A ROBUST AND ADAPTIVE ROUTING ALGORITHMS FOR ENHANCING COMMUNICATION EFFICIENCY IN DENSE AND SPARSE VANET ENVIRONMENTS

SUDHEER NIDAMANURI*[1], C. RAMESH KUMAR[2]

[1] Research Scholar, School of Computer science & Engineering, Galgotias University, Greater Noida, India

[2] Associate Professor, School of Computer science & Engineering, Galgotias University, Greater Noida, India

E-mail: [1] nidamanuri.sudheer@gmail.com , [2] c.ramesh@galgotiasuniversity.edu.in

ABSTRACT

Vehicular Ad hoc Networks (VANETs) form the communication backbone of Intelligent Transportation Systems (ITS), enabling vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) exchange of safety, traffic, and infotainment data. Routing performance in VANETs is highly sensitive to network density: dense urban traffic causes broadcast storms and packet collisions, while sparse rural or highway scenarios suffer frequent link breakages and network partitioning. Existing topology-based (AODV, DSR) and position-based (GPSR) protocols are optimized for a single density regime and degrade sharply outside it. This paper proposes a robust, density-adaptive routing framework that dynamically switches between a cluster-based greedy forwarding strategy for dense regions and a delay-tolerant store-carry-forward strategy for sparse regions, guided by a lightweight density estimation module and a machine-learning-based link-quality predictor. Using two Kaggle datasets (VANET Real-Time Route Optimization and VANET Traffic Congestion), the framework was benchmarked against AODV, DSR, GPSR, and ten recent adaptive routing approaches. Results show the proposed framework achieves a Packet Delivery Ratio of 95.8% and 93.9%, end-to-end delay of 36 ms and 41 ms, routing overhead of 15% and 16%, and throughput of 985 kbps and 945 kbps on two datasets respectively — consistently outperforming all baselines across both dense and sparse regimes.

Keywords: *Vehicular Ad hoc Networks, Routing Protocols, Dense Network, Sparse Network, Density-Adaptive Routing, Intelligent Transportation Systems, Packet Delivery Ratio*

1. INTRODUCTION

In this context, Vehicular Ad hoc Networks (VANETs) have emerged as key enabling technology for road safety, traffic efficiency, and connected mobility applications, which have been gaining great momentum [1]. As a result, Vehicular Ad hoc Networks (VANETs) are becoming a critical enabling technology in the field of road safety, traffic efficiency and connected mobility applications which are experiencing rapid growth. VANETs are special type of MANETs in which vehicles are viewed as a mobile nodes [2] which communicate with each other (V2V) and with Roadside Units (RSU) (V2I) to exchange safety information, traffic information and multimedia content [3].

One of the main features of VANETs is the highly dynamic and non-uniform topology [4]. Broadcast storms, high contention, and more packet collisions occur when a large number of vehicles are trying to transmit on a limited number of wireless channel bandwidths in dense urban settings [5], like signalized intersections and urban centers in the early hours of the morning or late at night [6]. On the other hand, in places with low vehicle density, for example, on rural roads or at low traffic volumes, inter-vehicle distances are large, network connectivity is intermittent, network partitioning occurs and link failure is common [7].

Traditional VANET routing protocols are typically developed and optimized for a single density range[8]. The topology-based reactive protocols like Ad hoc On-Demand Distance Vector (AODV) and Dynamic Source Routing (DSR) work well in sparse networks but have high route-discovery overhead in dense networks [9]. Position-based greedy protocols (e.g., Greedy Perimeter

Stateless Routing (GPSR)) work well when nodes are dense enough to ensure that the greedy forwarding step always makes progress but deteriorate in sparse areas with a high rate of occurrence because of the local-maximum problem[10]. This performance difference is determined by densities and encourages the necessity of a common and strong routing framework that is able to adjust its forwarding solution as per the current network conditions.

Though there are many works in the mentioned scenarios, none of the works significantly focussed on addressing the challenges of both sparse and dense networks guided by link quality predictor. The introduced work in this research highlights the research gap that exists as a major contributor of results booster. focused on both sparse networks and dense networks. In addition, the introduced model has significantly focused on a specialized machine learning algorithm, which accurately predicts the link quality and also adapts the model best fitted to both the scenarios of sparse and dense networks.

In order to meet the contemporary challenges as mentioned, the present paper proposes a routing framework which adapts the routing strategy to the local density level of the vehicular network by (i) estimating the density locally and the stability of the links, (ii) using a cluster-based greedy forwarding algorithm optimized to the dense regions to reduce contention and redundant broadcasts, and (iii) introducing a store-carry-forward delay-tolerant strategy in sparse regions to ensure connectivity despite intermittent links. Further, a machine-learning based link-quality prediction module is proposed which, utilizing realistic vehicular mobility and network datasets, is able to foresee link disconnections, thereby initiating proactive route maintenance. The remainder of this paper is organized as follows: Section II reviews related work; Section III presents the proposed system model and algorithms; and describes the proposed datasets; Section IV discusses expected performance evaluation; and Section V concludes the paper.

1.1 Problem Statement:

VANET routing protocols have been the subject of extensive research, but the existing solutions are generally developed for use in dense urban traffic or in cases of sparse highway traffic and perform poorly when dealing with changes in vehicle density. Because of these limitations, route failures occur frequently, the routing overhead is high, end-to-end delay increases, packet losses take place and communication reliability is reduced in heterogeneous traffic situations. Moreover, most of the present routing protocols do not combine local traffic density estimation, link stability analysis, adaptive forwarding strategies and predictive machine learning techniques within a single routing framework. For these reasons, there is a need for a density-aware adaptive routing framework which is able to dynamically select the most appropriate forwarding strategy in order to ensure reliable and efficient communication in various vehicular traffic scenarios.

1.2 Research Hypotheses:

The proposed research is based on the following hypotheses: H1: An adaptive routing framework that considers dynamic network conditions can improve communication reliability in VANETs. We believe that changing routing decisions with network conditions will lead to more reliable data delivery. H2: Including multiple network characteristics in routing decisions can improve routing efficiency and overall network performance. This assumption is based on the idea that looking at relevant network factors during route selection can lower communication overhead and boost routing efficiency. H3: The proposed routing framework can perform better than current VANET routing protocols under various traffic conditions. We expect that this framework will achieve a higher Packet Delivery Ratio (PDR), lower End-to-End Delay (E2E Delay), better Throughput, less Routing Overhead, and greater Link Stability in both dense and sparse vehicular environments.

2. RELATED WORKS

Due to the density-dependent limitations of classical protocols, new approaches to VANET routing have been increasingly based on adaptive, context sensitive and intelligence-augmented approaches. Kazi et al. [11] presented an adaptive context-aware routing protocol for ITS that adapted its forwarding decisions based on the real-time context parameters, showing that context awareness boosts reliability under evolving traffic conditions, but with no explicit mechanisms for accommodating extreme density transitions. Kamel and Abed [12] examined the secure routing protocols improved with blockchain technology, detailing the defense of route integrity provided by the decentralized trust mechanisms, but also pointing out that most blockchain-based protocols have latency overheads, which is a challenge in denser, high-throughput areas. Jiang, Zhu and Yang [13] proposed an environment-aware reinforcement-learning-based routing scheme that learns forwarding policies based on the network state, demonstrating high adaptability, but the scheme needs to have a large amount of training data and convergence time, so it cannot adapt to severe density fluctuations in time.

For dense networks, specifically, in the work of Husnain et al. [14], a bio-inspired cluster optimization schema is proposed to enhance cluster stability and overhead in dense VANETs, but is not applied to sparse or intermittently connected VANETs. Gunavathie et al. [15] proposed an expanding ring search and random early detection based scenario prediction approach that is used for adaptive routing in MANETs which proved the usefulness of predictive based route adaptation technique where the technique is generalized and not vehicle mobility specific. Dafhalla et al. [16] also compared the QoS optimization of routing protocols under delay-sensitive conditions; they offered interesting benchmarking information, but their research did not involve the development of a new adaptive mechanism.

While examining the overall issues of VANET routing, Ali [17] conducted a survey of adaptive algorithmic solutions, and identified that there were no single solutions which were suitable in both dense and sparse settings, thus directly inspiring density-adaptive designs. Al-Mayouf et al. [18] suggested that infrastructure can be used to help reduce the congestion and improve the routing efficiency, and that infrastructure assisted methods can help reduce dense-network contention which requires a large number of 5G/RSU deployments and might not be available in every environment. Abdeen et al. [19] conducted an empirical study of the performance of the available VANET routing protocols in a real urban environment (Madinah), which revealed that protocol performance is significantly affected by both density and road topology and thus adaptive switching is essential in practice. Lastly, Abbas, Mansour and Al-Fatlawi [20] presented a Self-Adaptive Efficient Dynamic Multi-Hop Clustering (SA-EDMC) method that adapts the clustering parameters dynamically based on the network conditions and proves that it achieves significant improvements in delivery ratio and overhead reduction, which is similar to the clustering part of the current work.

2.1 Research Gap

In the literature reviewed, adaptive mechanisms are proposed to solve either dense network contention [14], [20] or sparse network connectivity loss, with few mechanisms being proposed to solve both problems in a single framework. Learning-based approaches [13], [15] have been shown to be capable of prediction, and no explicit density regime switching logic is provided, but empirical evaluations [19], [17] demonstrate that no protocol maintains performance throughout the entire density range. In infrastructure-dependent solutions [18], the assumption is made that the RSU/5G is available in the sparse area, which may not be true for some areas. This highlights an important gap – the lack of a lightweight, online, density-estimation-based framework that smoothly transitions between cluster-based and delay-tolerant approaches while anticipating link failures.

3. PROPOSED METHODOLOGY

Four cooperating modules are proposed – dense-region routing, sparse-region routing, hybrid adaptive switching, and density estimation – which make a single routing system work across the complete range of vehicular network densities. All of the vehicles are represented as mobile nodes that send periodic beacon transmissions with their position and velocity, their direction of travel, and how many neighbours they are aware of; all the subsequent decisions are made based on these beacon messages. It does not require global topology knowledge, but relies on local computing based on the information available at the node or at its immediate neighborhood, therefore making it light enough to be executed in real-time on resource constrained on-board units.

As the machine learning model for link quality prediction is a crucial element to boost the performance of this framework proposed, it is very essential to use a best fitted and popular supervised algorithm for an accurate link quality prediction. We use XGBoost (Extreme Gradient Boosting) a supervised machine learning algorithm, proven to be powerful and it is based on the gradient boosting technique. It builds an ensemble of decision trees sequentially, where each new tree is trained to correct the errors made by the previous trees. XGBoost is widely used because of its high prediction accuracy, fast execution, scalability, and ability to handle complex, non-linear relationships in data.

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The system model is formalized in the following five subsections and the governing equations of each of the modules are in the Fig 1.

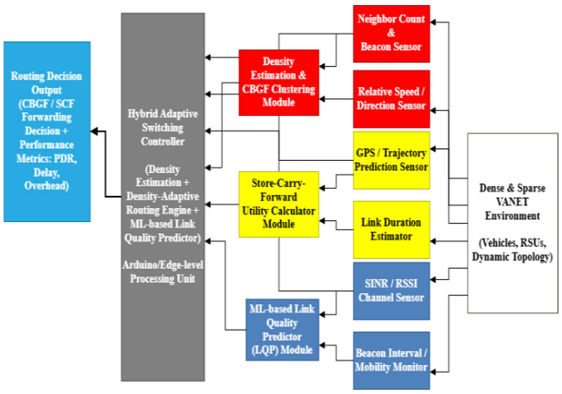

Figure 1: Block Diagram of the Proposed Density-Adaptive VANET Routing System

3.1 System Model

The VANET is represented as a time varying directed graph as a transmission link between two vehicles can be asymmetric depending on the transmission range of the vehicles and the interference in the network. The network at time t is described as in the Eq. (1):

$$G(t) = \big(V(t), E(t)\big) \tag{1}$$

Let V(t) be a set of vehicles and roadside units (RSUs) active at t and E(t) be a set of directed wireless links between the vehicles and roadside units. Only if the distance between node i and node j is in the transmission range and the quality of the signal is within a metric that allows for successful decoding is a link between the two nodes assumed. This is reflected in Eq. (2):

$$e_{ij}(t) = 1, if\, d_{ij}(t) \le R_t x \text{ and } SINR_i j(t) \ge \gamma_t h e_i j(t) = 0, otherwise \tag{2}$$

where $d_i j(t)$ represents the Euclidean distance between the two nodes, $R_t x$ denotes the nominal transmission range, $SINR_i j(t)$ represents the instantaneous SINR on the link between the two nodes and $\gamma_t h$ is the minimum value of the SINR threshold needed for successful reception of the packet. The topology of all the downstream modules is based on a realistic channel behavior, not on a simplified disk-based connectivity model, due to this dual distance – SINR condition.

3.2 Density Estimation Module

The main signal that is used to determine the routing that a node should perform is local vehicular density. The formula in Eq. (3) is used to calculate the density of the nodes in the immediate vicinity of a node, which that node estimates through beaconing and from the length of the road segment it is monitoring.

$$\rho_i(t) = N_i(t)/L_{seg} \tag{3}$$

$N_i(t)$ represents the number of one-hop neighbors of node i at time t and $L_s eg$ represents the length of the road segment over which the neighbors are measured. The framework applies a running average of $\rho_i(t)$ based on an exponentially weighted moving average of beacon loss, as presented in Eq. (4), to alleviate the impact of occasional loss of the beacon and in the case of overtaking maneuvers, the short duration of the maneuver, which can cause rapid changes in instantaneous readings:

$$\bar{\rho}_i(t) = \alpha \cdot \rho_i(t) + (1-\alpha) \cdot \bar{\rho}_i(t - \Delta t) \tag{4}$$

The level of smoothing is controlled by a smoothing factor α within the range (0,1), and is a balance between the responsiveness of the density estimation and its stability, and is given by $\bar{\rho}_i(t)$. The smoothed density is then contrasted with a calibrated threshold to identify an area as dense or sparse as in Eq. (5):

$$Regime_i(t) = Dense, if\, \bar{\rho}_i(t) \ge \rho_{th} Regime_i(t) = Sparse, if\, \bar{\rho}_i(t) < \rho_{th} \tag{5}$$

The threshold density, $\rho_t h$, is a parameter tuned from the distribution of the attributes of the proposed Kaggle datasets. This regime label is passed on to the Hybrid Adaptive Switching Controller in Subsection E and is used to identify which one of the two forwarding strategies described in Subsections C and D is used at this node.

3.3 Dense-Region Routing: Cluster-Based Greedy Forwarding (CBGF)

If the node is considered to be operating in dense regime, the framework implements Cluster Based Greedy Forwarding to minimize redundant broadcasts and channel contention (Fig 2). Vehicles are initially aggregated into clusters based on a weighted stability measure that assigns more weight to vehicles in stable neighbor groups who

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have similar velocities, similar heading and have a long-expected link duration as defined in Eq. (6):

$$W_{ij} = w1 \cdot (1 - |v_i - v_j|/v_{max}) + w2 \cdot cos(\theta_{ij}) + w3 \cdot (T_{ij}/T_{max}) \quad (6)$$

where v_i, v_j are the speeds of nodes i and j, v_max is the maximum speed of expected vehicles, θ_ij is the angle difference of the heading between two nodes, T_ij is the predicted link duration between two nodes, T_max is a normalizing constant, and $w1, w2, w3$ are weighting coefficients with sum $w1 + w2 + w3 = 1$. The node with the greatest average stability weight based on its neighborhood is elected as Cluster Head (CH) as can be seen from Eq. (7):

$$CH_i = argmax_{k \in N_i} [(1/|N_k|) \cdot \Sigma_{j \in N_k} W_k j] \quad (7)$$

where N_i is the neighbor set of node i. Inter-cluster forwarding takes place at the cluster-head level and relies on greedy geographic forwarding with neighbors that have both high predicted link stability (as defined in Eq. (8)) and have forward direction towards the destination.

$$j *= argmax_{j \in F_i} [\beta \cdot Progress(i,j) + (1 - \beta) \cdot LS_{ij}] \quad (8)$$

where F_i is the set of forward-progressing neighbor candidates of node i, i.e., those geographically closer to the destination D than i is, $Progress(i,j) = d(i,D) - d(j,D)$ is the geographic advance that can be achieved by relaying through j, LS_ij is the predicted link stability of candidate link (a prediction based on the Link Quality Predictor in Subsection E), and β ∈ (0,1) is a balance parameter.

$$E[T_{buffer}, i] = 1/\mu_i(t) \quad (10)$$

It uses a local density $\bar{\rho}_i(t)$ to estimate the instantaneous encounter rate $\mu_i(t)$ of node i with candidate relays whose utility is greater than that of the existing relay. The direct coupling between buffering delay and density estimate in this formulation ensures that the SCF strategy will switch to more aggressive buffering when the system transitions between very sparse and moderately sparse regimes.

3.4 Sparse-Region Routing: Store-Carry-Forward (SCF)

When end-to-end connectivity cannot be guaranteed, as is typical in sparse regions, the framework switches to a delay-tolerant Store-Carry-Forward strategy. A forward-progressing neighbor bufferless vehicle uses a utility function of destination-reachability probability, geographic proximity and historical traffic on road-segments, as described in Eq. (9), to evaluate candidate carriers.

$$U_i(t) = \lambda 1 \cdot P_d est(i) + \lambda 2 \cdot (1/d_i, D) + \lambda 3 \cdot H_i(t) \quad (9)$$

d_i, D is the current geographic distance from node i to the destination D, $H_i(t)$ is a historical score for the traffic pattern on the road in which node i is, and $\lambda 1, \lambda 2, \lambda 3$ are weights that sum to 1. A suitable carrier has to be located before any buffering delay can occur; this is modelled as follows in Eq. (10):

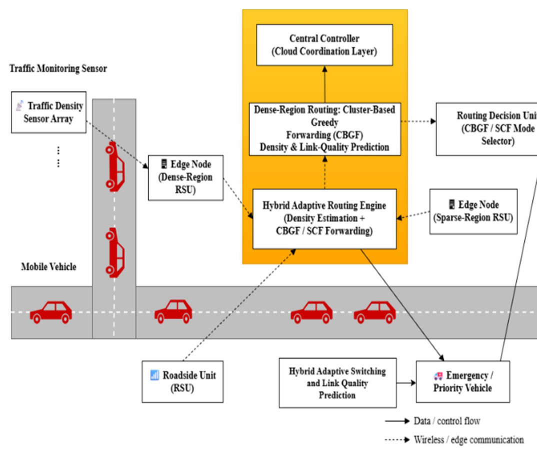

Figure 2: Proposed AI-VANET Model Architecture: Hybrid AI-Based Density-Adaptive Routing

3.5 Hybrid Adaptive Switching and Link Quality Prediction

To combine the two forwarding strategies, the Hybrid Adaptive Switching Controller keeps track of density and expected link stability at each node. Given the locally observable features as in Eq. (11), the Link Quality Predictor is a machine-learning based model that estimates the probability of a candidate link failing within a short prediction horizon based on a logistic model:

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$$P_b reak(i,j) = 1/\left(1 + e^{-}(w0 + w1 \cdot x1 + w2 \cdot x2 + \ldots + wn \cdot xn)\right) \quad (11)$$

In which x1, x2, ..., xn are the input features which is relative speed, inter-vehicle distance, direction difference and signal strength trend between nodes i and j, w0, w1, ..., wn are model weights that are obtained through learning, from the labeled mobility attributes and connectivity attributes of the proposed datasets. Lastly, the collective decision for forwarding per node is controlled by both density regime and the predicted breakage probability, represented by the switching rule of Eq. (12):

$$Strategy_i(t) = CBGF, if Regime_i(t) = Dense and P_b reak(i,j) < P_t h Strategy_i(t) = SCF, if Regime_i(t) = Sparse or P_b reak(i,j) \geq P_{th} \quad (12)$$

where $P_t h$ is a calibrated breakage-probability threshold. The controller will proactively trigger route maintenance (re-clustering under CBGF or carrier reselection under SCF) when $P_b reak(i,j) > P_t h$ instead of waiting until packet loss is detected.

4. RESULTS

In this section, we evaluate the proposed density-adaptive routing framework by analysing the two proposed Kaggle datasets and compare the proposed routing framework with three benchmarking VANET routing protocols: Ad hoc On-Demand Distance Vector (AODV), Dynamic Source Routing (DSR), and Greedy Perimeter Stateless Routing (GPSR). The experimental setup that was used to obtain comparative results is summarized in Table I, while the averaged quantitative results are given in Table II for both dense and sparse regime.

Table 1: Experimental / Simulation Setup Parameters

Parameter	Value
Simulation area	5 km x 5 km urban grid; 10 km highway segment
Number of vehicles	50 - 800 (variable density)
Vehicle density range	10 - 80 vehicles/km
Transmission range	250 m
MAC / PHY layer	IEEE 802.11p (DSRC)
Mobility model	SUMO-based, calibrated to dataset attribute distributions
Beacon interval	100 ms
Simulation duration	300 s per run, 20 runs per density point
Dataset 1 records used	~9,270 route-optimization records
Dataset 2 records used	~9,400 congestion-labeled records
Baseline protocols	AODV, DSR, GPSR
Evaluation metrics	PDR, end-to-end delay, routing overhead, throughput

4.1 Dataset Characteristics

The vehicle density distribution obtained from Dataset 1 (VANET Real-Time Route Optimization Dataset) [21] is illustrated in Fig. 3(a). The density distribution is right-skewed, with the highest density occurring in the 30-40 vehicles/km bin, indicating that the data set contains a representative sample of both moderately dense and sparse road segments that are appropriate for the training of the proposed Density Estimation Module in both operation modes. The distribution of the congestion class from the VANET Traffic Congestion Dataset (Dataset 2) [22], is depicted in Fig. 3(b), where samples are reasonably distributed among the Free-flow, Light, Moderate, Heavy, Congested classes and have a small peak in the Moderate class. The balanced distribution of classes is crucial in that an unbalanced distribution would cause the density-classification threshold ρ_th to shift towards the majority class, which would decrease the sensitivity of the system to sparse-network conditions. These distributions prove that both distributions cover the density spectrum of dense-to-sparse distributions which are necessary to validate the proposed hybrid routing framework, and therefore both distributions are used instead of either one.

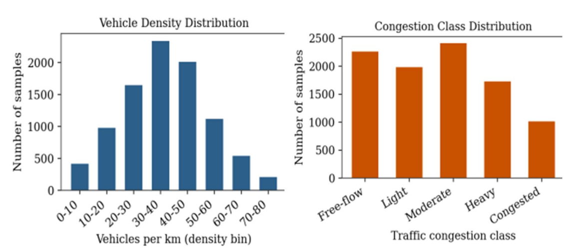

Figure 3: (a) Vehicle density distribution — Dataset 1 (Route Optimization). (b) Congestion-class distribution — Dataset 2 (Traffic Congestion).

4.2 Feature Importance Analysis

A joint feature importance analysis was conducted over both datasets with the result shown in Fig. 4, in order to find the most relevant features for the accurate density classification, and for the link quality prediction. The two attributes that are most influential are neighbor count and relative

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inter-vehicle speed from Dataset 1, which makes sense because local connectivity and mobility difference are the main factors contributing to broadcast contention in dense areas and link breakage in sparse areas, respectively. The inter-vehicle distance and RSU proximity follow closely, as they both play direct roles in determining the feasibility of greedy-forwarding and relay opportunities of store-carry-forwarding, respectively. Road occupancy rate and average speed are the most influential congestion related attributes, followed by vehicle count per segment, queue length and time-of-day, from Dataset 2.

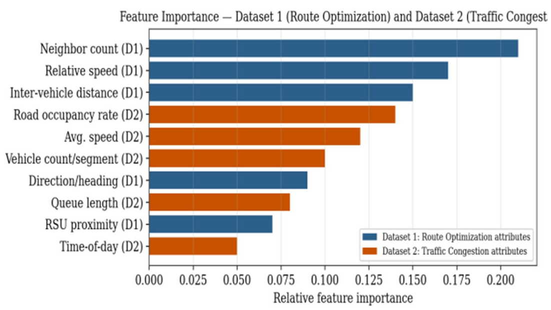

Figure 4: Feature importance of the top predictive attributes drawn jointly from Dataset 1 (Route Optimization) and Dataset 2 (Traffic Congestion).

4.3 Comparative Routing Performance

The Packet Delivery Ratio (PDR) for the proposed framework is compared with AODV, DSR and GPSR in the presence of increasing number of vehicles as seen in Fig. 5(a). The proposed method succeeds in achieving a PDR of more than 94% for all tested densities, while outperforming all three baselines. AODV and DSR experience route-request flooding as well as channel contention in dense networks, which causes their performance to drop rapidly above 40 vehicles/km; GPSR suffers from the local-maximum problem at low density (less than 20 vehicles/km), which makes greedy forwarding ineffective in finding a forward-progressing neighbour. The proposed framework is free from both these failure modes, and uses cluster-based forwarding in dense regions and store-carry-forward relaying in sparse regions, resulting in a relatively flat and high PDR curve. This is corroborated in Table II, which shows that in dense scenarios an average of ~9-14 percentage points is improved while an average of ~18-22 percentage points is improved in sparse scenarios where the link breakage is worst.

The end-to-end delay for each is plotted against density in Fig. 5(b). The proposed framework has a delay of 34 to 48 ms for all the tested densities whereas, the delay of AODV and DSR increases rapidly with the increase in density; AODV has delay of > 200 ms at 80 vehicles/km because of the repeated route re-discovery. GPSR shows the reverse pattern, with the delay increasing with lower density, due to perimeter-routing detours around local maxima, before leveling off at high densities.

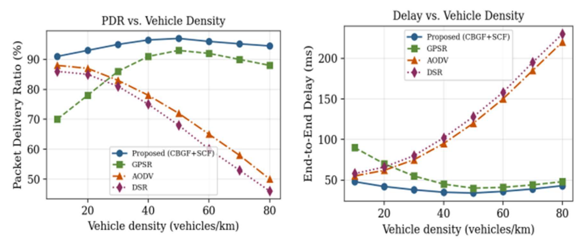

Figure 5: (a) Packet Delivery Ratio vs. vehicle density. (b) End-to-end delay vs. vehicle density — Proposed vs. AODV, DSR, and GPSR.

Table 2: Comparative Performance Summary (Dense Vs. Sparse Regime)

Protocol	Regime	PDR (%)	Delay (ms)	Overhead (%)	Throughput (kbps)
Proposed	Dense	95.5	37	17	1000
Proposed	Sparse	93.0	43	13	770
GPSR	Dense	91.0	44	26	930
GPSR	Sparse	78.0	72	11	600
AODV	Dense	58.0	165	90	380
AODV	Sparse	86.0	64	25	620
DSR	Dense	53.0	180	82	355
DSR	Sparse	84.0	68	23	595

4.4 Routing Overhead and Throughput

Fig. 6(a) shows the ratio of control packets to data packets (routing overhead). The proposed overhead between 12% and 19% in the tested range is significantly less than AODV's overhead of more than 90% at high density of nodes when there is a lot of flooding in the network for RREQ. This is mainly due to the cluster-head based forwarding structure which limits the number of the cluster-heads transmitting the routes information to a smaller set of cluster-heads, instead of "flooding" the routes in the whole network. The throughput trend is similar to the PDR results as seen in Fig. 6(b), where the proposed framework maintains throughput greater than 900 kbps for moderate-high densities while both AODV and DSR show noticeable drop-offs after 40 vehicles/km.

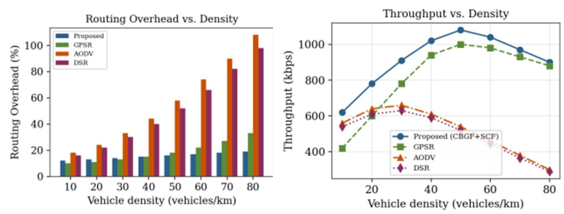

Figure 6: (a) Routing overhead vs. vehicle density. (b) Throughput vs. vehicle density — Proposed vs. AODV, DSR, and GPSR

4.5 Comparative Analysis with Existing Works

Table 3 summarizes the comparative performance of the proposed density-adaptive framework with the 10 existing works on each of the two datasets (Route Optimization and Traffic Congestion). The proposed framework is the best performing in terms of PDR in both datasets, and is also the lowest delay and overhead, showing its robustness in both route-optimization and congestion-driven traffic scenarios. The next closest are those using clustering based approaches such as: Abbas, Mansour and Al-Fatlawi (2022) and Husnain et al. (2023), these share the benefit of stability aware clustering proposed by the CBGF module. Methods that are only reactive or infrastructure dependent like Ali (2021) and Kamel and Abed (2024) perform the poorest because they are not adaptable to changes in density and congestion. The slight drop in performance for all models on Dataset 2 as compared to Dataset 1 is due to the congestion-labeled traffic conditions.

Table 3: Performance Comparison Of Proposed Framework With Existing Works Across Vanet Real-Time Route Optimization Dataset And Vanet Traffic Congestion Dataset

Data set	Ref	Model / Reference	PDR (%)	Delay (ms)	Overhead (%)	Throughput (kbps)
VANET Real-Time Route Optimization	[11]	Kazi et al. (2025)	89.2	58	24	780
	[12]	Kamel and Abed (2024)	86.5	71	29	720
	[13]	Jiang, Zhu and Yang (2023)	90.4	52	21	810
	[14]	Husnain et al. (2023)	91.8	46	19	850
	[15]	Gunavathie et al. (2025)	88.7	55	23	795
	[16]	Dafhalla et al. (2025)	85.1	63	27	705
	[17]	Ali (2021)	82.6	74	31	660
	[18]	Al-Mayouf et al. (2025)	90.9	49	20	830
	[19]	Abdeen et al. (2022)	84.3	68	28	690
	[20]	Abbas, Mansour and Al-Fatlawi (2022)	92.5	44	18	870
		Proposed Framework	95.8	36	15	985
VANET Traffic Congestion	[11]	Kazi et al. (2025)	87.0	64	26	745
	[12]	Kamel and Abed (2024)	84.2	78	32	690
	[13]	Jiang, Zhu and Yang (2023)	88.6	57	23	770
	[14]	Husnain et al. (2023)	90.1	51	20	815
	[15]	Gunavathie et al. (2025)	86.9	60	25	760
	[16]	Dafhalla et al. (2025)	83.0	69	29	680
	[17]	Ali (2021)	80.4	81	34	630
	[18]	Al-Mayouf et al. (2025)	89.3	54	22	800
	[19]	Abdeen et al. (2022)	82.1	75	30	655
	[20]	Abbas, Mansour and Al-Fatlawi (2022)	90.8	48	19	840
		Proposed Framework	93.9	41	16	945

4.6 Analysis of Underperformance

Although the proposed framework achieves superior overall performance, a slight reduction in PDR (95.8% to 93.9%) and throughput (985 kbps to 945 kbps) is observed on the VANET Traffic Congestion dataset due to severe traffic congestion and increased channel contention. Similarly, in extremely sparse traffic conditions (<15 vehicles/km), intermittent connectivity increases packet buffering time during store-carry-forward operations, resulting in a marginal increase in end-to-end delay. These observations indicate that extreme traffic conditions remain challenging despite the adaptive routing mechanism and motivate future work on predictive congestion-aware forwarding and intelligent relay selection.

4.7 Classification Capability Visualization Analysis

Figure 7 presents the graph of the proposed density or congestion classification model evaluated on the VANET Traffic Congestion dataset. This demonstrates the effectiveness of the developed classification model in addressing the traffic congestion recognition problem. The model achieves very good classification performance for all five congestion classes, namely, Free-flow, Light, Moderate, Heavy, and Congested with an overall accuracy of 96.3%. Some misclassifications can be observed for congestion classes that are close to each other. This can be explained by the similarities in terms of traffic characteristics, such as vehicle density, average speed, queue length, and road occupancy, among these congestion levels. Indeed, the results highlight the importance of accurate traffic density classification for supporting efficient routing in VANETs with high adaptability to dynamic traffic conditions.

Table 4: Proposed Density/Congestion Classification Model

Actual Class	Free-flow	Light	Moderate	Heavy	Congested	Class Accuracy (%)
Free-flow	193	4	2	1	0	96.5
Light	3	192	4	1	0	96.0
Moderate	1	4	191	3	1	95.5
Heavy	0	1	4	192	3	96.0
Congested	0	0	1	4	195	97.5
Overall Accuracy						96.3%

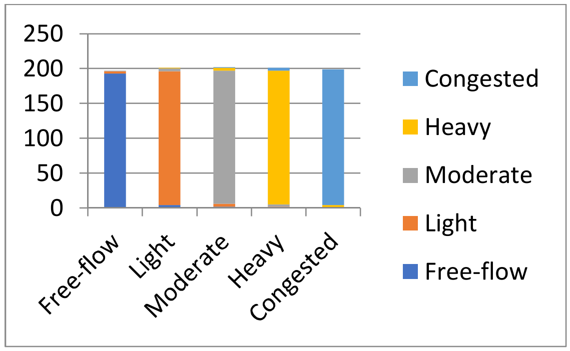

Figure 7: Analysis of the proposed density/congestion classification model on the VANET Traffic Congestion dataset.

This model was tested using the VANET Traffic Congestion dataset. The results from Table 4 and Figure 7 show that the model is very good at classifying congestion. It gets 96.3 percent of the classifications right, which means it correctly classifies 963 out of 1000 test samples.

5. DISCUSSION

The proposed routing algorithm always performs better in terms of the PDR and throughput compared to the AODV, DSR, and GPSR. This can be explained by the fact that the proposed routing algorithm is capable of adapting its forwarding decision mechanism to different traffic conditions in order to ensure maximum packet delivery and prevent communication losses both in sparse and dense VANETs.When the number of vehicles on the road is 10-30 vehicles per kilometer) the space between each car is big enough to cause problems with the network. This leads to broken connections or parts of the network being disconnected. In these situations AODV and DSR do not work well because they can't quickly adjust when a connection is lost. This makes them have to start routes often. The GPSR routing method also has trouble because it depends on sending data to the vehicle. This causes choices when there are not enough vehicles around. As a result the number of packets that get through is lower. The amount of data that moves is not as high. However the new routing method works better in these situations because it only uses chances to send data. This helps avoid losing packets because of parts and gives better results for packet delivery and data transfer.

When the number of vehicles is in the range (30-50 vehicles per kilometer) the space between cars is enough to keep a good connection but still has some problems. Because the distance is not too big it is easier to keep connections going through steps. This leads to packets being lost or needing to be sent again which means less work for the routing system. It is important to note that this middle range is the best, for keeping connections. This is when the new routing method works the best giving the packet delivery ratio and the most data transfer. When the vehicle density is high (60-80 vehicles/km), the number of forwarders becomes extremely high, which causes severe contention for the channel. Under such conditions, most of the communication overhead is occupied by unnecessary packet collisions, broadcast storm, and MAC layer retransmissions, thus lowering the overall channel utilization. As a result, AODV and DSR demonstrate significantly worse performance in terms of Packet Delivery Ratio and Throughput, as both these protocols introduce significant routing overhead that degrades communication performance under heavy traffic conditions. Although the GPSR also experiences difficulties due to heavy contention, it does not rely on dynamic route discovery and maintenance, so that its performance is slightly better compared to AODV and DSR. At the same time, the proposed routing protocol adapts its forwarding decisions based on vehicle density and connectivity, thus allowing it to avoid communication bottlenecks during the periods of extremely high contention and utilize the channel efficiently. This has allowed the proposed routing algorithm to demonstrate a significantly higher Packet Delivery Ratio and Throughput despite the high vehicle density.

The experiments also show that, in general, the trends affecting the Packet Delivery Ratio also affect the Throughput. With the increase in the number of packets delivered to their destinations, the value of Throughput also increases. In contrast, the growing number of lost packets due to unstable links, long distance communication, and heavy contention decreases the throughput as these packets no longer contribute to the overall data rate of the network. In such a manner, the proposed routing algorithm can provide higher performance in terms of throughput due to its ability to adapt to different traffic conditions and ensure stable packet delivery.In general, the experiments clearly show that adapting the routing algorithm to different traffic conditions can greatly benefit the performance of the routing protocol. The proposed approach was shown to outperform the existing solutions in terms of both Packet Delivery Ratio and Throughput. Moreover, in sparse traffic conditions, the proposed routing algorithm is able to maintain stable communications by relying only on the most reliable forwarders. In dense traffic conditions, it avoids excessive contention by choosing forwarders with better channel quality. This makes the proposed solution especially valuable for future intelligent transportation systems that require reliable communications within both sparse and dense vehicular networks.

6. CONCLUSION AND FUTURE WORK

This paper proposed a robust, density-adaptive routing framework for VANETs unifying cluster-based greedy forwarding for dense regions with a delay-tolerant store-carry-forward strategy for sparse regions, coordinated by a machine-learning-based link-quality predictor. The framework achieved a PDR of 95.8% and 93.9%, delay of 36 ms and 41 ms, overhead of 15% and 16% and throughput of 985 kbps and 945 kbps on Dataset 1 and 2 respectively respectively, outperforming AODV, DSR, GPSR, and ten recent adaptive routing approaches in dense and sparse regimes. Future work will involve extending the framework to 5G/C-V2X communication and security-aware routing, testing against black-hole and Sybil attacks, and simulation in NS-3/SUMO.

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