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Learning Automata Based-AODV Routing Protocol for Inter-vehicle Communication: A Simulation Approach

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Abstrak− Ad-hoc On-Demand Distance Vector (AODV) merupakan protokol routing yang digunakan dalam jaringan Mobile Ad-hoc Network (MANET) dan secara eksperimental diterapkan dalam Vehicular Ad-hoc Networks (VANETs) untuk mendukung komunikasi Vehicle-to-Vehicle (V2V). Namun, AODV standar dapat menyebabkan penurunan responsivitas akibat aliran informasi yang berlebihan dalam lingkungan VANET. Oleh karena itu, penelitian ini mengusulkan Learning Automata-based AODV (LA-AODV), yaitu pengembangan AODV berbasis reinforcement learning untuk meningkatkan pemilihan node relay dan responsivitas komunikasi dalam VANET. LA-AODV mempertimbangkan parameter kendaraan secara real-time dalam proses seleksi node relay guna mengoptimalkan Quality of Service (QoS) serta secara tidak langsung berkontribusi dalam mengurangi insiden di jalan raya. Hasil simulasi menggunakan Network Simulator 3 (NS-3) pada skenario lalu lintas berbasis grid menunjukkan bahwa LA-AODV memiliki kinerja lebih baik dibandingkan AODV dalam hal Packet Delivery Ratio (PDR), rata-rata end-to-end delay, throughput, dan overhead komunikasi. Penerapan Learning Automata dalam pemilihan node relay pada LA-AODV terbukti mampu meningkatkan QoS komunikasi V2V, menjadikannya solusi yang sesuai untuk aplikasi transportasi cerdas dan jaringan kendaraan pintar berbasis komunikasi V2V. Penelitian ini berkontribusi dalam pengembangan protokol AODV untuk komunikasi V2V, khususnya dalam studi VANET, dengan meningkatkan efisiensi dan keandalan komunikasi antar kendaraan.

Kata Kunci: Komunikasi V2V; Learning Automata; AODV Routing Protocol; NS3; Vehicular ad-hoc network.

Abstract−The Ad-hoc On-Demand Distance Vector (AODV) routing protocol is a Mobile Ad-hoc Network (MANET) routing protocol that is experimentally used in Vehicular Ad-hoc Networks (VANETs) to support Vehicle-to-Vehicle (V2V) communication. Unfortunately, the standard AODV can lead to degraded responsiveness due to excessive information flow in the VANET environment. The research proposed a Learning Automata-based AODV (LA-AODV) that integrates reinforcement learning for enhanced relay node selection and communication responsiveness in VANET. By considering real-time vehicle parameters during relay node selection, LA-AODV optimizes Quality of Service (QoS) and indirectly reduces road incidents. Simulation results using Network Simulator 3 (NS-3) in a grid traffic scenario demonstrate and validate that LA-AODV outperforms AODV regarding Packet Delivery Ratio (PDR), average end-to-end delay, throughput, and communication overhead. Using Learning Automata for relay node selection in LA-AODV improves the QoS of V2V communication, making it suitable for applications in smart transportation and intelligent vehicle networks supported with V2V communication in each vehicle. This research contributes to the field by improving the AODV protocol for V2V communication, especially in VANET research.

Keywords: V2V Communication; Learning Automata; AODV Routing Protocol; NS3; Vehicular ad-hoc network.

1. INTRODUCTION

The conventional AODV protocol suffers from excessive information flow and reduced inter-vehicle communication responsiveness in Vehicular Ad-hoc Networks (VANETs) [1] and [2]. This is primarily due to suboptimal relay node selection caused by dynamic vehicle quantity fluctuations on busy roads [3] and [4]. Several drawbacks contribute to these limitations. Firstly, AODV employs a reactive routing approach, which leads to increased control message exchange [5] and longer route setup times in dense networks [6] and [7]. Secondly, periodic route maintenance in AODV consumes network resources despite no active data transmission, resulting in unnecessary control message exchanges and increased network overhead [8]. AODV cannot adapt routing decisions based on real-time information such as vehicle speed, acceleration, or communication quality, leading to suboptimal relay node choices and degraded Quality of Service (QoS) performance [9]. These limitations hinder the overall efficiency and responsiveness of V2V communication systems in VANETs [10].

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This research study addresses challenges in V2V communication, specifically relay node selection, which affects inter-vehicle communication efficiency in VANET. The proposed LA-AODV integrates the Learning Automata (LA) method into AODV to optimize relay node selection and enhance inter-vehicle communication responsiveness. LA-AODV outperforms traditional AODV and other approaches in terms of performance, as demonstrated through simulations. Several studies address the challenges encountered in the AODV routing protocol to support V2V communication to optimize the relay node selection process, such as the implementation of Prediction Node Trends on AODV [11] and [12], Mobility and Detection Aware AODV (MDA-AODV) [13], *FLOdingaWareness-AODV* (FLOW-AODV) [14], Cluster-based communication approach by applying learning automata-assisted prediction [20], channel reservation method using learning automata concept VANET [15], and multipath routing strategy using PSO, leapfrog algorithm, and learning automata [16], Performance Evaluation of IEEE 802.11p in 5G Network [17].

This research enhances the QoS of V2V communication in VANETs. The proposed LA-AODV approach optimizes relay node selection based on real-time vehicle information such as positions, speeds, accelerations, and communication qualities. Using Network Simulator 3 software, LA-AODV is evaluated and compared to the traditional AODV routing protocol. The evaluation results show that LA-AODV outperforms AODV and enhances the QoS of V2V communication, which contributes to developing more efficient V2V communication systems and improving traffic management and road safety in VANET scenarios.

The paper comprises six sections: introduction, related work, proposed method, simulation model, results and discussion, and conclusion. The introduction provides context and outlines challenges. The related work section reviews existing literature. The proposed method details the new approach. The simulation model outlines tools and parameters. Results and discussion analyze findings. The conclusion summarizes contributions and suggests future research.

2. RELATED WORKS

Priyambodo *et. al* [8] AODV routing protocol has advantages over drawbacks, confirmed through extensive experimentation. Fine-tuning default settings can optimize AODV, showing positive outcomes in delay, load, and retransmission efforts. In mobile node scenarios, AODV outperforms OLSR regarding Packet Delivery Ratio, throughput, and packet loss rates. However, AODV exhibits more increased delays than OLSR. It is crucial to understand the influence of parameters like RREQ_RETRIES and MAX_RREQ_TIMEOUT on AODV compared to OLSR.Similar to previous research conducted by Yasser *et. Al* [18], AODV proves suitable for mobile node scenarios despite different simulation environments (VANET and MANET). Conducting extensive experiments enhances V2V communication system performance.

Bamhdi [19] DP-AODV improves network performance with over 200 nodes by mitigating interference, increasing packet delivery, reducing overhead, enhancing throughput, decreasing interference, and shortening delays. Power transmission is determined by distance information, maintaining connectivity while reducing power consumption.

Malik and Sahu [20] Optimizing the AODV routing protocol is crucial for VANET environments with increased vehicle mobility. Delays caused by enhanced connectivity and fast-moving nodes can cause information overload. Developing tailored AODV routing protocols can support specialized communication schemes like V2V communication has successfully developed an AODV routing protocol that considers vehicle movement, ensuring stable routes even in congested traffic situations. Abdel-Halim and Fahmy [21] focused on prediction-based routing protocols in VANETs. Prediction in routing protocols optimizes relay node cluster selection during request and reply packet exchanges. It supports link stability for efficient data communication and collision avoidance, enhancing driving safety. Bali *et. al* [22] explored the development of efficient communication clusters in Vehicular Cyber-Physical Systems. They suggested a centralized approach that utilized a cloud-based backbone to enhance vehicle clusters, resulting in a robust system for connected vehicles.

According to Saritha *et. al* [16], one effective way to enhance network QoS is by utilizing multipath routing. This method involves a combination of learning automata, leap-frog algorithm[23], and PSO[24] to discover the best transmission paths, detect possible link failures, and obtain more stable paths. By improving node clustering for each path, this approach yields superior QoS parameters compared to other AOMDV-based techniques. Hasanzadeh-Mofrad and Rezvanian [25] delved into the theoretical concepts of learning automata techniques, which involve a system of rewards and penalties to improve reinforcement learning. Although their study did not focus on VANET or network scenarios, it hinted at the possibility of its application in those contexts. Homaei et al. introduced DDSLA-RPL, a system that enhances network graphs using learning automata. It modifies parameter weights based on environment feedback, improving network service quality and extending node lifespan. Compared to previous methodologies, DDSLA-RPL is more precise and adaptable[26].

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3. RESEARCH METHODOLOGIES

3.1 Learning Automata Based AODV

LA-AODV is an adaptive approach that optimizes AODV routing in ad hoc networks and V2V communication. It adjusts probabilities based on feedback, improving QoS parameters like latency, packet loss, and energy efficiency. Follow these steps to implement the LA-AODV routing protocol.

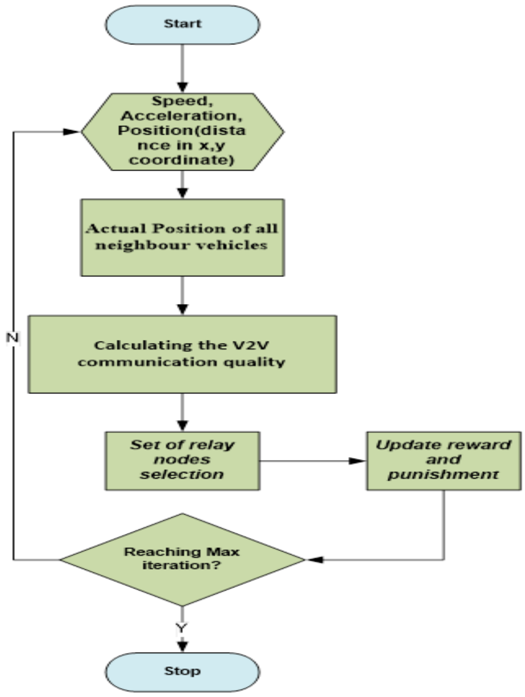

Figure 1. The Flowchart Diagram of LA-AODV

In Figure 1, the LA-AODV protocol uses GPS to locate neighboring and destination nodes. Vehicles share future location predictions with neighbors to select relay nodes. The Communication Quality Index is calculated using velocity and acceleration, and relay nodes are chosen based on the Total Weighted Ratio (TWR) score, favoring stable communication. LA-AODV ensures effective V2V communication through dynamic decision-making and reliable relay node selection.

3.2 Actual Position Prediction

The LA-AODV protocol in vehicular communication networks involves two steps: predicting vehicles' current and future positions based on speed and relative parts, and determining their actual positions by identifying velocity and acceleration parameters, as stated in Eq. (1).

$$INITpos_i = \sum_{i=1}^{i \leq N} actual_{pos_x}, actual_{pos_y}, v_i \quad (1)$$

Equation 1 outlines the different variables the LA-AODV protocol uses to route and position vehicles in the vehicular communication network accurately. The variables include the position of vehicle i on the x and y axes, represented by $INITpos_i$, the speed of the car vi,, the number of vehicles within the transmission range (N) to determine proximity, and the specific node or vehicle under reference (i) To make informed routing decisions in vehicular communication networks, the LA-AODV protocol utilizes equation 2. This equation predicts a vehicle's future position by taking into account its current velocity, acceleration, and elapsed time.

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

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

The prediction process uses variables and equations to estimate a vehicle's future position based on its current velocity, acceleration, and elapsed time. This helps inform routing decisions in vehicular communication networks. The LA-AODV protocol leverages these calculations to predict future vehicle positions. The LA-AODV protocol employs two equations to predict future vehicle positions through the analysis of current positions and velocity changes over time describe in Eq. (4) and Eq. (5).

$$pred_{pos_{x+3}} = pred_{pos_x} + \sum_{t \wedge t+3}^{t<K} \left(\left(\frac{\Delta v_t}{t}\right) + \left(\frac{1}{2}(\Delta v_t)\right) * t^2 \right) \quad (4)$$

$$pred_{pos_{y+3}} = pred_{pos_y} + \sum_{t \wedge t+3}^{t<K} \left(\frac{\Delta v_t}{t}\right) + \left(\frac{1}{2}(\Delta v_t)\right) * t^2 \quad (5)$$

Eq. (4) and Eq. (5) accurately predict a vehicle's future position. Eq. (4), labelled as pred_pos$_{(x+3)}$, estimates the x-coordinate status of the car at a future time (t+3) based on its current position (pred_posx) and the accumulated change in velocity (Δ_{vt}) over a time interval (t to t+3). The summation of velocity changes (Δ_{vt}) during the period from t to t+3 is represented by ∑(t && t+3)^(t<K), with t<K indicating that the summation is performed within the maximum iteration time (K). Similarly, the second equation, represented by pred_pos$_{(y+3),}$ predicts the future y-coordinate position of the vehicle. It takes into account the current y-coordinate place (pred_pos$_y$), the summation of velocity changes (Δ_{vt}) multiplied by the time interval (t), and a factor of 1/2 (t2). The equation is crucial for making informed routing decisions and enhancing the overall performance of vehicular communication networks. It is imperative to utilize these equations for optimal results.

The LA-AODV protocol incorporates an analysis step using the equation $pred_{acc_{xy}}$to estimate the total prediction of the positions of neighbouring vehicles based on the predicted x and y coordinates at two interval prediction points. The $pred_{acc_{xy}}$ is describe in Eq. (6).

$$pred_{acc_{xy}} = MIN \quad (6)$$

This equation considers the square root of the difference between the squared distances in the x and y directions and respectively, summed over all vehicles i and time intervals t within the maximum prediction time K. The variable N represents the number of vehicles within the transmission range. This analysis provides valuable information about the predicted positions of neighbouring vehicles, enabling better routing decision-making and improving the LA-AODV protocol's overall efficiency in vehicular communication networks.

3.3 Calculating the Quality Index of Communication with Neighbor Vehicles

The communication stability index measures how stable communication is between nodes. If it is less than or equal to 1, communication is regular. If it exceeds 1, communication is unstable. The maximum communication radius is 2500 grid units divided into a grid of 50 units. This index provides valuable insights into the reliability of network connections describe in Eq. (7).

$$comm_{ij} = \left| \left(\frac{pred_{acc_{xy}}}{Max_{rad}} \right) \right| \quad (7)$$

As defined in Eq. (7), the communication stability index evaluates the stability of communication between nodes. It is determined by dividing the total prediction accuracy of all neighbouring vehicles, $pred_{acc_{xy}}$, by the maximum communication radius, Max_{rad}. If the resulting index, $comm_{ij}$, is less than or equal to 1, it indicates regular communication. Conversely, if the index exceeds 1, it signifies unstable

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transmission. The communication quality of a node is evaluated by summing up the reciprocal values of communication stability indices with connected nodes within the radius.

$$comm_{quality_i} = \left(\sum_{i}^{i<N} \left(\frac{1}{comm_{stability_{ij}}} \right) \right) \tag{8}$$

Eq. (8) expresses this relationship. The variable w_q, which ranges from 0 to 1, represents the weight assigned to the communication quality index, with a value of 0.2. In detail, $comm_{stability_{ij}}$ represents the communication quality between node I and node j within the communication radius. On the other hand, $comm_{quality_i}$ represents the communication quality of node i concerning all connected nodes within the communication radius.

3.4 Set of Relay Nodes Decision Making

Eq. (9) calculates the TWR) for each vehicle in a vehicular communication network by combining weighted factors. These factors include the differences in velocity, acceleration, and direction between the next-hop and destination nodes and the communication quality index. The total weight assigned to these factors, denoted as wtotal, is set to 1 denotes in Eq. (10).

$$TWR_i = \sum_{i=1}^{i} N \left(\left(w_v * (|v_n - v_d|) \right) + \left(w_a * (|a_n - a_d|) \right) + \left(w_d * (|c_n - c_d|) \right) + \left(w_q * \left(comm_{quality_i} \right) \right) \right) \tag{9}$$

where,

$$w_{total} = w_v + w_a + w_c + w_q = 1 \tag{10}$$

The TWR serves as a threshold value to assess whether a vehicle is optimal or suboptimal. If the value of a neighbouring node exceeds the TWR, it indicates suboptimal performance, while a value less than or equal to the TVS implies an optimal state. The weights assigned to velocity, acceleration, direction, and communication quality range from 0 to 1, with specific values assigned to each: $w_v = 0.4$, $w_a = 0$.

The decision for selecting relay nodes in the vehicular communication network is based on the TVS and the future TVS values of next-hop vehicles. If a next-hop car is optimal and the communication stability is stable or increasing, it is selected as a relay node. If the next-hop vehicle is optimal but lacks communication stability, it is still set as a relay node. On the other hand, if the next-hop vehicle is in a suboptimal state, regardless of the communication stability, it is ignored and not chosen as a relay node.

Table. 1 - Relay Nodes Selection Rules

Current TWR	TWR in t+1	TWR in t+3	Relay Nodes Selection
Optimal	Stable	Stable	Selected
		Less stable	Selected
	Less stable	Stable	Selected
		Less stable	Ignore
Less Optimal	Ignore	Ignore	Ignore

In Table 1, to assess a vehicle's performance, we look at its speed, acceleration, and direction. Optimal cars have the smallest TWR value among neighbours, while less optimal ones exceed the minimum. We evaluate next-hop vehicles and classify their state as "stable" or "less stable" based on TWR and Future TWR differences. LA-AODV algorithm selects reliable relay nodes based on stability, communication quality, and optimal condition. These nodes are then multicast to other nodes for reliable communication.

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3.5 Simulation Model

The LA-AODV simulation model evaluates the routing protocol in VANETs by simulating communication scenarios to analyze key metrics. The LA-AODV Model is shown in Figure 2.

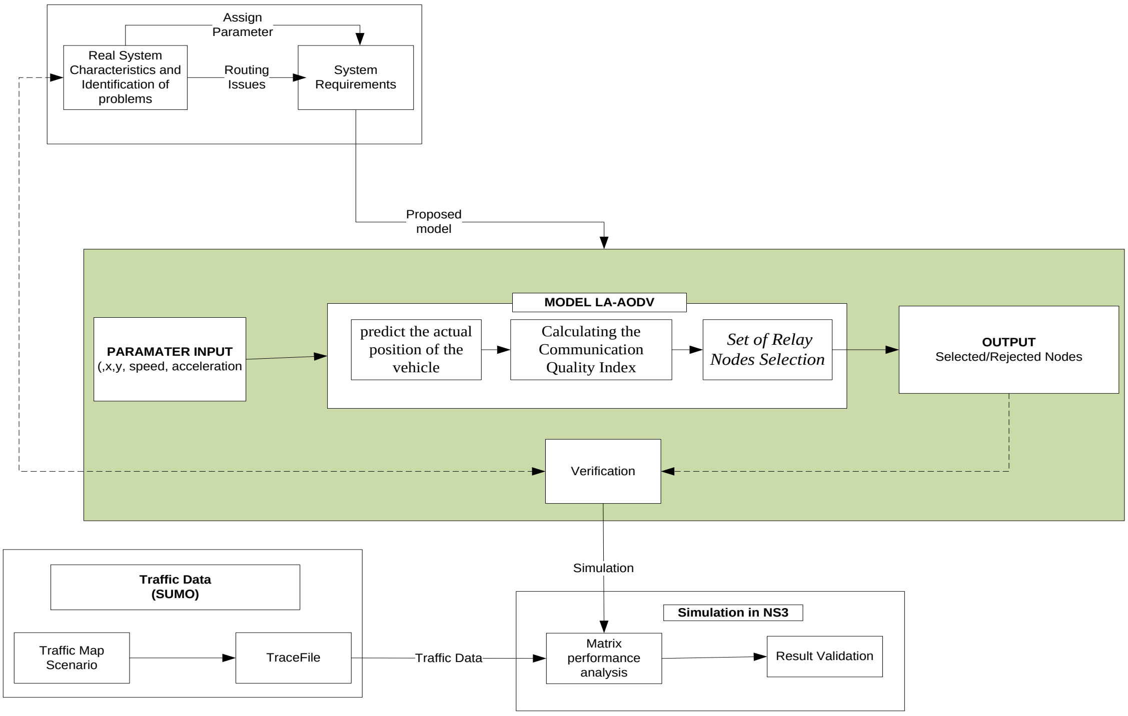

Figure 2. The LA-AODV Simulation Model

We conducted a simulation of LA-AODV to study routing issues and tested it in traffic scenarios using SUMO and NS3 on Linux Ubuntu 20.02. The simulation involved a network of cars on a highway area with a single roundabout, following Indonesia's left-hand traffic rules. We simulated wireless access for the vehicular environment (WAVE) using a network of cars on a highway area with a single roundabout, following Indonesia's left-hand traffic rules. The simulation lasted 10 to 50 seconds and included 20 to 75 vehicles with a default road type described in Figure 3.

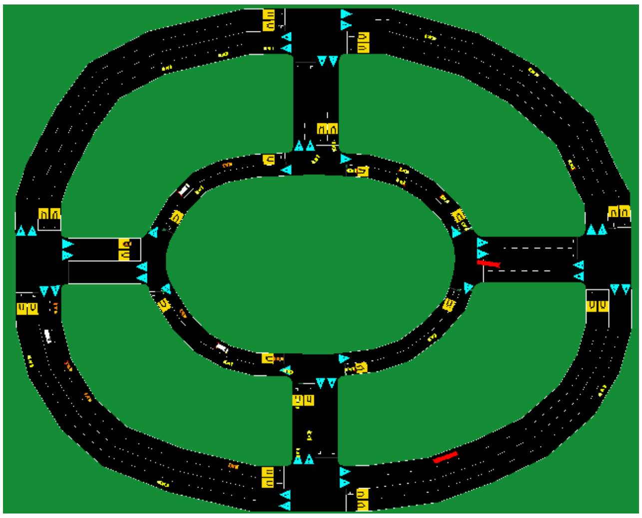

Figure 3. Traffic Simulation Area

Figure 3 shows a simulation of vehicles with predetermined mobility using a 9.5 Mbit/s data rate. The simulation speed was set to 0.01 simulation step, and transmission power was set to 23 dBm for reliable communication. Table 2 contains essential information for analyzing vehicular communication, such as

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simulation times and node numbers. This data can help researchers gain insight into the dynamics of vehicular communication systems.

Table 2 - Simulation Variables

No.	Simulation Variables	Values
1	Simulation time	10, 50 (in seconds)
2	Number of nodes	20, 25, 30, 40, 55 (vehicles)
3	Initial speed	15 (in meters per second)
4	Mobility	1
5	Transmission Rate (TxRate)	0fdmRate9MbpsBW10MHz
6	Routing Protocol	LA-AODV, AODV
7	Standard	802.11p (Wireless Access in Vehicular Environments)
8	Frequency	5.9 GHz

The NS3 document presents a detailed list of variables and their corresponding values for a vehicular communication scenario in Table 2. The simulation runs for 10 or 50 seconds, depending on the scenario, and involves varying vehicles ranging from 20 to 55. The vehicles move at a constant speed of 15 m/s, and the mobility is set at 1. The study compares the LA-AODV and AODV routing protocols, utilizing 802.11p wireless communication at 5.9 GHz. The insights obtained from the experiment can help evaluate the performance of vehicular communication.

4. RESULT AND DISCUSSION

The Section assess the effectiveness of the LA-AODV protocol in facilitating V2V communication. By analyzing simulation results such as Flow ID, Packet Loss Ratio, Packet Delivery Ratio, Average Throughput, End-to-End Delay, and End-to-End Jitter, we will compare the performance of the LA-AODV protocol with the standard AODV protocol. We aim to pinpoint areas of strength and weakness to enhance V2V communication.

5.1 Flow ID

The plot in Figure 4 summarizes the total number of nodes and flooding identifiers (flow ID) for the LA-AODV and AODV protocols at two different time intervals: 10 seconds and 50 seconds.

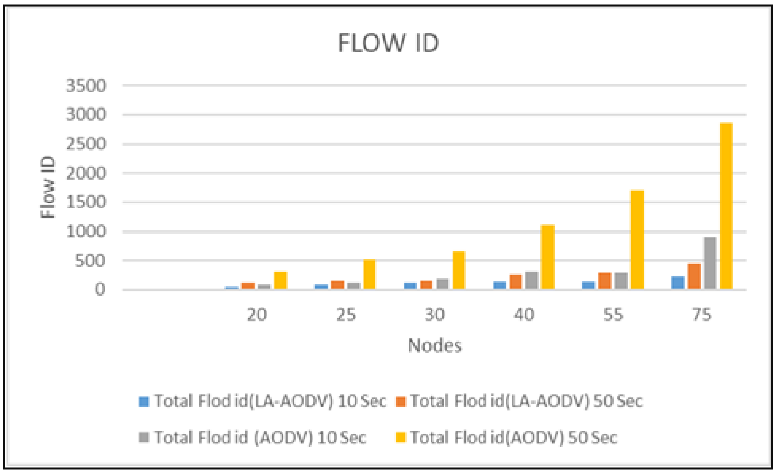

Figure 4. This figure depicts a Flow ID Comparision

In Figure 4, the number of nodes ranged from 20 to 75 at the 10-second interval, while the count of food IDs varied from 54 to 227. At the 50-second mark, the number of nodes remained the same, but the count of flow IDs increased from 122 to 452. Similarly, for AODV, the number of nodes and flood ID count increased as the time interval increased. At the 10-second mark, the number of nodes ranged from 88 to 897, and the count of flow IDs varied from 309 to 2865. At the 50-second interval, the number of nodes and flow ID count remained constant. Overall, an increase in the time interval from 10 to 50 seconds resulted in higher flow ID counts for both LA-AODV and AODV protocols, indicating increased communication activity and information dissemination.

Flow ID impacts communication networks, congestion, resource utilization, and overhead. A high-flow ID causes performance degradation and network strain, while a low-flow ID improves performance and reduces

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overhead. Balancing flow ID optimizes network performance and resource management. Network administrators must manage flow ID carefully to balance capacity, efficiency, and performance.

5.2 Packet Loss Ratio

Figure 5 shows how LA-AODV and AODV protocols perform concerning packet loss ratios over different periods and node configurations. A higher percentage means more lost packets due to congestion, lack of resources, or poor routing decisions.

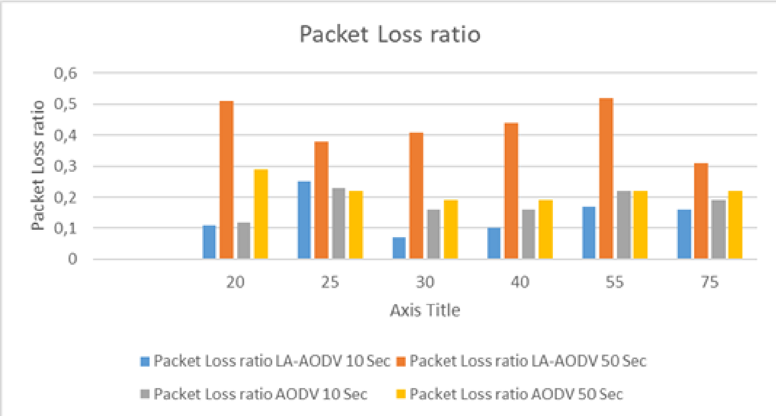

Figure 5. This figure depicts a Packet Loss Ratio Comparison.

In Figure 5, As network performance simulations are prolonged, the packet loss ratios tend to rise, indicative of network congestion and degradation over time. Both LA-AODV and AODV protocols display a rise in packet loss ratios as the number of nodes increases, owing to intensified competition for resources. This bears significant consequences for critical V2V applications and highlights the importance of congestion management and guaranteeing adequate network resources.

5.3 Packet Delivery Ratio

Figure 6 illustrates the comparison of packet delivery ratios between the LA-AODV and AODV protocols in both the 10-second and 50-second simulation durations. For V2V communication, the LA-AODV protocol is superior to AODV regarding packet delivery. It exhibits a higher level of consistency in delivering packets and reliability across different network sizes and simulation durations. LA-AODV is a suitable choice for critical applications that necessitate dependable data transmission.

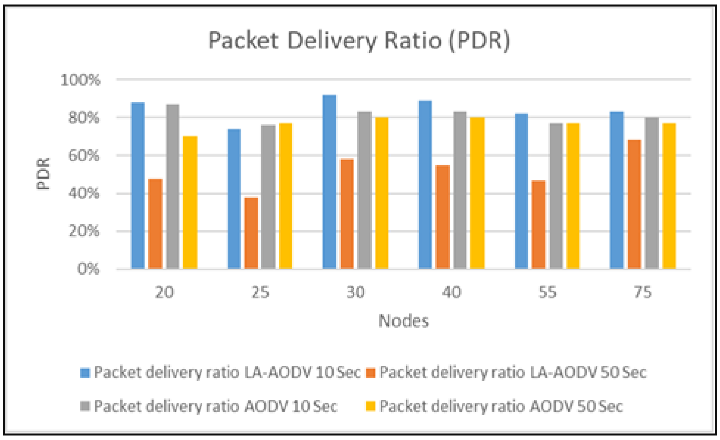

Figure 6. This figure depicts a Packet Delivery Ratio Comparision

In Figure 6, delivery ratios of LA-AODV and AODV protocols were compared for different network sizes and simulation durations. LA-AODV outperformed AODV consistently in packet delivery ratios across all scenarios, indicating its effectiveness in V2V communication. LA-AODV's adaptive and efficient routing mechanisms mitigate congestion, minimize collisions, and optimize data delivery, ensuring reliable and

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successful packet transmission. Selecting the appropriate protocol, such as LA-AODV, is crucial in providing robust and dependable data transmission, supporting the seamless operation of V2V applications in real-world vehicular environments.

5.4 Average Throughput

Figure 7 is included to provide a visual representation of the average throughput performance of the LA-AODV and AODV protocols in V2V communication scenarios. Figure 5 illustrates the average throughput values (in Kbps) for different network sizes (20, 25, 30, 40, 55, and 75 nodes) and simulation durations (10 seconds and 50 seconds).

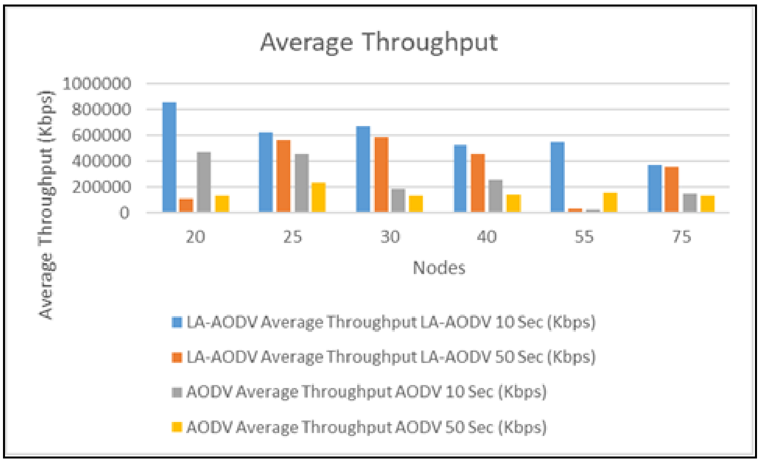

Figure 7. This figure depicts an Average Throughput Comparison

In Figure 7, the LA-AODV protocol outperforms AODV's higher average throughput. This is a proof to faster data transmission, making it ideal for real-time applications such as cooperative driving and collision avoidance. On the other hand, AODV's lower throughput may hinder efficiency and increase latency, ultimately affecting V2V communication negatively. By choosing the LA-AODV protocol, one can improve data transmission rates, decrease communication delays, and enhance the overall performance of V2V communication networks, making them more efficient and reliable.

5.5 End to End Delay

Figure 8 presents the end-to-end delay measurements for both the LA-AODV and AODV protocols in V2V communication. The graph shows the increasing trend of end-to-end delays as the total number of nodes in the network increases, regardless of the protocol used.

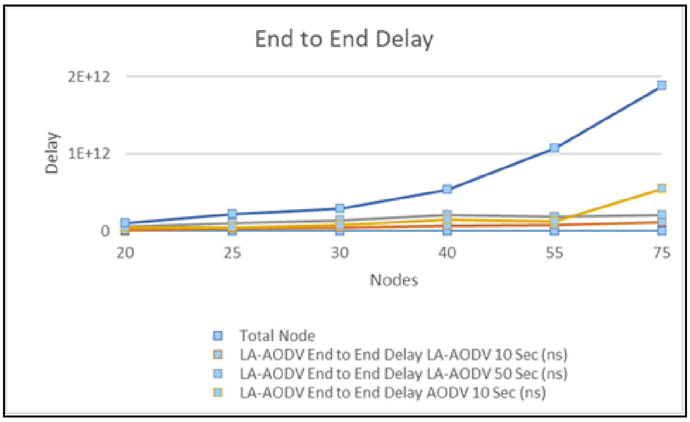

Figure 8. This figure depicts an End to End Delay Comparison

When comparing the LA-AODV and AODV protocols, Figure 8 reveals that LA-AODV generally exhibits lower end-to-end delays across different total node counts. This indicates that LA-AODV enables faster and more efficient packet delivery, leading to reduced delays in V2V communication. The superior performance

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of LA-AODV in minimizing end-to-end delays has the potential to greatly improve the responsiveness and timeliness of V2V applications, thereby enhancing safety and coordination among vehicles. In conclusion, Figure 8 underscores the impact of end-to-end delays on V2V communication. The increasing trend of delays with higher node counts highlights the challenges of maintaining low-latency communication in densely populated V2V networks. However, the lower end-to-end delays exhibited by the LA-AODV protocol suggest its superiority in ensuring timely and efficient packet delivery.

5.6 End to End Jitter

Jitter refers to the variation in packet delay, indicating the inconsistency or irregularity in packet arrival times. High jitter can disrupt the timing and synchronization of V2V applications, affecting the reliability and performance of communication. Figure 9 presents the jitter comparison between LA-AODV and AODV.

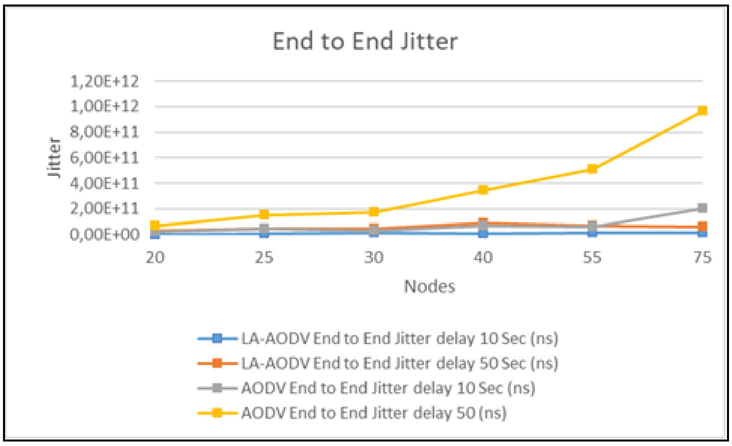

Figure 9. This figure depicts a End to End Jitter Comparison

In Figure 9, LA-AODV has lower jitter delays than AODV, making it more stable and predictable for V2V communication. The reduced jitter improves coordination and efficiency, while the higher jitter in AODV introduces inconsistencies that can compromise reliability. Choosing LA-AODV enhances performance, responsiveness, and reliability in dynamic V2V environments.

5. CONCLUSION

To summarize, after analysing performance metrics in V2V communication scenarios, it is evident that the LA-AODV protocol outperforms AODV in terms of efficiency. The LA-AODV consistently exhibits lower Total Flood ID, Packet Loss Ratio, End-to-End Delay, and Jitter Delay, which indicates its superior ability to disseminate control messages, reduce transmission delays and variability, and mitigate packet loss. Additionally, the LA-AODV protocol demonstrates a higher Packet Delivery Ratio, Average Throughput, and Goodput, proving its effectiveness in achieving successful data delivery, utilizing network resources efficiently, and transmitting a larger volume of valuable data.

By implementing the LA-AODV protocol in V2V communication systems, their overall performance and effectiveness can be significantly enhanced, ultimately improving safety and coordination among vehicles on the road. Future research in V2V communication should focus on scalability, performance under high load, robustness in dynamic environments, comparative studies with other protocols, and security resilience of the LA-AODV protocol. These research areas will enhance our understanding of LA-AODV's potential to improve V2V communication in terms of efficiency, reliability, and security.

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