides a foundation for addressing this research's problem statement and objectives.

Previous studies have focused on the challenges associated with the AODV protocol, particularly in V2V communication. Notable examples include the implementation of Prediction Node Trends on AODV [9]-[10], Mobility and Detection AODV (MDA-AODV) [11], and the innovation of Flooding-awareness-AODV (FLOW-AODV) [12], which have shown improved packet delivery ratio and average delay performance compared to standard AODV. Researchers have also explored cluster-based communication approaches by integrating learning automata-assisted prediction [13] and applying the learning automata concept for channel reservation [14]-[15], explicitly addressing handoff calls in the

VANET environment [16]. Multipath routing strategies have also been proposed, utilizing Particle Swarm Optimization (PSO) [17], the leap-frog algorithm [18], and adaptive prediction models [19] to ensure optimal channel availability for V2V communication within VANET, incorporating elements of reinforcement learning [20]. The AODV protocol in V2V communication needs improvement to ensure adequate QoS due to packet loss, high latency, and network congestion. This study aims to address these challenges by proposing a Smart AODV Routing Protocol that dynamically adapts to network conditions and optimizes QoS metrics. [21].

As a contribution, the research introduces the LA-AODV protocol to enhance V2V communication in VANETs. LA-AODV uses learning automata for dynamic network adjustments and optimizes relay node selection. Performance evaluation shows LA-AODV outperforms AODV in PDR, throughput, end-to-end delay, jitter, flood identifier management, and packet loss under various conditions. These findings highlight LA-AODV's potential for improving QoS in V2V communication, addressing AODV's limitations, and advancing reliable, efficient communication in intelligent transportation networks. The study includes related works, the research design and the proposed approach in Section 2, the comparison between LA-AODV and AODV in the results and discussion in Section 3 and the conclusion in Section 4.

2. Research Method

The study uses simulation to improve V2V communication quality with a learning automata-driven AODV routing protocol. The simulation allows for evaluating and analyzing the proposed protocol in a controlled environment. The Smart AODV Routing Protocol leverages learning automata [22] principles to dynamically adapt to changing network conditions and optimize QoS performance in V2V communication scenarios. The essential advantage of our protocol is that it overcomes the limitations of traditional AODV routing by incorporating learning automata, which bring intelligence to the routing process. To validate the effectiveness of our protocol, we will conduct simulations using two powerful tools, the widely used Network Simulator 3 (NS3) and the specialized Simulation of Urban Mobility (SUMO) [23]. The NS3 [24] offers extensive functionalities such as protocol modeling, traffic generation, and comprehensive performance evaluation, while SUMO replicates realistic vehicular mobility patterns. We will use NS3 to evaluate the performance of our Smart AODV Routing Protocol in diverse V2V communication scenarios.

The SUMO traffic simulation package replicates realistic vehicular mobility patterns. By integrating SUMO with NS3, we can evaluate our protocol's performance in various traffic conditions. We aim to demonstrate the effectiveness of the Smart AODV Routing Protocol in improving QoS performance in V2V communication scenarios. Researchers can gather data on the protocol's performance and assess the impact of the learning automata-driven approach on the quality of service in V2V communication.

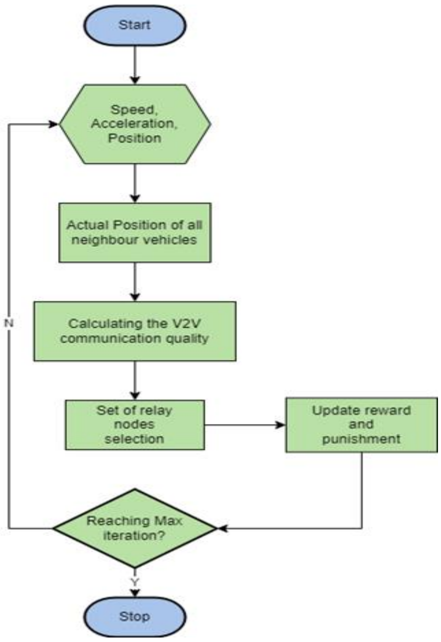

Figure 1. LA-AODV Steps

Figure 1 shows how the LA-AODV (Learning Automata AODV) operates in an ad hoc vehicle network for vehicle-to-vehicle (V2V) communication. The protocol uses GPS services to detect vehicle locations and predicts future positions based on speed and relative position. It selects relay nodes based on the Total Weighted Ratio (TWR) score, ensuring stable communication. Nodes with a TWR between 0.6 and 1 are chosen, while those below 0.6 are excluded. This approach enhances the protocol's performance and reliability, as stated in Equation 1.

$$INITpos_i = \sum_{i=1}^{i \le N} actual_{pos_x}, actual_{pos_y}, v_i \tag{1}$$

The LA-AODV protocol relies on Eq. (2) to accurately route and position vehicles within a vehicular communication network. This equation factors in various variables, including the x and y position of vehicle *i* (represented by $INITpos_i$), the speed of the car (v_i), the number of vehicles within transmission range (N), and the specific node or vehicle under reference (*i*) to determine proximity. Next, the LA-AODV protocol utilizes two equations in vehicular communication networks to determine vehicle proximity and future positions. These equations consider factors such as vehicle speed, the number of vehicles within transmission range, and elapsed time to make informed routing decisions that prevent road accidents, as stated in Equation 2 and Equation 3.

$$pred_{pos_x} = \sum_{i=1,t=1}^{i \le N, t \le K} \left(actual_{pos_x} + (v_t.t) + \left(\frac{1}{2}(\Delta v)\right) * 2 \right) \tag{2}$$

$$pred_{pos_y} = \sum_{i=1,t=1}^{i \le N, t \le K} \left(actual_{pos_y} + (v_t.t) + \left(\frac{1}{2}(\Delta v)\right) * 2 \right) \tag{3}$$

Where:

$\Delta v_x = (v_t - v_{t-1})$, at the beginning of iteration $v_{t-1} = 0$,
$\Delta v_y = (v_t - v_{t-1})$, at the beginning of iteration $v_{t-1} = 0$
And

t: Prediction time, where t = 1, 2, 3, ..., and t < K,
K: Maximum iteration,
i : *vehicle i,*
N: Total number of vehicles within the transmission range,
v_t: Vehicle speed at time t.

Equation 2 is used to predict a vehicle's position on the *x-axis* at a specific time (t), while Equation 3 takes into account the vehicle's status, speed, nearby vehicles, and iteration time to predict its position on the *y-axis*. Accurate positioning is essential for efficient communication, and variables *t* and *K* ensure precise predictions within the maximum iteration time. These equations are utilized by LA-AODV to predict vehicle positions, leading to improved efficiency of the vehicular communication network. Vehicles multicast to exchange data, determining their minimum predicted position. This data updates routing tables to determine the vehicle's state with minimum distance and speed, using Equation 4.

$$pred\_acc_{xy} = \sqrt{\left(\left|\Delta pred\_pos_x - \Delta pred\_pos_y\right|\right)} \tag{4}$$

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

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

Equation 4 calculates the prediction of vehicle positions($pred\_acc_{xy}$), considering the changes along the x and y axes. This calculation method utilizes $\Delta pred_pos_x$and $\Delta pred_pos_y$values, which are derived from Equation 5 and Equation 6. In Equation 4, the predicted position change along the x-axis is actively determined by subtracting the expected position at time t + 1 ($pred\_pos_{x+1}$) from the actual prediction of the vehicle's position 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 $pred\_pos_{y+1}$ subtracted from $pred\_pos_y$ as state in Equation 6. The variable $pred\_acc_{xy}$ predicts the positions of nearby vehicles over a specific timeframe, considering their expected *x* and *y* coordinates at two points.

Equation 7 uses the Euclidean Distance equation to find the minimum value to compare vehicle movement optimally changes along the x and y axes for each vehicle over two prediction time intervals.

$$pred\_acc_{xy} = MIN\left(\sum_{i=1,\ t=1}^{i\le N, t\le K} \sqrt{\begin{matrix}\left(\left|pred_{pos_{x+1}} - pred_{pos_x}\right|\right)^2 - \\ \left(\left|pred\_pos_{y+1} - pred_{pos_y}\right|\right)^2\end{matrix}}\right) \tag{7}$$

Equation 8 forecasts and compares the vehicle positions to make informed routing decisions. By actively calculating changes in coordinates and passively evaluating their Euclidean distance, this equation identifies the most efficient routing conditions for responsive vehicle communication. After calculating expected positions, the next step is to assess communication reliability with the next-hop node before selecting relay nodes. The communication stability index calculation between node *i* and *node j* is denoted in Equation 8.

$$comm\_stability\_index_{ij} = \left|\left(\frac{pred\_acc_{xy}}{Max_{rad}}\right)\right| \tag{8}$$

Where:

$$comm\_stability\_index_{ij} = \begin{Bmatrix} stable, & if \le 1 \\ unstable, if & > 1 \end{Bmatrix}$$

The LA-AODV protocol includes Equation 8, which introduces the communication stability index $comm\_stability\_index_{ij}$. This metric is crucial in assessing communication stability between nodes, specifically *i* and *j*. To calculate this index, the total predicted positions of neighboring vehicles (represented by $pred\_acc_{xy}$) are divided by the maximum communication radius (Max_{rad}), which covers an area of 50 grids in width and length, set at 2500 grid units. When the $comm\_stability\_index_{ij} \le 1$ value is one or lower, it means that the communication environment between nodes *'i'* and *'j'* is stable. On the other hand, when the value is higher than 1, it suggests an unstable communication scenario.

Upon assessing the communication quality between node *'i'* and its neighboring vehicles, based on their distance for two prediction time intervals, *'t' and 't+1'*, the subsequent phase entails assigning a weight to each vehicle. This weight is determined by factoring in variables such as the vehicle's speed, acceleration, position, and the outcome of the communication quality calculation for node 'i', as defined by Equation 9.

$$TWR_i = \sum_{i=1}^{i\ to\ N}\left(\left(f_s * (|s_n - s_d|)\right) + \left(f_a * (|a_n - a_d|)\right) + \left(f_d * (|d_n - d_d|)\right) + \left(f_q * (comm\_quality_i)\right)\right) \tag{9}$$

Where:
0.6 >= TWR >= 1, Optimal, and TWR <= 0.59, suboptimal.

The LA-AODV protocol utilizes Equation 9 to compute the Total Weight Route (TWR), a critical measure for evaluating the route's standard. TWR considers multiple factors such as speed, distance, acceleration, and communication quality, each assigned a weight factor equal to 1 as defined by Equation 10.

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

Equation 10 combines factors with specific weights to create a balanced evaluation for the LA-AODV protocol, ensuring that speed, distance, acceleration, and communication quality are all considered in selecting the best route for vehicular communication. TWR is a crucial criterion that provides a comprehensive assessment of route quality. Upon reaching its final decision state, the FSA machine activates the Learning Rate (α) and notifies neighboring nodes when selected as a relay node. The LRI algorithm (α) [25] assigns rewards or penalties to decisions made, as specified in Equation 11.

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

Equation 11 of the LRI algorithm adjusts the learning rate (α) based on past experiences. Rewards set the learning rate to 1, while penalties reduce it to 0. The value of the fine-tunes variable of the algorithm's learning rate is related to its decision-making abilities. Equation 12 illustrates adding value 'a' to TWR_{update} in the prediction iteration (t+1).

$$TWR_{update} = \sum_{i=1,\ t=1}^{i\leq N,t\leq K} (TWR_i + \alpha) \tag{12}$$

Equation 12 updates the TWR value, enabling continuous fine-tuning and adjustment of TWR values for various vehicles or modes using the learning rate *α*. TWR values adapt to changing network conditions and routing decisions, resulting in dynamic and responsive routing decisions during the simulation. Ultimately, this improves communication and routing performance within the vehicular network. The value of *α* is critical in shaping the TWR values and routing decisions throughout the maximum simulation *K*.

2.1 Simulation Model and Design

The study uses a simulation to replicate real-world V2V communication scenarios in a virtual network environment. It aims to emulate diverse V2V communication scenarios accurately and evaluates the proposed LA-AODV routing protocol. The simulation design leverages the widely used NS3 platform for network simulation research.

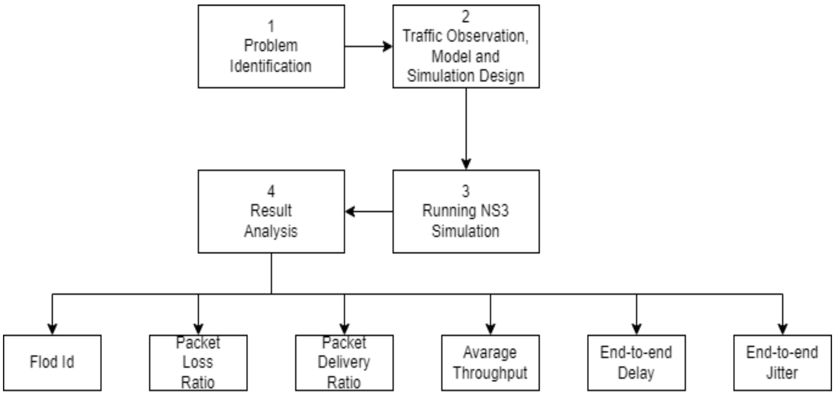

Figure 2. The Process Structure of Simulation Design

The simulation design in Figure 2 compares AODV and LA-AODV protocols in various V2V communication conditions. The simulation analyzes performance metrics like Total Flood ID, Packet Loss Ratio, Packet Delivery Ratio, Average Throughput, End-to-End Delay, and End-to-End Jitter. Using NS3, the simulation evaluates the efficiency of AODV and LA-AODV in different V2V communication scenarios. It aims to provide insights into the effectiveness of LA-AODV within dynamic vehicular networks. The simulation covers multiple scenarios, environmental settings, traffic patterns, and the implementation of the LA-AODV protocol. For further details, refer to Figure 3.

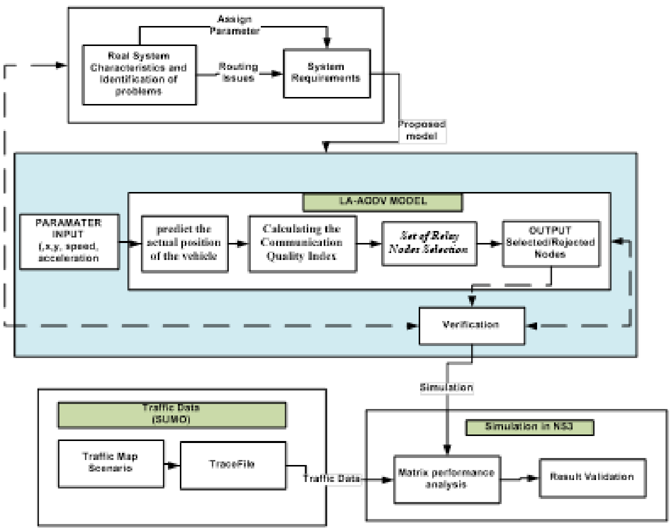

Figure 3. The Process Structure of LA-AODV Model and the Simulation Design[8]

Figure 3 outlines the steps involved in modeling and simulating a system. The process begins with visual observations of the natural system to identify its unique characteristics and understand its operational rules. A model and simulation design is developed once the system's requirements are defined. The model is then tested through simulations using real-world traffic data to ensure its performance aligns with the natural system's expectations and requirements. Finally, a validation is conducted to verify the model's accuracy in representing the system's critical aspects. The simulation covers parameters such as total nodes, simulation time, route selection, node speed, initial position, node movement, network map, protocol types, traffic, and QoS metrics, as shown in Table 1. These parameters are systematically explored to gain insights into the protocols' capabilities and limitations under diverse conditions.

Table 1. V2V communication simulation parameter setup

No	Parameter	Value(s)
1	Total number of actual Nodes (vehicles)	20,25,30,40, and 55 nodes
2	Simulation time (s)	10,50,100,150, and 200 second
3	Route Selection	Random route selection
4	Node Speed	Random speed
5	Initial node position	Random position
6	Node Movement	All moving nodes
7	Network Map Configuration	Customized Network Map
8	Type of Protocol	AODV dan LA-AODV
9	Type of traffic	Passenger cars only, Left-hand drive.
10	Perfomence Matrix (QoS)	Flood ID, PLR, PDR, Average Throughput, End-to-end Delay, End-to-end Jitter
11	LA-AODV parameter setup	fs : 0.4 ; fa : 0.3 ; fd : 0.3 ; α: 1;Reward : 1; Penalty : 0

The simulation environment used to evaluate the efficacy of AODV and LA-AODV routing protocols is determined by several parameters, as outlined in Table 1. These parameters play a crucial role in shaping the simulation environment and evaluating the performance of the protocols under various conditions. The vehicular network consists of 20 to 55 nodes. Simulations are conducted to assess protocol performance under different network sizes and simulation times ranging from 10 to 200 seconds. The simulation employs random route selection and variable node speeds to mimic real-world scenarios. Performance metrics evaluated include Flood ID, PLR, PDR, Average Throughput, End-to-end Delay, and End-to-end Jitter for AODV and LA-AODV protocols. LA-AODV's learning automata-driven behavior is optimized using specific parameter values such as state change probability, action change probability, direction change probability, learning rate, reward, and penalty.

2.2 Quality of Service Performance Matrix

PDR, formulated in Equation 13, signifies the ratio of successfully received packets to the total number of packets sent within a unit time interval. A higher PDR indicates enhanced network performance and the success rate of the employed routing protocol.

$$PDR = \frac{DataReceived}{DataSent} \tag{13}$$

The Packet Delivery Ratio (PDR) measures the proportion of successfully received packets compared to the total number of packets sent. A higher PDR value indicates better network performance and routing protocol success. The formula measures the ratio of unsuccessfully delivered packets to the total sent. Maintaining a low PLR is crucial for secure V2V communication.

$$PLR = \frac{DataLoss}{TotalDataSent} \tag{14}$$

The Packet Loss Ratio (PLR), as defined in Equation 14, evaluates the ratio of packets that were unsuccessfully delivered to the overall number of packets sent across the communication network. It serves as a critical metric to assess the reliability of V2V communication. The average end-to-end delay, as expressed in Equation 15, signifies the average time taken by packets to reach their destination. This metric is essential for evaluating the efficiency of the communication network.

$$AVG\_delay_i = \frac{\sum_{i=0}^{n}(treceived[i] - tsent[i])}{packet\_counter} \quad (15)$$

The Average End-to-End Delay in Equation 15 measures the average time packets travel from the source to their destinations. Denoted as *AVG_delay_i*, it assesses network efficiency. A lower average delay signifies more effective packet delivery, contributing to network performance.

$$AVG\_throughput = \frac{Amount\_of\_Packets\_Sent}{Total\_Data\_Sending\_Time} \quad (16)$$

The Average Throughput, calculated using Equation 16, is essential for evaluating network performance by measuring data transmission efficiency. It is determined by dividing the total number of successfully received packets by the destination device within a specific time interval by the duration of that interval. A higher average throughput indicates more effective data transfer, while lower values suggest slower transmission rates. End-to-end jitter, defined in Eq. (17), measures the variation in delay caused by the queue length during data processing and the reassembly of data packets and is crucial for evaluating network stability and reliability.

$$Jitter = \frac{Delay\_Variation}{n-1} \quad (17)$$

End-to-end jitter, defined by Equation 17, measures network stability by evaluating delay variation during data processing and packet reassembly. Lower jitter values indicate a more stable network, which is crucial for real-time communication and control systems.

3. Results and Discussion

In the previous chapters, we outlined the proposed enhancements to the AODV routing protocol, including integrating LA-AODV mechanisms. This chapter presents simulation results and discusses performance metrics. The aim is to analyze the effectiveness of the LA AODV protocol compared to the AODV protocol and its impact on Vehicular Ad Hoc Networks (VANETs). The findings are discussed in the context of improving QoS in V2V communication and offer insights into how LA-AODV can improve real-world scenarios. The Total Flood ID is an important metric that counts flooding messages in the network at specific time intervals. The table provides TFI data for two routing protocols at different intervals, and the study's findings are shown in Figure 4.

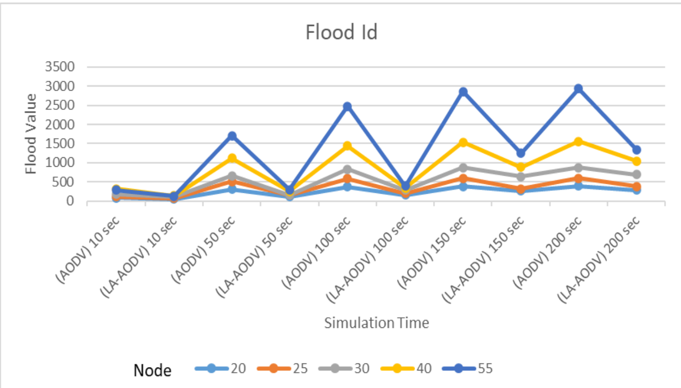

Figure 4. Comparasion of Flood Id Routing Protocols AODV and LA-AODV

Figure 4 compared the Flood ID of AODV and LA-AODV protocols in scenarios with 20 nodes at 10-second intervals. AODV had a Flood ID of 88, while LA-AODV had a Flood ID of 54. AODV's Flood ID grew to 390 at 200 seconds, while LA-AODV's reached 291. This pattern was consistent across different node densities, with AODV consistently starting with a higher Flood ID than LA-AODV. LA-AODV performs better than the other methods in dynamic and densely populated vehicular networks due to its optimized flooding mechanism. LA-AODV reduces redundancy, improves flood identifier management, and enhances network responsiveness, reliability, and resource optimization. Its adaptive flood identifier management through learning automata enhances V2V communication. Ultimately, LA-AODV offers superior message dissemination efficiency, network responsiveness, and resource optimization, making it an effective vehicular communication system. PLR evaluates the ratio of packets that were unsuccessfully delivered to the overall number of packets sent across the communication network. It serves as a critical metric to assess the reliability of V2V communication describe in Figure 5.

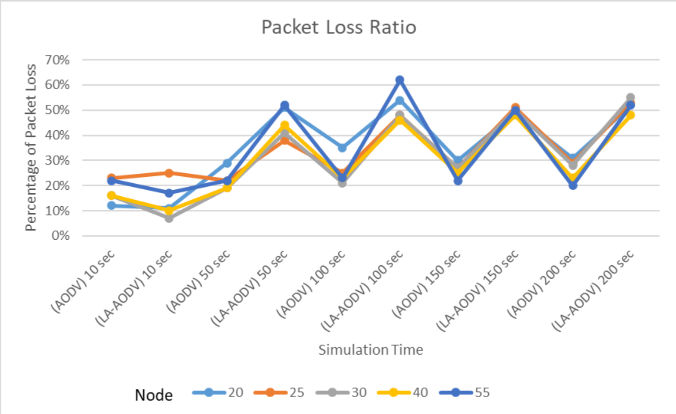

Figure 5. Comparasion of Packet Loss Ratio Routing Protocols AODV and LA-AODV

The PLR in Figure 5 is crucial for assessing V2V communication protocol reliability. In a study comparing AODV and LA-AODV, AODV initially had a 12% PLR at 10 seconds with 20 nodes, while LA-AODV had 11%. Over time, AODV's PLR fluctuated, reaching 31% at 200 seconds, while LA-AODV consistently maintained a lower PLR, peaking at 52%. LA-AODV consistently showed a lower and more stable Packet Loss Rate (PLR) than AODV, making it better suited for reliable communication in dynamic vehicular networks. The result is crucial for safety-critical V2V applications like collision avoidance and cooperative driving. By reducing the Packet Loss Ratio, LA-AODV offers superior reliability and contributes to enhanced safety and efficiency in vehicular communication networks. PDR signifies the ratio of successfully received packets to the total number of packets sent within a unit time interval. A higher PDR indicates enhanced network performance and the success rate of the employed routing protocol as described in Figure 6.

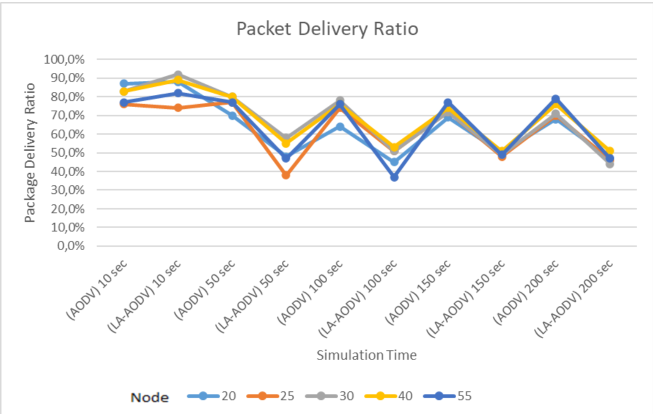

Figure 6. Comparasion of PDR Routing Protocols AODV and LA-AODV

The analysis in Figure 6 compares the AODV and LA-AODV protocols in V2V communication. At 20 nodes and 10 seconds, AODV has an initial PDR of 87.0%, while LA-AODV achieves 88.0%. Over time, AODV's PDR declines to 68.0% at 200 seconds, while LA-AODV maintains a more consistent PDR of 47.0%. LA-AODV generally exhibits a more stable and improved Packet Delivery Ratio than AODV across different node densities. LA-AODV's stability and efficiency make it promising for safety-critical V2V scenarios. Average throughput evaluating the performance of the network. It is calculated by dividing the total number of successfully received packets by the destination device within a specific time interval by the duration of that interval, depicted in Figure 7.

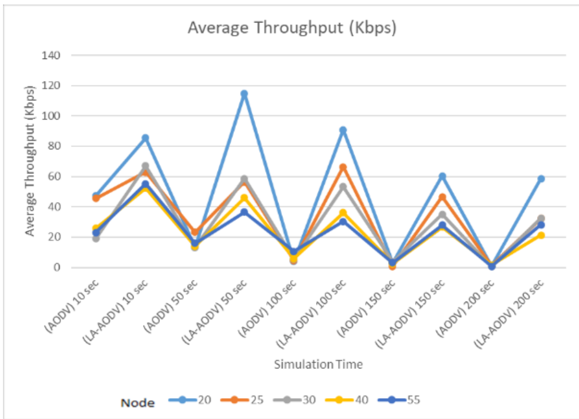

Figure 7. Comparison of Average Throughput of Routing Protocols LA-AODV and AODV

The data in Figure 7 compares the average throughput of AODV and LA-AODV. AODV's throughput fluctuates more, while LA-AODV maintains a consistently higher throughput. As the number of nodes increases, the superiority of the LA-AODV protocol becomes more pronounced. At 30 nodes, AODV starts with an average throughput of 18.92 Kbps at 10 seconds, while LA-AODV begins with a higher throughput of 66.99 Kbps. Throughout the simulation, AODV's throughput increases sporadically, reaching 0.63 Kbps at 200 seconds, whereas LA-AODV maintains a more consistent and higher throughput, decreasing to 32.50 Kbps. At 40 nodes, AODV starts with an average throughput of 25.89 Kbps at 10 seconds, while LA-AODV begins with a slightly higher throughput of 52.52 Kbps. AODV's throughput fluctuates, reaching 21.42 Kbps at 200 seconds, whereas LA-AODV maintains a more stable throughput, decreasing to 1.61 Kbps. At 55 nodes, AODV starts with an average throughput of 23.04 Kbps at 10 seconds, while LA-AODV begins with a slightly higher throughput of 55.22 Kbps. AODV's throughput shows fluctuations, reaching 28.19 Kbps at 200 seconds, while LA-AODV maintains a more stable throughput, decreasing to 28.19 Kbps. These results underscore the role of learning automata in the LA-AODV protocol, which significantly enhances the network's data transmission capabilities, thereby improving average throughput. The End-to-End Delay metric, measured in nanoseconds (ns), indicates the total time a data packet travels through the network, as depicted in Figure 8.

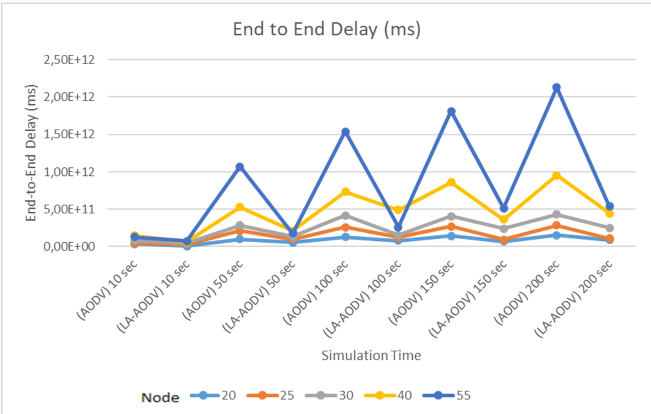

Figure 8. Comparison of End-to-End Delay Routing Protocols LA-AODV and AODV

Figure 8 compares the End-to-End Delay performance of AODV and LA-AODV routing protocols in V2V communication. AODV initially shows a delay of 3.76E+10 ns, compared to LA-AODV's lower delay of 6.84E+09 ns. As the simulation progresses, AODV's delay steadily increases, peaking at 9.07E+10 ns by the 200-second mark, while LA-AODV consistently maintains a lower delay, culminating at 9.07E+10 ns. LA-AODV consistently outperforms AODV in minimizing End-to-End Delay across different scenarios. The superior effectiveness of LA-AODV in reducing End-to-End Delay is not just a theoretical advantage. It holds significant practical implications, particularly in real-time applications such as autonomous driving and cooperative collision avoidance. By ensuring prompt information exchange among vehicles, LA-AODV facilitates timely decision-making and actions in safety-critical scenarios. This, in turn, leads to improved responsiveness in V2V communication, thereby enhancing overall system efficiency. LA-AODV emerges as a reliable and practical solution for supporting real-time communication in dynamic V2V networks, underscoring the real-world relevance of this research. The End-to-End Jitter Delay metric measures the variability in data packet arrival times in a network. Analyzing jitter is essential for evaluating communication system stability. Figure 9 provides detailed data for two routing protocols across node densities and time intervals.

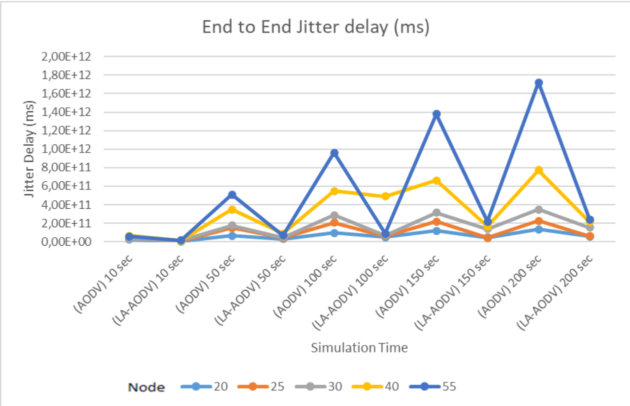

Figure 9. Comparison of End-to-End Jitter Delay Routing Protocols LA-AODV and AODV

Figure 9 examines the End-to-End Jitter Delay of the AODV routing protocol and the LA-AODV protocol in V2V communication. The End-to-end jitter represents the variations in packet arrival times, which indicates the stability and predictability of the communication environment. When tested with 20 nodes and an initial 10-second interval, AODV exhibits an End-to-End Jitter Delay of 2.15E+10 ns, while LA-AODV shows a lower jitter at 2.52E+09 ns. AODV's jitter increases gradually as the simulation progresses, peaking at 5.72E+10 ns by the 200-second mark, while LA-AODV maintains consistently lower jitter, reaching the same peak. Similar trends are observed across node densities and time intervals, highlighting LA-AODV's consistent outperformance in minimizing Jitter Delay. LA-AODV protocol's consistent pattern of reduced jitter across diverse scenarios enhances stability in V2V communication, contributing to improved overall system reliability. It minimizes variations in packet arrival times, making it a robust solution for real-time communication in dynamic V2V networks. Its potential to significantly enhance the reliability and predictability of V2V communication fosters safer and more dependable vehicular networks.

4. Conclusion

In conclusion, the LA-AODV routing protocol has consistently outperformed the conventional AODV protocol in V2V communication scenarios. LA-AODV has shown superior Flood ID management, with significantly lower scores than AODV (54 compared to AODV's 88) at 20 nodes. Additionally, LA-AODV effectively reduces Packet Loss Ratio (PLR), maintaining lower percentages (11% compared to AODV's 12% at 20 nodes). LA-AODV also achieves higher Packet Delivery Ratio (PDR) values (88.0% compared to AODV's 87.0% at 20 nodes) and has better throughput (85.34 Kbps against AODV's 47.26 Kbps at the same node density). LA-AODV's efficiency extends to reducing End-to-End Delay and Jitter, consistently maintaining lower values across diverse scenarios.

The findings confirm that LA-AODV is a reliable solution for improving QoS in V2V communication, contributing to safer and more intelligent transportation systems. LA-AODV consistently outperforms the traditional AODV protocol across various metrics and network conditions. Its adaptability through learning automata-based techniques effectively optimizes QoS metrics. The result underscores the significant role of intelligent routing protocols in enhancing the reliability and efficiency of V2V communication. LA-AODV shows promise in addressing the challenges in V2V communication and has the potential to enhance QoS significantly in dynamic vehicular networks. Further research and practical implementation of LA-AODV in real-world scenarios are needed to validate its effectiveness and contribute to the evolution of intelligent transportation systems.

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