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The Implementation of VANET Routing Protocol for Vehicular Communication Using NS3 and SUMO

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Abstract *–* Vehicular Ad-hoc Networks (VANETs) are dynamic wireless systems enabling vehicles to exchange data such as speed, location, and direction. A core component in VANETs is the routing protocol, with Ad-hoc On-Demand Distance Vector (AODV) being widely used. However, AODV struggles in highly dynamic environments, leading to reduced performance in throughput and end-to-end delay. This study proposes an improved AODV protocol using the Learning Automata approach (LA-AODV), which enhances relay node selection for better routing efficiency. The performance of LA-AODV is evaluated against standard AODV using NS-3 and SUMO simulations, focusing on key Quality of Service (QoS) metrics: throughput, packet delivery ratio, packet loss, and end-to-end delay. Simulation results show that LA-AODV significantly increases throughput (up to 90.84 Kbps) and reduces end-to-end delay by 20–35%, while lowering communication complexity (15–25% fewer Flow IDs). However, LA-AODV suffers from higher packet loss (up to 62%) and lower delivery ratios (37–92%) compared to AODV. This performance trade-off highlights LA-AODV's improved data efficiency at the cost of reliability. To mitigate delivery issues, solutions such as buffer tuning, adaptive queuing, or hybrid protocols are suggested. Future research should address these challenges and examine LA-AODV's scalability in larger VANET deployments.

Keywords – *V2V communication; AODV routing protocol; Connected Vehicle; LA-AODV; NS3 Simulation*

I. INTRODUCTION

The development of communication technology has changed the transportation industry, especially in terms of personal vehicles such as automobiles [1]. Today, smart cars have been equipped with advanced technology that allows vehicles to communicate with each other. Utilizing Wi-Fi technology known as Dedicated Short Range Communication (DSRC), DSRC is a special form of wireless communication that operates over short distances and is commonly used for data exchange between vehicles[2]. In addition, research is also growing in the field of Vehicle-to-vehicle (V2V) communication on the Vehicular Ad-Hoc Network (VANET) [3]. VANET allows vehicles to communicate directly with each other over a peer-to-peer network [4]-[5], [6]. Through V2V communication within the VANET network, vehicles can exchange information about position, speed, and direction of movement with other vehicles in the vicinity [5]. Measurement of distance between vehicles allows smart cars to detect precautions such as alerting the driver or even activating an automatic braking system to avoid collisions[6]. Thus, the driver can receive real-time information useful for running the vehicle safely and efficiently[7].

VANET technology has the potential to be a solution to overcome problems such as network traffic congestion[8], and identify more efficient network routes [9]-[10]. V2V communication in the VANET network has attracted significant attention from researchers, industry, and government due to its implementation which is important for improving vehicle safety in future generations[11]. The routing protocol is one of the key components in V2V communication in the VANET network to ensure effective and efficient data transmission between vehicles [12]. One of the commonly used routing protocols in Vehicle-to-vehicle communication on VANET networks is the Ad-hoc On-demand Distance Vector (AODV). AODV[13] is a protocol that can be applied to large-scale ad hoc networks, where routes to destination nodes are always updated[14]. This is possible because AODV uses sequence numbers as well as memory for routing table processing and reduces link redundancy[15].

The advantages of AODV as a simple routing protocol in V2V communication on the VANET network are indispensable because its implementation does not involve complicated algorithms[16],[17]. it exhibits significant limitations in dynamic vehicular environments. AODV is inherently reactive and lacks predictive mechanisms, which makes it ill-suited for rapidly changing network topologies caused by high vehicle mobility[18][19]. As vehicles frequently enter and leave communication ranges, AODV struggles to maintain stable routes, resulting in frequent link breakages and repeated route discoveries. These disruptions introduce high end-to-end delay, increase routing overhead, and degrade packet transmission reliability, especially under high-speed or high-density scenarios[20]. Furthermore, AODV does not consider vehicle speed, direction, or position when selecting relay nodes, leading to inefficient routing decisions and poor adaptation to network dynamics. These issues collectively limit its effectiveness in time-sensitive applications such as collision avoidance or cooperative driving [15]. To address this gap, this research proposes an enhanced AODV protocol, namely Learning Automata-based AODV (LA-AODV), which incorporates machine learning methods to improve routing performance in dynamic V2V environments. Unlike conventional AODV, LA-AODV dynamically adapts to network conditions by optimizing relay node selection, reducing delay, and improving packet delivery rates.

This situation shows that the AODV routing protocol has not been optimally used in V2V communication on VANET networks involving fast and dynamic vehicle movements [21]. Therefore, further development and modification of this protocol is needed to create better and more effective solutions. One proposed modification of the AODV protocol is LA-AODV, which incorporates machine learning methods to improve the performance of the routing protocol. To measure routing protocol performance, metrics that reflect Quality of Service (QoS) are needed, such as Flow ID, Packet Loss Rate, Packet Delivery Ratio, Throughput, and End-to-End Delay[22].

Therefore, performance analysis of LA-AODV and AODV routing protocols is very important to determine which protocol is superior in V2V communication on VANET networks[23]. This analysis was run through NS3 and SUMO simulation software, to test routing protocol performance in various scenarios and V2V communication conditions on VANET networks [16]-[17]. The purpose of this research is expected to be one of the valuable suggestions in the application and development of V2V communication routing protocols on VANET in the future, to provide more efficient and optimal communication services between vehicles.

II. RESEARCH METHODOLOGY

In this study, AODV protocol modifications were carried out by considering the parameters of speed, acceleration, and direction of the nearest node (neighbor node) to predict the actual position of the vehicle. Then, measurements of the communication quality index with all nearby vehicles are made before the set of relay nodes is selected until the maximum estimated time is reached. The Learning Automata-AODV (LA-AODV) steps are described in Figure 1.

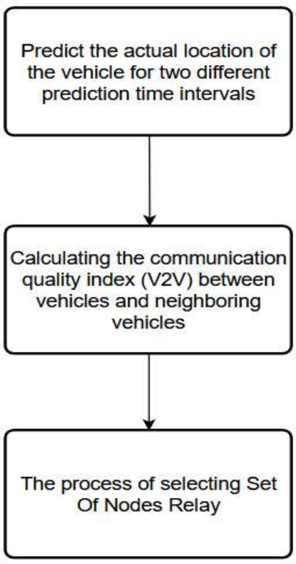

Fig 1. LA-AODV Methods[25]

Figure 1 show the steps of AODV learning automata (LA-AODV) in using AODV learning automata (LA-AODV) in an ad hoc vehicle network V2V communication. This figure assumes that the source node can detect the location of the neighbors and the destination node through the GPS service.

Each vehicle uses independent computing power to predict its future location and then broadcasts the prediction to all neighboring nodes. This allows each node to have periodic information about the actual location of the vehicles, which serves as a starting point for determining if the node can be selected as a relay. However, in the NS-3 simulation, there are limitations because NS-3 cannot use location services to determine the real-time location of each vehicle. Therefore, it is necessary to adjust by adding x and y coordinate fields to the HELLO package structure, as shown in Table 1. This change allows NS-3 to periodically update the vehicle's location within a defined prediction area.

Table 1. Modification of HELLO Packet Structure on adaptive LA-AODV

Dst IP Address	Dst Sequence Number	Hop Count	
Lifetime	Speed	Acceleration	
		X	y

Table 1 explains that the HELLO packet structure of the LA-AODV protocol has been modified by adding x and y coordinates as coordinates on the two-dimensional map of the grid. In addition, the HELLO packet contains information about the vehicle's direction, speed, and acceleration on the source and destination nodes[26]. Target node coordinates can be recognized when the target node is stationary or stationary, where they remain in the same place for a certain period. With this information, each node can estimate the location of the vehicle in the future period and use that information to determine whether a particular node can become a relay node or not.

2.1 Prediction of the Actual Location of the Vehicle

The main step of LA-AODV focuses on predicting the actual location of the vehicle at the moment and three seconds ahead based on changes in speed and relative position of the vehicle. The table mentioned then describes the input and output variables involved in predicting those locations in general. Thus, the purpose of the explanation is to provide a brief overview of the primary steps of the LA-AODV and the variables involved in predicting the location of the vehicle.

Table 2. Input Output of the Actual Prediction of the Proposed Vehicle

Input	Process	Output

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x and y coordinates	Set the x and y coordinates on the grid map.	Predict the actual location of a vehicle
Vehicle speed	Set the speed of the vehicle at x and y coordinates at time t	Speed of each vehicle (v).
Prediction of the actual location of the vehicle at time t	Predicting the location of x and y at time t becomes input in calculating Prediction of the position of the x and y coordinates at time t + 3	Predicting the location of x and y coordinates at time t+3

Table 2 shows the input and output variables of the process to predict the actual location of the vehicle. The input variable contains the x and y coordinates of the vehicle and the speed of the vehicle at time t. While the output variable is the prediction of the actual location of the vehicle at time t + 1 and t + 3. Table 3 Show the pseudocode of LA-AODV

Table 3. LA-AODV Pseudocode

Algorithm 1. Learning Automata based-AODV

```
FOR each entry j in m_ipv4AddressEntry
    addr = j.first
    rte = j.second

    IF m_nb.IsNeighbor(addr) is true
        nt++
        dx = m_x - rte.GetX()
        dy = m_y - rte.GetY()
        dis = sqrt((dx*dx) + (dy*dy))
        modSpeed = fs * abs(m_speed1 - rte.GetSpeed1())
        modAccel = fa * abs(m_accel1 - rte.GetAccel1())
        modDistance = fd * dis
        TWR_total = modSpeed + modAccel + modDistance

        IF addr is equal to m_ipv4.GetAddress(1, 0).GetLocal()
            reward = 1
            node.setSelected(true)
        ELSE
            reward = 0.5
            node.setSelected(false)
        END IF

        delta_reward = reward - rte.getPrevReward()
        rte.setWeight(rte.getWeight() + alpha * delta_reward)
        rte.setPrevReward(reward)
        TWR_total = TWR_total + (alpha * reward)
    END IF
END FOR
```

The Learning Automata-based AODV algorithm show in Table 3 enhances the relay node selection process in VANETs by integrating adaptive learning techniques. It iterates through the IPv4 address table to analyze each neighbor node. For each node, the algorithm calculates the distance between vehicles, speed differences, and acceleration differences, applying weights to these metrics to compute a total weighted reward (TWR). If the node matches the local address, it is rewarded highly and marked as selected; otherwise, it receives a moderate reward. The reward difference is used to adjust the node's weight dynamically, ensuring that the algorithm prioritizes nodes with optimal mobility characteristics. This approach allows the protocol to adaptively optimize routing decisions based on real-time vehicular dynamics. The prediction process at time t is carried out using formulas in (1) and (2).

$$\boldsymbol{pred\_loc_x} = \sum_{i=1,t=1}^{i \le N, t \le M} \left(\boldsymbol{actual\_loc_x} + (\boldsymbol{v_t} \,.\, \boldsymbol{t}) + \left(\tfrac{1}{2}(\Delta \boldsymbol{v})\right) * \boldsymbol{2}\right) \quad (1)$$

$$\boldsymbol{pred\_loc_y} = \sum_{i=1,t=1}^{i \le N, t \le M} \left(\boldsymbol{actual\_loc_x} + (\boldsymbol{v_t} \,.\, \boldsymbol{t}) + \left(\tfrac{1}{2}(\Delta \boldsymbol{v})\right) * \boldsymbol{2}\right) \quad (2)$$

Eq (1) and (2) are used to predict the x and y -and coordinate location of a vehicle at time t. To calculate, the actual location of the vehicle on the x-axis will be added with the estimated average speed of the vehicle. The calculation is based on the position of the vehicle at time t $pred\_lok_x \Delta v_x pred\_lok_x$ multiplied by the difference in the speed of the vehicle while it is running at time t with the speed at the previous time, which is described in formulas (1) and (2).

This process is repeated iteratively until it reaches M and is carried out by several N vehicles.$v_t v_t - 1$. LA-AODV calculates the predicted location of the vehicle at time t+3 on both axes. The 3-second prediction time was chosen to take into account the rapid network topology changes in the VANET environment, requiring adjustments to the prediction time duration. Formulas (3) and 4 calculate the predicted location of the x and y coordinates of each vehicle at t + 3.

$$\boldsymbol{pred\_loc_{x+3}} = \boldsymbol{pred\_loc_x} + \sum_{\boldsymbol{t}\ \&\&\ \boldsymbol{t+3}}^{\boldsymbol{t < M}} \left(\left(\frac{\Delta \boldsymbol{v_t}}{\boldsymbol{t}}\right) + \left(\frac{1}{2}(\Delta \boldsymbol{v_t})\right) * \boldsymbol{t^2}\right) \quad (3)$$

$$\boldsymbol{pred\_loc_{y+3}} = \boldsymbol{pred\_loc_y} + \sum_{\boldsymbol{t}\ \&\&\ \boldsymbol{t+3}}^{\boldsymbol{t < M}} \left(\left(\frac{\Delta \boldsymbol{v_t}}{\boldsymbol{t}}\right) + \left(\frac{1}{2}(\Delta \boldsymbol{v_t})\right) * \boldsymbol{t^2}\right) \quad (4)$$

Eq (3) and (4) describe a way to predict the location of all vehicles at time t + 3 on the x and y axes. This prediction is based on the location of the vehicle at the previous time, i.e., as well as the acceleration and average speed of the vehicle at the previous time. $pred\_lok_x pred\_lok_y v_{t-3}$. Each vehicle multicasts, so that information can be obtained from other vehicles in the vicinity (neighbor vehicles) and vice versa. After that, all information obtained from neighbor vehicles is accumulated to obtain the minimum predicted location value of all neighbor vehicles. This information is important for updating the routing table in each vehicle and is used as input to determine the state of the vehicle with the minimum distance and speed using formula (5)

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$$\boldsymbol{pred\_acc_{xy}} = \boldsymbol{pred\_acc_{xy}MIN}\left(\sum_{i=1,t=1}^{i\le N,t\le M}\sqrt{(|\boldsymbol{pred_{loc_{x+3}}} - \boldsymbol{pred\_loc_x}|)^2 - (|\boldsymbol{pred\_loc_{x+3}} - \boldsymbol{pred\_loc_x}|)^2}\right) \quad (5)$$

Eq (5) is used to find a minimum value that represents the ratio of changes in vehicle movement on the x and y axes at two predicted time intervals. The smaller the movement of the vehicle, the better, and vice versa the greater the range of movement the less optimal.

2.2 Selection of a Set of Relay Nodes

Eq (6) calculates the Threshold Vehicle State (TVS) on each vehicle in a V2V communication network by combining factors that have a certain weight. These factors include the difference in speed, acceleration, direction between the next vehicle and the destination vehicle, and the communication quality index. The total weight given to these factors, referred to as TWR_total, is set as 1 as seen in formula (6).

$$\boldsymbol{TVS_i} = \sum_{i=1}^{i} \boldsymbol{N}\left((\boldsymbol{w_v} * (|\boldsymbol{v_n} - \boldsymbol{v_d}|)) + (\boldsymbol{w_a} * (|\boldsymbol{a_n} - \boldsymbol{a_d}|)) + (\boldsymbol{w_d} * (|\boldsymbol{c_n} - \boldsymbol{c_d}|)) + \left(\boldsymbol{w_q} * \left(\boldsymbol{comm_{quality_i}}\right)\right)\right) \quad (6)$$

Eq (6) describes how the selection of next-hop nodes is done by considering the average speed, acceleration, and direction of node I compared to the number of nodes present. Calculated and used as a threshold to determine whether vehicle I is in optimal or suboptimal state. The vehicle is said to be optimal if it has the lowest value compared to the TVS of its neighboring nodes. Conversely, the vehicle is said to be less optimal if it is above the minimum value of other nodes. $TVS_i TVS_i$ TVS_i

2.3 Learning Automata on AODV

Eq (7) is the process of updating (Δ_d) to the value of R in a V2V communication network at time t + 3. If a node is ignored, the R-value remains unchanged. However, if a node is selected, the R penalty will be added by 1 at this point. Conversely, if a node is selected and receives a reward, the updated R-value is calculated.

$$\Delta_d(\boldsymbol{t}+\boldsymbol{3}) = \begin{Bmatrix} \boldsymbol{R(t), if d_{ignore} = 0, penalty} \\ \boldsymbol{R(t) + 1, if d_{seleted} = 1, reward} \end{Bmatrix} \quad (7)$$

The next update is at time T+3 and related rewards. If a node has a value that is better than the TVS_update threshold, it is considered optimal performance and receives a reward. However, if the value is below or equal to the threshold, then the node is considered suboptimal and penalized. This process lasts until time t reaches threshold M. In Eq (8) calculate the TVS_update, which determines the optimality of nodes based on consideration factors. variable R represents the actual value that describes the performance of the node. This value changes over time as the node receives a reward or penalty based on decisions made in the renewal process.

$$TVS_{update} = \frac{1}{N} * \sum_{i=1}^{i} R \quad (8)$$

By combining rewards and penalties into R values, the system adaptively adjusts node performance based on the response and outcome of actions performed. This allows dynamic customization to optimize node performance in V2V communication networks.

III. Results And Discussion

The simulation analysis metrics will give you an idea of the extent to which LA-AODV has an advantage over AODV in terms of network performance. The resulting analytical data provides important information that helps us understand how effective the network or simulation being evaluated is.

3.1. Flow ID

One of the first things that can be noticed is the total number of nodes in the network(which gives an idea of how large and complex the network under study is. The results of Flow ID can be seen in Figure 2.

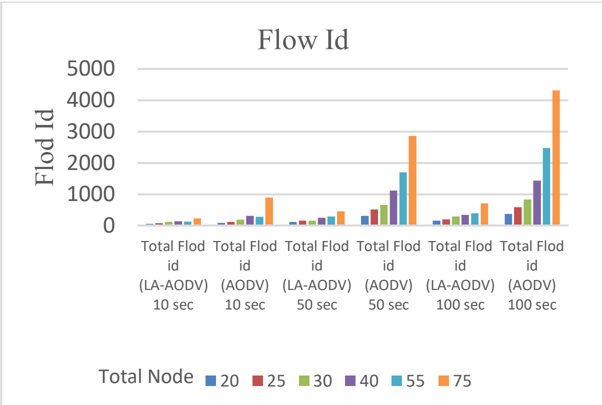

Fig 2. Comparison of Flow ID routing protocols LA-AODV and AODV

Based on Figure 2, the communication complexity of the LA-AODV protocol tends to be lower than AODV when the number of nodes in the network is increasing and the simulation period is getting longer. on a total of 20 nodes, (LA-AODV) has a relatively lower Flow ID compared to (AODV) at each observation time. There is an increase in communication complexity from 10 seconds to 100 seconds.

In general, (LA-AODV) has a lower flow ID value compared to (AODV) on a total of 20 nodes. Low Flow ID (LA-AODV) indicates less complexity of network traffic, potentially reducing conflicts or higher overhead. Differences in Flow ID values between (LA-AODV) and (AODV) can impact network resources. The lower the Flow ID value, the better the network performance in terms of resources. This analysis implies that routing protocols (LA-AODV) tend to have lower Flow ID rates compared to (AODV). This may indicate that protocol modification (LA-AODV) with Learning performs well in reducing communication complexity on the network.

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3.2. Packet Loss Ratio

This Packet Loss Ratio indicates how large a proportion of packets are lost in the delivery process. The results of the comparison of AODV and LA-AODV Packet Loss Ratio are shown in Figure 3.

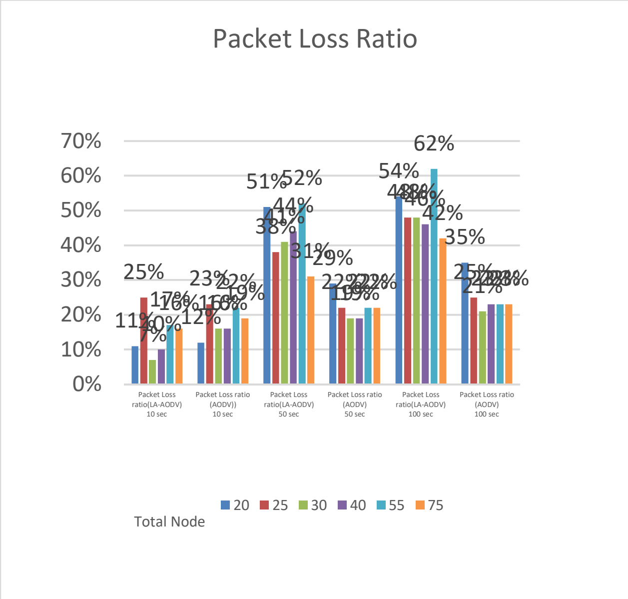

Fig 3. Comparison of LA-AODV and AODV Packet Loss Ratio

Comparative Analysis can be seen in Figure 3 that the Packet Loss Ratio tends to vary depending on the routing protocol used, simulation time, and number of nodes in the network. In general, the Packet Loss Ratio (LA-AODV) results tend to be higher than (AODV). (LA-AODV) has significant variation between time scenarios and the number of nodes in the network. In the longer time scenarios of 50 sec and 100 sec, the Packet Loss Ratio (LA-AODV) tends to increase, indicating an increase in packet loss with the highest value at 52% on node 55 time 50 seconds and 62% on node 55 time 100 seconds.

The number of nodes in the network also affects the Packet Loss Ratio (LA-AODV), with increases in the number of nodes and simulation time likely to increase packet loss. The Packet Loss Ratio (AODV) also shows variations depending on time scenarios and the number of nodes in the network. In some cases, the Packet Loss Ratio (AODV) is lower than (LA-AODV) with the lowest value at 19% at node 30, 40 times 50 seconds, and 21% at node 30 time 100 seconds, the results indicate better performance in packet loss. Increased simulation time and the number of nodes in the network tend to increase the Packet Loss Ratio (AODV), although not as large as that of the protocol (LA-AODV).

This analysis implies that the routing protocol (LA-AODV) tends to have a higher packet loss rate compared to (AODV). This may indicate that protocol modification (LA-AODV) with Learning has poor performance in terms of packet loss.

3.3. Packet Delivery Ratio

The LA-AODV packet delivery ratio has a significant variation between time scenarios and the number of nodes in the network. The Packet Delivery Ratio (AODV) also shows variations depending on time scenarios and the number of nodes in the network. In some cases, the Packet Delivery Ratio (AODV) is higher compared to the Packet Delivery Ratio (LA-AODV), indicating better performance in package delivery. The results of the PDR comparison can be seen in Figure 4.

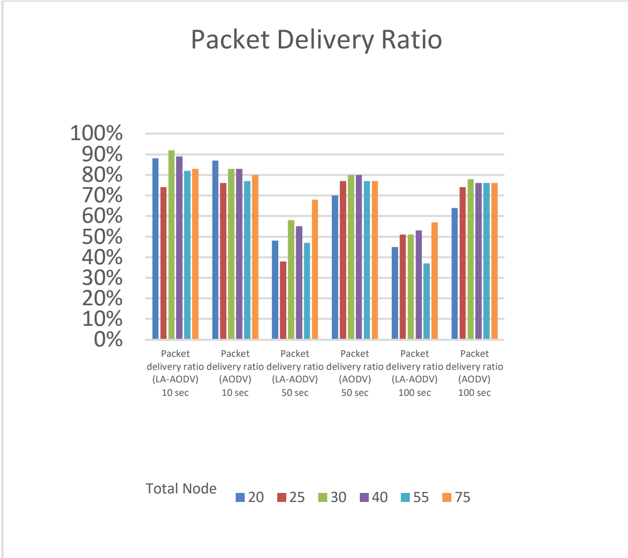

Fig 4. Comparison of PDR LA-AODV and AODV

Based on the comparison of PDR LA-AODV and AODV in Figure 4, the results of Packet Delivery Ratio analysis for routing protocols (LA-AODV) and (AODV) on various time scenarios and the number of nodes in the network. The Packet Delivery Ratio (LA-AODV) shows significant variation depending on the time scenario and the number of nodes in the network. In general, the Packet Delivery Ratio (LA-AODV) tends to be lower than the Packet Delivery Ratio (AODV). In the 10-second time scenario, the Packet Delivery Ratio (LA-AODV) ranges from 74% to 92% with an increase in the number of nodes. In the 50-second time scenario, the Packet Delivery Ratio (LA-AODV) ranges from 38% to 58% with an increase in the number of nodes. In the 100-second time scenario, the Packet Delivery Ratio (LA-AODV) ranges from 37% to 57% with an increase in the number of nodes.

The Packet Delivery Ratio (AODV) also shows variations depending on time scenarios and the number of nodes in the network. In general, the Packet Delivery Ratio (AODV) tends to be higher than the Packet Delivery Ratio (LA-AODV). In the 10-second time scenario, the Packet Delivery Ratio (AODV) ranges from 76% to 87% with an increase in the number of nodes. In the 50-second time scenario, the Packet Delivery Ratio (AODV) ranges from 70% to 80% with an increase in the number of nodes. In the 100-second time scenario, the Packet Delivery Ratio (AODV) ranges from 64% to 78% with an increase in the number of nodes. This analysis implies that the AODV routing protocol tends to have a higher packet delivery rate compared to LA-AODV. This shows that modification of routing protocols using Learning Automata on AODV has not been able to achieve the efficiency and reliability of packet delivery.

3.4. Average Throughput

High average throughput in V2V communication on VANET networks means there is sufficient capacity to transfer data at high speeds between vehicles. With high Average Throughput, the risk of data packet loss or delay can be minimized, ensuring important information can be sent and received quickly and accurately. The results of the comparison of the Average throughput of LA-AODV and AODV are in Figure 5.

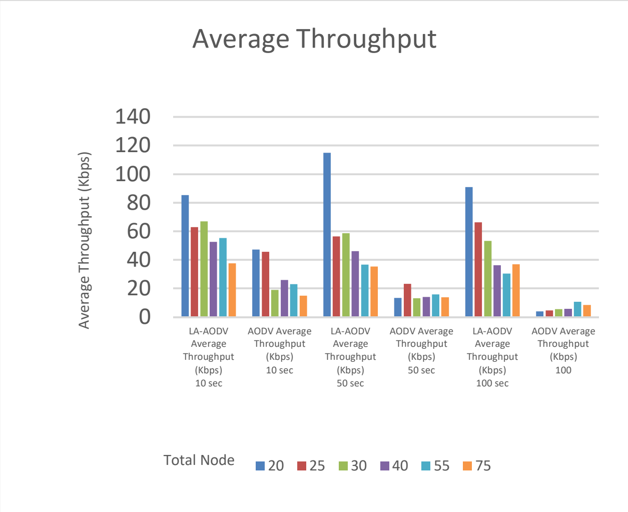

Fig 5. Comparison of Average throughput of LA-AODV and AODV

A comparative analysis of Average throughput in Figure 5, shows that in the 10-second time scenario, the average throughput of LA-AODV ranges from 37.5406 Kbps to 85.3425 Kbps, with the highest average at total node 20 and the lowest average at total node 75. In the 50-second time scenario, the average throughput of LA-AODV ranges from 35.3186 Kbps to 114.821 Kbps, with the highest average at total node 20 and the lowest average at total node 75. In the 100-second time scenario, the average throughput of LA-AODV ranges from 30.2889 Kbps to 90.8452 Kbps, with the highest average at total node 20 and the lowest average at total node 75. In the 10-second time scenario, the average AODV throughput ranges from 4.0365 Kbps to 47.2603 Kbps, with the highest average on total node 20 and the lowest average on total node 100.

In the 50-second time scenario, the average AODV throughput ranges from 4.65076 Kbps to 23.3256 Kbps, with the highest average at 25 total nodes and the lowest average at 100 total nodes. In the 100-second time scenario, the average AODV throughput ranges from 5.81214 Kbps to 14.1218 Kbps, with the highest average at 40 total nodes and the lowest average at 100 total nodes. The impact of the data is that the LA-AODV routing protocol tends to have a higher average throughput compared to AODV in various scenarios. This shows that modifying routing protocols using Learning Automata on AODV can improve data transmission efficiency. In longer-time scenarios, the difference in throughput between the two protocols becomes more significant. This analysis implies that the LA-AODV routing protocol has a higher average throughput rate compared to AODV. This suggests that modification of routing protocols using Learning Automata on AODV is capable of increasing enough capacity to transfer data at high speeds between vehicles.

3.5. End-to-End Delay

In a fast and dynamic highway situation, information sent between vehicles must arrive in a very short time to support informed decision-making in real-time. For example, when a vehicle detects a hazard or emergency, such as sudden braking or an obstacle in the road, the information must immediately reach other vehicles in the vicinity for them to react quickly. The results of the End to end-to-end delay comparison can be seen in Figure 6.

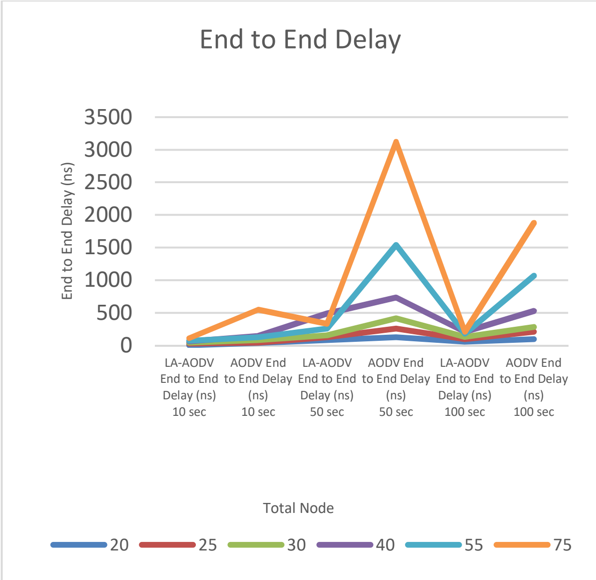

Fig 6. Comparison of End-to-End Delay LA-AODV and AODV

Figure 6 shows a comparison of End to End Delay (LA-AODV) and (AODV), at a total of 20 nodes, (LA-AODV) has a relatively lower End-to-End Delay compared to (AODV) at each observation time. There was an increase in End-to-End Delay packet delivery time from 10 seconds to 50 seconds but later decreased by 100 seconds for both protocols. In general, (LA-AODV) has a lower End-to-End Delay value compared to (AODV) on a total of 20 nodes. Low End-to-End Delay (LA-AODV) indicates an increase in packet delivery efficiency, potentially resulting in faster communication within the network. The difference in End-to-End Delay values between (LA-AODV) and (AODV) can have an impact on network service quality.

The lower the End-to-End Delay value, the better the network performance in terms of packet delivery time. In real network implementations, this difference in End-to-End Delay values can affect real-time applications that require fast response times, such as video streaming or voice communication. Thus, the implications of the data analysis results show that the use of the LA-AODV routing protocol has a lower End-to-End Delay compared to the AODV protocol. This shows that modification of routing protocols using Learning Automata on AODV can improve the efficiency of sending packets between vehicles

IV. CONCLUSION

The comparative analysis of LA-AODV and AODV highlights a critical performance trade-off. LA-AODV, enhanced with Learning Automata, significantly improves Flow ID efficiency, average throughput, and end-to-end delay, making it suitable for dynamic vehicular environments. These gains result from its ability to adaptively select optimal relay nodes based on real-time mobility metrics. However, these improvements come at the cost of increased packet loss and reduced delivery ratios, primarily due to the delay in convergence during the learning process. On the other hand, AODV, with its simpler and more immediate routing mechanism, maintains better reliability in terms of packet loss and delivery but lacks performance in terms of throughput and delay under dynamic conditions. To make LA-AODV more reliable and practical for large-scale deployment, future research should focus on: Accelerating the convergence of the Learning Automata algorithm by introducing adaptive learning rates or reinforcement adjustment mechanisms. Integrating hybrid routing strategies that combine reactive and proactive approaches to mitigate packet loss during route discovery and learning phases. Enhancing buffer management and queuing policies to temporarily store packets during route learning delays. Leveraging cross-layer design, where information from lower layers (MAC, physical) assists in more accurate relay selection and route maintenance. Testing scalability and stability of LA-AODV in denser and more heterogeneous VANET environments to evaluate real-world feasibility.

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