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Learning Automata-Based AODV to Improve V2V Communication in A Dynamic Traffic Simulation

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Abstract: The study introduces the learning automata-based AODV (LA-AODV) protocol to enhance vehicle-to-vehicle (V2V) communication in dynamic vehicular Ad-hoc networks (VANETs). Existing routing protocols, such as Ad-hoc on-demand distance vector (AODV) protocols, face significant challenges, including low data transfer rates, higher delay times, lower throughput, and data congestion resulting from rapidly changing network topologies. LA-AODV addresses these issues by optimizing the quality of service (QoS) through the real-time selection of relay nodes based on vehicle speed, distance, and actual position parameters. Simulations were conducted at the Gadjah Mada university (UGM) roundabout in Yogyakarta, Indonesia, using SUMO and NS3 simulators. LA-AODV outperforms AODV with Packet Delivery Ratios ranging from 95% to 99% and Average Throughputs between 36.90 Kbps and 56.50 Kbps. Although LA-AODV exhibits slightly higher End-to-End Delays, it effectively mitigates Packet Loss Ratios ranging from 1% to 4%. These enhancements optimize routing decisions, reduce communication overhead, and enhance network resource utilization.

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 VANETs [1, 2]. The drawback of AODV is primarily due to suboptimal relay node selection caused by dynamic vehicle quantity fluctuations on busy roads [3]. Several drawbacks contribute to these limitations. Firstly, AODV employs a reactive routing approach, which leads to increased control message exchange [4] and longer route setup times in dense networks [5, 6]. Secondly, periodic route maintenance in AODV consumes network resources despite no active data transmission, resulting in unnecessary control message exchanges and increased network overhead [7]. AODV routing decisions do not adapt to real-time information like vehicle speed and acceleration, causing suboptimal relay node selection and degraded QoS performances [8]. These limitations hinder the overall efficiency and responsiveness of V2V communication systems in VANETs [9].

Several studies address the challenges encountered in the AODV routing protocol to support V2V communication, such as implementing prediction node trends on AODV [10] and [11], mobility and detection aware AODV (MDA-AODV)[12], flooding-awareness-AODV (FLOW-AODV) that achieves better packet delivery ratio and average delay compared to standard AODV [13], Cluster-based communication approach by applying learning automata-assisted prediction [14], channel reservation method using learning automata concept for handoff calls in VANET environment [15], and multipath routing strategy using PSO, leap-frog algorithm, and learning automata to ensure channel availability for V2V communication in VANET [16] 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.

This study develop A new method called LA-AODV to improve vehicle-to-vehicle communication. This technique combines the learning automata (LA) method with the AODV routing protocol to address the challenges encountered in V2V communication. The main objective of LA-AODV is to optimize the selection of relay nodes, which enhances the effectiveness of V2V communication. LA-AODV achieves this by utilizing real-time information on vehicle positions, speeds, and accelerations to predict and select more responsive relay node clusters in dynamic traffic scenarios.

The problem statement of the study is to improve QoS in V2V communication in dynamic VANETs by assessing QoS parameters like PDR, throughput, delay, and jitter performances to enhance relay node selection, alleviate information overload, and prevent accidents in dynamic traffic situations. We used NS-3 simulations to evaluate the LA-AODV approach's effectiveness compared to standard AODV for traffic management.

The study includes related works in section 2, the research design in section 3, the proposed approach in section 4, and the comparison between LA-AODV and AODV in the results and discussion of section 5. The conclusion is in section 6.

2. Related works

DDSLA-RPL [17] uses learning automata to adjust parameter weights and improve network service quality and node lifespan. DDSLA-RP is more precise and adaptable, but it still needs improvement in various situations. The choice of technique should consider the specific characteristics of the network and the limitations of fuzzy, K-means, and C-means clustering. DP-AODV and LA-AODV are routing protocols for vehicular communication networks. DP-AODV dynamically adjusts power, while LA-AODV uses machine learning to select intelligent relay nodes for optimized QoS parameters and communication efficiency.

Extensive experiments have shown that the benefits of AODV outweigh its drawbacks. By adjusting the default settings, the AODV routing protocol can be optimized to determine appropriate V2V communication ranges, minimize delays in intra-vehicle communication, and incorporate real-world measurements. The impact of route request parameters, such as *RREQ_RETRIES and MAX_RREQ_TIMEOUT, on AODV* compared to OLSR must be understood. AODV achieves an average packet delivery ratio (PDR) of 84.6% in mobile node scenarios, outperforming OLSR. It also shows higher throughput and lower packet loss rates (10.4% compared to OLSR's 19.50%). However, AODV has longer delays (0.1722ms) than OLSR (0.022ms) [7]. AODV suits mobile node scenarios despite different simulation environments of MANET; extensive experiments are necessary to improve performance in V2V communication systems in VANET [18,19].

High-density nodes and high mobility in vehicular networks can cause packet congestion, loss, power wastage, and disrupted paths. DP-AODV [20] dynamically adjusts transmission power to optimize QoS parameters and improve network performance. Another protocol, LA-AODV, selects relay nodes based on real-time vehicle parameters to achieve the same objective. However, both routing protocols aim to optimize quality of service (QoS) parameters and improve communication efficiency in dynamic vehicular network. Prediction based approach in routing protocols optimizes relay node cluster selection during request and reply packet exchanges [21].

MAODV-ACO [22] is an ant colony optimization-based method that enhances the packet delivery ratio (PDR) and minimizes delay, ensuring secure data transmission over a mobile Ad hoc network. Compared to other routing protocols, the PDR of MAODV-ACO is significantly high at 99.66% for 100 nodes. However, further improvements and comparisons with alternative optimization algorithms are necessary to enhance MAODV's overall efficiency. However, further improvements and comparisons with alternative optimization algorithms are essential to enhance the MAODV's overall efficiency, adaptability, optimization potential, and trade-offs between adaptability and security is crucial before determining whether LA-AODV is a suitable alternative to improve MAODV.

3. Research design

The research design comprises several vital phases. Initially, the study identifies critical issues in contemporary vehicle communication systems. These issues encompass challenges related to network instability, data congestion, and

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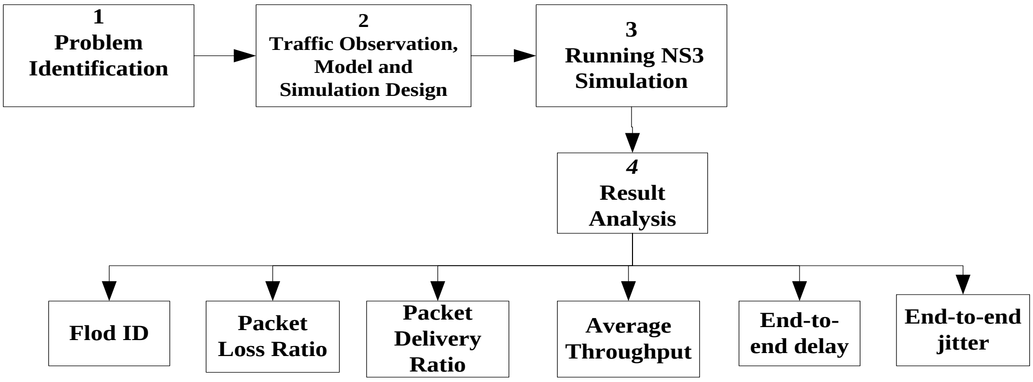

Figure. 1 The process structure of research design

Table 1. V2V communication simulation parameter setup

No	Parameter	Value(s)
1	Total number of actual Nodes (vehicles)	Random, based on Poisson distribution
2	Simulation time (s)	300, 400,500, 600, and 700 seconds
3	Traffic Scenario	• Freeflow (prob 0.55)* • steady flow (prob 0.33) *, • traffic jam (prob 0.1) * **Based on Poisson Distribution*
4	Route Selection	Random route selection
5	Node Speed	Random speed
6	Initial node position	random position
7	Node Movement	All moving nodes
8	Data Packets Configuration	Real time traffic data packets from UGM traffic maps
9	Type of protocol	AODV dan LA-AODV
10	Type of traffic	Passenger cars only, Left-hand drive.
11	Performances Matrix (QoS)	PDR, end to end d*elay, average throughput, Packet loss ratio, end to end Jitter*
12	LA-AODV parameter Setup	*fs* : 0.4 ; *fa* : 0.3 ; *fd* : 0.3 ; α: 1; *Reward* : 1; *Penalty* : 0

communication delays. Subsequently, the research proceeds to develop a comprehensive model and simulation design. This design aims to replicate real-world scenarios accurately. Fig. 1 describes the research design.

The simulation environment is pivotal in this research framework, as shown in Fig. 1. Linux Ubuntu 20.02 is the chosen operating system for simulations, providing a stable and reliable foundation for the experiments. During the simulation phase, data collection is a critical aspect. They are involved in generating XML trace files while executing NS3 simulations. These trace files are instrumental in capturing essential connectivity data between vehicle nodes.

Following data collection, the research transitions into the data analysis phase. Here, the collected data is meticulously scrutinized and assessed to evaluate the performance of LA-AODV in the context of V2V communication. The research design comprises several vital phases. Initially, the study identifies critical issues in contemporary vehicle communication systems. These issues encompass challenges related to network instability, data congestion, and communication delays. Subsequently, the research proceeds to develop a comprehensive model and simulation design. This Design aims to replicate real-world scenarios accurately.

Two primary tools are employed to achieve this: SUMO (Simulation of urban mobility) for traffic modeling and NS3 for communication modeling. This study employs various analytical metrics to compare its

3.1 The simulation environment

We conducted an assessment of our V2V communication model using software tools. Specifically, we used SUMO-GUI [23] to build complex traffic system models incorporating passenger-vehicle interaction in various traffic scenarios. To ensure a comprehensive evaluation of our communication protocols, we also utilized NS3 v3.35, a discrete-event simulator known for its proficiency in model the network communication[24]. To seamlessly integrate mobility and communication aspects, we coupled SUMO with NS3, bridging the gap between traffic model and network communication simulations.

3.2 Simulation setup

The simulation assesses a range of traffic scenarios across different time intervals. These scenarios include Freeflow, Steady flow, and Traffic Jam. Table 1 shows Simulation parameter setup used in this study.

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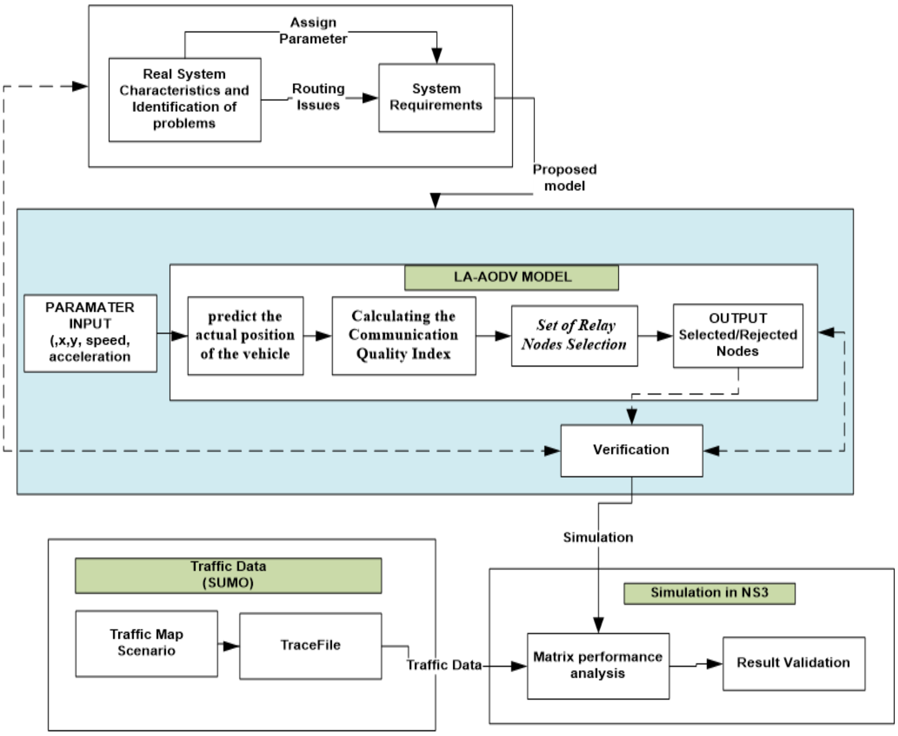

Figure 2. The process structure of LA-AODV Model and the simulation design.

Table 1 simulates real-world vehicular communication scenarios with varying parameters. Performance evaluation measure with simulation times ranging from 300 to 700 seconds. Traffic scenarios are unpredictable and include free flow (0.55), steady flow (0.33), and traffic jams (0.1). We simulate three traffic scenarios, free flow, steady flow, and traffic jams, to evaluate the LA-AODV protocol's performance in real-world traffic conditions. By simulating realistic vehicle movement and using real-time traffic data packets, we assess the protocol's efficiency using metrics such as Packet Delivery Ratio, delay, throughput, loss ratio, and Jitter. Our analysis provides insights into protocol effectiveness in dynamic and unpredictable traffic.

Efficient vehicular communication depends on three crucial factors: speed (*fs*), acceleration (*fa*), and distance (*fd*). Each factor has its importance, where a higher value of speed *fs* prioritizes speed. The *fa* emphasizes acceleration, and *fd* emphasizes distance. LA-AODV sets the learning rate parameter (α) to 1 to make optimal routing decisions. The system rewards favorable decisions with 1, while suboptimal selections are penalized with 0. To calculate the likelihood of a vehicle's appearance occurring a certain number of times within a set time frame in various traffic scenarios, Eq. (1) presents the Poisson distribution formula.

$$P(X = k) = \frac{e^{-\lambda} * \lambda^{-k}}{k!} \quad (1)$$

The poisson distribution denoted in Eq. (1) tracks the number of cars passing through a particular point. The formula utilizes *e*, which represents Euler's number (approximately 2.71), and λ, the average rate of events occurring during the given period. The factorial *k!* is also employed, representing the product of all positive integers from 1 to *k*. In simulations, the Poisson distribution predicts the likelihood of observing several vehicles passing a location based on the average event rate λ.

3.3. Simulation model and traffic observation,

We created a comprehensive model and simulation that explains the proposed LA-AODV approach. The simulation covers various scenarios, environmental settings, traffic patterns, and the implementation of the LA-AODV protocol. Refer to Fig. 2 for further details on the design.

Fig. 2 provides an overview of the modeling and simulation process. The modeling process commences with visual observations of the natural system to be modeled. The aim is to identify the system's characteristics, operational rules, and potential issues to formulate system requirements. Subsequently, a model and simulation design are developed to represent the observations of the natural

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Figure. 3 The network map of the UGM roundabout and the surrounding area represents the real-world situation

system. The next step involves testing the proposed model, necessitating simulations that examine the proposed model based on traffic data adjusted to real-world scenarios. Following this, a final validation is conducted to ensure that the model and data accurately and appropriately represent the critical aspects of the system.

3.3.1. Traffic observation

The UGM roundabout consists of four lanes for two-way traffic, allowing vehicles to enter and exit the roundabout and make a U-turn. While navigating the roundabout, following the "give way to the right" rule and completing a full circle is essential. However, the study neglected to account for potential obstacles, such as pedestrians, parked vehicles, and motorized vehicles entering or exiting side roads, as illustrated in Fig. 3.

In Fig. 3, traffic from the roundabout faces a traffic light-controlled intersection on Terban Road, 200m away. Vehicles entering or exiting Mirota Kampus may face obstructions at the entrance of SMK BOPKRI 1 and SMP BOPKRI 3 on Jl. Terban. The road narrows to one lane as it joins the roundabout. The flow from Terban Road to Colombo Road is denser than in other directions, and parked vehicles/offices may obstruct Jl. Colombo. Cik Di Tiro road may also face obstructions from parked two-wheelers, pedestrian crossings, and rickshaws—lastly, Jl. Pancasila may have congestion during events. To minimize collision risks at the UGM roundabout, coordinate vehicle movements by regulating speed, maintaining a safe distance, and precise vehicle positioning. Equipped vehicles can exchange real-time information to adapt to dynamic traffic conditions.

4. Proposed approach

LA-AODV model has three components: input parameters, model, and output components. Input parameters include velocity, acceleration, coordinates, and time to predict current and future vehicle positions. The model calculates the communication quality index with neighbor vehicles to select relay nodes based on communication stability with neighboring cars.

The LA-AODV routing protocol actively chooses relay nodes with a *Total weighted ratio* (TWR) score between 0.6 and 1, as these nodes guarantee stable communication. Nodes having a TWR below 0.6 get excluded from consideration. We consistently assign a reward value of 1 to promote the selection of relay nodes with TWR between 0.6 and 1, ensuring that these selected relay nodes positively enhance the protocol's performance and reliability. LA-AODV protocol ensures accurate car parts estimation and informed routing decisions in vehicular communication networks by predicting vehicles' current and future positions based on their speed and relative position and determining actual positions using velocity and acceleration parameters, as stated in Eq. (2).

$$INITpos_i = \sum_{i=1}^{i \leq N} actual_{pos_x}, actual_{pos_y}, v_i \quad (2)$$

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 Eq. (3) and Eq. (4).

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

$$pred_{pos_y} = \sum_{i=1,t=1}^{i \leq N, t \leq K} \left(actual_{pos_y} + (v_t . t) + \left(\frac{1}{2} (\Delta v) \right) * 2 \right) \quad (4)$$

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.

Eq. (3) is used to predict a vehicle's position on the *x-axis* at a specific time (t), while Eq. (4) 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 Eq. (5).

$$pred\_acc_{xy} = \sqrt{\left(\left|\Delta pred\_pos_x - \Delta pred\_pos_y\right|\right)} \tag{5}$$

Where:

$$\Delta pred\_pos_x = (pred\_pos_{x+1} - pred\_pos_x) \tag{6}$$

$$\Delta pred\_pos_y = \left(pred\_pos_{y+1} - pred\_pos_y\right) \tag{7}$$

Eq. (5) 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 Eq. (6) and Eq. (7). In Eq. (5), 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, Eq. (5), 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 Eq. (7). 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.

Eq. (8) Using 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.

$$pred_{acc_{xy}} = MIN\left(\sum_{i=1,\ t=1}^{i\leq N, t\leq K} \sqrt{\left(\left|pred_{pos_{x+1}} - pred_{pos_x}\right|\right)^2 - \left(\left|pred\_pos_{y+1} - pred_{pos_y}\right|\right)^2}\right) \tag{8}$$

Eq. (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* denote in Eq. (9).

$$comm\_stability\_index_{ij} = \left|\left(\frac{pred\_acc_{xy}}{Max_{rad}}\right)\right| \tag{9}$$

Where:

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

The LA-AODV protocol includes Eq. (9), 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 $comm\_stability\_index_{ij} \leq 1$ 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 Eq (10).

$$TWR_i = \sum_{i=1}^{i\ to\ N}\Big(\big(f_s * (|s_n - s_d|)\big) + \big(f_a * (|a_n - a_d|)\big) + \big(f_d * (|d_n - d_d|)\big) + \big(f_q * (comm\_quality_i)\big)\Big) \quad (10)$$

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

The LA-AODV protocol utilizes Eq. (10) 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 Eq. (11).

$$w_{total} = f_s + f_a + f_d + f_q = 1 \quad (11)$$

Eq. (11) combines multiple factors by assigning specific weights to each parameter to create a balanced evaluation of all parameters. LA-AODV protocol uses this mechanism to ensure that speed, distance, acceleration, and communication quality are all considered while selecting the best route. This results in an effective routing mechanism for vehicular communication. TWR is a crucial criterion for routing decisions within the protocol, providing a comprehensive assessment of route quality.

The FSA machine activates the learning rate (α) upon reaching its final decision state. Subsequently, the source node notifies neighboring nodes that it has been selected as a relay node, providing them with associated reward and penalty information. In this study, we utilized the LRI algorithm[25] as the learning rate (α), which assigns rewards or penalties to each decision made specified in Eq. (12).

$$\alpha_{t+1} = \begin{Bmatrix} Q\,(t), \quad \alpha_{selected} = 1, reward \\ Q(t)\ + 1, \alpha_{ignore} = 0, \quad punishment \end{Bmatrix} \quad (12)$$

Eq. (12) 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 13 illustrates adding value 'a' to TWR_{update} in the prediction iteration (t+1).

$$TWR_{update} = \sum_{i=1,\ t=1}^{i\le N, t\le K}(TWR_i + \alpha) \quad (13)$$

Eq. (13) 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.

4.1 Quality of services performances matrix

The study will compare the effectiveness of LA-AODV, a newly proposed routing model, to the previous AODV routing method using analytical metrics. These metrics include Flood ID, PDR, PLR, Throughput, Delay, and Jitter, which will evaluate LA-AODV's capability to meet dynamic traffic demands and determine the quality of V2V communication service.

4.1.1. Packet delivery ratio

Packet delivery ratio (PDR) It is defined as the number of packets successfully received by the total number of packets sent in a unit time interval [26]. The PDR calculation is defined in Eq. (14).

$$PDR = \frac{Data_{received}}{Data_{sent}} \quad (14)$$

Eq. (14) determines the PDR value by dividing the amount of data received by a destination node ($Data_{received}$) by the amount of data sent by a source node ($Data_{sent}$). An optimal ratio is achieved when the data received is equal to the data sent. A higher PDR ratio indicates better network performance and the success rate of the routing protocol used.

4.1.2. Packet loss ratio (PLR)

Packet loss rate (PLR) is a metric used to measure the number of packets not delivered successfully compared to the total number sent within a communication network. PLR determined in Eq. (15).

$$PLR = \frac{Data_{loss}}{TotalData_{sent}} \quad (15)$$

Eq. (15) emphasizes maintaining a low PLR for secure and effective V2V communication. A high PLR can pose safety risks, traffic congestion, and loss of driver confidence, underscoring the importance of reliable V2V communication protocols[27].

4.1.3. Average end-to-end delay

Average end-to-end delay (avg_delay_i) represents the average time packets take to reach their destination[28]. Eq. (16) calculates the average delay for all packets that reach their destination.

$$avg\_delay_i = \sum_{i=0}^{n} \frac{t_{received}[i] - t_{sent[i]}}{packet\_counter} \quad (16)$$

Eq. (16) calculates the average delay experienced by each packet in reaching its destination. By summing up the differences between the time a packet is received by node i ($t_{received[i]}$) and the time it was sent by the same node ($t_{sent[i]}$), this formula computes the average delay (avg_delay_i) of all successfully delivered packets ($packet\_counter$ r). It divides it by the total number of such packages (n).

4.1.4. Average Throughput

Average Throughput *(avg_throughput)* is calculated by dividing the total number of successfully received packets by the destination device during a specific interval by the interval duration as shown in Eq. (17).

$$\text{avg\_}throughput = \frac{Amount\ of\ packet\ sent}{total\ data\ sending\ time} \quad (17)$$

Eq. (17) calculates the average throughput, a crucial metric for assessing network performance. It is determined by dividing the number of data packets sent by the time taken for transmission. Higher values indicate efficient transfer, while lower values are associated with slower rates [29].

4.1.5. End-to-end jitter

End-to-end jitter refers to the variation in delay caused by the queue length during data processing and the reassembly of data packets at the end of transmission due to previous failures. The end-to-end jitter delay is stated in Eq. (18).

$$jitter = \frac{Delay\ variation}{(n-1)} \quad (18)$$

Eq. (18) measures delay time deviation in a network. It is calculated by taking the difference between the maximum and minimum delay values and dividing that difference by the number of delay samples minus one *(n-1)*. Jitter evaluates data transmission consistency in a network.

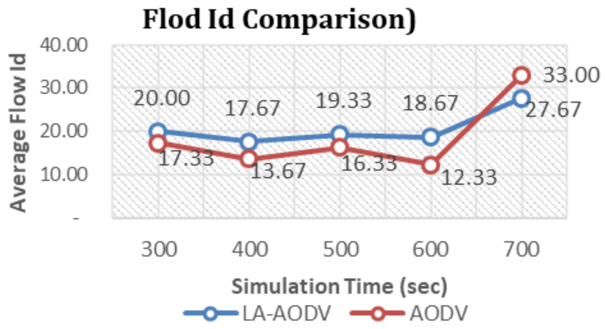

Figure. 4 AODV and LA-AODV Flod ID comparison across the 300 to 700-second timeframe in V2V communication scenarios

5. Result and discussion

In this study, we evaluate the QoS parameters in V2V communication by comparing LA-AODV with a customized standard AODV module from NS3. We customized the AODV module to match the specific traffic scenarios in our study and compared its simulation results with those of LA-AODV. We chose this approach because our research utilizes real-world traffic scenarios (UGM Traffic) specific to our study rather than conforming to scenarios in previous studies. However, we still adhere to the established principles from prior research. We are looking at key metrics like the Packet Loss Ratio, Packet Delivery Ratio, Average Throughput, end-to-end delay, and end-to-end jitter. Fig. 4 illustrates the trends in the Total Flod ID for the 300-700 second period in V2V communication scenarios.

Fig. 4 data consistently show that AODV has a lower Total Flod ID than LA-AODV over all time intervals. Prove that AODV generates fewer routing control messages, resulting in lower overhead on the V2V communication network than LA-AODV. AODV is the best choice for minimizing control message overhead in safety-critical V2V applications.

LA-AODV generates more routing control messages than AODV due to its adaptive mechanisms for selecting relay nodes based on real-time traffic conditions. The situation makes LA-AODV adaptable and responsive in V2V communication, justifying its slightly higher routing overhead in rapidly changing traffic dynamics. While AODV minimizes overhead and ensures stable communication, LA-AODV enhances adaptability, particularly in dynamic traffic scenarios.

Next, we analyze the packet loss ratio (PLR) trends between 300 and 700 seconds in V2V

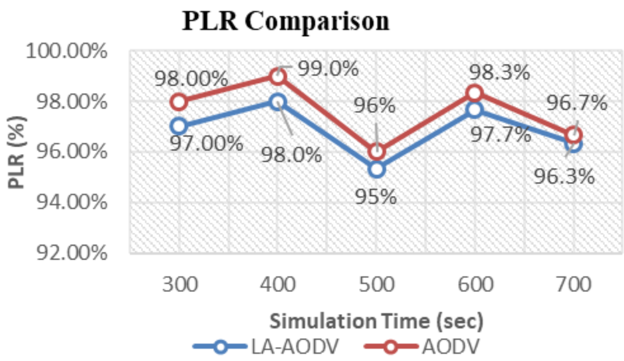

Figure. 5 PLR Comparison across the 300 to 700-second timeframe in V2V communication scenarios

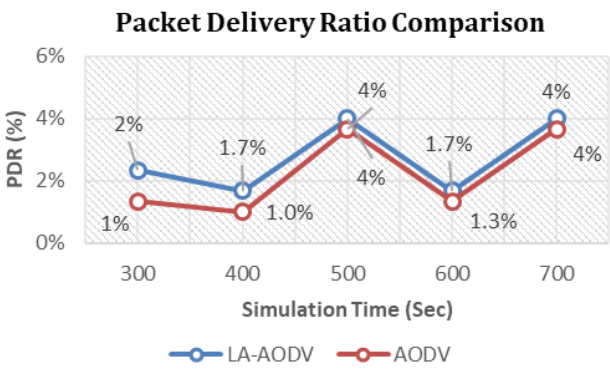

Figure. 6 PDR Comparison across the 300 to 700-second timeframe in V2V communication scenarios

communication and compare AODV and LA-AODV's ability to maintain data packet integrity. Fig. 5 shows the PLR comparison results.

Fig. 5 shows that AODV consistently had a higher Packet Loss Ratio than LA-AODV at all time intervals. While AODV had a packet loss ratio of 1% at 300 seconds, LA-AODV had a slightly better ratio of 2%. This trend continued at 400 seconds (AODV: 1%, LA-AODV: 1.7%), 500 seconds (AODV: 4%, LA-AODV: 4%), 600 seconds (AODV: 1.3%, LA-AODV: 1.7%), and 700 seconds (AODV: 4%, LA-AODV: 4%). Although both protocols maintained relatively low packet loss ratios, LA-AODV held a slight advantage in preserving packet integrity.

The insights from Fig. 4 highlight the significance of LA-AODV in V2V communication. LA-AODV is more reliable than AODV in preventing packet loss, which is crucial for scenarios where data integrity is paramount. It consistently maintains a lower Packet Loss Ratio than AODV, making it the preferred choice for such applications. However, AODV offers advantages such as lower routing overhead and enhanced adaptability. Therefore, choosing between AODV and LA-AODV should be a well-considered decision, aligning with the specific priorities and requirements of the V2V communication use case.

Referring to Fig. 6, which represent the trends in packet delivery ratio (PDR) across the 300 to 700-second timeframe in V2V communication scenarios.

Fig. 6 shows that LA-AODV outperforms AODV in terms of PDR throughout the simulation, making it more efficient in transmitting data packets within V2V communication. Its sustained high PDR underscores LA-AODV's reliability, especially in safety-critical V2V applications where data integrity is priority.

The results demonstrate that LA-AODV consistently outperforms AODV in terms of PDR at various time intervals: 300 seconds (LA-AODV: 97.0%, AODV: 98.0%), 400 seconds (LA-AODV: 98.0%, AODV: 99.0%), 500 seconds (LA-AODV: 95.0%, AODV: 96.0%), 600 seconds (LA-AODV: 97.7%, AODV: 98.3%), and 700 seconds (LA-AODV: 96.3%, AODV: 96.7%).

In contrast, AODV exhibits a lower and relatively unstable PDR in Fig. 5, indicating that it may face difficulties in delivering data packets successfully, resulting in a lower success rate. Although AODV has the advantage of lower routing overhead and adaptability, its lower PDR indicates a potential trade-off between packet delivery success and other performance aspects in V2V communication scenarios. On the other hand, LA-AODV prioritizes data integrity and completeness, ensuring successful data packet delivery.

Next, we evaluated the performance based on the average throughput, which measures the average rate of successful data packet transmission in Kbps (Kilobits per second). Fig. 7 represents the result of average throughput through all simulation scenarios.

Upon analyzing Fig. 7, it is apparent that LA-AODV outperforms AODV in Average Throughput across all tested time intervals. LA-AODV delivers a much higher and more stable Average Throughput compared to AODV. AODV exhibits variable Average Throughput values across different time intervals. At 300 seconds, AODV achieves an Average Throughput of 33.09 Kbps, which remains steady at 400 seconds (33.09 Kbps) and gradually increases to 36.90 Kbps at 500 seconds. However, at 600 seconds, there is a dip in Average Throughput to 36.90 Kbps, followed by a subsequent increase to 42.39 Kbps at 700 seconds.

In contrast, LA-AODV displays a more stable and slightly higher Average Throughput performance. At 300 seconds, LA-AODV achieves an Average Throughput of 40.54 Kbps, which maintains consistency at 400 seconds (40.54 Kbps). As the

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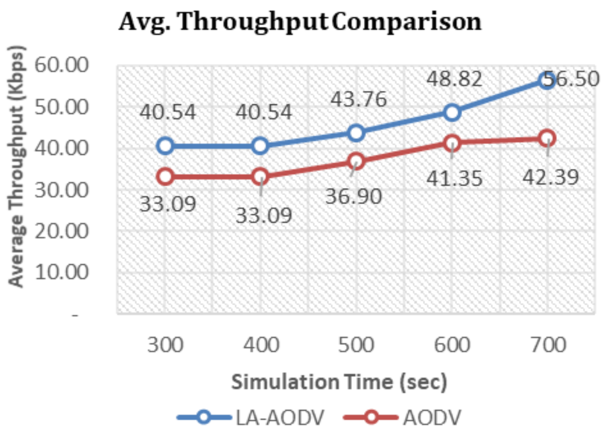

Figure. 7 Average throughput comparison results for all traffic scenarios within the simulation

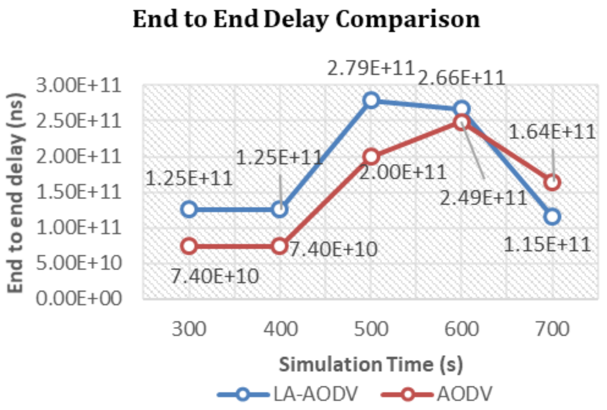

Figure. 8 The end to end delay comparison performance for all traffic scenarios

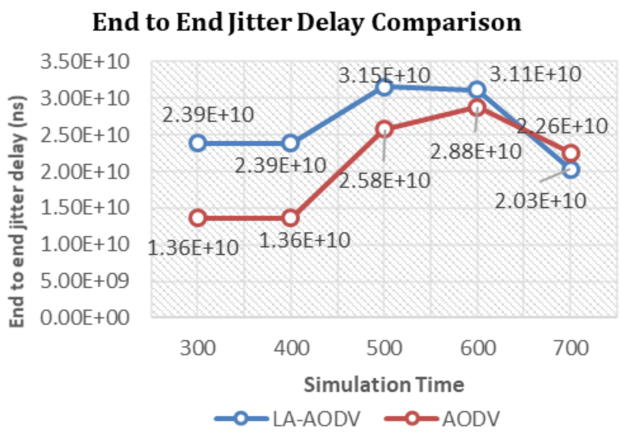

Figure. 9 The end-to-end jitter comparison results for all traffic scenarios within the simulation time range of 300 to 700 seconds

simulation progresses, LA-AODV keeps its superior average throughput, reaching 43.76 Kbps at 500 seconds and 48.82 Kbps at 600 seconds. At the final time interval of 700 seconds, LA-AODV boasts an impressive average throughput of 56.50 Kbps.

LA-AODV's high average throughput is crucial for delivering data in V2V communication networks, particularly for high data throughput scenarios. In contrast, AODV's variable and lower average throughput make it less suitable for high data transfer rate applications. AODV works better for smooth or congested light traffic situations, while LA-AODV is a viable alternative for various traffic conditions.

A detailed examination of end-to-end delay concerning Fig. 8 offers valuable insights into the performance of AODV and LA-AODV in vehicle-to-vehicle (V2V) communication contexts.

According to Fig. 8, AODV performs better than LA-AODV in achieving lower end-to-end delay values across different time intervals; at 300 seconds, AODV's end-to-end delay is 7.40E+10 ns, which remains stable at 400 seconds. It slightly increases to 2.00E+11 ns at 500 seconds and gradually rises to 2.49E+11 ns at 600 seconds, while at 700 seconds, it is 1.64E+11 ns.

In contrast, LA-AODV records consistently higher end-to-end delay values throughout the analyzed time intervals. At 300 seconds, LA-AODV's end-to-end delay is notably higher at 1.25E+11 ns, which remains consistent at 400 seconds. As the simulation continues, LA-AODV's End-to-End Delay increases, reaching 2.79E+11 ns at 500 seconds and 2.66E+11 ns at 600 seconds. At 700 seconds, LA-AODV's end-to-end delay is 1.15E+11 ns.

The result shows that AODV consistently performs better than LA-AODV regarding End-to-End Delay across all time intervals. AODV's ability to maintain lower delay values suggests its effectiveness in facilitating faster data packet transmission from source to destination within the V2V communication network. This advantage can be significant when reducing communication latency is crucial, such as real-time applications in V2V communication. On the other hand, LA-AODV exhibits higher and unstable end-to-end delay values, which may render it unsuitable for applications requiring minimal communication latency.

End-to-end jitter Delay, measured in nanoseconds (ns), is critical in assessing the reliability and predictability of data packet transmission within a network. The end-to-end jitter comparison is shows in Fig. 9.

Fig. 9 demonstrates a consistent trend throughout the evaluated time intervals: AODV consistently maintains lower End-to-End Jitter Delay values than LA-AODV. At 300 seconds, AODV records an End-to-End Jitter Delay of 1.36E+10 ns, which remains relatively stable at 400 seconds (1.36E+10 ns). There is a minor increase to 2.58E+10 ns at 500 seconds, followed by a gradual rise to 2.88E+10 ns at 600 seconds. Finally, at 700 seconds, AODV reports an end-to-end jitter delay of 2.26E+10 ns.

In contrast, LA-AODV consistently exhibits higher end-to-end jitter delay values across all time intervals. At 300 seconds, LA-AODV's end-to-end jitter delay is notably higher at 2.39E+10 ns, which maintains consistency at 400 seconds (2.39E+10 ns). As the simulation progresses, LA-AODV's End-to-End Jitter Delay rises, reaching 3.15E+10 ns at 500 seconds and increasing to 3.11E+10 ns at 600 seconds. Finally, at 700 seconds, LA-AODV records an end-to-end jitter delay of 2.03E+10 ns.

This comprehensive analysis reinforces that AODV consistently outperforms LA-AODV concerning end-to-end jitter delay. AODV's ability to maintain lower jitter values indicates its efficiency in delivering data packets with more consistent and predictable transmission times within the V2V communication network. The situation is particularly advantageous in applications where minimal communication jitter is imperative, ensuring that data packets are delivered precisely. Conversely, LA-AODV exhibits higher and less predictable end-to-end jitter delay values. While LA-AODV offers other advantages, such as adaptability and higher throughput, its higher jitter levels may pose challenges in scenarios where precise timing is essential. Hence, selecting AODV and LA-AODV should align with the specific jitter tolerance requirements and priorities of the V2V communication use case.

6. Conclusion

The comparison of AODV and LA-AODV performance across various QoS metrics provides valuable insights into their suitability for V2V communication in different scenarios. AODV exhibits a relatively high PDR ranging from 96.0% to 99.0%, along with a packet loss ratio between 1.0% and 4.0%. Its Average Throughput ranges from 33.09 Kbps to 42.39 Kbps. On the other hand, LA-AODV achieves PDR between 95.0% and 98.3%, with a packet loss ratio spanning 1.7% to 4.0%. It consistently outperforms AODV in Average Throughput, ranging from 40.54 Kbps to 56.50 Kbps. While LA-AODV demonstrates slightly lower PDR and a similar packet loss ratio, its superior average throughput makes it a favorable choice for applications that demand rapid and consistent data exchange.

Overall, LA-AODV reduces packet loss and improves packet delivery success rates, making it an ideal choice for data-intensive applications that require reliable and fast data exchange. The decision between AODV and LA-AODV should be strategic, considering the specific characteristics and priorities of the given V2V communication scenario.

The study enhances the AODV-based routing protocol for V2V communication in VANET by introducing LA-AODV, which outperforms the conventional AODV in achieving higher packet delivery ratios and improved average throughputs. When selecting between the two protocols, consider scenario characteristics. LA-AODV suits safety-critical applications, while AODV is preferable when minimizing network control message overhead is the primary concern. The choice should be strategic to optimize network efficiency and reliability.

Although we recognize the significance of benchmarking against the latest methods, our main focus was to evaluate LA-AODV's performance in specific and realistic situations. In future studies, comparisons with other established methods could be incorporated to gain a better understanding of LA-AODV's strengths and limitations. Nonetheless, the approach we chose for our research objectives allowed us to gain a thorough understanding of LA-AODV's performance in real-world V2V communication scenarios.

Conflicts of interest

The authors declare there is no conflict of interest in this study.

Author contributions

Conceptualization, Bintoro, and Priyambodo; methodology, Bintoro, and Priyambodo; software, Bintoro; validation, Priyambodo; formal analysis, Priyambodo; investigation, Bintoro, Priyambodo; resources and data curation, Bintoro; writing—original draft preparation, Bintoro; writing—review and editing, Priyambodo; visualization, Bintoro; supervision, Priyambodo; project administration, Bintoro, and Priyambodo; funding acquisition, Bintoro, and Priyambodo.

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