Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Enhancement of the AODV routing protocol for VANET based on intelligent link quality estimation

Hamida Ikhlef

hamidaikhlef@univ-jijel.dz

University of Jijel

Ali Melit

University of Jijel

Research Article

Keywords: VANET, AODV, Link Quality, LSENN, Machine Learning, Routing Protocols

Posted Date: August 5th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-10165760/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: No competing interests reported.

Enhancement of the AODV routing protocol for VANET based on intelligent link quality estimation

Hamida Ikhlef[1*] and Ali Melit[1]

[1*]computer science, University of Jijel, LaRIA Laboratory, Algeria.

*Corresponding author(s). E-mail(s): hamidaikhlef@univ-jijel.dz;
Contributing authors: ali_melit@yahoo.fr;

Abstract

This paper proposes an enhanced version of the AODV routing protocol for Vehicular Ad Hoc Networks (VANET), based on the integration of advanced link quality metrics and an intelligent classification model called LSENN (Link State Estimation Neural Network). Unlike conventional AODV, which relies mainly on hop count, the proposed approach incorporates physical-layer parameters such as inter-vehicle distance, vehicle speed, RSSI (Received Signal Strength Indicator), and OFDM (Orthogonal Frequency Division Multiplexing) decoding error to better assess link reliability. The LSENN model classifies links into three states: connected, transitional, and disconnected, enabling more informed and reliable routing decisions. Simulation results demonstrate that AODV-LSENN significantly improves packet delivery ratio, reduces end-to-end delay, and lowers jitter, particularly in low to medium density network scenarios. However, performance gains become limited in high density scenarios due to increased channel congestion and MAC-layer collisions.

Keywords: VANET, AODV, Link Quality, LSENN, Machine Learning, Routing Protocols

1 Introduction

The increasing occurrence of traffic congestion and road accidents in recent years has motivated the development of more efficient routing protocols for Vehicular Ad Hoc Networks (VANET). These protocols must ensure the reliable and timely dissemination of critical information, such as hazard warnings, accident notifications, and traffic conditions, among vehicles (V2V) as well as between vehicles and roadside infrastructure (V2I). However, VANET are characterized by several challenging constraints, including [1, 2]:

- High node mobility.
- Highly dynamic network topology.
- Significant variability of the wireless communication channel.

These characteristics frequently lead to communication link instability and route disruptions. Therefore, it is essential to design routing protocols capable of predicting link stability and selecting robust routes in real time.

In this context, this paper proposes an enhancement of the AODV routing protocol through the integration of link quality metrics combined with an intelligent link classification model, referred to as the **Link State Estimation Neural Network (LSENN)** [3]. The proposed approach aims to improve route reliability and network performance by incorporating physical-layer information into the routing decision process, thereby enabling more accurate link quality assessment and proactive route management in highly dynamic VANET environments.

The rest of this article is organized as follows: Section 2 summarizes some methods found in the literature on improving the AODV protocol. Section 3 presents the basic principles of the proposed protocol. Section 4 describes the improvement of the LSENN model for adaptation to dynamic environments, and Section 5 presents the routing procedure of AODV-LSENN. Section 6 provides a detailed description of simulation results obtained using the NS-3 simulator. Finally, Section 7 concludes the article.

2 Related Work

Numerous studies have focused on improving the performance of the AODV protocol in VANET. A first category of approaches integrates link quality metrics into routing decisions. The **Expected Transmission Count (ETX)** metric was introduced as a high throughput routing metric for wireless multi-hop networks and has been widely adopted to improve reliability [4]. Several AODV variants incorporating **ETX** or **LET (Link Expiration Time)** based metrics have demonstrated improvements in packet delivery ratio (PDR), throughput, and end-to-end delay by selecting more stable communication links [5, 6]

A second category aims to reduce routing overhead and mitigate the broadcast storm problem associated with Route Request (RREQ) flooding. Protocols such as AODV_EXT introduce adaptive rebroadcast mechanisms based on local network density, reducing unnecessary transmissions and improving scalability in dense ad hoc networks [7].

Other works have explored the integration of intelligent decision-making techniques into routing protocols. Learning Automata-based approaches dynamically adapt forwarding decisions according to network conditions, improving Quality of Service (QoS) and reducing transmission delays [8].

Bio-inspired routing methods have also attracted attention. Ant Colony Optimization (ACO) techniques have been applied to AODV to improve path selection based on route quality and stability, leading to more robust routing behavior in highly dynamic environments [9].

In addition, several studies have investigated MAC-layer enhancements for IEEE 802.11p VANET communications. Contention window optimization and adaptive MAC mechanisms have been shown to reduce latency and improve packet reception probability in urban vehicular scenarios [10].

Finally, comprehensive surveys have analyzed the different families of AODV enhancements, including link quality aware, energy aware, security oriented, and QoS oriented protocols [11, 12].

These studies generally conclude that routing performance in dynamic vehicular environments can be significantly improved through the integration of advanced link quality metrics and adaptive mechanisms.

3 Proposed Method: AODV-LSENN Routing Protocol

This work proposes an enhanced version of the AODV routing protocol, referred to as **AODV-LSENN (Link State Estimation Neural Network)**, designed to overcome the limitations of conventional AODV through intelligent link quality estimation based on artificial neural networks.

Unlike the traditional AODV protocol, which primarily relies on the hop-count metric for route selection [13], the proposed AODV-LSENN protocol adopts an adaptive routing strategy that incorporates multiple physical-layer metrics to improve route reliability, stability, and overall communication performance in Vehicular Ad Hoc Networks.

The proposed approach consists of four main components: continuous physical-layer monitoring, link State classification using LSENN, proactive link management, and adaptive learning mechanism.

3.1 Continuous Physical-Layer Monitoring

The first component of AODV-LSENN continuously collects real-time information from the IEEE 802.11p physical layer. The monitored parameters include:

- Received Signal Strength Indicator (RSSI).
- Inter-vehicle distance.
- Relative vehicle speed.
- OFDM decoding error (Error _Pr (Preamble Decoding Error) and Error_Pa (Payload Decoding Error)).

These metrics provide an accurate description of the current communication conditions and are used to evaluate the quality and stability of wireless links between neighboring vehicles.

3.2 Link state classification using LSENN

The collected physical-layer metrics are processed by a neural network model called LSENN. The objective of this model is to classify each communication link into one of the following three states:

- **Connected:** stable and reliable link.
- **Transient:** potentially unstable link.
- **Disconnected:** unreliable link likely to fail.

The LSENN model exploits machine learning techniques to discover complex relationships among link quality metrics and predict the future state of communication links. This intelligent classification mechanism enables the routing protocol to make more informed forwarding decisions by prioritizing reliable links and avoiding unstable ones.

3.3 Proactive link management

Unlike conventional AODV, which reacts only after a link failure occurs [13], AODV-LSENN incorporates a proactive route maintenance mechanism. When the LSENN model predicts that a link is transitioning toward an unstable state, the protocol generates an early warning and initiates preventive actions. This mechanism allows:

- Avoiding degraded communication links.
- Activating alternative routes before link failure.
- Reducing route breakages and packet losses.
- Improving routing continuity in highly dynamic VANET environments.

Such proactive behavior is particularly important in VANETs due to frequent topology changes caused by vehicle mobility.

3.4 Adaptive learning mechanism

To cope with rapidly changing network conditions, the LSENN model is continuously updated during network operation. This online learning capability enables the model to:

- Adapt to topology changes caused by vehicle mobility.
- Learn from newly observed communication patterns.
- Adjust to varying traffic conditions.
- Improve classification accuracy over time.

Consequently, the routing protocol remains effective under different VANET scenarios and network densities.

4 LSENN Model Architecture and Parameter Configuration

Several modifications were made to the LSENN model in order to adapt it to the simulation context and provide real-time estimation of link states to the routing protocol, thereby enabling better decision-making. We also replaced the learning type with reinforcement learning, allowing the model to progressively improve its classification capabilities through continuous interaction with the environment.

The activation function of the hidden layer was replaced with the ReLU (Rectified Linear Unit) function, which provides better performance than the sigmoid function in terms of convergence and accuracy. However, the softmax function was retained in the output layer. After extensive experimentation with different network architectures and training parameters.

The final LSENN configuration summarized in Table 1 was selected.

Parameter	Value
Number of input neurons	5
Number of output neurons	3
Number of hidden layers	3
Neurons per hidden layer	38
Hidden activation function	ReLU
Output activation function	Softmax
Cost function	Cross-Entropy

Table 1 LSENN Model Configuration

5 Routing Procedure of AODV-LSENN

The routing process is divided into three major phases:

5.1 Link Quality Estimation

Whenever a node receives a packet, it extracts information about its neighboring nodes, including RSSI, distance, relative speed, and OFDM decoding error. These measurements are fed into the LSENN model, which estimates the current state of each communication link. The extracted metrics are widely recognized as indicators of link quality and stability in highly dynamic wireless environments.

The proposed link-quality estimation phase is described by Algorithm 1 and Algorithm 2.

Algorithm 1 Physical Layer Monitoring Phase

Require: Vehicular network topology
Ensure: Feature vectors $X(i, j)$

for each node i **do**
  for each neighboring node j **do**
    Collect:
    RSSI(i, j)
    Distance $d(i, j)$
    Relative speed $v(i, j)$
    OFDM decoding errors $Error_Pr$ and $Error_Pa$
    Construct feature vector:
      $X(i, j) = \{RSSI, d, v, Error_Pr, Error_Pa\}$
  end for
end for

Algorithm 2 Link Quality Estimation Using LSENN

Require: Feature vector $X(i, j)$
Ensure: Link state $State(i, j)$

for each link (i, j) **do**
  $State(i, j) \leftarrow LSENN(X(i, j))$ ▷ Link classification
  if $State(i, j) = 1$ **then**
    Link State ← CONNECTED
  else if $State(i, j) = 2$ **then**
    Link State ← TRANSIENT
  else
    Link State ← DISCONNECTED
  end if
end for

5.2 Route Discovery

When a source node needs to communicate with a destination and no valid route exists, it initiates a route discovery process by broadcasting a Route Request (RREQ) packet according to the AODV procedure.

Upon receiving an RREQ packet, each intermediate node evaluates the quality of the incoming link using the LSENN model:

- Links classified as disconnected or transient are discarded.
- Links classified as connected are considered eligible and the RREQ is forwarded.

The destination node (or an intermediate node possessing a valid route) generates a Route Reply (RREP) packet. If multiple routes are available, the source node selects the optimal route according to the following criteria:

1. Highest link-quality level (connected).
2. Minimum hop count in case of equal link quality.

The route discovery phase of the proposed AODV-LSENN protocol is presented in Algorithm 3.

Algorithm 3 Route Discovery Phase

Require: Source node S, Destination node D, Link states estimated by LSENN
Ensure: Optimal route between S and D

if node S needs to communicate with node D and no valid route exists **then**
  S broadcasts a Route Request packet
  for each intermediate node i receiving the RREQ **do**
    $State(i, j) \leftarrow LSENN(X(i, j))$
    if $State(i, j)$ = DISCONNECTED **or** $State(i, j)$ = TRANSIENT **then**
      Discard the RREQ
    else
      Forward the RREQ
    end if
  end for
end if

5.3 Route Maintenance

During data transmission, nodes continuously monitor the state of active links using HELLO, RREQ, RREP, and data packets. When a link is classified as disconnected or transient, the protocol:

- Generates a Route Error (RERR) message.
- Activates an alternative route if available.
- Otherwise initiates a new route discovery process.

This proactive maintenance strategy significantly reduces route interruptions and improves communication reliability in VANET environments. The details of the route maintenance phase are presented in Algorithm 4.

Algorithm 4 Route Maintenance Phase

Require: Active routes and link states estimated by LSENN
Ensure: Updated and reliable routing paths

for each active link (i, j) **do**
  Periodically update:
    $State(i, j) \leftarrow LSENN(X(i, j))$
  if $State(i, j)$ = DISCONNECTED **or** $State(i, j)$ = TRANSIENT **then**
    if an alternative route exists **then**
      Activate the alternative route
    else
      Initiate a new route discovery process
    end if
  end if
end for

6 Performance Evaluation Metrics

To assess the effectiveness of the proposed AODV-LSENN routing protocol and compare it with the conventional AODV protocol, several standard Quality of Service (QoS) metrics commonly used in VANET performance evaluation are considered. These metrics provide quantitative measurements of routing reliability, efficiency, and communication stability.

6.1 Packet Delivery Ratio (PDR)

The Packet Delivery Ratio (PDR) represents the percentage of successfully received packets relative to the total number of transmitted packets. It is one of the most important indicators of routing reliability and network performance. The PDR is calculated as follows 1.

$$PDR = \frac{N_{recv}}{N_{sent}} \times 100 \tag{1}$$

where:

- N_{sent}: is the total number of transmitted packets.
- N_{recv}: is the total number of successfully received packets.

A higher PDR indicates a more reliable routing protocol and better network connectivity.

6.2 Packet Loss Ratio (PLR)

The Packet Loss Ratio (PLR) measures the percentage of packets that fail to reach their destination during transmission. This metric reflects the impact of link failures, interference, collisions, and routing disruptions on network performance [9], [11]. The PLR is defined as follows 2.

$$PLR = \frac{N_{\text{sent}} - N_{\text{recv}}}{N_{\text{sent}}} \tag{2}$$

Since PLR and PDR are complementary metrics, PLR can also be expressed as shown in Equation 3.

$$PLR(\%) = 100 - PDR(\%) \tag{3}$$

Or, when the PDR is normalized, as shown in Equation 4.

$$PLR = 1 - PDR \tag{4}$$

A lower PLR value indicates better routing efficiency and link reliability.

6.3 End-to-End Delay

The End-to-End Delay corresponds to the average time required for a packet to travel from the source node to the destination node. This metric includes all delays experienced during packet transmission, such as route discovery delays, queuing delays, propagation delays, processing delays, and retransmission delays. It is computed as shown in Equation 5

$$D_{E2E} = \frac{1}{N} \sum_{i=1}^{N} (t_{\text{recv},i} - t_{\text{sent},i}) \tag{5}$$

where:

- N is the total number of successfully received packets;
- $t_{\text{sent},i}$ is the transmission time of packet i;
- $t_{\text{recv},i}$ is the reception time of packet i.

Lower delay values indicate faster packet delivery and better network responsiveness.

6.4 Average Jitter

Jitter represents the variation in packet delay between consecutive packets. It is a critical metric for evaluating communication stability, especially for real-time and safety-critical VANET applications such as collision avoidance and emergency message dissemination. The average jitter is computed as shown in Equation 6.

$$J_{\text{avg}} = \frac{1}{N-1} \sum_{i=2}^{N} |D_i - D_{i-1}| \tag{6}$$

where:

- N is the total number of received packets;
- D_i is the end-to-end delay of packet i;
- D_{i-1} is the end-to-end delay of the previous packet;
- $|D_i - D_{i-1}|$ denotes the delay variation between two consecutive packets.

A lower jitter value indicates more stable packet transmission and better Quality of Service (QoS).

7 Simulation Setup

7.1 Simulation Environment and Tools

The simulation framework adopted in this study is based on a clear separation between the network simulation layer and the machine learning module. This modular architecture facilitates the development, validation, and performance evaluation of the proposed AODV-LSENN routing protocol while ensuring the reproducibility of experimental results. The main components of the simulation environment are described below.

7.1.1 NS-3.40 Network Simulator

The NS-3.40 network simulator is used to implement the VANET scenario and evaluate the routing performance under realistic vehicular communication conditions. NS-3 provides detailed models of network protocols and wireless communication technologies, making it one of the most widely used simulators for VANET research [14, 15]. The simulator is used to model:

- Vehicular nodes.
- Road Side Units (RSUs).
- IEEE 802.11p wireless communications.
- The AODV routing protocol.
- Vehicular mobility and wireless channel propagation.

NS-3 provides a realistic environment for evaluating routing performance while accounting for both physical-layer and MAC-layer characteristics.

7.1.2 OpenAI Gym Platform

The OpenAI Gym platform is employed to integrate the learning module into the routing process. OpenAI Gym is an open-source framework widely used for machine learning and reinforcement learning applications [16]. In the proposed architecture:

- A neural network based agent (LSENN) receives link quality metrics as inputs, including RSSI, inter-vehicle distance, relative speed, and OFDM decoding errors.
- The model performs inference to classify the current state of communication links.
- The generated outputs correspond to link-quality labels (Connected, Transient, or Disconnected).
- A reward mechanism based on classification accuracy is used.
- The model parameters are continuously updated through online learning.

7.1.3 ns3-gym Interface

The ns3-gym framework provides a seamless interface between NS-3 and OpenAI Gym [17]. It enables:

- The transmission of network measurements generated by NS-3 to the LSENN model.
- The integration of machine-learning decisions into the routing process.

- The synchronization of network simulation and learning operations.

This interaction is essential for implementing an intelligent routing mechanism capable of adapting to dynamic VANET environments.

7.2 Simulation Scenario

To evaluate the performance of the proposed AODV-LSENN protocol, simulations are conducted in a realistic urban Manhattan-grid scenario, which is widely used in VANET studies due to its ability to accurately reproduce urban traffic conditions [18]. The simulated environment is characterized by:

- High vehicle density.
- Multiple road intersections.
- Building-induced obstacles.
- Complex radio propagation conditions.
- Frequent topology changes due to vehicle mobility.

Such a scenario provides a challenging environment for evaluating routing protocols under realistic VANET operating conditions.

7.3 Simulation Parameters

The simulation parameters used throughout the experiments are summarized in Table 2.

Parameter	Value
Simulation time	150 s
Number of vehicles	10, 20, 40, 60, 80
MAC protocol	IEEE 802.11p
Propagation model	Path Loss, Shadowing, Fast Fading, Doppler
Vehicle speed	5–20 m/s
Simulation area	500×500 m^2
Packet size	256 Bytes
HELLO interval	1 s
Packet transmission interval	0.5 s

Table 2 Simulation parameters

8 Simulation Results

8.1 Packet Delivery Ratio (PDR)

Figure 1 illustrates the variation of PDR as a function of network density for both AODV-LSENN and conventional AODV.

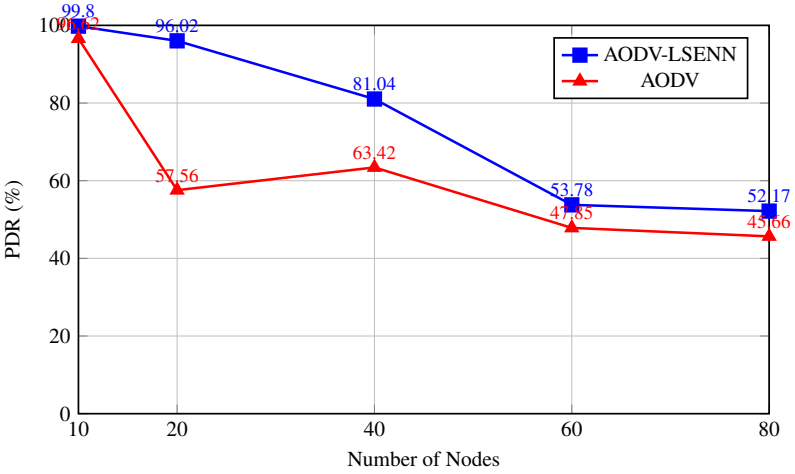


Figure 1 Comparison of the packet delivery ratio as a function of the number of nodes

For a low-density scenario (10 vehicles), both protocols achieve high delivery rates. AODV-LSENN attains a PDR of 100%, whereas conventional AODV achieves 95.03%. This improvement can be attributed to the LSENN model's ability to identify and select more stable communication links.

As network density increases to a medium level (40 vehicles), the superiority of AODV-LSENN becomes more evident. The proposed protocol achieves a PDR of 83.87%, compared with 65.46% for AODV. This significant gain results from the neural-network-based link-quality estimation mechanism, which enables the routing protocol to select more reliable routes and avoid unstable links. Consequently, packet losses and route failures are substantially reduced.

In high-density scenarios (80 vehicles), the performance of both protocols decreases due to increasing network congestion. AODV-LSENN achieves a PDR of 52.61%, while AODV reaches 49.48%. The reduction in delivery performance is mainly caused by channel contention, packet collisions at the IEEE 802.11p MAC layer, and radio channel saturation.

Overall, the results demonstrate that integrating an intelligent link-quality prediction mechanism significantly enhances routing performance, particularly under medium-density VANET conditions. Although the performance gains become smaller at very high densities, AODV-LSENN consistently outperforms conventional AODV.

8.2 Packet Loss Ratio (PLR)

Figure 2 presents the Packet Loss Ratio obtained for both AODV and the proposed AODV-LSENN protocol under different network densities.

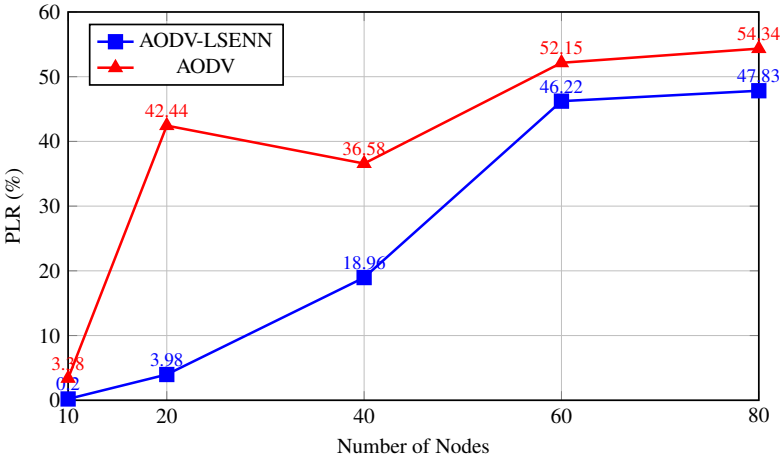


Figure 2 Comparison of the packet loss ratio as a function of the number of nodes

The results indicate that the PLR increases as the number of vehicles grows for both protocols. This behavior is expected because higher node density leads to increased channel contention, packet collisions, and interference in IEEE 802.11p networks .

However, AODV-LSENN consistently achieves a lower PLR than conventional AODV. The difference is particularly noticeable for medium-density scenarios (20–40 vehicles), where the LSENN model efficiently identifies stable links and avoids unreliable routes. As a result, packet drops caused by frequent link failures are significantly reduced.

For high-density scenarios (60–80 vehicles), the PLR increases substantially for both protocols due to:

- channel congestion.
- MAC-layer collisions in IEEE 802.11p.
- wireless medium saturation.
- increased routing overhead.

Nevertheless, AODV-LSENN maintains a lower packet loss rate because its neural network based link quality estimation enables more reliable route selection and proactive route maintenance.

8.3 Average End-to-End Delay

Figure 3 illustrates the average delay achieved by AODV-LSENN and the conventional AODV protocol under different network densities.

For a low-density network (10 vehicles), AODV-LSENN achieves a significantly lower delay of 12.6 ms, compared to 38.98 ms for AODV. This improvement results from the LSENN model's ability to select stable communication links and reduce unnecessary route discoveries and retransmissions.

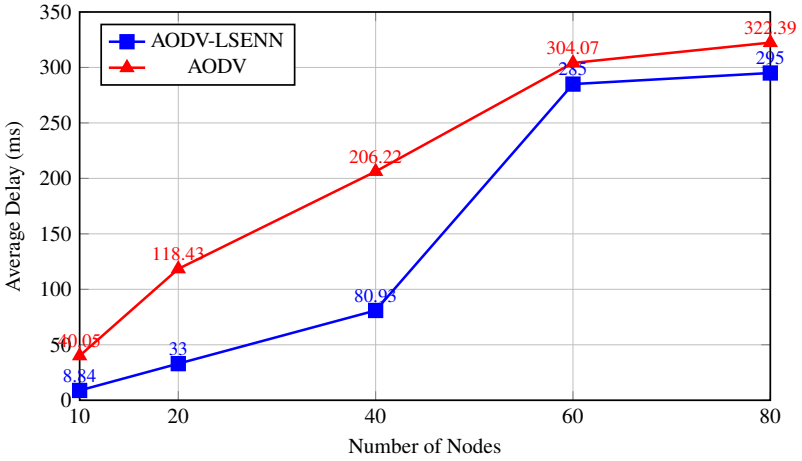


Figure 3 Comparison of the average delay as a function of the number of nodes

As network density increases to a medium level (40 vehicles), the performance gap becomes even more pronounced. The average delay reaches 86.98 ms for AODV-LSENN, while AODV experiences a delay of 251.11 ms. This substantial improvement can be attributed to the proactive link management mechanism integrated into AODV-LSENN, which anticipates link failures before they occur and consequently reduces route reconstruction operations.

Under high-density conditions (80 vehicles), the average delay increases for both protocols, reaching 305.64 ms for AODV-LSENN and 317.62 ms for AODV. The degradation is mainly caused by:

- Increased wireless interference.
- Channel congestion.
- MAC-layer packet collisions.
- Longer queuing delays.

Despite these challenging conditions, AODV-LSENN maintains lower latency thanks to its intelligent link-quality prediction and route-selection strategy.

These results confirm that incorporating machine-learning-based link estimation into the routing process can significantly reduce communication delays in highly dynamic VANET environments.

8.4 Average Jitter

Figure 4 illustrates the evolution of average jitter as a function of network density for both routing protocols.

The results show that jitter increases with network density for both AODV and AODV-LSENN. This increase is primarily caused by higher channel contention, MAC-layer collisions, and fluctuations in packet transmission delays.

Nevertheless, AODV-LSENN consistently demonstrates superior stability compared to the traditional AODV protocol. For example, in a medium-density scenario

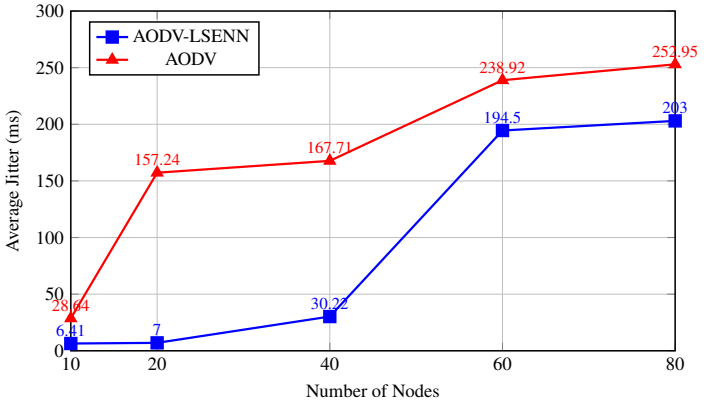


Figure 4 Comparison of the average jitter as a function of the number of nodes

(40 vehicles), the average jitter is only 11.88 ms for AODV-LSENN, whereas AODV exhibits a much higher jitter of 203.68 ms.

This significant improvement is mainly due to the LSENN-based link classification mechanism, which:

- Selects more stable communication links.
- Avoids unreliable routes.
- Reduces route breakages
- Minimizes packet retransmissions.

Consequently, packet transmission becomes more predictable, resulting in lower delay variations and improved communication stability.

Overall, the obtained results demonstrate that AODV-LSENN provides more consistent and reliable packet delivery than conventional AODV, making it particularly suitable for VANET applications that require strict QoS guarantees and low delay variability.

9 Conclusion

The enhancement of the AODV routing protocol proposed in this paper is based on the integration of advanced link-quality metrics combined with an intelligent machine learning based classification model. This approach enables a more accurate assessment of communication link conditions and supports more efficient route selection in highly dynamic VANET environments.

The simulation results demonstrate that the proposed AODV-LSENN protocol significantly improves routing performance compared with the conventional AODV protocol. Notable improvements are observed in terms of Packet Delivery Ratio (PDR), end-to-end delay, Packet Loss Ratio (PLR), and network stability, as reflected by lower jitter values. These performance gains are particularly evident in low- and medium-density network scenarios, where the proactive prediction of link degradation helps reduce route failures, packet retransmissions, and route discovery overhead.

However, under high-density traffic conditions, the performance of both protocols is still affected by inherent wireless communication challenges, including channel congestion, interference, medium contention, and MAC-layer collisions associated with the IEEE 802.11p standard. Although AODV-LSENN continues to outperform conventional AODV in such scenarios, the achievable gains become more limited due to these network constraints.

In summary, the integration of an intelligent link-quality estimation model into the AODV routing process represents a promising solution for enhancing the reliability, robustness, and efficiency of VANET communications. Furthermore, this work opens new perspectives for the development of next-generation intelligent routing protocols that leverage artificial intelligence and deep learning techniques to adapt dynamically to rapidly changing vehicular network conditions.

Declarations

- Funding: Not applicable.
- Competing interests: The authors have no conflicts of interest to declare that are relevant to the content of this article.
- Ethics approval:
  - This material is the authors' own original work, which has not been previously published elsewhere.
  - The paper is not currently being considered for publication elsewhere.
  - The paper reflects the authors' own research and analysis in a truthful and complete manner.
  - All sources used are properly disclosed (correct citation).
- Consent to participate: Not applicable.
- Consent for publication: Not applicable.
- Availability of data and materials: Data available on request from the authors.
- Code availability: Code available on request from the authors.
- Authors' contributions:
  - Hamida Ikhlef: conceived of the presented idea, performed the experiments, analyse of the results, writing and original draft preparation.
  - Ali Melit Supervision and approved the final manuscript.

References

[1] Hasrouny, H., Samhat, A.E., Bassil, C., Laouiti, A.: Vanet security challenges and solutions: A survey. Vehicular Communications **7**, 7–20 (2017)

[2] Karne, R., Sreeja, T.: Review on vanet architecture and applications. Turkish Journal of Computer and Mathematics Education **12**(4), 1745–1749 (2021)

[3] Ikhlef, H., Bourebia, S., Melit, A.: Link state estimator for vanets using neural networks. Journal of Network and Systems Management **32**(1), 10 (2024)

[4] De Couto, D.S., Aguayo, D., Bicket, J., Morris, R.: A high-throughput path metric for multi-hop wireless routing. In: Proceedings of the 9th Annual International Conference on Mobile Computing and Networking, pp. 134–146 (2003)

[5] Al-Rabayah, M., Malaney, R.: A new scalable hybrid routing protocol for vanets. IEEE transactions on vehicular technology **61**(6), 2625–2635 (2012)

[6] Windianto, W., Djanali, S., Husni, M.: Optimasi routing pada protokol aodv_ext dengan menggunakan link expiration time (let). JUTI: Jurnal Ilmiah Teknologi Informasi, 143–151 (2015)

[7] Kanakaris, V., Ndzi, D.L., Ovaliadis, K., Yang, Y.: A new rreq message forwarding technique based on bayesian probability theory. EURASIP Journal on Wireless Communications and networking **2012**(1), 318 (2012)

[8] Abolhasan, M., Wysocki, T., Dutkiewicz, E.: A review of routing protocols for mobile ad hoc networks. Ad hoc networks **2**(1), 1–22 (2004)

[9] Dorigo, M.: Ant colony optimization. Scholarpedia **2**(3), 1461 (2007)

[10] Mohammed, D., Mansor, M.B., Hock, G.C.: Implement routing protocols for vanet in a one-way environment. In: AIP Conference Proceedings, vol. 2804, p. 020014 (2023). AIP Publishing LLC

[11] Tripp-Barba, C., Zaldívar-Colado, A., Urquiza-Aguiar, L., Aguilar-Calderón, J.A.: Survey on routing protocols for vehicular ad hoc networks based on multimetrics. Electronics **8**(10), 1177 (2019)

[12] Alameri, I., Komarkova, J., Al-Hadhrami, T., Lotfi, A.: Systematic review on modification to the ad-hoc on-demand distance vector routing discovery mechanics. PeerJ Computer Science **8**, 1079 (2022)

[13] Perkins, C., Belding-Royer, E., Das, S.: Ad hoc on-demand distance vector (aodv) routing. Technical report (2003)

[14] Henderson, T.R., Lacage, M., Riley, G.F., Dowell, C., Kopena, J.: Network simulations with the ns-3 simulator. SIGCOMM demonstration **14**(14), 527 (2008)

[15] Riley, G.F., Henderson, T.R.: The ns-3 network simulator. In: Modeling and Tools for Network Simulation, pp. 15–34. Springer, Berlin, Heidelberg (2010)

[16] Brockman, G., Cheung, V., Pettersson, L., Schneider, J., Schulman, J., Tang, J., Zaremba, W.: Openai gym. arXiv preprint arXiv:1606.01540 (2016)

[17] Gawłowicz, P., Zubow, A.: ns3-gym: Extending openai gym for networking research. arXiv preprint arXiv:1810.03943, 1–8 (2018)

[18] Ramakrishnan, B., Nishanth, R.B., Joe, M.M., Shaji, R.: Comprehensive analysis of highway, manhattan and freeway mobility models for vehicular ad hoc network. International Journal of Wireless and Mobile Computing **9**(1), 78–89 (2015)