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Lookahead VANET Routing: Mobility-aware Deep Neural Network-based Vehicular Communications

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Abstract

Vehicular ad hoc networks (VANETs) face persistent challenges in maintaining reliable message routing and communication. Existing methods often rely on exhaustive path comparisons or excessive control messages, making them unsuitable for high-mobility environments. Motivated by these limitations, a Deep neural network (DNN)-based Lookahead routing scheme is proposed that utilizes local spatial-temporal information to enable real-time, globally efficient next-hop decisions. A novel grid-based representation of the vehicular environment is introduced to enable learning-based routing using local observations. First, an analytical model is introduced to minimize per-hop transmission time, effectively reducing end-to-end delay without requiring global topology awareness. Secondly, a U-Net-style DNN is proposed and trained to perform predictive, learning-based

routing in dynamic vehicular environments, significantly reducing computational overhead. Empirical evaluations demonstrate that the proposed method outperforms two state-of-the-art baselines by increasing throughput and packet delivery ratio by **5-10%**. Additionally, the outage probability is reduced from **58%** to **45%** and from **91%** to **82%**, demonstrating robustness in high mobility.

Keywords: Deep Neural Networks, Intelligent Transportation Systems, Mobility-aware routing, Vehicular Networks

1 Introduction

Vehicular ad hoc networks (VANETs) are a core part of intelligent transportation systems (ITS). VANETs support safety-critical and data-intensive services such as collision avoidance, cooperative traffic management, infotainment, and autonomous driving assistance [1, 2]. These services require reliable, low-latency, and scalable communication, even under rapid topology changes, intermittent connectivity, and heterogeneous traffic density [3–5]. In such environments, routing decisions must be made quickly and remain effective over short communication windows. The inherent characteristics of vehicular environments, such as high mobility, frequent link breakages, and non-uniform spatial distributions render traditional mobile ad hoc network (MANET) routing strategies insufficient. Multi-hop message routing decisions are often made either based on instantaneous local observations without considering future implications, or through global path discovery mechanisms that are computationally expensive and quickly obsolete.

Existing VANET routing protocols are commonly grouped into geographical-based, heuristic-based, architecture-specific, machine learning (ML), reinforcement learning (RL), and bio-inspired or meta-heuristic approaches [1, 3, 5–7]. Geographic routing uses position information and digital maps to guide forwarding decisions. It can scale well in sparse settings, but it depends on accurate localization and frequent control exchange. Heuristic methods often rely on single-hop indicators such as distance, signal strength, or delay. They are computationally simple, but they do not capture temporal changes in link quality and may degrade multi-hop performance. Route discover in reactive routing adds delays and control overhead, leading to discovered paths being outdated in high-mobility scenarios. Existing studies have identified limitations in reactive routing as well as learning-based approaches. Some ML models still lack the correlation-recovery capability needed for future high-demand vehicular systems [1], while RL-based routing can suffer from large Q-tables, generalization issues, and added control overhead [5]. The limitation in existing schemes point to a clear problem. Several of the solutions depend on fixed infrastructure, global topology knowledge, or expensive path discovery, while few rely only on instantaneous local observations. As a result, routing decisions either become costly to compute or completely fail to reflect the spatio-temporal dynamics of vehicular networks. This creates the need for a lightweight and decentralized routing method that uses real-time local information while still capturing future network behavior for efficient multi-hop communication.

To specifically cater to this challenge, we proposes a deep neural network (DNN)-based Lookahead routing framework for efficient and adaptive VANET routing. The goal of the proposed scheme is to use myopic local forwarding while avoiding centralized bottlenecks and computation load.

The proposed framework has two components. First, an analytical model formulates next-hop selection as a one-hop lookahead optimization problem. A source node selects the neighbor that minimizes the estimated end-to-end (E2E) transmission time to the destination. The design of forward-looking decision making does not required explicit multi-hop path computation. Second, a supervised deep learning model learns this decision process through a grid-based representation of the vehicular environment. The DNN model captures spatial distribution and temporal dynamics in a compact form and supports inference with lower computational complexity. The proposed scheme operates in a fully decentralized manner. It does not require global state information, infrastructure support, or frequent control signaling. The main contributions of this work are summarized as follows:

- We propose an analytical routing model that reduces outage probability and transmission delay by relying only on local spatial and temporal information for efficient next-hop selection.
- We design a supervised deep learning-based routing framework built on a modified U-Net architecture, where dynamic vehicular environments are represented as a 3-channel grid. This design enables fast routing decisions with lower computational cost.
- Extensive simulation results show that the proposed method reduces transmission time, improves throughput, and increases packet delivery ratio (PDR) by up to 10% compared with existing state-of-the-art approaches. The method also reduces outage probability from 58% to 45% and from 91% to 82%, demonstrating stronger robustness in highly mobile scenarios.

The remainder of this paper is organized as follows. A detailed literature review is outlined in 2. Section 3 presents the system model and problem formulation. Section 4 describes the proposed Lookahead routing framework. Section 5 reports the training procedure, performance evaluation, and complexity analysis. Finally, Section 6 concludes the paper.

2 Literature Review

Recent studies on routing in VANETs have explored diverse strategies including bus-assisted forwarding, link-reliability-aware routing, metaheuristic optimization, clustering, security-aware routing, software-defined networking, and learning-based methods. Figure 1 illustrates a brief summary of existing research works. Modern ITS demand routing protocols that balance high mobility, intermittent connectivity, and quality of service (QoS) requirements. The existing literature shows that routing design in VANETs is increasingly shifting from purely shortest-path or greedy forwarding mechanisms toward context-aware, predictive, and intelligent decision frameworks. At the same time, most works remain specialized to a limited objective such as delay,

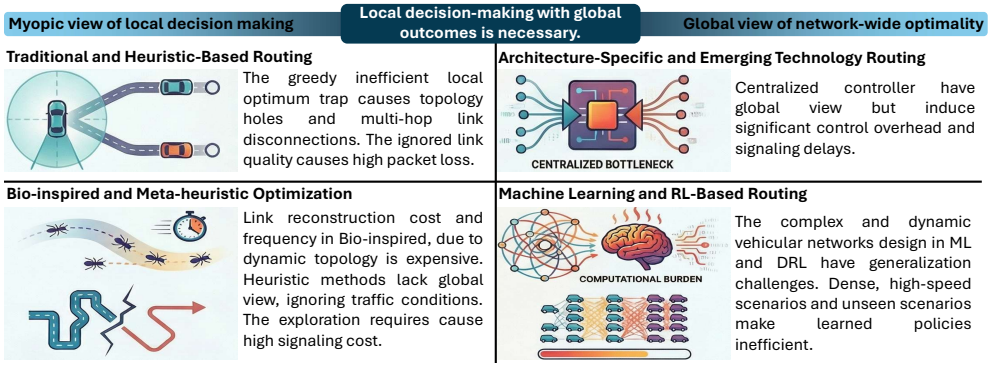


Fig. 1 Summarized findings of different routing strategies in vehicular networks

packet delivery, trust, or overhead, rather than jointly addressing the broader routing challenges of highly dynamic vehicular environments.

2.1 Traditional and Heuristic-Based Routing

Traditional and heuristic-based routing protocols in VANETs exploit geographical information, predictable mobility patterns, or multi-criteria forwarding rules to improve packet delivery. There exist substantial work that rely on public transportation routes, whereas others incorporate link prediction, environmental awareness, or relay stability into routing decisions. The following works summarize representative contributions in this category.

A Bus-based routing technique (BRT) in [8] proposed to exploit the regular mobility of buses by classifying vehicles into backbone buses/vehicles and by constructing forwarding paths according to temporal distance. The main contribution of this study is a two-phase design consisting of a temporal-distance learning stage and a data delivery stage, together with a maintenance mechanism to handle forwarding issues. BRT's reliance on predictable bus routes and additional infrastructure limits effectiveness in situations with inconsistent mobility or insufficient transit support. A similar scheme in [9] proposed to exploit parked vehicles in parking areas as stable relay nodes to bypass obstacles and coverage holes during emergency message dissemination. The parking-area-assisted spider-web routing (PASRP) model combined digital maps, multi-mode greedy forwarding, and dynamic priority scheduling to improve delivery reliability and delay performance. Nevertheless, the protocol depends on the availability of suitable parked-vehicle support and has a much higher routing overhead than greedy perimeter stateless routing (GPSR) because of request-spider control packets. Authors in [10] combined zone-based route discovery with proactive link failure prediction to reduce unnecessary message flooding and anticipate route breakages. The proposed scheme is the joint improvement of route establishment and maintenance through controlled route-request dissemination and mobility-aware link monitoring. However, the method does not specifically address the intersection-centric behavior

Table 1 Traditional and architecture-specific related works on vehicular networks routing. [RREQ= Route request message, SINR= Signal-interference-noise ratio]

Technique	Objective(s)	Decision Parameters	Metrics
BRT: Bus-based Routing (2020) [8]	Minimize time to reach gateway	temporal distance to RSUs, bus trajectory	Delivery time, overhead
PASRP: Parking Assisted (2020) [9]	Emergency data dissemination	Parked vehicle locations	Delay, PDR, Routing overhead
Zone-based route discovery (2020) [10]	Control RREQ flooding; avoid breakages	Geographical zones, mobility info	Routing load, E2E delay, PDR
Multilevel adaptive routing (2020) [11]	Portray 3D links accurately	SINR, buffer queue, corrected GPS	PDR, E2E delay
HERO: Inter/Intra Path (2021) [12]	Professional road segment selection	Angle, distance, buffer, fading	PDR, latency, overhead
SPDR: Speed Aware (2022) [13]	Message dissemination with stability	RDA range, relative velocity	Message Delivery Ratio, Average Dissemination Delay, throughput
Clustering under SDN (2020) [14]	Balance cellular cost and delay	distance to RSU, link capacity	Hop count, overhead ratio
SURFER: Hybrid SDN (2021) [15]	balance latency, cost, connectivity	COST, LAT, SINR, PC	PDR, Delay, Routing overhead, Node traffic
Trust-aware routing (2021) [16]	Security vs. black/gray holes	Waiting time, trust score	Trust score, E2E delay
Pattern Discovery (2023) [17]	minimize latency via prediction	distance to hole node, similarity	PDR, total delay
6G-ARP (Mod-AODV) (2025) [6]	high-performance 6G IoT	link throughput, hops	Average PDR, Delay

and road-constrained movement typical of urban VANETs because it was created in the context of source routing for mobile networks.

A multilevel adaptive routing approach in [11] modeled link reliability in three-dimensional complex scenarios such as overpasses and tunnels while correcting global positioning system (GPS) errors through a Kalman filter. The study is a unified adaptive routing framework that integrates accurate positioning, vehicle dynamics, shadow fading, queue state, and multilevel node characteristics into the routing decision process. Its limitation is the reliance on accurate estimation and fusion of many parameters, which increases model complexity and may reduce robustness under sensing or estimation errors. Hawbani *et al.* in [12] proposed HERO, a multi-criteria heuristic routing protocol that decompose routing into, interpath road-segment selection and intrapath relay-vehicle selection. The main contribution of this work is a distributed heuristic framework that jointly considers distance, connectivity, relative

Table 2 Machine learning and Bio-inspired related works on vehicular networks routing. [RREQ= Route request message, SINR= Signal-interference-noise ratio]

Technique	Objective(s)	Decision Parameters	Metrics
UAV-assisted communications (2021) [18]	detect malicious nodes	QoS value, distrust value	PDR, delay, overhead
IV2XQ: Intersection RL (2022) [19]	Avoid congested roads	traffic flow, distance	PDR, delay, overhead
Evolved Dijkstra / Deep RL (2023) [20]	minimize E2E delay in FD	link delay, FD node density	E2E delay
UniFaVa: HV-Opt. (2023) [21]	Optimal GV/UAV route	rate, residual energy, reliability	outage, hops, energy
Energy-efficient ML routing (2023) [22]	Energy-efficient offloading	Position, speed, energy	PDR, throughput, energy
Grouped RSU Q-learning (2024) [2]	manage traffic via RSU groups	hop count, rewards	PDR, lifetime, broadcasts
PRCQ: CNN+Q-learning (2025) [23]	Maximize delivery success	node similarity, mobility	Delivery success ratio, average hops, delay
Cuckoo Search (2020) [24]	Find shortest Hamiltonian path	SNR, average velocity	Route reliability score
SPIDER: Predictive (2022) [25]	Low-latency reliable exchange	Link lifetime, jitter	Delay, jitter, PDR
Self-healing ACO (2022) [26]	Multiplex stable paths	CP, pheromones, repair	E2E delay, time overhead, throughput
HHO: Harris Hawks (2023) [27]	Optimal CH selection stability	CH stability, mobility	overhead, cluster lifetime
EO-C: Equilibrium Optimization (2025) [28]	green routing survival	Particle concentration	packets sent, energy
CLORP: Lion Optimization (2025) [7]	reduce RREQ congestion	energy, velocity, fitness	PDR, CH lifetime, overhead

speed, movement direction, buffer size, and fading to improve delivery ratio, latency, and overhead. A limitation of HERO is the complexity associated with combining several metrics and heuristic probability models, which may require careful tuning under stochastic traffic conditions. Authors in [13] proposed SPDR: speed and position aware routing, which dynamically adjust the forwarding-neighbor range hop-by-hop based on relative velocity. While this method claim to improves message stability, reduce delay, and enables group mobility awareness, it does not generalize well to multi-hop routing optimization.

2.2 Architecture-Specific and Emerging Technology Routing

Architecture-specific routing studies in VANETs increasingly incorporate emerging techniques of software defined network (SDN), blockchain, full-duplex (FD) communication, unmanned aerial vehicle (UAV) assistance, and 6G-oriented design to address security, delay, and connectivity challenges. The general goal is to move beyond conventional ad hoc routing by leveraging infrastructure support, architectural coordination, or advanced communication models.

Qi *et al.* in [14] studied routing in a hybrid dedicated short-range communications (DSRC) and cellular vehicle-to-everything (C-V2X) vehicular network and proposed a traffic-differentiated clustering routing mechanism under an SDN-enabled architecture. The formulated tradeoff between E2E delay and cellular bandwidth cost is addressed through centralized clustering and a two-stage heuristic delivery algorithm. However, the framework depends on hybrid communication support and centralized architectural coordination, which may increase deployment complexity and reduce practicality in decentralized scenarios. A secure SDN-based routing protocol for the Internet of Vehicles in [15] proposed SURFER, that integrated distributed SDN control with blockchain-based consensus to secure routing among road-side units (RSUs). The study takes routing intelligence into an SDN-enabled roadside architecture for long-distance forwarding with security support that improves packet delivery, latency, and routing overhead. However, SURFER strongly depends on SDN-capable RSU infrastructure and blockchain-assisted support, which increases architectural complexity and reduces effectiveness when RSUs are sparse or unavailable.

A secure trust-aware cross-layer routing protocol in [16] for VANETs integrated trust evaluation into both channel access and packet-forwarding decisions to counter routing attacks. The cross-layer incorporation of trust management is used to mitigate malicious behaviors such as black hole, gray hole, and denial-of-service attacks while protecting routing performance. The trust management introduced additional monitoring and decision overhead, and its effectiveness depends on the accuracy and timeliness of behavioral observations. A clustering-based routing protocol with path pattern discovery in [17] incorporated vehicle movement prediction and pattern extraction into delay-oriented forwarding decisions. The integration of future path continuity information into clustering-based routing better reflected anticipated mobility behavior. The routing performance depends strongly on the quality of movement-pattern discovery, and inaccurate or nonstationary mobility patterns can reduce the expected delay benefits. Authors in [6] proposed an adaptive QoS-aware routing protocol (6G-ARP) that focused on emerging 6G requirements, including extreme mobility and heterogeneous industrial Internet of things (IoT) environments. The path-selection strategy is based on throughput and hop count to improve reliability and latency in highly distributed ad hoc settings. However, the scheme remains limited by its reliance on relatively simple QoS metrics, its lack of broader treatment of heterogeneous 6G space–air–ground conditions.

2.3 Machine Learning and Reinforcement Learning Based Routing

Reinforcement learning (RL) has emerged as a prominent routing paradigm in VANETs due to effective learned policies from interactions and experience and continuous learning model. Existing studies have applied Q-learning, hierarchical RL, and hybrid deep learning frameworks to improve relay selection, path planning, and routing adaptation under dynamic vehicular conditions.

An innovative study in [18] extended routing design beyond purely terrestrial vehicular forwarding by jointly considering routing efficiency, security, and UAV-assisted communication However, the limitation is its dependence on UAV support and artificial intelligence (AI)-driven decision modules which introduces additional implementation complexity, cost, and coordination requirements for large-scale deployment. An intersection-based IV2XQ routing scheme in [19] used Q-learning to determine intersection sequences and location-based relaying between intersections. The study incorporated vehicle density into a multidimensional Q-table to improve routing decisions while reducing routing overhead. However, the method depends on historical traffic flow and RSU-assisted forwarding, which limits real-time adaptation to instantaneous link conditions only. In [20], an evolved Dijkstra algorithm was proposed to select next-hop nodes based on shortest path criteria, later enhanced using a deep Q-network to reduce E2E delay. This study reformulated E2E routing under full-duplex communication assumptions and the design of graph-based and learning-based solutions tailored to that setting. A limitation is that the computational speed is constrained by the complexity of identifying maximal full-duplex-connected subgraphs, and the framework also relies on the availability of full-duplex-capable vehicles. Authors in [21] consider a flying ad hoc networks (FANET)–VANET architecture (UniFaVa), where both ground and aerial vehicles are used in routing path. The solution considered applying hypervolume-based multi-objective optimization to jointly improve data rate and energy efficiency. Multiple ML models were trained to estimate connectivity duration between aerial and terrestrial vehicles, relying on a centralized inference engine accessed via network APIs. Although this enables flexible and potentially accurate predictions, the centralized architecture introduces scalability limitations, communication delays, and a single point of failure.

Authors in [22] introduce a machine-learning-based centralized dynamic clustering algorithm that employs fuzzy c-means and a distance–power variant for energy-efficient routing in VANETs. Exhaustive evaluation across SUMO, NetSim, and MATLAB showed improvements in packet delivery, delay, and energy consumption, using mobility and residual energy features to select stable cluster heads (CHs). However, the centralized clustering process does not fully resolve QoS issues in highly dynamic environments and leaves scalability, security robustness, and real-world validation insufficiently addressed. A hierarchical reinforcement learning scheme in [2] grouped RSUs to maintain local and global Q-tables for routing support. The goal is to reduce computational complexity through RSU grouping while enabling V2V routing decisions based on localized link-table information. The proposed solution is strongly dependent on fixed RSU infrastructure, and the overhead of Q-table maintenance and lookup is not fully discussed. Authors in [23] proposed a probabilistic routing

framework based on convolutional neural network (CNN)-based feature extraction with Q-learning (PRCQ), to select relays in vehicular edge networks. The scheme integrated learned latent node representations with reinforcement learning to estimate transition probabilities and optimized long-term routing returns in uncertain and dynamic environments. However, the approach requires considerable computing and storage resources, and it is further limited by simulation-only validation and the lack of detailed discussion on scalability and model generalization.

2.4 Bio-inspired and Meta-heuristic Optimization

Bio-inspired and meta-heuristic routing methods have been extensively investigated for VANETs to improve route discovery, clustering, and forwarding stability under highly dynamic conditions. These studies typically exploit nature-inspired search behaviors to optimize path selection, cluster-head election, or route maintenance according to metrics such as reliability, energy, mobility, and signaling cost.

A discrete cuckoo search-based route discovery framework in [24] is proposed for IoT-based VANETs. The cuckoo search is adapted to discrete routing through inverse mutation and a reliability-oriented objective function for loop-free shortest Hamiltonian paths. However, the method remains computationally demanding in dense deployments, and its metaheuristic nature raises concerns regarding scalability and online applicability in rapidly changing vehicular topologies. An interesting social-computing-inspired predictive routing scheme (SPIDER) in [25] combined context-aware movement prediction with social-aware relay selection under software-defined vehicular networks control. The design of a predictive forwarding framework targets low-latency and reliable packet delivery through coordinated software-defined support and mobility-aware relay decisions. The scheme strongly depends on accurate historical data, predictive modeling quality, and software-defined infrastructure, which reduces its effectiveness when traffic patterns are highly irregular or infrastructure support is limited. Authors in [26] presented a self-healing routing strategy based on ant colony optimization, incorporating a self-repair mechanism that monitors pheromone levels and repairs links before complete route failure occurs. However, the ant-colony search and repair processes enhanced route durability it also introduce additional computational and signaling complexity, especially when compared with simpler intersection-based routing methods.

A novel VANET clustering algorithm based on Harris hawks optimization (HHO) in [27] applied a population-based metaheuristic to cluster-head selection in dynamic vehicular search spaces. In [27], a population-based metaheuristic Harris Hawks optimization (HHO) was used to select cluster heads in dynamic vehicular search spaces. The use of modern swarm-intelligence optimizer improved critical routing efficiency factors of clustering quality and stability. Nevertheless, the method suffers from parameter sensitivity, considerable computational burden, and slow convergence in high mobility VANETs. Authors in [28] proposed a nature-inspired multi-objective clustering protocol using the equilibrium optimizer (EO-C). A composite fitness-based cluster-head selection framework jointly targets energy consumption across nodes, network lifetime, and reliability within an SDN-enabled and IoT-oriented setting. However, practical issues such as control overhead, convergence cost, and deployment

realism are insufficiently addressed. Authors in [7] introduced a lion optimization-based routing protocol (CLORP) that selects the fittest cluster heads considering energy, distance, and velocity. The innovative solution integrated bio-inspired optimization with clustered AODV-style routing and gateway-assisted communication to improve routing efficiency and reduce control overhead in Internet of vehicles (IoV) scenarios. However, the complexity of real-time optimization and the challenge of balancing multiple competing fitness criteria in dynamic vehicular networks is still a major issue. While the evaluation also provides limited evidence regarding scalability and computational costs.

2.5 Research Gap

Existing studies have reported promising routing improvements in VANETs, but most existing solutions are optimized for a limited set of objectives, such as delay minimization, packet delivery enhancement, trust reinforcement, or infrastructure-assisted forwarding. The studies rely on handcrafted heuristics, metaheuristic optimization, or strong architectural assumptions, including bus backbones, parked-vehicle assistance, SDN control, blockchain support, UAV relays, and hybrid DSRC/C-V2X environments. Even recent learning-based and predictive approaches fall short, as they are typically tailored to specific routing settings rather than offering a unified design that simultaneously addresses mobility dynamics, reliability, scalability, and practical deployment. Table 1 and 2 outlines a summery of existing research studies on VANET message routing. A major unresolved issue is the lack of a truly lightweight and infrastructure-independent routing framework that can operate using only immediate local information, such as one-hop or two-hop neighborhood knowledge. Another important limitation of the current literature is its frequent dependence on fixed or semi-fixed infrastructure. Several advanced protocols assume the continuous availability of RSUs, predictable bus trajectories, parked vehicles, dedicated UAVs, or other supporting entities that may not exist in rural roads, sparse deployments, or disaster-affected environments. Bio-inspired and optimization-based approaches can improve route quality and reliability, but their iterative computation and control overhead may be inconsistent with the stringent latency requirements of safety-critical or emergency vehicular applications.

These limitations highlight a clear opportunity for a routing framework that replaces global path planning with immediate contextual decision-making based only on local neighboring vehicles. A significant research gap remains in the design of a lightweight, prediction-aware, next-hop-oriented routing model that is adaptive, distributed, and reliable under highly dynamic vehicular conditions while avoiding excessive infrastructure dependence and optimization overhead. This article explores the possibility of filling this research gap.

3 System Model

Consider a vehicular network consisting of N vehicles denoted by the set $\mathcal{V} = \{v_1, v_2, \ldots, v_N\}$. Each vehicle $v_i \in \mathcal{V}$ is characterized by its instantaneous speed ψ_{v_i}, direction of movement θ_{v_i}, communication range ρ_i, and current location in a 2D

Table 3 List of used symbols with description.

Symbol	Description
N	Total number of vehicles in the network
$\mathcal{V}$	Set of all vehicles, $\mathcal{V} = \{v_1, v_2, \ldots, v_N\}$
v_i, v_s, v_d	Vehicle indexed by i, source, destination
ψ_{v_i}	Instantaneous speed of vehicle v_i
θ_{v_i}	Direction of movement of vehicle v_i
ρ_i, ρ_s	Communication range of vehicle v_i, v_s
$\rho_{\max}$	Maximum allowable communication range
$\mathbf{r}_i(t)$	Position vector of vehicle v_i at time t
$x_i(t), y_i(t)$	Cartesian coordinates of vehicle v_i at time t
$\mathcal{N}_s(t)$	Neighbor set of source vehicle v_s at time t
$d_{i,j}(t)$	Euclidean distance between vehicles v_i and v_j at time t
d_0	Reference distance in the path-loss model
γ	Path-loss exponent
$h_{i,j}(t)$	Instantaneous channel gain between v_i and v_j at time t
$\overline{h}_{i,d}(t)$	Average channel gain between v_i and v_d over the lookahead window
P_i	Transmission power of vehicle v_i
w_i	Bandwidth allocated to vehicle v_i
N_0	Noise power spectral density
$R_{i,j}(t)$	Instantaneous transmission rate from v_i to v_j at time t
$R_{s,i}(t+\tau)$	Predicted transmission rate between v_s and v_i at time $t+\tau$
$\overline{R}_{i,d}(t)$	Average transmission rate between v_i and v_d
$R_{\min}$	Minimum acceptable transmission-rate threshold
τ	Prediction step / lookahead time index
$\mathcal{T}$	Number of future time steps required to transmit D bits
T	Lookahead window length
D	Data size to be transmitted (in bits)
$\tau_{s,i}(t)$	Estimated transmission time from v_s to v_i
$\overline{\tau}_{i,d}(t)$	Average transmission time from v_i to v_d
$\tau_{si,\max}(t)$	Normalization factor for $\tau_{s,i}(t)$
$\overline{\tau}_{id,\max}(t)$	Normalization factor for $\overline{\tau}_{i,d}(t)$
$\overline{d}_{i,d}(t)$	Average distance between v_i and v_d over the lookahead window
$\mathcal{M}_i(t)$	Composite cost metric for candidate next-hop vehicle v_i
α, β	Weighting coefficients satisfying $\alpha + \beta = 1$
$i^*(t)$	Index of the selected best next-hop vehicle at time t

grid given by coordinates $\mathbf{r}_i(t) = (x_i(t), y_i(t))$. Among these, a source vehicle $v_s \in \mathcal{V}$ intends to transmit a message to a destination vehicle $v_d \in \mathcal{V}$. At any given time t, the source vehicle v_s can forward a packet to a subset of vehicles within its communication range, defined below as neighborhood set:

$$\mathcal{N}_s(t) = \left\{ v_j \in \mathcal{V} \;\middle|\; \|\mathbf{r}_s(t) - \mathbf{r}_j(t)\|_2 \leq \rho_s \right\} \tag{1}$$

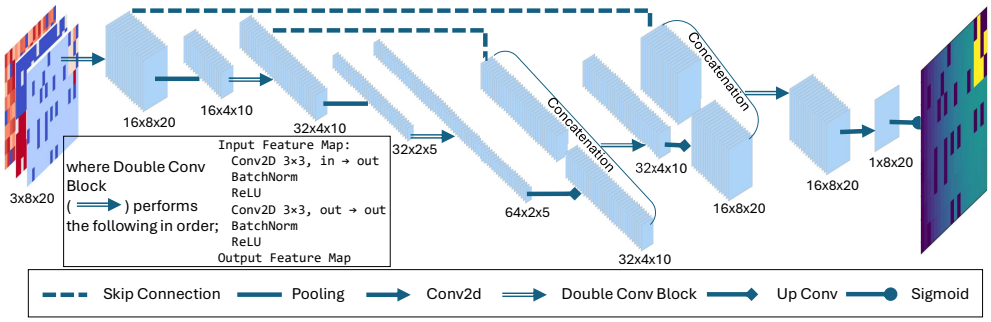


Fig. 2 The proposed U-Net style deep neural network for the DNN-based Lookahead scheme

The instantaneous transmission rate from v_i to v_j at time t considering path loss and fading, is modeled using the Shannon capacity formula:

$$R_{i,j}(t) = w_i \cdot \log_2 \left(1 + \frac{P_i \cdot h_{i,j}(t)}{N_0 \cdot w_i}\right), \tag{2}$$

where w_i is the bandwidth, P_i is the transmission power, $h_{i,j}(t)$ is the time-varying channel gain (including path loss and fading), N_0 is the noise power spectral density (in W/Hz), and $N_0 \cdot w_i$ is the total noise power over the channel.

The channel gain $h_{i,j}(t)$ is modeled based on a distance-dependent path loss function. Assuming free space transmission between each vehicle and the vehicles in its neighborhood, the channel gain can be approximated as: $h_{i,j}(t) = \left(\frac{d_0}{d_{i,j}(t)}\right)^{\gamma}$, where $d_{i,j}(t) = \|\mathbf{r}_i(t) - \mathbf{r}_j(t)\|_2$ is the Euclidean distance between vehicles v_i and v_j at time t, d_0 is a reference distance (typically 1 meter), γ is the path loss exponent (commonly between 2 and 5). Assuming each vehicle moves at a uniform speed in a fixed direction, its position at time $t + \tau$ with time horizon τ can be estimated:

$$x_i(t + \tau) = x_i(t) + \psi_{v_i} \cdot \tau \cdot \cos(\theta_{v_i}), \tag{3}$$

$$y_i(t + \tau) = y_i(t) + \psi_{v_i} \cdot \tau \cdot \sin(\theta_{v_i}), \tag{4}$$

where $\mathbf{r}_i(t) = (x_i(t), y_i(t))$ is the current position of vehicle v_i, ψ_{v_i} is its speed, and θ_{v_i} is its direction (in radians). The Euclidean distance at $t + \tau$ between v_i and v_j is given by:

$$d_{i,j}(t + \tau) = \|\mathbf{r}_i(t + \tau) - \mathbf{r}_j(t + \tau)\|_2 \tag{5}$$

Using this mobility-aware distance, the time-evolving channel gain $h_{i,j}(t + \tau)$ and corresponding transmission rate $R_{i,j}(t + \tau)$ can be similarly estimated at $(t + \tau)$. Table 3 describes all the symbols used throughout this article for reference.

4 The Proposed Lookahead Routing Scheme

4.1 Analytical Model

Efficient VANETs routing requires consideration of geographical position, mobility, communication channel characteristics, and the temporal dynamics of network changes. To account for the dynamic and time-varying nature of transmission rates, a predictive estimation of transmission time over two time-varying channels is adopted, i.e. from v_s to next-hop v_i and from v_i to v_d. Let D be the data size (in bits) to be transmitted, and let $R_{s,i}(t+\tau)$ denote the estimated transmission rate between v_s and v_i at time $t+\tau$. The expected time required to transmit D bits from v_s to v_i is given by:

$$\tau_{s,i}(t) = \min\left\{\mathcal{T} : \sum_{\tau=1}^{\mathcal{T}} R_{s,i}(t+\tau) \geq D\right\} \tag{6}$$

Considering that the link between v_i to v_d might not always be in communications range and have very long distances, we estimate the average distance over a Lookahead window of T future time steps. Accounting for vehicle mobility and the resulting variation in distances over time (granularity of 1 second), the average distance between v_i to v_d is $\overline{d_{i,d}}(t) = \frac{1}{T}\sum_{\tau=1}^{T} d_{i,d}(t+\tau)$. Subsequently, average rate ($\overline{R_{i,d}}(t)$) and average transmission time ($\overline{\tau_{i,d}}(t)$) using channel $\overline{h_{i,d}}(t)$ over average distance $\overline{d_{i,d}}(t)$ can be estimated as $\overline{R_{i,d}}(t) = w_i \cdot \log_2\left(1 + \frac{P_i \cdot \overline{h_{i,d}}(t)}{N_0 \cdot w_i}\right)$ and $\overline{\tau_{i,d}}(t) = \frac{D}{\overline{R_{i,d}}(t)}$. Using transmission times $\tau_{s,i}(t)$ and $\overline{\tau_{i,d}}(t)$, between v_s to next-hop v_i and from v_i to v_d, respectively, a composite metric for the next hop v_i's suitability is formulated using weighted sum equation, as given below:

$$\mathcal{M}_i(t) = \alpha \cdot (\tau_{s,i}(t)/\tau_{si,max}(t)) + \beta \cdot (\overline{\tau_{i,d}}(t)/\overline{\tau_{id,max}}(t))\,, \tag{7}$$

where $\alpha + \beta = 1$ are weights to control trade-off between current hop (v_s to v_i) and progress towards destination (v_i to v_d).

$\mathcal{M}_i(t)$ is a predictive cost metric that captures the quality and stability of the multi-hop link between v_s and v_d via neighbors ($\mathcal{N}_s(t)$). The best-suited intermediate vehicle $i^*(t)$ is chosen by minimizing the objective function:

$$\begin{aligned} i^*(t) = \arg\min_{i \in \mathcal{N}_s(t)} \quad & \mathcal{M}_i(t) \\ \text{subject to} \quad & d_{s,i}(t) \leq \rho_s, && \text{(C1)} \\ & \rho_s \leq \rho_{\max}, && \text{(C2)} \\ & d_{i,d}(t) < d_{s,d}(t), && \text{(C3)} \\ & R_{s,i}(t) \geq R_{\min}, && \text{(C4)} \end{aligned} \tag{8}$$

where $d_{s,i}(t) \leq \rho_s$ ensures communication feasibility, $\rho_s \leq \rho_{\max}$ limits the transmission range, $d_{i,d}(t) < d_{s,d}(t)$ guarantees forward progress toward the destination, and $R_{s,i}(t) \geq R_{\min}$ enforces a minimum acceptable transmission rate.

In the analytical Lookahead routing scheme, the v_s evaluates all neighboring candidates $v_i \in \mathcal{N}_s(t)$ by computing the corresponding $\mathcal{M}_i(t)$. The $\mathcal{M}_i(t)$ calculation using Equation 7 requires location and mobility information of only the neighboring

vehicles ($\mathcal{N}_s(t)$) and destination (v_d), i.e. readily available via basic safety messages (BSMs). The node that minimizes the objective in Equation 8 is selected as the next-hop forwarder. Once selected, this vehicle v_i assumes the role of the new source (v_s), and the process repeats until the packet is delivered to the destination vehicle v_d.

4.2 DNN-based Model

To reduce the computational overhead of evaluating all neighbor candidates in real-time, a DNN-based Lookahead scheme is introduced. Each vehicle is assumed to have access to a pre-trained model that accepts a 3-channel grid representation of the environment, where each grid cell encodes vehicle presence, direction, and speed, or represents an empty space. Given this 3-channel input, the DNN predicts the efficient next-hop decision. The same process is recursively applied at each hop until the data successfully reaches the destination. The trained model outputs a grid of action probabilities, where the cell with the highest value corresponds to the next-hop that best minimizes the routing objective. The model takes as input a 3-channel tensor representing grid-wise spatio-temporal features of the local vehicular environment. The training dataset is constructed using input-output pairs, where the action probabilities are derived from our proposed analytical model. Algorithm 1 outlines the process of the proposed scheme in both analytical and DNN-based Lookahead routing solutions. Given the $\mathcal{N}_s(t)$ and v_d, a vehicle inexpensively identifies next hop (v_i) that minimizes the objective identified in Equation 8.

The proposed DNN model illustrated in Figure 2 is based on a U-Net inspired convolutional neural network architecture to efficiently predict inexpensive routing actions in dynamic vehicular environments. U-Net [29] is well-suited for this spatial prediction task due to its ability to capture fine-grained local features while preserving global spatial context. This is achieved through skip connections that transfer information directly from the encoder (down-sampling) to the decoder (up-sampling) pathways. Our model architecture consists of an encoder-decoder structure connected through a bottleneck. The encoder (first five layers) progressively captures higher-level spatial abstractions through two sequential convolutional blocks, each containing two convolutional layers followed by batch normalization and ReLU activations. Max-pooling operations reduce spatial dimensions, enabling hierarchical feature extraction. The bottleneck further distills these features into compact representations. The decoder (second five layers) subsequently reconstructs spatial predictions from these compact representations. Transposed convolution layers expand the spatial dimensions, progressively recovering the grid-based resolution. Skip connections from corresponding encoder layers preserve high-resolution spatial information, which is required for accurate localization predictions on the grid. The final convolutional layer returns the tensor with the equivalent shape as of the grid, representing the predicted probabilities, where the sigmoid activation ensures that all action probabilities lie within $[0, 1]$ range. The training objective of the model is to minimize the mean squared error (MSE) between the predicted action probabilities and the ground-truth probability distributions derived from simulations.

Algorithm 1 The proposed lookahead routing scheme

Input: Source v_s, destination v_d, data size D, prediction horizon T
Initialize $v_i \leftarrow v_s$
while $v_i \neq v_d$ **do**
    Obtain neighborhood set $\mathcal{N}_s$ for current v_i
    if Analytical scheme **then**
        for all $v_j \in \mathcal{N}_s$ **do**
            Compute composite metric $\mathcal{M}_j$ using Equation 7
        end for
        Select $i^* = \arg\min_{v_j \in \mathcal{N}_s} \mathcal{M}_j$
    else if DNN-based scheme **then**
        Construct 3-channel grid input (location, direction, speed)
        Predict next-hop i^* using trained DNN model
    end if
    Forward packet to v_{i^*}
    Update $v_i \leftarrow v_{i^*}$ and $\mathcal{N}_s$
end while

5 Performance Evaluation

Comprehensive performance evaluation is conducted through a custom event-driven simulator implemented in Python with SimPy, enabling direct comparison between the proposed schemes and existing solutions. The scenario generator, generates 3-channel two-dimensional grids of size 8×20 cells, where each cell represents a physical space of 5×5 meters. This corresponds to a road segment of 40 meters in width and 100 meters in length, representing a highway-like layout. Each cell can either be empty or occupied by a single vehicle. Vehicle placements and properties are updated every simulation step, with a granularity of 1 second. In the communications module, each vehicle is initialized with the following parameters: a unique ID, position (x, y), speed (in m/s), direction (in degrees), and standard wireless parameters such as communication range (20 meters), transmission power, bandwidth, and noise power. Transmission power and channel noise set to 1 mW and 10^{-10} W, respectively. Each vehicle maintains a forwarding buffer, while connectivity monitoring is initiated only by the source node (v_s). For each setting, a total of 20,000 packets are generated. Each packet is simulated in a distinct scenario with randomly assigned source, destination, and vehicles characteristics, running over a 20-second time window.

The decision making modules (analytical, DNN-based, speed and position aware dynamic routing (SPDR) [13], evolved Dijkstra [20]) accept the snapshot and provide the chosen path using their inference engines. The proposed (analytical and DNN-based) Lookahead schemes are implemented with three variations based on the predictive window (T) value, i.e. 1 sec ($T = 1$), 2 sec ($T = 2$), and 5 sec ($T = 5$). In the proposed analytical solution, a vehicle receiving local neighbor and destination information selects the next hop that minimizes the EMA-based transmission time ($\mathcal{M}$). In contrast, the DNN-based solution constructs a 3-channel input image from

Table 4 DNN-based training and performance evaluation

Time	MAE	MSE	Accuracy Top-1	Top-1 Average distance	Accuracy Top-5
Highway					
1 sec	0.00442114	0.00023671	76.14	0.4084	98.9
2 sec	0.00527049	0.00033618	65.48	0.6624	97.68
5 sec	0.00519498	0.00031429	58.58	0.9964	94.7
10 sec	0.00504183	0.0003294	56.72	1.4092	89.26
Random					
1 sec	0.00953632	0.0017001	55.46	2.4472	71.82
2 sec	0.00788433	0.00089467	65.78	0.7218	96.66
5 sec	0.01451362	0.0025426	36.86	1.919	87.26
10 sec	0.01805927	0.00371669	21.7	2.9674	76.36

the received data and feeds it to the trained model. The model predicts action probabilities for all neighbors, offering both the best and candidate next hops. Once the next hop is determined, the packet is forwarded toward the destination. The proposed solution (and variations) are thoroughly compared with two existing routing schemes of evolved Dijkstra [20] and SPDR [13] algorithms. The evolved Dijkstra[20] scheme initially transforms the network in a connected and directed graph where the shortest path is selected as the best graph-based route.

For every nearby vehicle, the shortest delay cost is considered between the source and the destination via neighbors. The SPDR scheme is implemented such that an RDA is selected and next hop is identified that is farthest in the updated RDA. The RDA range (ρ_{RDA}) is identified in the SPDR scheme as given by:

$$\rho_{RDA}(t) = \rho_s - \Delta\psi_{min} \cdot t - \sigma \cdot (\Delta\psi_{max} - \Delta\psi_{min}) \cdot t, \tag{9}$$

where ψ_{min} and ψ_{max} represent minimum and maximum velocity difference between v_s and its neighbors, respectively.

5.1 Dataset and DNN Training

To evaluate the performance of our U-Net-style DNN model, eight datasets for highway and random mobility models scenarios are used [30]. Each dataset contains 5,000 snapshots, formatted as 3-channel input images, and is used to train the DNN-based Lookahead routing model. The role channel encodes vehicle function using discrete labels: 0 for empty, 3 for general vehicles, 5 for vehicles in transmission range, 7 for source, and 9 for destination. The speed channel contains real-valued speeds of vehicles sampled uniformly in $[4, 8]$ m/s. The third direction channel, encodes motion direction. For highway scenarios, values are restricted to $\{0°, 180°\}$. In random scenarios, directions can take any value in $[0°, 359°]$. The designed CNN-based DNN model keeps

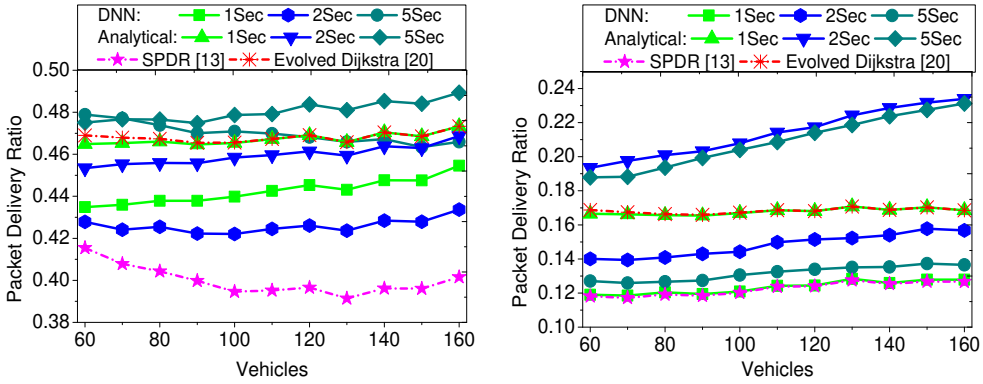
the 3-channel grid input form intact throughout the training to learn spatial-temporal mobility patterns, and predict the action probabilities to match with our analytical solution.

The adopted U-Net-style architecture takes an input tensor of size $H \times W \times 3$, which is converted into PyTorch channel-first format $3 \times H \times W$ before being processed by the network. The encoder consists of two convolutional blocks followed by max-pooling. The first encoder block maps 3 input channels to 16 feature maps, and the second maps 16 to 32 feature maps. Each convolutional block contains two 3×3 convolution layers with same padding, Batch Normalization, and ReLU activation. Down-sampling is performed using 2×2 max-pooling with stride 2 after each encoder block. The bottleneck block maps 32 channels to 64 channels using the same double-convolution design. The decoder is composed of two transposed convolution layers with kernel size 2×2 and stride 2, which up-sample the bottleneck features from 64 to 32 channels and then from 32 to 16 channels. Skip connections are used at both decoding stages by concatenating the up-sampled features with the corresponding encoder outputs, resulting in decoder inputs of 64 and 32 channels, respectively. A final 1×1 convolution maps the 16-channel decoder output to a single-channel prediction grid, and a sigmoid activation is applied to generate values in the range $[0, 1]$, interpreted as action probabilities over candidate next-hop positions. Figure 2 illustrates our modified U-Net-style implementation.

The trained DNN therefore produces one output score for each cell in the spatial grid, while preserving the original input resolution through the encoder-decoder structure. During inference, the model is loaded from a saved checkpoint and evaluated in inference mode without gradient computation. The output is a single-channel probability map in which higher-valued cells indicate more favorable forwarding actions. The best next hop is selected from this predicted map by matching the highest-probability cell to the corresponding vehicle position in the input role channel.

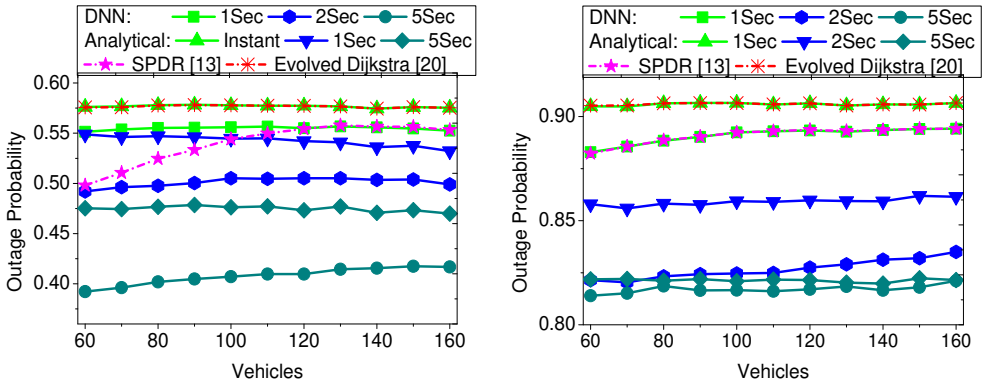
Table 4 shows the evaluation metrics for the proposed DNN-based Lookahead schemes, using mean absolute error (MAE) and MSE for the trained model. The goal of the proposed DNN model is to predict the optimal next-hop vehicle for message routing, evaluated using Top-1 and Top-5 accuracy. The trained model outputs a grid of action probabilities, where each cell represents a candidate next hop. Top-1 accuracy measures whether the highest-probability prediction matches the ground-truth next hop. Top-5 accuracy reflects whether the ground-truth is among the five highest-probability predictions, regardless of order, indicating the model's ability to identify the most promising forwarding options even if not ranked perfectly. To further quantify prediction quality, we also report the average Top-1 distance between the predicted best cell and the ground-truth next-hop cell, which reflects the spatial error of the selected forwarding action even when the exact top prediction is not correct.

The results demonstrate that the proposed model design effectively learns the relation of 3-channel grid input of high mobility VANETs, and achieves the lowest MAE and MSE in 1 sec and 2 sec ($T = 2$) Lookahead schemes for both highway and random scenarios. The trained DNN-model can predict Top-5 candidates with high percentage of 98%+ for highway, and 96%+ for random (1 sec and 2 sec). Still, the average Top-1 distance in the predicted as compared to the ground truth increases from 0.4



(a) Highway scenario $\{0°, 180°\}$. (b) Random scenario $[0°, 359°]$.

Fig. 3 Packet delivery ratio comparison in highway and random scenarios.



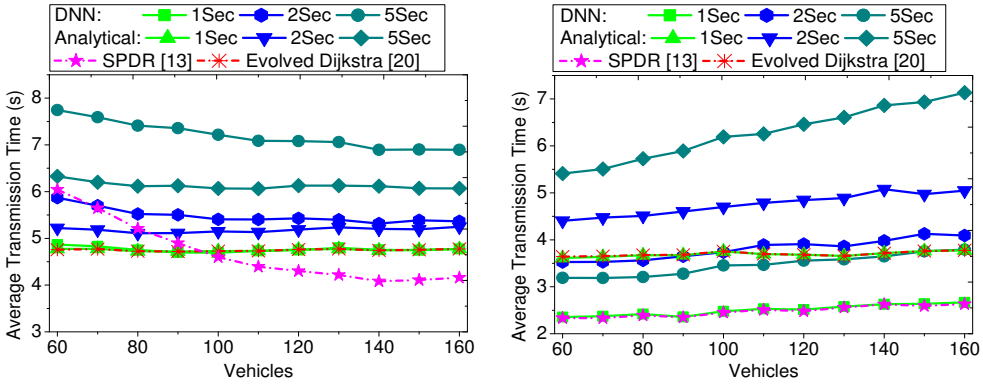
(a) Highway scenario $\{0°, 180°\}$. (b) Random scenario $[0°, 359°]$.

Fig. 4 Outage probability comparison in highway and random scenarios.

to 2.9 when Lookahead time is increased. However, when predicting routing decisions considering 5 ($T = 5$) and 10 seconds ($T = 10$) ahead under random scenarios, the model's performance drops notably. This exposes a key limitation of our U-Net-based CNN: its reliance on spatial features makes it less effective at establishing relations with random direction over longer horizons as compared to shorter Lookahead window.

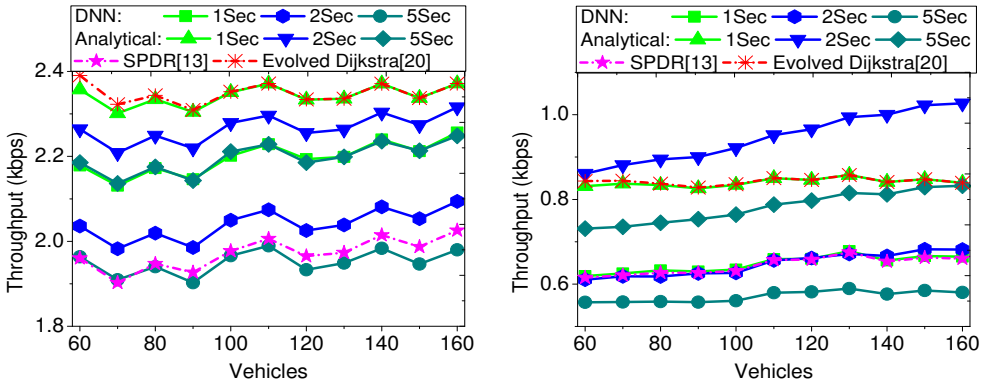
5.2 Comparative Results and Observations

The results present a comprehensive evaluation of the considered routing schemes across highway and random mobility scenarios, respectively. The performance is assessed using key metrics including packet delivery ratio (PDR), outage probability, transmission time, throughput, and hop count. To systematically examine robustness under varying network sparsity and dynamics, the number of vehicles in the grid is gradually increased, thereby emulating increasingly constrained and volatile communication environments. We compare the proposed Lookahead routing (the analytical



(a) Highway scenario $\{0°, 180°\}$. (b) Random scenario $[0°, 359°]$.

Fig. 5 Average transmission time comparison in highway and random scenarios.

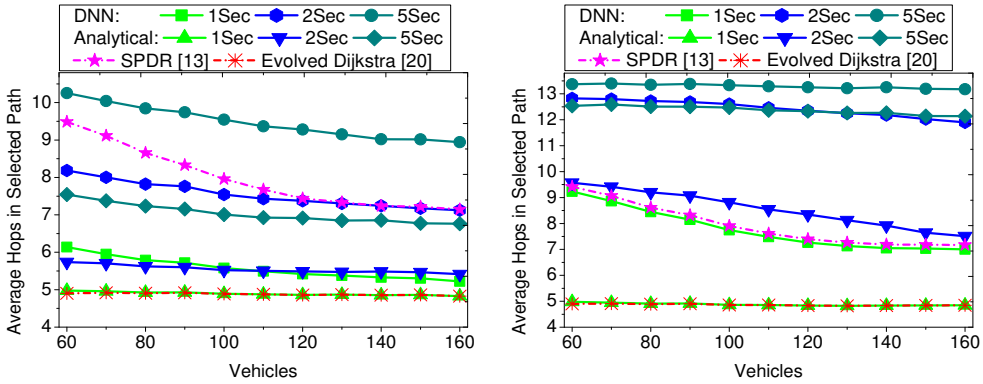


(a) Highway scenario $\{0°, 180°\}$. (b) Random scenario $[0°, 359°]$.

Fig. 6 Average throughput comparison in highway and random scenarios.

and DNN-based implementations) with two state-of-the-art benchmarks, SPDR [13] and evolved Dijkstra [20].

Figures 3(a) and 3(b) illustrate the PDR performance for highway and random scenarios, respectively. The longer Lookahead horizon of 2 and 5 seconds improves packet delivery. Specifically, the proposed Lookahead with 5 seconds prediction horizon consistently achieves the highest PDR, reaching approximately 49% in the highway scenario and 23% in the random scenario. This improvement is due to the ability to anticipate future link stability and select forwarding nodes that remain viable over a longer duration. In contrast, evolved Dijkstra achieves 47% and 17%, respectively, while SPDR attains only 40% and 13%. Both analytical and DNN-based Lookahead with 1-second prediction horizon perform similarly to evolved Dijkstra, as its limited prediction horizon restricts its ability to account for future mobility patterns. These results clearly show the importance of mobility pattern recognition in improving E2E PDR reliability of highly dynamic networks. The outage probability in Figures 4(a) and 4(b) is defined as the ratio of disconnection time to the total communications



(a) Highway scenario $\{0°, 180°\}$. (b) Random scenario $[0°, 359°]$.

Fig. 7 Average number of hops comparison in highway and random scenarios.

duration of 20 seconds. The proposed Lookahead schemes with 2-second and 5-second horizons achieve the lowest outage probabilities across both scenarios, reaching approximately 50% in highway and 83% in random environments. In comparison, evolved Dijkstra exhibits the highest outage rates (55% and 91%, respectively), primarily due to its reliance on instantaneous topology without incorporating future link changes. This demonstrates that even a 2-second prediction horizon can significantly enhance route stability by mitigating frequent link disconnection.

Figures 5(a) and 5(b) present the average transmission time of E2E data delivery. SPDR [13] achieves the lowest transmission time, as it prioritizes short-range hops that typically offer better instantaneous channel conditions, resulting in higher data rates and faster packet forwarding. Evolved Dijkstra [20], the proposed Lookahead with 1 second prediction horizon and SPDR show shorter transmission time due to their selection of the current shortest path, leading to better transmission rates. On the other hand, the proposed Lookahead with 2 and 5 seconds prediction horizons experiences higher transmission time. This behavior is due to its preference for longer-range hops that are more stable over the prediction window and better aligned with long-term source - destination connectivity. The increase in per-hop transmission cost illustrates a trade-off with improved reliability and reduced outage. An interesting but obvious observation is that the short-term efficiency is suited for low mobility and long-term robustness is suited for high mobility networks.

Throughput performance is shown in Figures 6(a) and 6(b). The proposed Lookahead with 1-second horizon and evolved Dijkstra schemes achieve the highest throughput in the highway scenario (Figures 6(b)), due to structured mobility patterns. However, in the random scenario, the 2 sec Lookahead variant outperforms all other methods, achieving approximately 20% higher E2E throughput. This shows an important aspect that the proposed Lookahead with prediction window performs well in random scenarios, which are the worst-case depiction of the real-world mobility pattern. However, the DNN-based Lookahead variants exhibit lower throughput compared to their analytical counterparts in the random scenario. This difference is due to the approximation errors in the learned model, which may not fully capture the

complex relationship between mobility dynamics and transmission rate, as formalized in Equation 7. The existing SPDR routing scheme performs poorly due to its greedy reduction of the routing decision area (RDA), which favors short hops but does not translate to multi-hop communications. The hop count of each established route using different schemes is shown in Figure 7(a) and 7(b). SPDR and the proposed Lookahead scheme with a 5-second horizon select a multi-hop path with the highest number of intermediate hops due to restricting forwarding regions (SPDR) and prioritize stable but potentially longer routes (5-second Lookahead), respectively. The proposed Lookahead with 1-second horizon and evolved Dijkstra [20] consistently achieves the lowest hop count by selecting shortest-path routes.

The DNN-based implementations closely follow the proposed analytical Lookahead scheme across all the metrics. Minor deviations are observed in the highway scenario due to its structural mobility pattern. A relatively more noticeable difference is present in the random mobility environment, which is also consistent with the prediction accuracy reported in Table 4. The improvement of the model to learn the spatio-temporal relation of the random vehicular mobility is an immediate future work. The overall results clearly demonstrate that no single routing strategy simultaneously optimizes all performance metrics without trade-offs. However, the proposed Lookahead schemes consistently provide a well-balanced solution by significantly reducing outage probability and improving PDR. The primary trade-offs include a slight increase in transmission time and hop count, particularly for the proposed Lookahead with longer horizons. The results highlight the effectiveness of incorporating predictive information into decentralized routing decisions for high-mobility VANET environments.

5.3 Communications and Computation Complexity

Communications: The communication overhead of routing protocols in VANETs are formulated using routing decisions process and required network-wide information. In exhaustive path discovery approaches, all possible simple paths between the source node v_s and destination node v_d are explored by considering every subset of the $N-2$ intermediate nodes. The number of candidate paths grows exponentially but it also results in a worst-case complexity of $\mathcal{O}(2^{N-2})$. The exhaustive search for paths is impractical for moderately sized or highly dynamic networks. The evolved Dijkstra's algorithm [20] is a graph-based routing methods, which reduces the complexity by systematically exploring nodes and edges. Each node and edge is processed at most once, leading to a complexity of $\mathcal{O}(N+E)$, where N and E denote the number of nodes and edges, respectively. The effective overhead depends on network density. The communications cost remains relatively low for evolved Dijkstra in sparse networks due to fewer edges, i.e. $E=\mathcal{O}(N)$. However, in dense scenarios E approaches $\mathcal{O}(N^2)$, increasing both computational and communication burden. The proposed Lookahead routing avoids the complete overhead of global path discovery. Instead, each node selects the next hop based on local information by evaluating its neighboring set $\mathcal{N}*s(t)$. Since decisions are made iteratively at each hop, the total communication complexity scales with both the number of hops Z and the size of the local neighborhood, resulting in $\mathcal{O}(Z\cdot\mathcal{N}*s(t))$. The proposed local search reduces control message exchange and avoids repeated network-wide updates, which is important in dynamic vehicular scenarios.

Computation: The computational cost of the proposed framework is determined by both the analytical formulation and the DNN-based inference process. The U-Net-style architecture operates on a grid-based representation of the local environment, typically defined as $C \times H \times W$, where $C = 3$ and $H = W$ denote the spatial dimensions. The encoder-decoder structure consists of L layers, where spatial resolution is progressively reduced and then reconstructed. The dominant cost arises from convolution operations, which can be expressed as $\mathcal{O}\left(\sum_{\ell=1}^{L} C_\ell \cdot H_\ell \cdot W_\ell \cdot K^2\right)$, where C_ℓ is the number of channels at layer ℓ, $H_\ell \times W_\ell$ is the feature map size, and K is the kernel size (typically $K = 3$). For a fixed architecture and input resolution, the network depth and channel dimensions remain constant, leading to an inference complexity that scales approximately as $\mathcal{O}(H \cdot W)$. Traditional routing schemes typically evaluate a cost function over all neighboring nodes, resulting in a per-decision complexity of $\mathcal{O}(\mathcal{N}' * s(t))$, where $\mathcal{N}' * s(t)$ denotes the average node degree. In contrast, the DNN-based approach performs decision-making through a single forward pass, followed by a simple selection step (e.g., argmax) to determine the next hop. Under bounded neighborhood conditions, this selection step incurs $\mathcal{O}(1)$ complexity. The resulting design shifts the complexity from repeated per-neighbor evaluations to a structured inference process, enabling consistent decision latency while maintaining scalability with respect to network size.

6 Conclusion and Limitation

This study presented analytical and DNN-based Lookahead schemes and demonstrated their ability to transform the VANET routing problem into a localized next-hop inference task. This transformation enables scalable, efficient, and real-time decision-making, advancing the development of intelligent and adaptive vehicular networks. The proposed solution enabled reliability with increase in 10% PDR and a reduction in outage probability (from 58% to 45% and 91% to 82%), without relying on excessive control overhead. Our proposed U-Net style DNN model effectively learns the spatial-temporal dynamics of VANETs, and is expected to act as a benchmark for similar problems. The proposed schemes outperform two existing state-of-the-art schemes, which highlights the potential of combining domain-specific models with learning-based intelligence for next-generation vehicular communications.

While the proposed DNN-based routing scheme offers computational and communications efficiency, its performance depends on the representativeness of the training data. Unseen scenarios, such as sudden topology changes or extreme densities, may lead to suboptimal decisions. Although inference is lightweight, deploying the U-Net model onboard vehicles requires dedicated memory, though the trained model size remains small (approximately 5 KB). Our experiments, summarized in Table 4, evaluate eight variations, including four DNN-based and four analytical-based schemes. Nevertheless, probabilistic DNN outputs while being non-deterministic offer opportunities for future extensions, such as alternate path discovery and load balancing.

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Data Availability. Data set used in this study is available online, Kumbhar, F.H., Jabbar, M.S.: "3-channel Representation of Highway and Random Vehicular Networks Scenario for DNN-based Lookahead Next-hop Routing", https://dx.doi.org/10.21227/x7jn-bk95

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Declarations

Conflicts of Interest. The authors declare that they have no conflict of interest.

Ethical Approval. Not applicable.

References

[1] Tang, F., Mao, B., Kato, N., Gui, G.: (2021) Comprehensive Survey on Machine Learning in Vehicular Network: Technology, Applications and Challenges. *IEEE Communications Surveys & Tutorials* **23**(3), 2027–2057 https://doi.org/10.1109/COMST.2021.3089688

[2] Yang, Q., Yoo, S.J.: (2024) Hierarchical Reinforcement Learning-Based Routing Algorithm with Grouped RSU in Urban VANETs. *IEEE Trans. on Intelligent Transportation Systems* **25**, 10131–10146 https://doi.org/10.1109/TITS.2024.3353258

[3] Balkus, S.V., Wang, H., Cornet, B.D., Mahabal, C., Ngo, H., Fang, H.: (2022) A Survey of Collaborative Machine Learning Using 5G Vehicular Communications. *IEEE Communications Surveys & Tutorials* **24**(2), 1280–1303 https://doi.org/10.1109/COMST.2022.3149714

[4] Ibn-Khedher, H., Laroui, M., Alfaqawi, M., Magnouche, A., Moungla, H., Afifi, H.: (2024) 6G-edge support of Internet of Autonomous Vehicles: A survey. *Transactions on Emerging Telecommunications Technologies* **35**(1), 4918 https://doi.org/10.1002/ett.4918 . Accessed 2026-03-19

[5] Nazib, R.A., Moh, S.: (2021) Reinforcement Learning-Based Routing Protocols for Vehicular Ad Hoc Networks: A Comparative Survey. *IEEE Access* **9**, 27552–27587 https://doi.org/10.1109/ACCESS.2021.3058388 . Accessed 2026-04-07

[6] Minh Quy, N., Thi Minh Hue, C., Vu Khanh, Q.: (2025) An Efficient Quality of Service Routing Protocol for 6G Ad Hoc Networks. *Transactions on Emerging Telecommunications Technologies* **36**(10), 70255 https://doi.org/10.1002/ett.70255 . Accessed 2026-03-19

[7] Ajaz, F., Naseem, M., Ramesh, J.V.N., Shabaz, M., Ahamad, G.: (2025) Cluster Based Lion Optimization Routing Protocol for Internet of Vehicles (clorp).

Transactions on Emerging Telecommunications Technologies **36**(3), 70089 https://doi.org/10.1002/ett.70089 . Accessed 2026-03-19

[8] Chaib, N., Oubbati, O.S., Bensaad, M.L., Lakas, A., Lorenz, P., Jamalipour, A.: (2020) BRT: Bus-Based Routing Technique in Urban Vehicular Networks. *IEEE Transactions on Intelligent Transportation Systems* **21**(11), 4550–4562 https://doi.org/10.1109/TITS.2019.2938871 . Accessed 2026-04-07

[9] Liu, H., Qiu, T., Zhou, X., Chen, C., Chen, N.: (2020) Parking-Area-Assisted Spider-Web Routing Protocol for Emergency Data in Urban VANET. *IEEE Transactions on Vehicular Technology* **69**(1), 971–982 https://doi.org/10.1109/TVT.2019.2954159 . Accessed 2026-04-07

[10] Khudayer, B.H., Anbar, M., Hanshi, S.M., Wan, T.-C.: (2020) Efficient Route Discovery and Link Failure Detection Mechanisms for Source Routing Protocol in Mobile Ad-Hoc Networks. *IEEE Access* **8**, 24019–24032 https://doi.org/10.1109/ACCESS.2020.2970279 . Accessed 2026-04-07

[11] Xu, C., Xiong, Z., Han, Z., Zhao, G., Yu, S.: (2020) Link Reliability-Based Adaptive Routing for Multilevel Vehicular Networks. *IEEE Transactions on Vehicular Technology* **69**(10), 11771–11785 https://doi.org/10.1109/TVT.2020.3018300 . Accessed 2026-04-07

[12] Hawbani, A., Wang, X., Al-Dubai, A., Zhao, L., Busaileh, O., Liu, P., Al-Qaness, M.A.A.: (2021) A Novel Heuristic Data Routing for Urban Vehicular *Ad Hoc* Networks. *IEEE Internet of Things Journal* **8**(11), 8976–8989 https://doi.org/10.1109/JIOT.2021.3055504 . Accessed 2026-04-07

[13] Han, R., Shi, J., Guan, Q., Banoori, F., Shen, W.: (2022) Speed and Position Aware Dynamic Routing for Emergency Message Dissemination in VANETs. *IEEE Access* **10**, 1376–1385 https://doi.org/10.1109/ACCESS.2021.3138960

[14] Qi, W., Landfeldt, B., Song, Q., Guo, L., Jamalipour, A.: (2020) Traffic Differentiated Clustering Routing in DSRC and C-V2X Hybrid Vehicular Networks. *IEEE Transactions on Vehicular Technology* **69**(7), 7723–7734 https://doi.org/10.1109/TVT.2020.2990174 . Accessed 2026-04-07

[15] Mershad, K.: (2021) SURFER: A Secure SDN-Based Routing Protocol for Internet of Vehicles. *IEEE Internet of Things Journal* **8**(9), 7407–7422 https://doi.org/10.1109/JIOT.2020.3038465 . Accessed 2026-04-07

[16] Baccari, S., Hadded, M., Touati, H., Muhlethaler, P.: (2021) A Secure Trust-aware Cross-layer Routing Protocol for Vehicular Ad hoc Networks. *Journal of Cyber Security and Mobility* https://doi.org/10.13052/jcsm2245-1439.1023 . Accessed 2026-04-07

[17] Xie, X., Navaei, Y.D., Einy, S.: (2023) A clustering-based routing protocol using

path pattern discovery method to minimize delay in vanet. *Wireless Communications and Mobile Computing* **2023**(1), 3776815 https://doi.org/10.1155/2023/3776815 https://onlinelibrary.wiley.com/doi/pdf/10.1155/2023/3776815

[18] Fatemidokht, H., Rafsanjani, M.K., Gupta, B.B., Hsu, C.-H.: (2021) Efficient and Secure Routing Protocol Based on Artificial Intelligence Algorithms With UAV-Assisted for Vehicular Ad Hoc Networks in Intelligent Transportation Systems. *IEEE Transactions on Intelligent Transportation Systems* **22**(7), 4757–4769 https://doi.org/10.1109/TITS.2020.3041746 . Accessed 2026-04-07

[19] Luo, L., Sheng, L., Yu, H., Sun, G.: (2022) Intersection-Based V2X Routing via Reinforcement Learning in VANETs. *IEEE Trans. on Intelligent Transportation Systems* **23**, 5446–5459 https://doi.org/10.1109/TITS.2021.3053958

[20] Zhou, M., Liu, L., Sun, Y., Wang, K., Dong, M., Atiquzzaman, M., Dustdar, S.: (2023) On Vehicular Ad-Hoc Networks With Full-Duplex Radios: An End-to-End Delay Perspective. *IEEE Trans. on Intelligent Transportation Systems* **24**(10), 10912–10922 https://doi.org/10.1109/TITS.2023.3279322

[21] Kumbhar, F.H., Shin, S.Y.: (2023) Innovating Multi-Objective Optimal Message Routing for Unified High Mobility Networks. *IEEE Trans. on Vehicular Technology* **72**, 6571–6583 https://doi.org/10.1109/TVT.2022.3232567

[22] Choksi, A., Shah, M.: (2024) Machine learning based centralized dynamic clustering algorithm for energy efficient routing in vehicular ad hoc networks. *Transactions on Emerging Telecommunications Technologies* **35**(1), 4914 https://doi.org/10.1002/ett.4914 . Accessed 2026-03-19

[23] Ma, H., You, J., Wu, H., Xing, L., Zhang, X.: (2025) A Probabilistic Routing Algorithm Based on CNN and Q-Learning for Vehicular Edge Network. *Transactions on Emerging Telecommunications Technologies* **36**(1), 70050 https://doi.org/10.1002/ett.70050 . Accessed 2026-03-19

[24] Bello-Salau, H., Onumanyi, A.J., Abu-Mahfouz, A.M., Adejo, A.O., Mu'Azu, M.B.: (2020) New Discrete Cuckoo Search Optimization Algorithms for Effective Route Discovery in IoT-Based Vehicular Ad-Hoc Networks. *IEEE Access* **8**, 145469–145488 https://doi.org/10.1109/ACCESS.2020.3014736 . Accessed 2026-04-07

[25] Zhao, L., Zheng, T., Lin, M., Hawbani, A., Shang, J., Fan, C.: (2022) Spider: A social computing inspired predictive routing scheme for softwarized vehicular networks. *IEEE Transactions on Intelligent Transportation Systems* **23**(7), 9466–9477 https://doi.org/10.1109/TITS.2021.3122438

[26] Liu, J., Weng, H., Ge, Y., Li, S., Cui, X.: (2022) A Self-Healing Routing Strategy Based on Ant Colony Optimization for Vehicular Ad Hoc Networks. *IEEE Internet of Things Journal* **9**(22), 22695–22708 https://doi.org/10.1109/JIOT.2022.

3181857 . Accessed 2026-04-07

[27] Ali, A., Aadil, F., Khan, M.F., Maqsood, M., Lim, S.: (2023) Harris Hawks Optimization-Based Clustering Algorithm for Vehicular Ad-Hoc Networks. *IEEE Transactions on Intelligent Transportation Systems* **24**(6), 5822–5841 https://doi.org/10.1109/TITS.2023.3257484 . Accessed 2026-04-07

[28] Beniwal, R., Kumar, N.: (2025) A Nature-Inspired Multi-Objective Green Routing Protocol for Iot-Enabled SDWSNs. *Transactions on Emerging Telecommunications Technologies* **36**(6), 70199 https://doi.org/10.1002/ett.70199 . Accessed 2026-03-19

[29] Ronneberger, O., Fischer, P., Brox, T.: U-net: Convolutional networks for biomedical image segmentation. In: Medical Image Computing and Computer-assisted intervention–MICCAI 2015: 18th International Conference, Munich, Germany, October 5-9, 2015, Proceedings, Part III 18, pp. 234–241 (2015). Springer

[30] Kumbhar, F.H., Jabbar, M.S.: 3-channel Representation of Highway and Random Vehicular Networks Scenario for DNN-based Lookahead Next-hop Routing. https://dx.doi.org/10.21227/x7jn-bk95