AI-VASNet: An AI-Driven Adaptive Data Dissemination Framework for Vehicular Ad Hoc and Sensor Networks

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ABSTRACT

Vehicular Ad Hoc and Sensor Networks (VASNETs) operate under high node mobility, rapidly changing network topology, and stringent latency constraints, making reliable data dissemination particularly challenging. Conventional routing protocols struggle to maintain stable communication in dense traffic conditions and under intermittent connectivity caused by frequent topology variations. To address these limitations, this paper introduces AI-VASNet, a hybrid adaptive routing framework that integrates Reinforcement Learning (RL) for adaptive forwarding decisions, Federated Learning (FL)-based link reliability inference, fuzzy Quality-of-Service (QoS) prioritization for traffic differentiation, and instability-aware neighbor filtering to reduce unreliable communication links. Unlike existing approaches that apply these mechanisms independently, AI-VASNet tightly combines them into a unified decision framework, enabling intelligent packet forwarding while preserving data privacy through decentralized learning. Simulation results demonstrate that AI-VASNet achieves up to an 18% improvement in Packet Delivery Ratio (PDR), reduces end-to-end latency by approximately 23%, and improves throughput by nearly 20% compared with six representative routing protocols, under high node density and mobility conditions. These findings indicate that AI-VASNet provides an adaptive and scalable routing solution for next-generation Vehicle-to-Everything (V2X) communication and Intelligent Transportation Systems (ITS).

Keywords-data dissemination; Federated Learning (FL); Reinforcement Learning (RL); Vehicular Ad Hoc and Sensor Networks (VASNETs)

I. INTRODUCTION

The rapid growth of Vehicular Ad Hoc and Sensor Networks (VASNETs) has enabled the development of next-generation Intelligent Transportation Systems (ITS) that rely on reliable, low-latency, and scalable data dissemination. Safety-critical applications, including accident notifications, cooperative perception, and hazard warnings, require timely and reliable information exchange between vehicles and roadside infrastructure in highly dynamic environments [1].

However, achieving consistent dissemination performance remains challenging due to high node mobility, intermittent connectivity, and heterogeneous wireless conditions. Conventional routing approaches, such as geocast, flooding-based schemes, and topology-driven protocols including Ad Hoc On-Demand Distance Vector (AODV) and Dynamic Source Routing (DSR), exhibit marked performance degradation as vehicular density and mobility increase, leading to packet losses, excessive transmission delays, and inefficient resource utilization. Consequently, traditional routing mechanisms struggle to meet the latency and reliability demands of emerging Vehicle-to-Everything (V2X) applications [2].

To address these limitations, recent research efforts have explored the use of Artificial Intelligence (AI) techniques to enhance data dissemination in vehicular networks [3].

Learning-based approaches aim to dynamically adjust dissemination strategies based on network conditions such as vehicle density, mobility patterns, and link quality. For example, authors in [4] proposed an adaptive learning-based dissemination framework for Unmanned Aerial Vehicle (UAV)-assisted vehicular networks aimed at real-time road-safety communication. Similarly, authors in [5] introduced a learning-based dissemination framework for UAV-assisted Internet of Things (IoT) networks that combines energy-aware path planning, device classification, and association to lower total energy consumption. Although both approaches rely on UAV-based infrastructure, they demonstrate how learning-driven adaptation effectively supports VASNET-relevant delay-sensitive dissemination tasks.

Reinforcement Learning (RL) has been widely utilized for adaptive routing and forwarding in VANET environments, where frequent topology dynamics necessitate continuous online decision-making [6]. Authors in [7] proposed TROVE, an RL-based framework that adapts routing behavior to dynamic driving contexts through entropy-based evidence evaluation. Authors in [8] presented an Improved Deep Reinforcement Learning (IDRL) routing model that adjusts routing decisions according to vehicle density and traffic patterns, thereby decreasing convergence time and control overhead while improving packet delivery performance. The introduction of an RL-based neighbor selection framework by authors in [9] demonstrates that learning-based adaptation can increase routing effectiveness under dynamic topology settings by incorporating mobility parameters like vehicle speed into routing decisions. Furthermore, authors in [10] proposed a deep RL-based approach for efficient big data offloading in vehicular networks. Additionally, authors in [11] introduced a Roadside Unit (RSU)-assisted traffic-aware routing framework based on Q-learning.

Quality-of-Service (QoS)-aware and optimization-based routing approaches have also been investigated to enhance reliability and service differentiation in VANETs [12]. Authors in [13] introduced DRLIQ, a routing method based on deep RL, aimed at enhancing QoS in infrastructure-less VANETs. Authors in [14] presented QBACC, an RL-based congestion control framework for Vehicle-to-Vehicle (V2V) communication that employs Q-learning to manage transmission rates under varying channel load. Furthermore, a hybrid routing strategy for cluster-based V2V communication that combines fuzzy logic and RL was proposed by authors in [15]. Their approach improves QoS-aware routing decisions by using RL for route optimization and fuzzy inference for cluster head selection.

In parallel, Federated Learning (FL) has attracted interest in vehicular networking as a decentralized learning paradigm that facilitates collaborative model training without the exchange of raw data. A mobility-aware decentralized FL framework was proposed by authors in [16] to resolve the challenges associated with vehicle mobility and resource constraints, resulting in enhanced training efficiency through coordinated learning strategies. Authors in [17] developed an adaptive split FL framework for vehicular edge intelligence, which employs a mobility-aware cut-layer strategy to reduce communication overhead and improve training efficiency, thereby illustrating the suitability of FL variants for scalable learning in highly mobile environments. Authors in [18] established an embedded FL framework for VANETs using edge devices to perform distributed vehicular mobility prediction, illustrating the feasibility and scalability of FL in vehicular infrastructures. However, their research focuses on traffic forecasting rather than adaptive, reliability-aware data dissemination.

Despite these advances, most learning-based vehicular networking approaches address individual objectives—such as routing adaptation, QoS optimization, congestion awareness, or decentralized model training—without a unified framework that jointly addresses these aspects. Consequently, the interaction between learning-based routing decisions, QoS-aware prioritization, and privacy-preserving model training remains insufficiently explored, particularly in highly dynamic vehicular environments. Furthermore, many existing AI-based approaches rely on a single learning paradigm (e.g., RL-only or FL-only), limiting their ability to adapt to diverse network conditions.

To address this gap, this paper proposes AI-VASNet, a comprehensive adaptive routing framework for VASNETs that integrates FL-based link reliability inference, RL-driven forwarding decisions, and fuzzy QoS-based traffic prioritization within a unified decision engine. This coordinated design enables intelligent and adaptive packet forwarding by jointly considering link reliability, forwarding strategy, and service differentiation, while preserving data privacy through decentralized learning. The effectiveness of this integrated design is further validated through ablation-based analysis (Section III), which demonstrates the contribution of each component to overall system performance.

A comparative analysis with existing routing approaches is presented in Table I.

The primary contributions of this paper are summarized as follows:

1. AI-VASNet is proposed as a self-adaptive routing framework for VASNETs that integrates FL-based link reliability inference, RL-based forwarding decisions, and fuzzy QoS-driven traffic prioritization within a cohesive routing architecture.
2. A controlled and reproducible evaluation methodology is developed, which evaluates performance under a variety of traffic densities and mobility patterns by utilizing established vehicular mobility models and a hybrid wireless channel configuration.
3. The proposed framework is evaluated against six representative vehicular routing schemes, with performance assessed in terms of Packet Delivery Ratio (PDR), end-to-end latency, and throughput.
4. FL is incorporated to facilitate privacy-aware decentralized model training, eliminating the need for raw vehicular data exchange while promoting collaborative learning across distributed nodes.

TABLE I. COMPARATIVE ANALYSIS OF AI-VASNET AGAINST EXISTING ROUTING APPROACHES

Work	Routing strategy	Learning paradigm	QoS support	FL capability	Link reliability & stability	Adaptivity to network dynamics	Limitation
[4]	UAV-assisted safety dissemination	FL + DRL	Partial	Yes	No	Yes	UAV-dependent; lacks QoS-aware routing
[5]	UAV-assisted energy-efficient dissemination	DRL	No	No	No	Yes	Energy-focused; no routing/QoS modeling
[7]	Trust-aware routing support	RL	No	No	Partial	Yes	Trust-based; lacks QoS, FL, or integrated routing decisions
[8]	DRL-based routing	DRL	No	No	Partial	Yes	No QoS prioritization or FL
[9]	RL-based neighbor selection	RL	No	No	Partial	Yes	Limited to neighbor selection only; not full dissemination or QoS-aware routing
[10]	Data offloading (V2V/V2I)	DRL	Partial	No	No	Yes	Offloading-focused; not routing or QoS-aware dissemination
[11]	RSU-assisted routing	RL	Partial	No	Yes	Yes	RSU-dependent; no FL or QoS
[13]	QoS-aware DRL routing	DRL	Yes	No	Partial	Yes	No FL or multi-criteria QoS prioritization
[14]	Congestion-aware transmission control	RL	Partial	No	No	Yes	Congestion-focused; not routing or QoS-aware dissemination
[15]	Cluster-based V2V routing	RL + fuzzy	Yes	No	Yes	Yes	No FL; lacks multi-layer decision framework
[16]	Decentralized FL training (no routing)	FL	No	Yes	No	Yes	FL-focused; not routing or QoS-aware forwarding
[17]	Edge intelligence (no routing)	Split FL	No	Yes	No	Yes	Training-focused; not dissemination or routing
[18]	Mobility prediction (no routing)	FL	No	Yes	No	Yes	Does not address routing, QoS, or dissemination decisions
AI-VASNet (proposed)	Adaptive VASNET data dissemination	RL + FL + fuzzy	Yes	Yes	Yes (reliability + instability-aware filtering)	Yes	—

II. METHODOLOGY

A. System Architecture

The proposed AI-VASNet architecture, shown in Figure 1, extends the VASNET framework by integrating learning-based decision support at vehicle nodes while maintaining the distributed V2X communication model. The architecture includes Vehicular Sensor Nodes (VSNs), RSUs, a Base Station (BS), and an FL coordinator. VSNs function as autonomous nodes where all forwarding intelligence is executed. Each vehicle generates safety messages and employs local network metrics, such as queue length and delay, for decision-making. Data dissemination and model exchange are facilitated by communication with neighboring vehicles and infrastructure.

RSUs act as intermediate gateways that collect model updates from vehicles and relay them to the BS via infrastructure links [19]. The BS provides backhaul connectivity to the FL coordinator. The FL coordinator aggregates locally trained model parameters received from vehicles and redistributes a global model, which enables collaborative learning without sharing raw data. All learning and forwarding decisions, including reliability estimation, RL-based selection, and QoS prioritization, are made locally at vehicle nodes, whereas infrastructure components provide only communication and coordination support. Each step of the proposed framework algorithm is described in the following subsections.

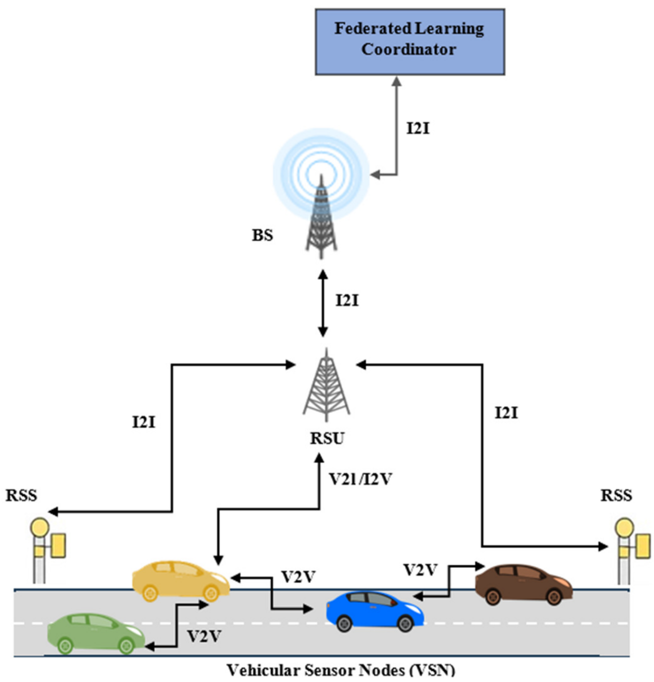

Fig. 1. System architecture of the proposed AI-VASNet framework.

B. Link Instability Assessment

AI-VASNet uses locally observed link-quality statistics to assess link instability at each vehicle node to avoid packet forwarding to unreliable neighbors [20]. This stage excludes neighbors whose recent communication behavior indicates unstable or degraded links due to mobility and wireless channel variations from the forwarding candidate set before reliability inference and RL-based decision-making [21]. Each vehicle calculates a link instability score $I_n(t)$ for each neighbor $n \in N$ by using packet reception behavior and channel variability. The score combines the complement of the Packet Reception Ratio (PRR) and the deviation of instantaneous Signal-to-Noise Ratio (SNR) from its recent average:

$$I_n(t) = \left(1 - PRR_{avg}(n,t)\right) + \lambda\left(SNR_n(t) - SNR_{avg}(n,t)\right) \quad (1)$$

where $PRR_{avg}(n,t)$ and $SNR_{avg}(n,t)$ denote windowed averages computed over the most recent W observations, and λ controls the relative contribution of SNR variation.

A sliding window of recent instability observations is maintained:

$$I(t) = \{I_n(\tau): n \in N,\ \tau \in [t - W + 1, \dots, t]\} \quad (2)$$

where $I_n(\tau)$ denotes samples of historical instability from all neighbors over a sliding window of length W.

The mean and standard deviation of recent instability are calculated from this pooled set:

$$\mu_I(t) = \mathrm{mean}(I(t)) \quad (3)$$

$$\sigma(t) = \mathrm{std}(I(t)) \quad (4)$$

An adaptive instability threshold is then defined as:

$$I_{th}(t) = \mu_I(t) + 3\sigma(t) \quad (5)$$

Neighbors with a current instability score that exceeds this threshold are considered unstable and are excluded from the candidate neighbor set used in subsequent stages. This adaptive filtering reduces packet loss and improves reliability inference and learning-based forwarding decisions.

C. Federated Learning–Based Link Reliability Inference

After excluding highly unstable neighbors, AI-VASNet estimates the expected forwarding reliability of the remaining candidate links through a learning-based reliability inference model, which has been trained using FL. This stage predicts the probability of successful packet delivery over each candidate link while enabling collaborative learning without exchanging raw communication data. For each eligible neighbor n, the vehicle creates a local feature vector using link-quality indicators already defined in the link instability assessment stage. The feature vector is defined as:

$$x_n(t) = \left(SNR_n(t), PRR_{avg}(n,t), age_n(t)\right) \quad (6)$$

where $age_n(t)$ indicates the elapsed time since the most recent successful packet exchange with the neighbor, representing temporal link continuity.

This feature vector allows vehicles to assess the reliability of forwarding a packet through a neighbor n, using local inference. The reliability estimate is calculated as:

$$\hat{h}_n(t) = f_\theta\left(x_n(t)\right) \quad (7)$$

where f_θ indicates a parameterized reliability inference model with parameters θ. The output $\hat{h}_n(t)$ is the predicted forwarding reliability of the link to neighbor n based on existing network conditions. The parameters of the reliability inference model are trained in a federated manner. Each vehicle updates its local model using observed link outcomes and periodically transmits model parameters to the FL coordinator. The coordinator aggregates updates using a federated averaging mechanism and disseminates the global model back to vehicles, which enables collaborative learning while preserving data locality and privacy. FL is used exclusively for training the reliability inference model [22].

D. Q-Learning for Reinforcement Routing

To facilitate adaptive next-hop selection in the face of swiftly evolving vehicular network conditions, AI-VASNet utilizes Q-learning–based RL at every vehicle node. Each vehicle is represented as an independent RL agent that interacts with its local network environment. At each packet forwarding decision instant t, the agent evaluates the current network state and chooses a forwarding action for one of the candidate neighbors [23]. The state representation is defined as:

$$s_n(t) = \left[SNR_n(t), PRR_{avg}(n,t), age_n(t), q(t)\right] \quad (8)$$

where $q(t)$ indicates the current local queue length, representing congestion conditions at the transmitting node. This state formulation enables the agent to simultaneously evaluate link quality, stability, and local congestion while making forwarding decisions.

Action selection is performed via an ϵ-greedy policy, which balances exploration and exploitation. With probability ϵ, the agent chooses a neighbor at random to explore, and with probability $1 - \epsilon$, it exploits past knowledge by choosing the neighbor with the maximum estimated Q-value:

$$a_{RL} = \mathrm{argmax} Q(s_n(t), n) \quad (9)$$

Subsequent to packet transmission, the reward function is computed as:

$$r_t = w_1 \cdot succ - w_2 \cdot D_{e2e}(p) \quad (10)$$

where succ is a binary indicator that denotes successful packet delivery, $D_{e2e}(p)$ is the end-to-end delay encountered by packet p, and w_1, w_2 are weighting coefficients that balance reliability and latency goals.

The Q-values are then modified using the standard Q-learning update rule:

$$Q(s,a) = Q(s,a) + \alpha[r_t + \gamma \max_{a'} Q(s',a') - Q(s,a)] \quad (11)$$

where:

- $Q(s,a)$ is the estimated long-term utility of taking action a when the system is in state s.

- α is the learning rate that regulates how strongly newly observed rewards influence existing Q-value estimates.
- γ is the discount factor that governs the tradeoff between immediate and future rewards.
- s' represents the new state that was observed following the execution of action a.
- a' denotes a potential action in the subsequent decision phase.

Through iterative updates, the agent gradually learns forwarding policies that favor neighbors with higher reliability and lower latency.

E. Quality-of-Service Priority Scoring

Packets generated by various applications exhibit diverse QoS requirements in vehicular environments. Fuzzy logic-based multi-criteria decision-making has been extensively studied for QoS-aware forwarder selection and service differentiation in VANETs [24]. Motivated by such approaches, AI-VASNet evaluates local network conditions, including queue length $q(t)$, and queuing delay $d_q(t)$, and maps them into linguistic variables through a Mamdani-type fuzzy inference system. The resulting inference output yields a normalized priority score $\mathrm{prio}(p)$, reflecting the urgency of packet forwarding.

F. Multi-Criteria Fusion & Next Hop Selection

Following the computation of link instability indicators, federated reliability estimates, RL-based forwarding preferences, and QoS priority scores, AI-VASNet consolidates these diverse outputs using a multi-criteria decision fusion mechanism to ascertain the final next-hop selection. The QoS priority score $\mathrm{prio}(p)$, derived from the fuzzy inference system, is utilized to adaptively allocate weights to the learning-based components. Higher-priority packets emphasize link reliability, whereas lower-priority packets permit a greater impact from RL. The priority-aware weighting functions are:

$$w_{rl}(p) = w_{rl}^{min} + \mathrm{prio}(p)\left(w_{rl}^{max} - w_{rl}^{min}\right) \qquad (12)$$

$$w_{fl}(p) = w_{fl}^{max} - \mathrm{prio}(p)\left(w_{fl}^{max} - w_{fl}^{min}\right) \qquad (13)$$

where w_{rl}^{min}, w_{rl}^{max}, w_{fl}^{min}, w_{fl}^{max} are the allowable weighting ranges for the RL and FL components, respectively.

A composite forwarding score is then computed for each candidate neighbor n:

$$s_n = w_{fl}(p)\hat{h}_n + w_{rl}(p)Q(s,a) - w_I I_n(t) \qquad (14)$$

where w_I is a fixed penalty coefficient that controls the effect of instability on the final decision, and other parameters appearing in the above equation are already defined in the preceding subsections.

The next hop is carefully chosen by selecting the neighbor that maximizes the composite score:

$$nh^* = \operatorname{argmax} s_n \qquad (15)$$

This fusion technique facilitates adaptive and context-aware forwarding by dynamically balancing reliability, learning-based adaptability, and link stability amid fluctuating network and traffic conditions.

G. Transmit and Learn

After selecting the next hop nh^*, the transmitting vehicle sends the packet to the chosen neighbor. The resulting feedback is used to compute the reward defined in (10), and the corresponding Q-value is updated according to (11). Simultaneously, vehicles engage in FL rounds at regular intervals by sending updated parameters of the reliability model to the coordinator, which then aggregates and redistributes the global model as outlined in Section II.C. The detailed algorithm of the proposed framework is presented in Algorithm 1.

```
Algorithm 1: AI-VASNet Packet Forwarding
Input: Packet p (with class tag c_p, TTL),
  Current neighbor set N, link metrics
  (SNR_n, PRR_n, age_n), local Q-table for RL
Output: Selected next hop nh* (or buffer /
  drop decision)
Step 1: Neighbor health filtering
  i.   Compute per-neighbor link
       instability score I_n(t) using (1)
  ii.  Define pooled history of
       instability scores using (2)
  iii. Compute mean and standard deviation
       using (3) and (4)
  iv.  Compute adaptive threshold using
       (5)
  v.   Filter and remove neighbors with
       I_n(t) ≥ I_th(t)
  vi.  If no valid neighbor remains,
       buffer p (if TTL allows);
       otherwise, drop p and exit
Step 2: Reliability prediction
  i.   For each non-filtered neighbor n ∈
       N, construct a local feature vector
       using (6)
  ii.  Estimate reliability using the
       local reliability inference model
       specified in (7)
Step 3: RL action
  i.   Construct the RL state vector with
       (8)
  ii.  Select a tentative next hop using
       ϵ-greedy policy specified in (9)
Step 4: QoS priority scoring
  i.   Fuzzify delay d_q, queue length q
  ii.  Select the rule base based on
       packet class c_p
  iii. Apply fuzzy inference to obtain
       priority score prio(p)
Step 5: Multi-criteria fusion & next hop
selection
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   i.   Compute priority-aware weights
        based on prio(p) utilizing (12) and
        (13)
   ii.  Compute composite score s_n using
        (14)
   iii. Select next hop nh* using (15)
Step 6: Transmit & learn
   i.   Transmit packet p to nh*
   ii.  Compute RL reward r_t with (10)
   iii. Update Q-values using (11)
   iv.  Participate in periodic federated
        updates as described in Section
        II.C
```

H. System Parameters

The performance of the proposed AI-VASNet is evaluated using a controlled simulation testbed setup according to the parameters outlined in Table II. The simulated environment encompasses a 1 km × 1 km (1,000 m × 1,000 m) mixed urban-suburban region. Vehicle densities range from 20 to 400 nodes, and maximum vehicle speeds of up to 90 km/h are considered, facilitating evaluation under sparse to dense traffic scenarios.

TABLE II. SIMULATION PARAMETERS

Parameter	Value
Simulation area	1,000 m × 1,000 m
Number of vehicles	20–400
Simulation time	300 s
Number of runs/seeds	5 runs (different seeds)
Communication standard	IEEE 802.11p (DSRC)
Carrier frequency	5.9 GHz
Data rate	6 Mb/s
Transmission range	250 m
Packet size	1,024 bytes
Mobility models	RWP, highway, urban
Direction change probability (RWP)	0.10
Lane change probability (highway)	0.05
Lane width (highway)	3.5 m
Turn probability (urban)	0.2
Vehicle velocity	10–90 km/h
Maximum queue length	100 packets
Packet generation rate	{1, 2, 4} packets/s/vehicle
Path-loss model	Two-ray ground reflection
Fading model	Rician
Shadowing model	Correlated log-normal

Every vehicle is outfitted with an IEEE 802.11p (DSRC) wireless interface that operates at 5.9 GHz, achieving a physical data rate of 6 Mb/s [25]. The nominal communication range is established at 250 m, aligning with standard assumptions for inter-vehicle communication in DSRC. The size of application packets generated during the simulation is fixed at 1,024 bytes. The 300 s duration of each simulation run is adequate to mitigate initialization bias and obtain reliable averaged measurements across multiple runs (different random seeds).

The Two-ray ground reflection model is employed to simulate wireless propagation, using Rician fading and correlated log-normal shadowing to accurately represent channel fluctuations [26].

To represent diverse mobility conditions, three models are utilized [27]: an urban grid with intersection behavior, a highway model with lane-based movement, and Random Waypoint (RWP) for unconstrained mobility. This setup allows a fair and consistent comparison of AI-VASNet with baseline protocols across heterogeneous vehicular conditions.

I. Performance Metrics

- PDR:

$$\mathrm{PDR} = \frac{P_{\mathrm{delivered}}}{P_{\mathrm{generated}}} \times 100\% \tag{16}$$

where $P_{\mathrm{delivered}}$ is the number of packets successfully received, and $P_{\mathrm{generated}}$ is the total number of packets generated.

- Average end-to-end delay:

$$D_{e2e} = \frac{\sum_{i=1}^{N_{\mathrm{delivered}}}(t_{\mathrm{delivery},i} - t_{\mathrm{generated},i})}{N_{\mathrm{delivered}}} \tag{17}$$

where $t_{\mathrm{generated},i}$ and $t_{\mathrm{delivery},i}$ denote the generation and delivery times of packet i, respectively.

- Throughput:

$$T = \frac{\text{Total successfully delivered data}}{\text{Simulation time}} \tag{18}$$

III. RESULTS AND DISCUSSION

Representative baseline routing and forwarding schemes, such as AODV, DSR, Epidemic Routing, Spray-and-Wait, Geocast, and Flooding, are compared with AI-VASNet. These schemes collectively encompass topology-based, probabilistic, location-based, and broadcast-based communication strategies. Performance is evaluated using PDR, end-to-end latency, and throughput under varying traffic density and mobility conditions. These metrics facilitate a thorough evaluation of scalability, efficiency, latency, and reliability in the context of escalating vehicular density and mobility. The results of the analysis of traffic load, node density, and mobility on protocol performance are presented and discussed in detail in this section.

Figure 2 illustrates the variation of PDR as traffic density increases. As the network size increases from 20 to 400 vehicles, all protocols experience a gradual decrease in PDR as a result of increased channel contention, interference, and packet collisions. AI-VASNet consistently surpasses all baseline schemes in PDR across all density levels, despite this trend. AI-VASNet maintains a PDR of approximately 50% at high densities (e.g., 400 vehicles), whereas conventional routing and broadcast-based protocols such as Flooding, Epidemic, AODV, and DSR experience substantially lower delivery ratios. This enhancement is indicative of the improved robustness of AI-VASNet in congested environments.

The performance improvements are the result of the combined application of RL-based next-hop selection and link reliability prediction. This approach allows for preferential forwarding over stable connections while simultaneously restricting excessive rebroadcasting. Consequently, AI-VASNet reduces packet losses that are a consequence of stale route propagation and unreliable links in dense vehicular environments.

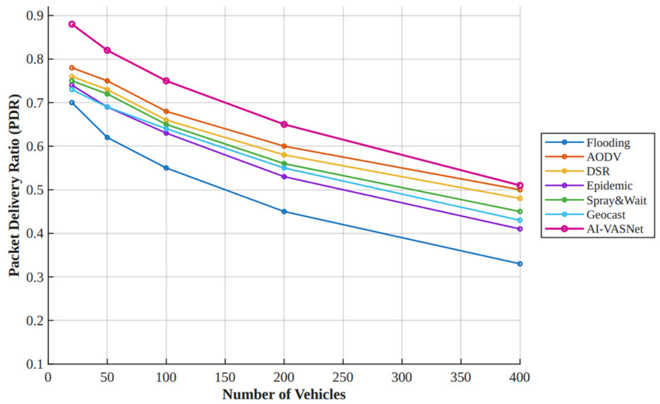

Fig. 2. PDR versus network density for AI-VASNet and baseline routing protocols.

Figure 3 demonstrates how the average end-to-end delay changes as the network size increases. As the number of vehicles increases, all protocols experience an increase in latency as a result of increased retransmissions, queuing delays, and higher channel contention. AI-VASNet consistently maintains a lower end-to-end latency across all network densities. The latency of AI-VASNet is significantly reduced in comparison to conventional routing and broadcast-based protocols at higher vehicular densities (e.g., 400 vehicles). This enhancement can be credited to the fuzzy QoS-based prioritization of packets, along with RL-guided next-hop selection, effectively minimizing excessive buffering and curtailing unnecessary rebroadcasting. As a result, AI-VASNet effectively reduces delays caused by congestion and attains a more consistent latency performance in densely populated vehicular settings.

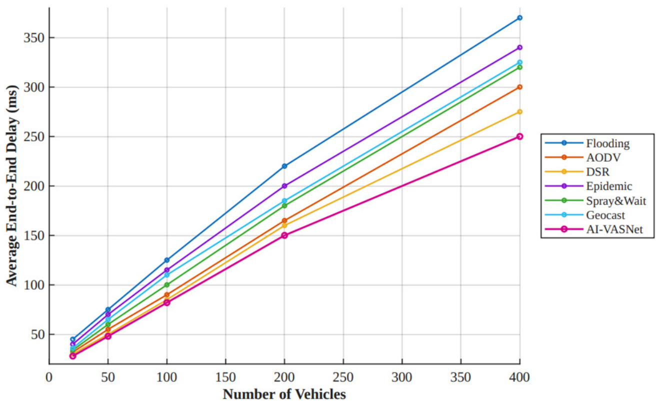

Fig. 3. Latency versus network density for AI-VASNet and baseline routing protocols.

Figure 4 depicts the variation of throughput in relation to increasing vehicle mobility speed. As vehicle speed increases from 10 to 90 km/h, all assessed protocols exhibit a consistent decrease in performance attributable to diminished connection lifetimes, frequent route interruptions, and heightened packet retransmissions resulting from rapid topology alterations. Despite this degradation, AI-VASNet consistently outperforms all baseline protocols across the full mobility range. Even at high speeds, AI-VASNet maintains a significant throughput advantage, showing increased resilience to mobility-induced link instability. This behavior can be attributed to AI-VASNet's predictive and learning-assisted forwarding method, which includes link reliability estimation and RL-based next-hop selection, allowing for early adaptation to link degradation. As a result, AI-VASNet reduces the impact of session disruptions while maintaining more effective data delivery than traditional reactive and broadcast-oriented routing systems under high mobility.

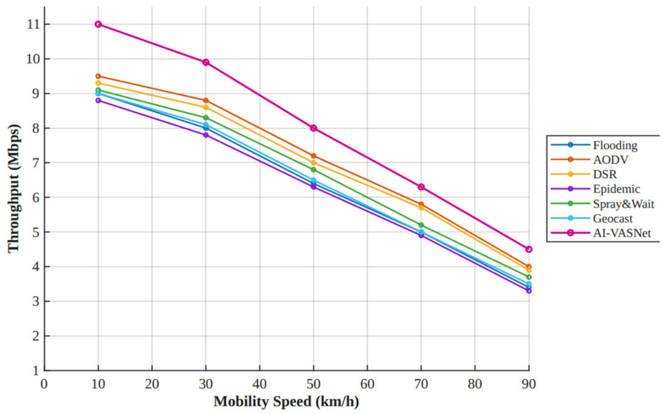

Fig. 4. Throughput vs vehicle mobility speed for AI-VASNet and baseline routing protocols.

Figure 5 depicts how the cumulative reward varies as the RL component in AI-VASNet is trained over numerous episodes. Each training episode corresponds to a fixed simulation interval during which routing decisions are assessed and rewards are accrued. At the start of training, the cumulative reward rapidly increases, indicating that the algorithm is learning to make better forwarding decisions through experience. Following around 100–120 training episodes, the cumulative reward ceases to show significant increases and stays relatively stable. This suggests that the learning process has stabilized, and further training does not significantly alter the routing decisions.

Subsequent to this phase, only minor fluctuations in reward are noted, primarily attributable to typical alterations in vehicle motion and wireless circumstances, rather than instability in the learning process. This behavior indicates that the RL component of AI-VASNet stabilizes post-training, yielding consistent routing decisions in dynamic network environments.

Figure 6 shows how the FL-trained reliability prediction model's accuracy changes across several rounds of aggregation. Accuracy is calculated as the ratio of correctly predicted linkoutcome instances to the total number of locally observed samples aggregated across rounds. The model's accuracy increases rapidly at the outset, suggesting that it is learning valuable patterns from the information shared by various nodes. The improvement in accuracy decreases with the number of federated rounds, stabilizing at about 87% after 40–50 rounds. This suggests that the FL process has completed its training and that the shared model has achieved convergence. Since only model updates are transmitted during federated aggregation, each vehicle can benefit from collaborative learning while training and using the model locally. This shows that the algorithm's underlying FL process is effective and stable.

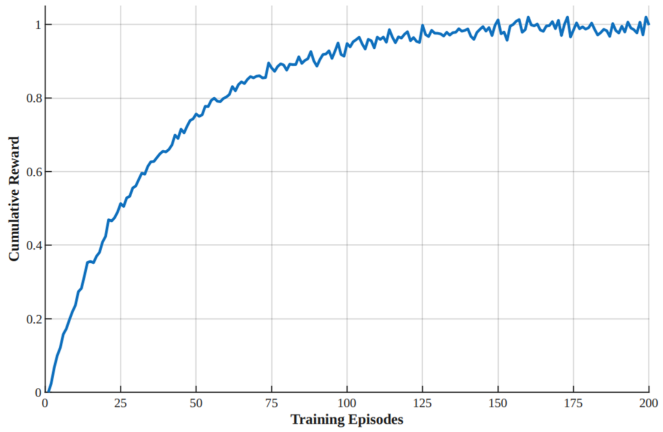

Fig. 5. Cumulative reward versus training episodes demonstrating RL convergence in AI-VASNet.

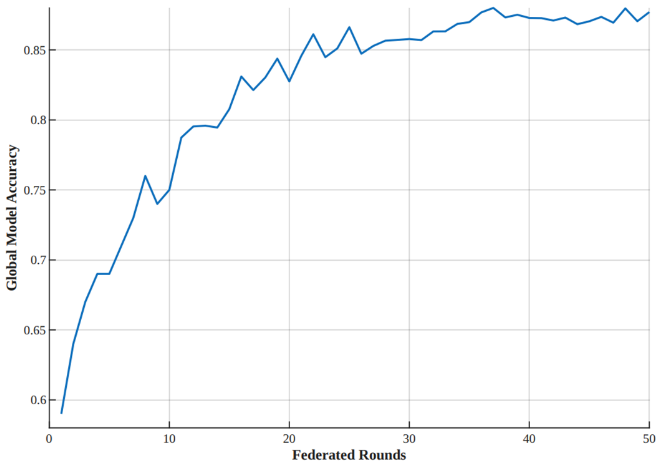

Fig. 6. Global reliability model accuracy versus federated aggregation rounds.

An ablation-based analysis of AI-VASNet is presented in Figure 7, demonstrating the effect of removing individual components on PDR. The full model achieves the highest performance (0.89), validating the effectiveness of the integrated RL, FL, QoS, and instability-aware design. The removal of the FL module (0.83) or the RL module (0.82) results in a significant drop in performance, suggesting that both learning components play a crucial role in enhancing forwarding effectiveness.

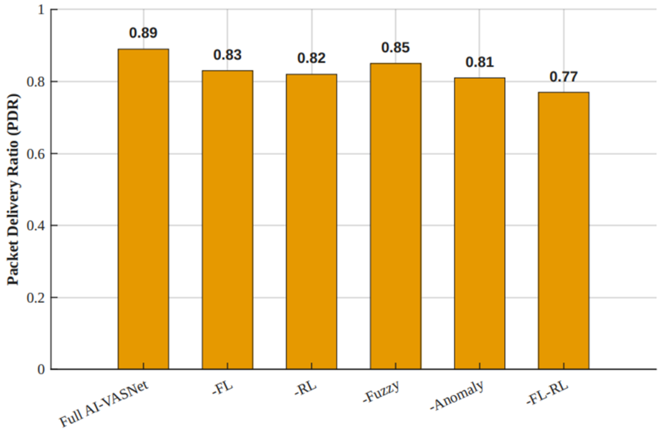

Fig. 7. Ablation study illustrating the impact of removing individual AI-VASNet components on PDR. The label "-Anomaly" corresponds to the removal of the link instability filtering mechanism described in Section II.B.

The elimination of the fuzzy QoS component (0.85) results in a moderate reduction in PDR, indicating that QoS-based prioritization improves forwarding efficiency, albeit its impact is not as significant as that of the learning-based components. Similarly, removing instability filtering (0.81) leads to a further decline in performance, underscoring the critical need to mitigate unreliable links in dynamic vehicular environments. The most significant decrease occurs when both FL and RL are eliminated (0.77), indicating that their combined influence is crucial to the overall effectiveness of AI-VASNet. These findings further support the limitation of single-paradigm learning approaches, such as RL-only or FL-only strategies, which are unable to capture the combined benefits of multi-component integration.

IV. CONCLUSION

The findings of this study demonstrate the efficacy of integrating complementary learning paradigms into a cohesive routing framework designed for highly dynamic vehicular networks. The integration of reliability inference, adaptive Reinforcement Learning (RL)-based forwarding, and Quality-of-Service (QoS)-aware prioritization into a coordinated decision process illustrates that AI-VASNet can significantly enhance routing performance in the face of challenging mobility and channel conditions.

Simulation results demonstrate consistent improvements in delivery reliability, reductions in latency, and improvements in throughput when evaluated against traditional routing methods. The observed improvements indicate that routing strategies that can continuously adapt to changing link quality and congestion conditions provide distinct benefits compared to static or solely heuristic-based mechanisms in dense Vehicle-to-Everything (V2X) environments. The findings emphasize the importance of decentralized, learning-assisted control in vehicular networking, particularly in scenarios where rapid topology changes hinder the efficacy of static forwarding rules. Hybrid adaptive routing strategies represent a promising direction for scalable and resilient next-generation V2X systems.

Future research will concentrate on expanding the framework to support emerging New Radio Vehicle-to-Everything (NR-V2X) and 5G/6G communication architectures. This will involve integrating energy-aware adaptations for electric and autonomous vehicles, as well as performing experimental validation through hardware-in-the-loop and real-world vehicular testbeds to assess deployment feasibility.

DECLARATION OF COMPETING INTERESTS

Not applicable to this work.

ACKNOWLEDGMENT

Not applicable to this work.

DATA AVAILABILITY

This study does not use any datasets that are publicly available or privately acquired. Results are generated via simulation, with the required parameters and methodological details outlined in the manuscript.

AI USE AND DECLARATION OF GENERATIVE AI USE

During the preparation of this work the authors used ChatGPT to assist in language refinement and structuring of the paper. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

REFERENCES

[1] J. Wang, C. Jiang, K. Zhang, T. Q. S. Quek, Y. Ren, and L. Hanzo, "Vehicular Sensing Networks in a Smart City: Principles, Technologies and Applications," *IEEE Wireless Communications*, vol. 25, no. 1, pp. 122–132, Feb. 2018, https://doi.org/10.1109/MWC.2017.1600275.

[2] N. H. Hussein, C. T. Yaw, S. P. Koh, S. K. Tiong, and K. H. Chong, "A Comprehensive Survey on Vehicular Networking: Communications, Applications, Challenges, and Upcoming Research Directions," *IEEE Access*, vol. 10, pp. 86127–86180, 2022, https://doi.org/10.1109/ACCESS.2022.3198656.

[3] B. Saoud *et al.*, "Artificial Intelligence, Internet of things and 6G methodologies in the context of Vehicular Ad-hoc Networks (VANETs): Survey," *ICT Express*, vol. 10, no. 4, pp. 959–980, Aug. 2024, https://doi.org/10.1016/j.icte.2024.05.008.

[4] J. Hao, R. Naja, and D. Zeghlache, "Adaptive federated reinforcement learning for critical realtime communications in UAV assisted vehicular networks," *Computer Networks*, vol. 247, June 2024, Art. no. 110456, https://doi.org/10.1016/j.comnet.2024.110456.

[5] A. S. Ali, A. A. Al-Habob, S. Naser, L. Bariah, O. A. Dobre, and S. Muhaidat, "Deep Reinforcement Learning for Energy-Efficient Data Dissemination Through UAV Networks," *IEEE Open Journal of the Communications Society*, vol. 5, pp. 5567–5583, 2024, https://doi.org/10.1109/OJCOMS.2024.3398718.

[6] R. A. Nazib and S. Moh, "Reinforcement Learning-Based Routing Protocols for Vehicular Ad Hoc Networks: A Comparative Survey," *IEEE Access*, vol. 9, pp. 27552–27587, 2021, https://doi.org/10.1109/ACCESS.2021.3058388.

[7] J. Guo *et al.*, "TROVE: A Context-Awareness Trust Model for VANETs Using Reinforcement Learning," *IEEE Internet of Things Journal*, vol. 7, no. 7, pp. 6647–6662, July 2020, https://doi.org/10.1109/JIOT.2020.2975084.

[8] P. Upadhyay *et al.*, "An improved deep reinforcement learning routing technique for collision-free VANET," *Scientific Reports*, vol. 13, no. 1, Dec. 2023, Art. no. 21796, https://doi.org/10.1038/s41598-023-48956-y.

[9] O. Sarker, H. Shen, and M. A. Babar, "Reinforcement Learning Based Neighbour Selection for VANET with Adaptive Trust Management," in *2023 IEEE 22nd International Conference on Trust, Security and Privacy in Computing and Communications (TrustCom)*, Exeter, United Kingdom, 2023, pp. 585–594, https://doi.org/10.1109/TrustCom60117.2023.00091.

[10] T. Akyildiz and H. Mahdavifar, "Deep Reinforcement Learning-Aided Strategies for Big Data Offloading in Vehicular Networks." arXiv, Dec. 19, 2025, https://doi.org/10.48550/arXiv.2512.17133.

[11] J. Wu, M. Fang, H. Li, and X. Li, "RSU-Assisted Traffic-Aware Routing Based on Reinforcement Learning for Urban Vanets," *IEEE Access*, vol. 8, pp. 5733–5748, 2020, https://doi.org/10.1109/ACCESS.2020.2963850.

[12] H. Al-Maliki, H. A. A. AL-Asadi, Z. A. Abduljabbar, and V. O. Nyangaresi, "Reliable Vehicular Ad Hoc Networks for Intelligent Transportation Systems based on the Snake Optimization Algorithm," *Engineering, Technology & Applied Science Research*, vol. 14, no. 6, pp. 18631–18639, Dec. 2024, https://doi.org/10.48084/etasr.8851.

[13] S. Ye, L. Xu, Z. Xu, and F. Wang, "A deep reinforcement learning-based intelligent QoS optimization algorithm for efficient routing in vehicular networks," *Alexandria Engineering Journal*, vol. 107, pp. 317–331, Nov. 2024, https://doi.org/10.1016/j.aej.2024.07.045.

[14] X. Liu, B. S. Amour, and A. Jaekel, "A Reinforcement Learning-Based Congestion Control Approach for V2V Communication in VANET," *Applied Sciences*, vol. 13, no. 6, Mar. 2023, Art. no. 3640, https://doi.org/10.3390/app13063640.

[15] W. Zhang, X. Yang, Q. Song, and L. Zhao, "V2V Routing in VANET Based on Fuzzy Logic and Reinforcement Learning," *International Journal of Computers Communications & Control*, vol. 16, no. 1, Jan. 2021, Art. no. 4123, https://doi.org/10.15837/ijccc.2021.1.4123.

[16] D. Chen, T. Deng, J. Jia, S. Feng, and D. Yuan, "Mobility-aware decentralized federated learning with joint optimization of local iteration and leader selection for vehicular networks," *Computer Networks*, vol. 263, May 2025, Art. no. 111232, https://doi.org/10.1016/j.comnet.2025.111232.

[17] X. Qiang, Z. Chang, C. Ye, T. Hämäläinen, and G. Min, "Split Federated Learning Empowered Vehicular Edge Intelligence: Concept, Adaptive Design, and Future Directions," *IEEE Wireless Communications*, vol. 32, no. 4, pp. 90–97, Aug. 2025, https://doi.org/10.1109/MWC.009.2400219.

[18] R. Valente, C. Senna, P. Rito, and S. Sargento, "Embedded Federated Learning for VANET Environments," *Applied Sciences*, vol. 13, no. 4, Feb. 2023, Art. no. 2329, https://doi.org/10.3390/app13042329.

[19] M. Piran, R. M. Garimella, and P. Babu, "Vehicular Ad Hoc and Sensor Networks: Principals and Challenges," *International Journal of Ad hoc, Sensor & Ubiquitous Computing*, vol. 2, no. 2, pp. 38–49, June 2011, https://doi.org/10.5121/ijasuc.2011.2204.

[20] R. Al-Qassas and M. Qasaimeh, "An empirical evaluation of link quality utilization in ETX routing for VANETs," *PeerJ Computer Science*, vol. 10, Sept. 2024, Art. no. e2259, https://doi.org/10.7717/peerj-cs.2259.

[21] J. Cao, Y. Bian, C. He, F. Liu, D. Xu, and Y. Guo, "Evaluation of Connectivity Reliability of VANETs Considering Node Mobility and Multiple Failure Modes," *Sensors*, vol. 25, no. 19, Oct. 2025, Art. no. 6073, https://doi.org/10.3390/s25196073.

[22] V. P. Chellapandi, L. Yuan, C. G. Brinton, S. H. Żak, and Z. Wang, "Federated Learning for Connected and Automated Vehicles: A Survey of Existing Approaches and Challenges," *IEEE Transactions on Intelligent Vehicles*, vol. 9, no. 1, pp. 119–137, Jan. 2024, https://doi.org/10.1109/TIV.2023.3332675.

[23] J. Lansky, A. M. Rahmani, and M. Hosseinzadeh, "Reinforcement Learning-Based Routing Protocols in Vehicular Ad Hoc Networks for Intelligent Transport System (ITS): A Survey," *Mathematics*, vol. 10, no. 24, Dec. 2022, Art. no. 4673, https://doi.org/10.3390/math10244673.

[24] S. K. Basha and T. N. Shankar, "Fuzzy logic based forwarder selection for efficient data dissemination in VANETs," *Wireless Networks*, vol.

27, no. 3, pp. 2193–2216, Apr. 2021, https://doi.org/10.1007/s11276-021-02548-8.

[25] Y. L. Morgan, "Notes on DSRC & WAVE Standards Suite: Its Architecture, Design, and Characteristics," *IEEE Communications Surveys & Tutorials*, vol. 12, no. 4, pp. 504–518, 2010, https://doi.org/10.1109/SURV.2010.033010.00024.

[26] N. Iturbe-Olleta, J. Bilbao, O. Iparraguirre, J. Mendizabal, and A. Brazalez, "An adjusted propagation model for ITS-G5 communications for improving the location of RSUs in real V2I deployments," *Vehicular Communications*, vol. 45, Feb. 2024, Art. no. 100716, https://doi.org/10.1016/j.vehcom.2023.100716.

[27] S. Sharma, S. Kour, and H. Sarangal, "Modeling and simulation of VANET routing protocols under realistic mobility patterns," *Scientific Reports*, vol. 16, no. 1, Feb. 2026, Art. no. 9130, https://doi.org/10.1038/s41598-026-36039-7.