

LEARNING AUTOMATA-BASED AODV ROUTING PROTOCOL TO IMPROVE V2V COMMUNICATION IN URBAN TRAFFIC SIMULATION

Ade Syahputra^{1*}; Ketut Bayu Yogha Bintoro²; Erssa Istary Yusuf³; Michael Marchenko⁴

Departement of Informatics Engineering, Faculty of Sciences, Technology and Design ^{1,2,3}
Trilogi University, Jakarta, Indonesia^{1,2,3}
<https://trilogi.ac.id/universitas/> ^{1,2,3}
adesyahputra@trilogi.ac.id^{1*}, ketutbayu@trilogi.ac.id^{2*}, erssa.istary@trilogi.ac.id³

Departement of Physics, Electronics and Computer System⁴
Dnipro National Univesity, Dnipropetrovsk, Oblast, Ukraine⁴
<https://www.nmu.org.ua/en/>⁴
michaelmarchenkoindoua@gmail.com⁴

(*) Corresponding Author
(Responsible for the Quality of Paper Content)



The creation is distributed under the Creative Commons Attribution-NonCommercial 4.0 International License.

Abstract— Network congestion, packet loss, and high latency in the AODV routing protocol are significant obstacles to achieving reliable vehicle-to-vehicle (V2V) communication. Consequently, an update to the AODV protocol is necessary. This research proposes the Learning Automata-based AODV (LA-AODV) routing protocol to address these issues. The LA-AODV protocol incorporates learning automata into the routing protocol by considering speed, acceleration, and x and y coordinates. The communication quality index with the nearest vehicles is measured before selecting a set of relay nodes until the maximum estimated time is reached. The primary objective of this study is to enhance the performance of V2V communications by reducing network congestion, packet loss, and latency. The results demonstrate that LA-AODV achieves a maximum packet delivery ratio (PDR) improvement of 4.0% and a throughput of up to 56.50 kbps, surpassing the performance of both AODV and DSDV protocols. These findings indicate the potential of LA-AODV to optimize V2V communications, thereby significantly improving transportation safety and efficiency. The research contributes to the field by providing a novel solution to enhance V2V communication quality in urban traffic scenarios, offering significant benefits in reduced latency, increased reliability, and overall better network performance.

Keywords: AODV, DSDV, LA-AODV, routing protocol, vehicular ad-hoc network.

Intisari— Kemacetan jaringan, kehilangan paket, dan latensi tinggi dalam protokol routing AODV merupakan hambatan signifikan untuk mencapai komunikasi kendaraan-ke-kendaraan (V2V) yang andal. Oleh karena itu, pembaruan protokol AODV diperlukan. Penelitian ini mengusulkan protokol routing AODV berbasis Learning Automata (LA-AODV) untuk mengatasi masalah ini. Protokol LA-AODV mengintegrasikan learning automata ke dalam protokol routing dengan mempertimbangkan kecepatan, percepatan, serta koordinat x dan y. Indeks kualitas komunikasi dengan kendaraan terdekat diukur sebelum memilih sekumpulan node relay hingga waktu estimasi maksimum tercapai. Tujuan utama dari penelitian ini adalah untuk meningkatkan kinerja komunikasi V2V dengan mengurangi kemacetan jaringan, kehilangan paket, dan latensi. Hasil penelitian menunjukkan bahwa LA-AODV mencapai peningkatan rasio pengiriman paket (PDR) maksimum sebesar 4,0% dan throughput hingga 56,50 kbps, melampaui kinerja protokol AODV dan DSDV. Temuan ini menunjukkan potensi LA-AODV untuk mengoptimalkan komunikasi V2V, sehingga secara signifikan meningkatkan keselamatan dan efisiensi transportasi. Penelitian ini berkontribusi pada bidang tersebut dengan menyediakan solusi baru untuk meningkatkan kualitas komunikasi V2V dalam skenario lalu lintas perkotaan, menawarkan manfaat signifikan dalam pengurangan latensi, peningkatan keandalan, dan kinerja jaringan yang lebih baik secara keseluruhan.

Kata Kunci: AODV, DSDV, LA-AODV, protokol routing, jaringan ad-hoc kendaraan.



INTRODUCTION

In the current scenario, where road accidents leading to fatalities are on the rise, the importance of "Vehicle to Vehicle" communication is paramount [1]. Protocols facilitate the transfer of data packets between vehicles and infrastructure, ensuring communication is efficient and reliable [2]. AODV exhibits performance degradation on high-traffic roads with fluctuating vehicle density due to suboptimal relay node selection [3]. AODV struggles in VANETs due to high network traffic and slow response times in dynamic vehicle communication [4], leads to frequent route discoveries and subsequently increases overhead [5], High Overhead [6], Constant route updates[7].

On the other hand, DSDV struggles in highly dynamic VANETs due to frequent updates and buffering limitations [8], increased packet loss in dense network condition [9], worse performance while number of hops is high [10]. Both AODV and DSDV protocols facing limit V2V communication in VANETs due to high traffic, slow response times, and scalability issues. To address the limitations of existing routing protocols in VANETs, we propose the Learning Automata Ad Hoc On-Demand (LAAODV) protocol, which leverages real-time vehicle position, acceleration, and speed data to dynamically predict and select clusters of responsive relay nodes, thereby enhancing the efficiency of V2V communication.

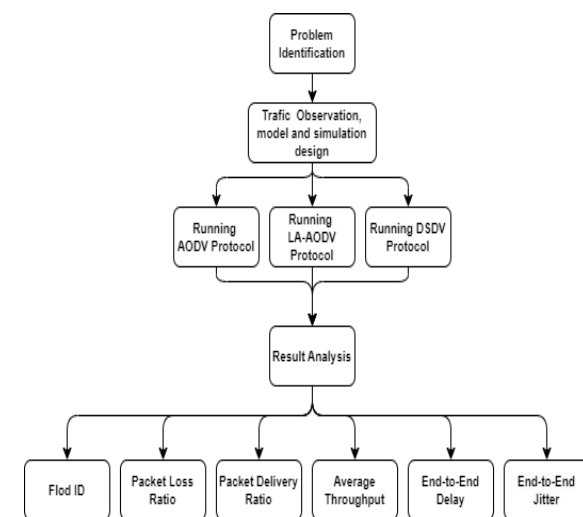
Research has explored ways to improve AODV routing for V2V communication, including methods like Prediction Node Trends on AODV [11], channel reservation method for handoff calls in VANETs, leveraging the concept of learning automata [12], Detect and prevent black hole attack in VANET using M-AODV [13], Detect and prevent flooding with FA-AODV in VANET [14], building block within a secure system that helps vehicles in a VANET safely access and share content [15], Implementation of domestic refit to improve the routing scenario with AOMDV [16], Implementing fuzzy logic to make T-AODV identify bad nodes [17].

Some research explores DDSLA-RPL, a method that uses learning automata to adjust network parameters. This approach improves service quality and extends node lifespan [18]. Despite its accuracy and flexibility, DDSLA-RP requires further refinement for diverse network scenarios. Methodology selection should be tailored to specific network characteristics, considering fuzzy clustering limitations [19]. Another study has investigated the use of the leap-frog algorithm to ensure reliable channel availability for V2V communication in VANETs. [20].

This study investigated QoS improvement in dynamic VANETs through V2V communication. It focused on key metrics like PLR, PDR, and delay to optimize relay selection and reduce information overload, ultimately aiming for safer traffic scenarios. LA-AODV uses learning automata to predict and select reliable relay nodes in dynamic VANETs. This improves V2V communication efficiency, especially in challenging traffic scenarios. LA-AODV has potential to enhance QoS and contribute to accident prevention in V2V networks.

MATERIALS AND METHODS

The research unfolds in distinct phases. The initial phase (Phase 1) focuses on a critical review of existing protocols, aiming to identify prominent challenges such as instability, network congestion, and delays experienced during V2V communication (Vehicle-to-Vehicle). Building upon this foundation, Phase 2 will involve real-world traffic observations. These observations, along with modeling and simulation design, will inform the development of a comprehensive model and simulation framework (Figure 1). This framework strives to realistically capture the dynamics of V2V communication scenarios.



Source: (Research Results, 2024)

Figure 1. The structure of process research

The simulation environment plays a critical role in our research, as depicted in Figure 1. We chose Linux Ubuntu 20.02 as the operating system for the simulations. During the simulation phase, data collection is crucial. We generate XML trace files through NS3 simulations, capturing essential connectivity data among vehicles. We employed SUMO-GUI [21] to create detailed traffic models with realistic passenger-vehicle interactions, and utilized NS3 v3.35, a well-respected network

communication simulator [22]. By integrating SUMO and NS3, we successfully combined traffic modeling and network communication simulations.

Data collection we use the UGM roundabout, a four-lane, two-way configuration allowing vehicle entry, exit, and U-turns. While the study emphasizes adherence to the "give way to the right" rule and completing a full circle, it acknowledges potential obstacles like pedestrians, parked vehicles, and side-road traffic (Figure 2).



Source: (Research Results, 2024)

Figure 2. The network map of the UGM roundabout and the surrounding area represents the real-world situation

The UGM roundabout presents complex traffic conditions with potential hazards, including dense traffic flow and congestion points at various locations. To navigate safely, drivers should prioritize collision avoidance and share real-time information. Our research analyzed LA-AODV's performance in V2V communication, identifying key issues and comparing it with AODV using various metrics.

This study evaluates diverse traffic scenarios, including freeflow, steady flow, and traffic jams, at various time intervals. The specific parameters used in the simulations are detailed in Table 1.

Table 1. V2V communication simulation parameter

No	Parameter	Value
1	Total number of actual Nodes (vehicles)	Random, based on Poisson distribution
2	Simulation time (s)	Free flow 300, 400,500, 600, and 700 seconds
3	Performances Matrix (QoS)	PDR, end to end delay, average throughput, Packet loss ratio, end to end Jitter
4	Traffic Scenario	<ul style="list-style-type: none"> Freeflow (prob 0.55) * steady flow (prob 0.33) * traffic jam (prob 0.1) * *Based on Poisson Distribution
5	Route Selection	Random route selection
6	Node Speed	Random speed
7	Initial node position	Random position
8	Data Packets Configuration	Data Packets Configuration
9	Type of protocol	AODV, LA-AODV, and DSDV
10	Type of traffic	Passenger cars only, Left-hand drive

No	Parameter	Value
11	Node Movement	All moving nodes
12	LA-AODV parameter Setup	fs: 0.4; fa: 0.3; fd: 0.3; α: 1; Reward: 1; Penalty: 0

Source: (Research Results, 2024)

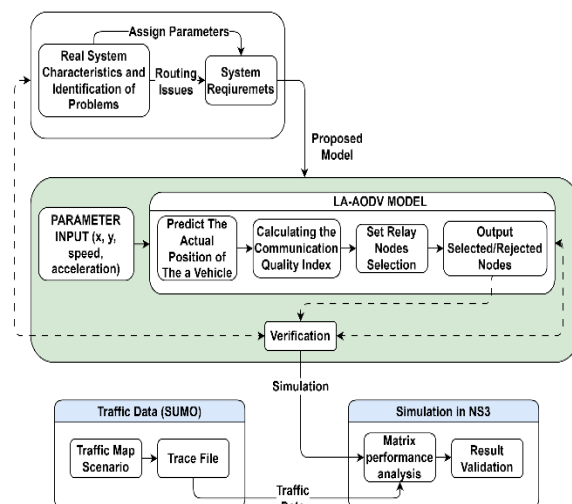
Traffic simulations use the Poisson distribution to predict the number of vehicles arriving, given an average traffic flow rate (λ). This calculation involves the average arrival rate (λ), Euler's number (e), and the specific number of vehicles ($v!$). It takes into account the randomness of vehicle arrivals.

V2V communication depends on speed, acceleration, and distance. The LA-AODV protocol uses a learning rate (α) of 1 for best routing. The Poisson distribution estimates the probability of a vehicle's frequency of appearance in different traffic situations.

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

Traffic simulations leverage the Poisson distribution (Eq. 1) to estimate vehicle arrivals based on average traffic flow (λ). This equation uses the average arrival rate (λ) and Euler's number (e) to calculate the probability of encountering a specific number of vehicles ($v!$), considering the randomness in arrival patterns.

The research methodology encompasses several crucial stages. The investigation first pinpoints key challenges in modern vehicle communication systems. Fig 3 illustrates the LA-AODV process and the simulation design.



Source: (Research Results, 2024)

Figure 3. LA-AODV process and the simulation design

The LA-AODV protocol, as shown in Figure 3, collects vehicle data (speed, acceleration, position) for V2V communication. It uses this data

to locate nearby vehicles and assesses communication quality for reliable information exchange.

LA-AODV protocol picks relay nodes with a TWR between 0.6 and 1 for stable communication, excluding nodes with TWR below 0.6. It uses speed and relative position to predict vehicle positions, and velocity and acceleration to determine actual positions, as per Eq. (2).

$$INITpos_j = \sum_{j=1}^{j \leq N} actual_{pos_x}, actual_{pos_y}, v_j \quad (2)$$

LA-AODV protocol uses Eq. (2) for accurate vehicle routing and positioning in a network. It considers variables like vehicle j's position ($INITpos_j$), speed (v_j), number of vehicles in range (N), and specific node (j) for proximity. It uses two equations, Eq. (3) and Eq. (4), considering vehicle speed, vehicles in range, and time, for routing decisions to prevent accidents.

$$pred_{pos_x} = \sum_{j=1, t=1}^{j \leq n, t \leq v} (actual_{pos_x} + (v_t \cdot t) + \left(\frac{1}{2}(\Delta v)\right) * 2) \quad (3)$$

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

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 $t = 1, 2, 3, \dots$, and $t < v$,

v : Maximum iteration,

j : vehicle j,

n : Total number of vehicles within the transmission range,

v_t : Vehicle speed at time t.

LA-AODV protocol uses Eq. (3) to estimate a vehicle's x-position at time (t), and Eq. (4) to predict the y-position considering the vehicle's status, speed, proximity, and iteration time. Precise positioning is key for effective communication. Variable "t" and "v" are crucial for accurate predictions within the maximum iteration time. These equations help predict vehicle positions, improving the network's efficiency.

In V2V communication, vehicles multicast data to predict future positions. This data is vital for updating routing tables and finding the vehicle's state with minimal distance and speed, as per Equation (5).

$$pred_acc_{xy} = \sqrt{(|\Delta pred_pos_x - \Delta pred_pos_y|)} \quad (5)$$

Where:

$$\Delta pred_pos_x = (pred_pos_{x+1} - pred_pos_x) \quad (6)$$

$$\Delta pred_pos_y = (pred_pos_{y+1} - pred_pos_y) \quad (7)$$

Anticipated vehicle coordinates ($pred_acc_{xy}$) are calculated using Eq. (5), considering x and y axis changes. It uses $\Delta pred_pos_x$ and $\Delta pred_pos_y$ from Eqs. (5) and (6). Eq. (5) computes x-axis position change by subtracting the predicted position at $t + 1$ ($pred_pos_{x+1}$) from the current ($pred_pos_x$). Similarly, it calculates y-axis displacement by subtracting the predicted next position $pred_pos_{y+1}$, from the current prediction, $pred_pos_y$, as in Eq. (7). The variable $pred_acc_{xy}$ predicts nearby vehicles' positions over time, considering their expected x and y coordinates.

Eq. (8) uses the Euclidean Distance formula to find the smallest value. This value is used to optimally compare changes in vehicle movement along x and y axes for each vehicle across two prediction intervals.

$$pred_acc_{xy} \cdot MIN \left(\sum_{j=1, t=1}^{j \leq n, t \leq v} \sqrt{\left(\frac{|pred_{pos_{x+1}} - pred_{pos_x}|^2 - (|pred_{pos_{y+1}} - pred_{pos_y}|)^2}{(pred_{pos_{y+1}} - pred_{pos_y})^2} \right)} \right) \quad (8)$$

Eq. (8) calculates and compares vehicle positions for routing decisions. It computes coordinate changes and measures their Euclidean distance to identify optimal routing for quick vehicle communication. After predicting positions, it evaluates communication reliability with the next node before selecting relay nodes. The communication stability index between node i and node j is computed as per Eq. (9).

$$comm_stability_index_{jt} = \left| \left(\frac{pred_acc_{xy}}{Max_{rad}} \right) \right| \quad (9)$$

Where:

$$comm_stability_index_{jt} = \begin{cases} stable, & if \leq 1 \\ unstable, & if > 1 \end{cases}$$

In the LA-AODV protocol, Eq. (9) calculates the communication stability index, $comm_stability_index_{jt}$, for nodes 'j' and 't'. It divides the total predicted positions of neighboring vehicles ($pred_acc_{xy}$) by the maximum communication radius Max_{rad} of 2500 grid units. A $comm_stability_index_{jt} \leq 1$ indicates stable communication, while a value over one indicates instability.

To calculate weights for node j 's neighbors, we assess their communication quality over two intervals, ' t ' and ' $t+1$ ', based on distance. This assessment, along with factors like speed, acceleration, and position, is used to compute each neighbor's weight, as per Equation (10).

$$TWR_j = \sum_{i=1}^n \left(\begin{aligned} & (f_s * (|s_p - s_d|)) + (f_a * (|a_p - a_d|)) + \\ & (f_d * (|d_p - d_d|)) + (f_q * (comm_quality_i)) \end{aligned} \right) \quad (10)$$

Where:

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

LA-AODV protocol uses Eq. (10) to calculate the Total Weight Route (TWR) for route quality evaluation. It considers speed, distance, acceleration, and communication quality, each with a weight of 1 as per Eq. (11).

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

LA-AODV protocol achieves efficient routing by considering factors like speed, distance, acceleration, and communication quality during route selection. Weights are assigned to these parameters in Eq. (11) for balanced evaluation. This approach enables informed routing decisions based on the TWR benchmark, leading to optimal routes and efficient data transmission.

When the Finite State Automaton (FSA) reaches its terminal decision state, it triggers the Learning Rate (α). The source node communicates its relay node selection to adjacent nodes, providing reward and penalty data. We used the Learning Rate Index (LRI) algorithm for the learning rate (α) in our research. This algorithm assigns rewards or penalties to each decision, as outlined in Equation (12).

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

The LRI algorithm (Eq. 12) adjusts the learning rate (α) dynamically, setting α to 1 for rewards and 0 for penalties. The fine-tuning variable in α affects decision-making. Eq. 13 shows how 'a' is added to the updated $[TWR_{update}$ for the next prediction iteration ($t+1$).

$$TWR_{update} = \sum_{j=1, t=1}^{j \leq n, t \leq v} (TWR_j + \alpha) \quad (13)$$

Eq. (13) updates TWR values to adapt to network changes and routing choices. Driven by the learning rate α , it enables agile routing decisions and enhances network communication and routing efficiency. The α value greatly impacts TWR values and routing decisions in the simulation.

This study compares LA-AODV, a new VANET routing model, with AODV and DSDV protocols. We test LA-AODV's performance in urban traffic and V2V communication quality using metrics like Flood ID, PDR, PLR, throughput, delay, and jitter.

a. Packet Delivery Ratio

PDR is success rate of packets reaching their destination [23]. It's a crucial metric for routing protocols, indicating network performance and protocol efficiency. A higher PDR means better performance.

b. Packet Loss Ratio

PLR is the percentage of data packets not reaching their destination. A low PLR is essential for dependable V2V communication. High PLR can cause safety risks, traffic jams, and loss of driver trust, highlighting the importance of strong protocols.

c. Average end-to-end delay

The average end-to-end delay is the mean time for packets to reach their destination [24], calculated by averaging the time difference between sending and receiving a packet.

d. Average Throughput

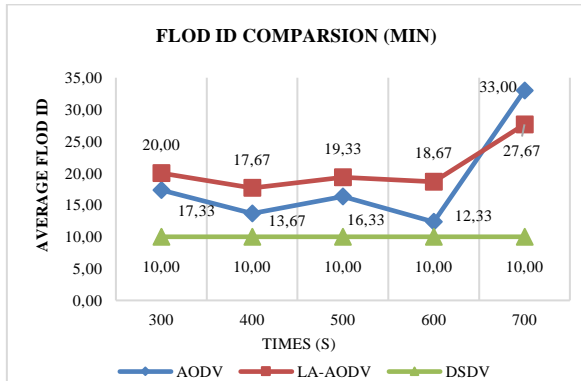
Network throughput is calculated as the ratio of sent data packets to transmission time. Higher values mean faster transfers, and lower values indicate slower speeds [25].

e. End-to-end jitter

End-to-end jitter defines end-to-end jitter as the fluctuation in the delay that data packets undergo during transmission [26]. Jitter, calculated from packet queueing and reassembly, is the difference between max and min delay values divided by delay samples minus one. It's crucial for evaluating network transmission consistency and reliability.

RESULTS AND DISCUSSION

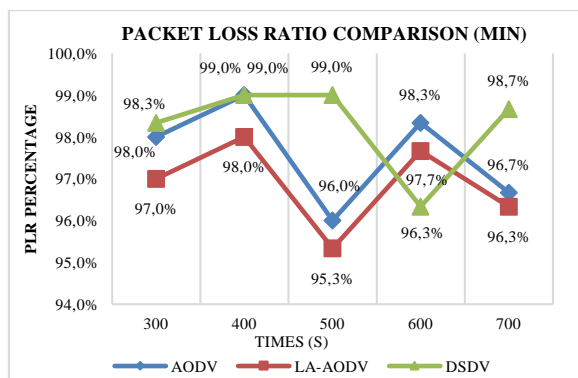
The research compares the QoS performance of LA-AODV, AODV, and DSDV protocols in V2V communication. It measures packet loss ratio, packet delivery ratio, average throughput, end-to-end delay, and end-to-end jitter. Figure 4 presents total flood ID trends in V2V communication from 300 to 700 seconds.



Source: (Research Results, 2024)

Figure 4. AODV, DSDV and LA-AODV Flod ID Comparison across the 300 - 700 second

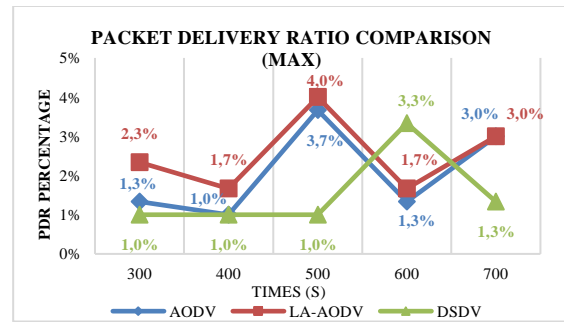
Figure 4 indicates DSDV (value 10) generates fewer V2V routing messages than LA-AODV and AODV. Despite more messages, LA-AODV optimizes connections based on traffic. We then examine PLR trends from 300 to 700s for V2V, comparing AODV, DSDV, and LA-AODV's data integrity. Results are in Figure 5.



Source: (Research Results, 2024)

Figure 5. PLR Comparison across the 300 - 700 second

Figure 5 shows DSDV's higher PLR compared to AODV and LA-AODV. LA-AODV slightly outperforms in packet preservation. In V2V, LA-AODV reduces packet loss, while AODV and DSDV minimize routing overhead and improve adaptability. Figure 6 illustrates the PDR trend for V2V from 300 to 700 seconds.



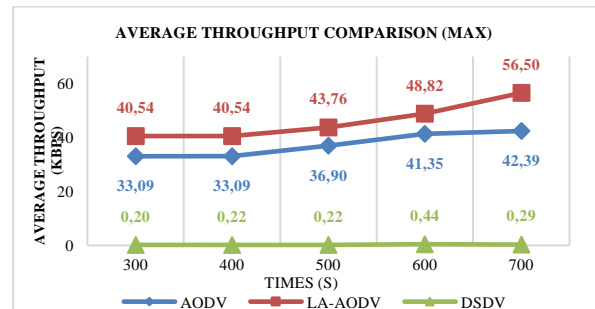
Source: (Research Results, 2024)

Figure 6. PDR Comparison across the 300 to 700-second

Figure 6 shows LA-AODV's superior PDR, making it ideal for safety-critical V2V applications. LA-AODV consistently outperforms AODV and DSDV at various intervals: 300s (LA-AODV: 2.3%, AODV: 1.3%, DSDV: 1.0%), 400s (LA-AODV: 1.7%, AODV: 1.0%, DSDV: 1.0%), 500s (LA-AODV: 4.0%, AODV: 3.7%, DSDV: 1.0%), 600s (LA-AODV: 1.7%, AODV: 1.3%, DSDV: 3.3%), and 700s (LA-AODV: 3.0%, AODV: 3.0%, DSDV: 1.3%).

DSDV's lower packet delivery ratio than AODV and LA-AODV suggests data transmission issues. DSDV favors less overhead and flexibility, while LA-AODV emphasizes data integrity for successful packet delivery.

Performance measured by average throughput in kbps, is depicted for all scenarios in Fig. 7.



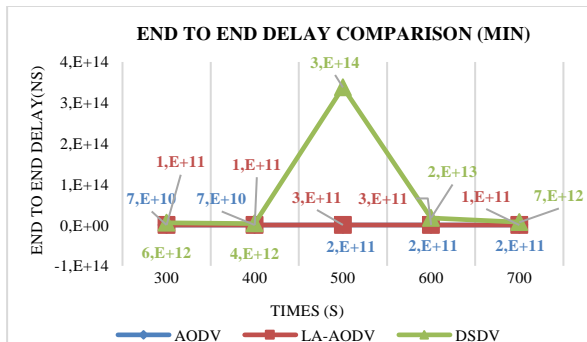
Source: (Research Results, 2024)

Figure 7. Average Throughput Comparison results for all traffic scenarios

Figure 7 shows LA-AODV consistently outperforming AODV and DSDV in throughput. AODV peaks at 4136 Kbps at 600s, while DSDV ranges from 0.20 to 0.44 Kbps. LA-AODV achieves high throughput, with 40.54 Kbps at 300s, 43.76 Kbps at 500s, 48.82 Kbps at 600s, and an average of 56.50 Kbps at 700s. LA-AODV's high throughput makes it a versatile choice for V2V communication.

An analysis of End-to-End Delay in Fig. 8 provides insights into AODV, LA-AODV, and DSDV performance in V2V communication.

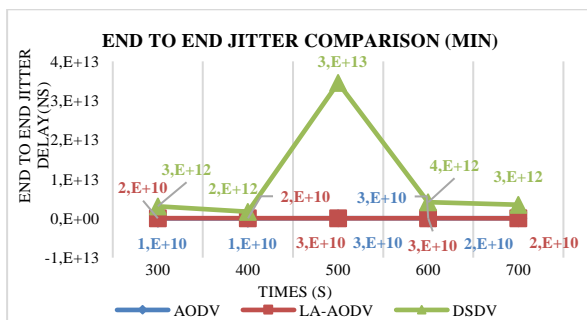




Source: (Research Results, 2024)

Figure 8. The End-to-End Delay comparison performance for all traffic scenarios

Figure 8 shows AODV and LA-AODV data curves converging at 500s due to DSDV's performance. AODV has lower delay values, with $7.40E+10$ ns at 300s, $2.00E+11$ ns at 500s, and $1.64E+11$ ns at 700s. DSDV and LA-AODV have higher delays, making AODV better for fast V2V transmission and unsuitable for latency-critical applications. End-to-end jitter delay is compared in Figure 9.



Source: (Research Results, 2024)

Figure 9. The End-to-End Jitter comparison results for all traffic scenarios

Figure 9 shows AODV consistently has lower End-to-End Jitter Delay than LA-AODV and DSDV. AODV's delay is $1.36E+10$ ns at 300s, slightly increases to $2.58E+10$ ns at 500s, and reaches $2.26E+10$ ns at 700s. DSDV's delay starts at $3.09E+12$ at 300s, peaks at $3.45E+13$ at 500s, and ends at $3.49E+12$ at 700s. LA-AODV consistently shows higher End-to-End Delay than AODV, with delays of $2.39E+10$ ns at 300s, $3.15E+10$ ns at 500s, $3.11E+10$ ns at 600s, and $2.03E+10$ ns at 700s. AODV, with lower End-to-End Jitter Delay than LA-AODV and DSDV, is crucial for applications needing less jitter and precise delivery in V2V networks.

CONCLUSION

In summary, LA-AODV has emerged as the top performer in data delivery reliability, achieving a maximum packet delivery ratio (PDR) of 4.0%. LA-

AODV also demonstrated consistent and stable throughput, reaching up to 56.50 kbps. AODV prioritized low latency and jitter, making it suitable for real-time applications, while DSDV minimized control message overhead but suffered from low PDR. Future research could evaluate protocols in diverse traffic conditions, explore hybrid approaches, and consider integrating security and assessing scalability.

REFERENCE

- [1] A. E. Mezher, A. A. AbdulRazaq, et al. R. K. Hassoun, "A comparison of the performance of the ad hoc on-demand distance vector protocol in the urban and highway environment", *Indones. J. Electr. Eng. Comput. Sci.*, vol. 30, no. 3, pp. 1509–1515, 2023, doi: 10.11591/ijeecs.v30.i3.pp1509-1515.
- [2] Y. Kumar, Isha, A. Malik, et al. A. K. Luhach, "Vehicular Ad Hoc Network: Routing Protocols", in *Communications in Computer and Information Science*, 2021, pp. 217–230. doi: 10.1007/978-981-16-3653-0_18.
- [3] K. Kandali et al. H. Bennis, "An Efficient Routing Protocol Using an Improved Distance-Based Broadcasting and Fuzzy Logic System for VANET", *Int. J. Intell. Eng. Syst.*, vol. 13, no. 6, pp. 81–93, 2020, doi: 10.22266/ijies2020.1231.08.
- [4] A. Ahmed et al. A. Tiwari, "Withdrawn: Aodv_Ext_Bp_Dsr – A hybrid AODV and DSR protocol", *Mater. Today Proc.*, no. xxxx, or. 12–15, 2021, doi: 10.1016/j.matpr.2020.12.877.
- [5] M. A. Al-Shabi, "Evaluation The Performance of MAODV and AODV Protocols In VANETs Models", *Int. J. Comput. Sci. Secur.*, no. 14, pp. 2020–2021, 2020.
- [6] A. Ahamed et al. H. Vakilzadian, "Impact of Direction Parameter in Performance of Modified AODV in VANET", *J. Sens. Actuator Networks*, vol. 9, no. 3, 2020, doi: 10.3390/JSAN9030040.
- [7] K. M. M. Uddin, N. Islam, et al. J. Akhtar, "Implementing AODV Routing Protocol in VANET using SDN", *Int. J. Comput. Appl.*, vol. 175, no. 32, pp. 32–37, 2020, doi: 10.5120/ijca2020920878.
- [8] P. K. Shrivastava et al. L. K. Vishwamitra, "Comparative analysis of proactive and reactive routing protocols in VANET environment", *Meas. Sensors*, vol. 16, no. May, p. 100051, 2021, doi: 10.1016/j.measen.2021.100051.



- [9] E. Safrianti, L. O. Sari, eta F. Saputri, "Performance Analysis Of DSDV, AOMDV and ZRP Routing Protocols Application Simulation In Pekanbaru Vehicular Ad Hoc Network (VANET)", *Bul. Pos dan Telekomun.*, vol. 18, no. 2, pp. 127–144, 2020, doi: 10.17933/bpostel.2020.180204.
- [10] M. Jan, S. Afsar, A. Mateen, M. Q. Yasin, B. Safdar, eta A. Rehman, "VANET routing Protocols :Implementation and Analysis Using NS3 and SUMO", *Int. J. Adv. Trends Comput. Sci. Eng.*, vol. 10, no. 3, pp. 1914–1919, 2021, doi: 10.30534/ijatcse/2021/591032021.
- [11] F. Belamri, S. Boulfekhar, eta D. Aissani, "A survey on QoS routing protocols in Vehicular Ad Hoc Network (VANET)", *Telecommun. Syst.*, vol. 78, no. 1, pp. 117–153, 2021, doi: 10.1007/s11235-021-00797-8.
- [12] G. A. Beletsioti, G. I. Papadimitriou, P. Nicolaitidis, E. Varvarigos, eta S. Mavridopoulos, "A Learning-Automata-Based Congestion-Aware Scheme for Energy-Efficient Elastic Optical Networks", *IEEE Access*, vol. 8, pp. 101978–101992, 2020, doi: 10.1109/ACCESS.2020.2996279.
- [13] S. Jain eta N. K. Sen, "A Review Paper of M-AODV Routing Protocol in VANET to Detect and Prevent Black Hole Attack", *Int. J. Res. Appl. Sci. Eng. Technol.*, vol. 10, no. 8, pp. 340–344, 2022, doi: 10.22214/ijraset.2022.46186.
- [14] B. A. TOSUNOGLU eta C. KOÇAK, "FA-AODV: Flooding Attacks Detection Based Ad Hoc On-Demand Distance Vector Routing Protocol for VANET", *Sak. Univ. J. Comput. Inf. Sci.*, vol. 5, no. 3, pp. 304–314, 2022, doi: 10.35377/saucis...1175613.
- [15] M. ul Hassan *et al.*, "ANN-Based Intelligent Secure Routing Protocol in Vehicular Ad Hoc Networks (VANETs) Using Enhanced AODV", *Sensors*, vol. 24, no. 3, 2024, doi: 10.3390/s24030818.
- [16] U. Kushwaha, R. J. Sir, D. Vishwakarma, eta M. Patel, "Fault Tolerance in Vehicular ad-hoc network with domestic refit ISSN NO : 0022-1945 Fault Tolerance in Vehicular ad-hoc network with domestic refit Page No : 1031", *J. Interdiscipl. Cycle Res.*, vol. XII, no. II, pp. 1031–1039, 2020.
- [17] F. Honarmand eta A. Keshavarz-Haddad, "T-AODV: A trust-based routing against black-hole attacks in VANETs", *Peer-to-Peer Netw. Appl.*, pp. 1–25, 2024, doi: 10.1007/s12083-024-01632-y.
- [18] M. H. Homaei, S. S. Band, A. Pescape, eta A. Mosavi, "DDSLA-RPL: Dynamic Decision System Based on Learning Automata in the RPL Protocol for Achieving QoS", *IEEE Access*, vol. 9, pp. 63131–63148, 2021, doi: 10.1109/ACCESS.2021.3075378.
- [19] S. Khadim, F. Riaz, S. Jabbar, S. Khalid, eta M. Aloqaily, "A non-cooperative rear-end collision avoidance scheme for non-connected and heterogeneous environment", *Comput. Commun.*, vol. 150, pp. 828–840, 2020, doi: 10.1016/j.comcom.2019.11.002.
- [20] B. B. Maaroo *et al.*, "Current Studies and Applications of Shuffled Frog Leaping Algorithm: A Review", *Arch. Comput. Methods Eng.*, vol. 29, no. 5, pp. 3459–3474, 2022, doi: 10.1007/s11831-021-09707-2.
- [21] J. Naskath, B. Paramasivan, Z. Mustafa, eta H. Aldabbas, "Connectivity analysis of V2V communication with discretionary lane changing approach", *J. Supercomput.*, vol. 78, no. 4, pp. 5526–5546, 2022, doi: 10.1007/s11227-021-04086-8.
- [22] S.-Z. Liu eta S.-H. Hwang, "Vehicle Anti-collision Warning System Based on V2V Communication Technology", in *2021 International Conference on Information and Communication Technology Convergence (ICTC)*, 2021, pp. 1348–1350. doi: 10.1109/ICTC52510.2021.9620948.
- [23] A. Al-Ahwal eta R. A. Mahmoud, "Performance Evaluation and Discrimination of AODV and AOMDV VANET Routing Protocols Based on RRSE Technique", *Wirel. Pers. Commun.*, vol. 128, no. 1, pp. 321–344, 2023, doi: 10.1007/s11277-022-09957-8.
- [24] K. Afzal, R. Tariq, F. Aadil, Z. Iqbal, N. Ali, eta M. Sajid, "An Optimized and Efficient Routing Protocol Application for IoV", *Math. Probl. Eng.*, vol. 2021, 2021.
- [25] A. T. Sasongko, G. Jati, B. Hardian, eta W. Jatmiko, "The Reliability of Routing Protocols as an Important Factor for Road Safety Applications in VANET-based Autonomous Cars", *J. Comput. Sci.*, vol. 16, no. 6, pp. 768–783, 2020, doi: 10.3844/jcssp.2020.768.783.
- [26] K. B. Y. Bintoro eta T. K. Priyambodo, "Learning Automata-Based AODV to Improve V2V Communication in A Dynamic Traffic Simulation", *Int. J. Intell. Eng. Syst.*, vol. 17, no. 1, pp. 666–678, 2024, doi: 10.22266/ijies2024.0229.56.