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Research Article

A QoS-Aware Hybrid Framework for Congestion Control and Message Scheduling in VANETs

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Abstract
Vehicular Ad Hoc Networks (VANETs) have emerged as a critical component in advancing the safety and efficiency of Intelligent Transportation Systems (ITS). In VANETs, vehicles exchange information primarily through two types of messages: periodic beacon messages for traffic management and event-driven messages for emergency notifications. While beacon messages convey essential data such as location, speed, and direction, excessive broadcasting in dense traffic scenarios can lead to severe network congestion, increased latency, and reduced reliability of safety-critical communications.
To address these challenges, this paper proposes a Dynamic Congestion Control scheme for VANETs (DCCV), which dynamically adjusts the transmission frequency of beacon messages based on real-time traffic density to reduce channel overload and improve packet delivery rates. Furthermore, a hybrid prioritization mechanism is introduced that leverages both static (e.g., message type) and dynamic (e.g., network conditions) factors to ensure timely transmission of high-priority messages while deferring lower-priority ones. This approach effectively preserves channel availability for emergency data dissemination.
Extensive simulation results demonstrate that the proposed DCCV framework significantly outperforms existing methods in terms of delivery rate, end-to-end delay, and overall network performance, making it a promising solution for congestion management in safety-critical vehicular networks.

Keywords: Wireless sensor network (WSN); Vehicular Networks; Vehicular ad-hoc network (VANET); Congestion Avoidance; Event-Based Messages; Congestion Recognition; Beacon Messages.

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1. Introduction

Vehicular Ad-hoc Networks (VANETs) represent a rapidly evolving technology with significant potential for future development. By enabling direct communication among vehicles and other devices, VANETs facilitate a range of services specifically tailored for vehicular environments [1]. These networks operate without relying on fixed infrastructure or centralized management units, which introduces both unique challenges and opportunities for research [2].

VANETs are distinguished from conventional networks by several characteristics, including high node mobility, frequent topological changes, and dense network deployment. While traditional networks also face issues such as configuration complexity, limited storage, and power constraints, congestion emerges as the most critical challenge in VANETs. Congestion particularly affects safety-critical applications, including accident notifications, emergency alerts, and warnings related to road conditions. Channel congestion typically occurs as vehicle density increases, leading to higher packet collisions and degraded network performance. Effective congestion control strategies are therefore essential to enhance the reliability and efficiency of vehicular communications [3].

As illustrated in Fig. 1, congestion control protocols in VANETs can be broadly classified into four categories based on the network layer at which they operate: (i) congestion-aware MAC protocols, functioning at the data link layer, (ii) congestion-aware routing schemes, operating at the network layer, (iii) dedicated congestion control mechanisms for the transport layer, and (iv) cross-layer protocols, which integrate functions across two or more layers [4].

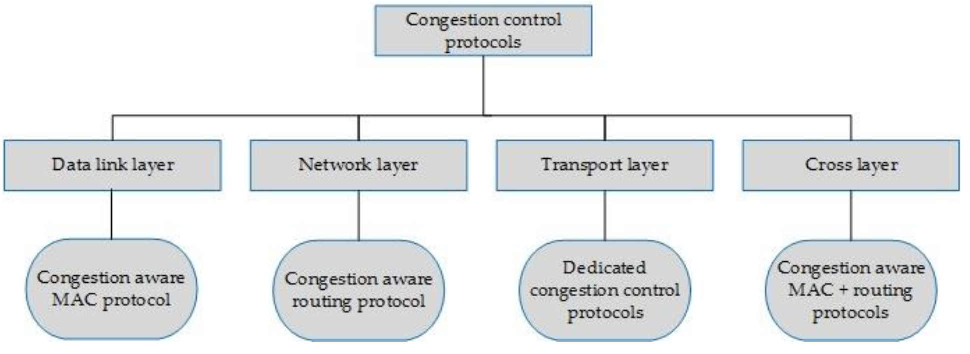

Fig.1. Classification of congestion control protocols

In VANETs, sensors continuously and simultaneously transmit vehicle and road information through relay nodes to base stations [5]. This high-volume data transmission significantly increases the risk of network congestion, packet loss, delayed reception at sinks, and elevated energy consumption. Various congestion control strategies have been proposed to address these issues, including measurement-based detection, buffer freezing, transmission power adjustment, and MAC layer blocking [6–9].

Congestion is particularly detrimental in safety-critical applications, as delays and packet loss can directly compromise passenger safety [10]. Consequently, congestion management in VANETs poses more stringent challenges than in conventional networks.

In this study, we propose a Dynamic Congestion Control scheme for safety applications in VANETs (DCCV), which consists of two main components: congestion detection and delay mitigation through the prioritization of critical packets. Simulation results demonstrate that the proposed DCCV framework outperforms existing methods in terms of throughput, end-to-end delay, control overhead, and packet delivery ratio, highlighting its effectiveness for safety-oriented vehicular communications

The main contributions and novelties of this paper can be summarized as follows:

1. **Dynamic Congestion-Aware Beacon Control Mechanism:** We propose a novel Dynamic Congestion Control scheme for VANETs (DCCV) that adaptively regulates the transmission of beacon messages based on real-time congestion status. Unlike static or periodic schemes, the proposed method dynamically adjusts the beaconing rate in response to traffic density and channel conditions, effectively reducing network overload and improving message delivery. In contrast to integrated approaches that simultaneously address beaconing and prioritization, our method decouples these two processes, which makes the scheme more lightweight, scalable, and easier to adapt to diverse traffic scenarios.
2. **Priority-Based Event Message Scheduling using Static and Dynamic Factors:** A dual-factor prioritization mechanism is introduced that considers both static parameters (e.g., message type) and dynamic network conditions (e.g., channel load and vehicle proximity) to ensure the timely delivery of high-priority event-based safety messages. This approach not only prevents delay in emergency communication but also explicitly differentiates itself from joint beacon-control-and-prioritization frameworks by providing a flexible prioritization logic that can be independently optimized.
3. **Congestion Avoidance through Intelligent Channel Management:** By deferring the transmission of lower-priority messages and creating transmission windows for emergency messages, our approach minimizes packet collisions and ensures channel availability for time-sensitive data, which is critical in safety-related applications. This channel management layer complements the proposed prioritization mechanism, resulting in a more robust communication strategy compared to existing integrated solutions.
4. **Performance Superiority through Extensive Simulation:** Through comprehensive simulation using realistic mobility and traffic models, we demonstrate that DCCV outperforms both classical schemes and recent integrated approaches in key metrics such as packet delivery ratio, end-to-end delay, network throughput, and control overhead. This confirms the effectiveness and novelty of the proposed framework.

These contributions position DCCV as a comprehensive and practical solution for congestion control and priority management in safety-critical vehicular networks, offering significant advancements over prior work in both methodology and performance.

The structure of this article is organized as below:

Section two focuses on reviewing related works and existing solutions. Section three introduces the proposed method, which is divided into two main parts: congestion detection and message prioritization. Section four is devoted to simulating the proposed method. Section five provides an analysis of the data and a review of the simulation results. Finally, section six presents the conclusions and outlines directions for future research.

2. Literature review

Ensuring vehicular safety has emerged as a central concern in modern intelligent transportation systems (ITS). In this context, several communication standards have been developed to support vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications, particularly in safety-critical applications. The IEEE 1609 and IEEE 802.11p standards, together with the SAE family, constitute the core of the WAVE (Wireless Access in Vehicular Environments) protocol stack, covering the full spectrum from the physical to the application layer in inter-vehicular communications [7]. These standards define essential parameters such as channel spectrum, message format, and delivery mechanisms that are vital for ensuring reliable and timely dissemination of safety messages. Typically, these messages are transmitted via carrier-sense multiple access with collision avoidance (CSMA/CA) protocols using DSRC/WAVE technology [11].

Despite the existence of such frameworks, congestion control in Vehicular Ad Hoc Networks (VANETs) remains a significant challenge, primarily due to their highly dynamic topology and frequent changes in traffic density. Compared to traditional fixed networks, congestion control in VANETs is relatively underdeveloped and exhibits several limitations [12–14]. Recent research has explored intelligent and adaptive techniques to address these challenges more effectively.

Among these approaches, reinforcement learning-based methods have gained prominence. For instance, a model proposed in [15] employs a Markov Decision Process (MDP) in conjunction with Q-learning to dynamically adjust beacon transmission rates, achieving a trade-off between situational awareness and channel load. Similarly, the Traffic Density-based Congestion Control Algorithm (TDCCA) presented in [16] utilizes vehicle-ID-based Cooperative Awareness Message (CAM) scheduling and mathematical traffic density estimation to mitigate channel congestion. Addressing security-induced traffic, [17] integrates a Local Outlier Factor (LOF) with Random Forest classifiers to optimize intrusion detection, thereby reducing IDS-related message overload and enhancing network robustness.

Advanced machine learning techniques have also been leveraged for traffic classification and congestion mitigation. Budholiya et al. [18] introduced a hybrid deep learning framework that combines YOLOv5 for vehicle detection, a Greedy-based Genetic Algorithm (GGA) for feature selection, and a CNN-LSTM architecture for traffic state classification. This method offers improved accuracy and reduced latency, contributing to real-time traffic monitoring and proactive congestion management.

In another significant contribution, St. Amour and Jaekel [19] proposed the Data Rate-based Congestion Control (DRCC) algorithm, a decentralized scheme that adjusts safety message data rates in response to real-time Channel Busy Ratio (CBR) measurements. Unlike iterative rate adjustment approaches, DRCC makes single-step optimal rate decisions, resulting in enhanced packet delivery, improved channel stability, and increased situational awareness, particularly in high-density scenarios.

Edge computing has also been harnessed to decentralize congestion management. The architecture presented in [20] integrates two core components: Vehicle Registration and Routing Communication (VARC) and Validation Filtering Message Caching (VFMC). By offloading computations to edge servers that analyze traffic flow and distribute timely alerts, the system significantly reduces latency and computational burden, providing efficient early-warning mechanisms and localized congestion control.

Further, VANET performance under dense traffic and QoS constraints has been improved through several innovative strategies. The Connected Dominating Set Forwarding (CDSF) technique proposed in [21] establishes a traffic-aware virtual backbone using dominator nodes selected based on connectivity, speed, and stability. By integrating alert thresholds based on travel-time distributions and employing Grant-Free Pattern Division Multiple Access (GFP-DMA), CDSF reduces queuing delays and enhances throughput. Simulation outcomes demonstrate marked improvements in packet delivery ratio, throughput, and latency reduction over baseline approaches.

In a complementary direction, the Adaptive Data Dissemination Protocol (AddP) [22] introduces an adaptive beaconing strategy based on local vehicle density, employing a hybrid relay selection metric that combines geographic and density-based factors. It includes a retransmission mechanism via neighboring nodes or RSUs and leverages XOR-based network coding to aggregate safety messages, minimizing channel occupancy. Simulation results affirm the protocol's high reliability and low delay in both urban and highway settings.

To meet future demands in 6G-enabled VANETs, the Traffic Congestion Control QoS (TCCQ) method introduced in [23] utilizes selective single-hop dissemination to immediate successors, thereby minimizing unnecessary broadcast and preserving bandwidth. By leveraging ultra-high-speed communication capabilities of 6G, TCCQ significantly enhances delay and jitter metrics while effectively scaling in dense networks.

Lastly, [24] presents an adaptive, server-assisted load balancing mechanism composed of three integrated modules: a Modified K-means Clustering algorithm for real-time vehicle grouping, an RSU-based scheduling policy prioritizing data flows, and a centralized load-balancing server for dynamic traffic distribution. This system improves routing efficiency, reduces energy consumption, and ensures scalable performance across variable topologies—making it particularly suitable for complex ITS environments.

Collectively, these research efforts offer complementary solutions to the multifaceted challenges of VANETs. The integration of such approaches holds promise for realizing resilient, low-latency, and scalable vehicular communication systems. Table 1 compares the most notable approaches discussed in this section and highlights the comparative advantages of all models.

Table 1- Summary of Some Existing Methods

Aspect / Ref	**Research Domain**	**Application Area**	**Methodology**	**Tools**	**Proposed Algorithms**	**Challenges Addressed**	**Strengths**	**Weaknesses**
[15]	Reinforcement Learning, VANET	V2V communication in VANETs	MDP modeling with reinforcement learning	RL environment traffic simulator	Q-Learning with dynamic reward function	Congestion–balance; message collision; delay in dense traffic	High delivery rate; adaptive to dynamic environments; low beacon error	Limited to transmission rate only; reward function design is complex
[16]	MAC-layer congestion control	Periodic CAM broadcast in dense networks	CAM scheduling based on traffic and vehicle ID	MATLAB /NS3	TDCCA with CAM-ID scheduling	Message collisions, increased latency under saturation	Improved success rate; lower delay and energy usage; adaptable to traffic state	No adaptive learning; relies on static estimation models
[17]	IDS, Security, Optimization	Security traffic handling in VANETs	Optimization of IDS traffic load	Python, Weka, IDS datasets	Lightweight IDS combining LOF and	Bandwidth overload from IDS traffic;	High detection accuracy; reduced false	Focused only on IDS; not applicable to standard

					Random Forest	detection inefficiency	positives and latency	VANET messages
[18]	Real-time vehicle detection and congestion prediction	Deep learning-based image classification and optimization	YOLOv5 for object detection, GGA for feature selection, Deep CNN-LSTM for classification	Python, YOLOv5 engine, TensorFlow/Keras	GGA + CNN-LSTM integrated with YOLOv5	Low prediction accuracy and long processing time in traffic analysis	High accuracy in detection, feature optimization, supports dynamic scenarios	High computation cost; slower inference in deep models
[19]	Safety message optimization	Decentralized adaptive control based on channel load (CBR)	Dynamic bitrate selection using CBR thresholds	OMNeT++, SUMO, VEINS simulator	Channel Busy Ratio + threshold-based adaptation	High channel load due to fixed bitrate; packet collision and loss	Efficient channel usage, fast convergence, independent of neighbor cooperation	Possible bitrate instability with rapid network changes
[20]	Intelligent transportation (ITS)	Distributed computing and message filtering via edge infrastructure	Edge servers, vehicle OBUs, caching systems	Edge servers, vehicular buffers, local communication interfaces	VARC + VFMC	Congestion due to message flooding and delayed alerts	Scalability, reduced central load, early congestion warnings	Depends on edge connectivity; extra infrastructure cost
[21]	Traffic Congestion Management in High-Density VANETs	Traffic Control and Packet Routing in Urban Vehicular Environments	CDSF: CDS-based backbone formation with alert-threshold-based forwarding	NS2 and SUMO	CDSF (Connected Dominating Set formation + GFP-DMA + stability-based node selection)	Traffic congestion, dynamic topology, routing overhead, packet loss, delay	Low delay, improved throughput, enhanced delivery ratio, fault-tolerant routing via backbone structure	Requires minimum node density and low-velocity vehicles for consistent CDS backbone stability
[22]	Safety-Critical Data Dissemination in VANET	Real-Time Hazard Warning Broadcast in Urban and Highway Scenarios	AddP: Adaptive multi-hop beacon-assisted protocol with density-aware relay selection	OMNeT++	Adaptive beaconing, relay selection (density + distance), XOR aggregation, dissemination monitoring	Broadcast storm, hidden terminal problem, message loss in sparse and dense scenarios	High reliability, efficient coverage, reduced delay, adaptable to both sparse and dense networks	Complex coordination, susceptible to beacon load in high-density scenarios
[23]	QoS Optimization in 6G-based VANETs	Vehicle-to-Vehicle Communication using 6G Infrastructure	TCCQ: Single-hop selective traffic status forwarding using 6G data rate	not specified	Single-hop selective forwarding + neighbor detection + broadcast suppression (6G)	Broadcast flooding, bandwidth overload, and network congestion	Efficient bandwidth usage, minimal broadcast overhead, high QoS under 6G conditions	Relies on 6G infrastructure, lacks support for multi-hop communication
[24]	VANETs, Intelligent Transportation Systems	Urban vehicular traffic management	Modified K-means Clustering; RSU-based scheduling policy; Congestion control via centralized load balancing server	VanetMobiSim + NS-2 (CANU extension)	Modified K-Means Clustering Algorithm (2) RSU-Based Scheduling Algorithm (3) Congestion Control via Load Balancing Server	Network congestion, RSU overload, high end-to-end delay, low packet delivery ratios	Dynamic traffic load distribution; improved PDR and latency; scalable to dense urban settings	Simulation-based only; lacks validation in real-world deployments; RSU-centric limitations remain

3. Methodology

The primary objective of this study is to develop an optimized strategy for mitigating congestion in vehicular networks. To this end, we introduce a novel and efficient approach, termed Dynamic Congestion Control for VANETs (DCCV), which leverages Support Vector Regression (SVR) and Genetic Algorithms (GA) to model and optimize key network parameters.

To specifically address congestion in safety-critical communications, the proposed framework implements a dynamic congestion control strategy for the timely delivery of safety messages. The approach is designed to reduce control overhead, alleviate broadcast storm issues, and improve packet delivery rates in vehicular networks. The operational steps of the DCCV method are illustrated in Fig. 2.

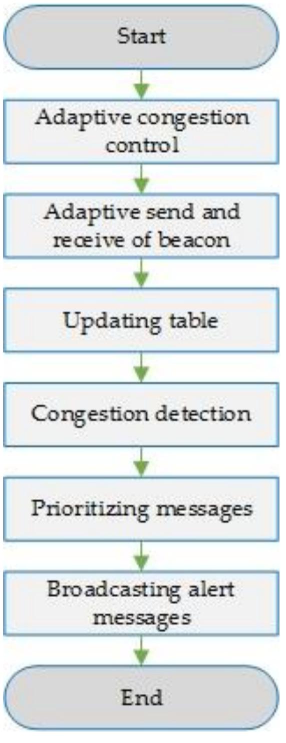

Fig.2. Operational modules of the proposed method

3.1.Sending and controlling beacon messages strategy

Beacon transmission is a fundamental mechanism for discovering and exchanging local information among one-hop neighbors in vehicular networks. Most existing studies have relied on periodic beaconing in their proposed approaches. However, in high-density traffic scenarios, frequent beacon transmissions can significantly increase the risk of packet collisions.

In the proposed method, instead of using static beacon intervals, a dynamic BM periodic beaconing mechanism is employed to mitigate packet collisions in dense networks. The mechanism adaptively adjusts the timing of subsequent beacon transmissions based on local vehicle density and congestion levels. In dense traffic conditions, the beacon interval is extended compared to sparse scenarios, thereby preserving channel availability for critical safety messages. Moreover, when the probability of collisions on the channel is high, the beacon interval is further increased to reduce interference and improve overall network performance.

The collision probability C is calculated using Equation (1). The interval between successive beacon messages (T_{beacon}) for node i is determined using Equation (2), where T_{min} represents the minimum periodic interval for all nodes (150 milliseconds), D_i denotes the density of node i within its one-hop neighborhood, ΔT is the time added by each vehicle to the scenario (20 milliseconds), and Rand [0,0.003] is a randomly generated time between 0 and 3 milliseconds. This random time prevents identical intervals from being assigned to vehicles with similar conditions.

$$C_i = \frac{\tau_i}{\varsigma_i} \qquad (1)$$

$$T_{beacon} = (T_{min} + (D_i C_i \Delta T)) - Rand[0, 0.003] \qquad (2)$$

τ_i is the incoming traffic rate and ς_i shows the outgoing traffic rate (service rate). The incoming traffic rate refers to the number of packets entering the physical layer from a single node within a unit of time. Similarly, the service rate represents the number of packets transmitted from the channel per unit of time. In the proposed method, the sending rate is dynamically adjusted based on the density and congestion level. Nodes experiencing high density or congestion adopt a longer interval between beacon transmissions.

When node i receives a BM beacon message, it updates its database with the relevant information, including the vehicle's ID and the content of the received beacon message.

3.2.Congestion detection strategy

This section reviews congestion detection techniques, with particular emphasis on event-based and neighbor event-based methods:

1. **Self-organizing event-based detection:** In this approach, the system monitors safety messages originating from the node itself and applies congestion control mechanisms accordingly. For example, when a vehicle generates safety messages at the application layer, congestion control is promptly initiated based on the predicted network load.
2. **Neighbor event-based detection:** This method focuses on safety messages received from neighboring nodes. Congestion is managed by adjusting the intervals between incoming messages. When a safety message originates from the node itself or a neighboring vehicle, the channel congestion level is periodically evaluated to determine whether it exceeds a predefined threshold.

The proposed communication channel design considers factors such as buffer size, channel occupancy, and utilization level. Channel occupation time is measured to represent the duration during which the wireless medium is busy due to transmissions from nearby vehicles, reflecting both network density and packet transmission rates.

Once the waiting time is determined, the channel usage level is computed based on the channel occupation period and the back-off period, as expressed in Equation 3. Specifically, ∑ denotes the total estimated channel occupation time for n messages detected within a Control Channel (CCH) interval. This computation allows effective regulation of channel usage, thereby supporting efficient congestion management in the network.

$$ch_{usage} = \sum \frac{w_{busy} \times D_{busy} + wt_{back-off} \times D_{back-off} + w_{AIFS} \times D_{AIFS}}{D_{CCH}} \times 100\% \quad (3)$$

Where w_{busy} shows the weighted factor of channel occupation time and D_{busy} represents the channel occupation length for each sensed message. $wt_{back-off}$ represents the weighted factor for the length of back-off period and $D_{back-off}$ represents the length of back-off period. w_{AIFS} represents the weighting factor of the message length, and D_{AIFS} represents the safety message length.

3.3.Congestion control strategy

The primary objective of the proposed congestion control strategy is to prioritize beacon and safety messages, determining the order in which messages are transmitted. To achieve effective congestion management, a message prioritization mechanism is employed that incorporates both static and dynamic factors. The static factor is derived from the message content, while the dynamic factor is based on prevailing network conditions. Specifically, vehicle velocity, signal-to-noise ratio (SNR), and the number of neighboring nodes is used to calculate the dynamic factor. This approach ensures that high-priority messages are transmitted without delay, while lower-priority messages are scheduled appropriately within the network, thereby optimizing overall message delivery and network performance. Prioritizing messages is directly related to $Static_{Factor}$ and $Dynamic_{Factor}$ and inversely related to $Message_{size}$. Beacon messages are labeled as priority 1 and warning messages (event-oriented) are labeled as priority 2. Unlike the $Static_{Factor}$, which uses message content to prioritize, the $Dynamic_{Factor}$ uses network characteristics including the SNR to prioritize messages. If the receiver node is located at location d, the SNR value is calculated according to equation (4) where T_p is the transmission power of the transmitter, I is the interference obtained by the transmission power of the active neighboring nodes around the node, and N Is the amount of noise. In this paper, we consider the number of neighbors in the receiver node. The aim of this method is to reduce the number of neighbors around the node, which will reduce the likelihood of sending and receiving messages within transmission range and thus reduce the interference. In this paper, we have used the node velocity criterion as a $Dynamic_{Factor}$ in prioritizing messages. This factor is normalized according to its transmission range. Higher priority should be assigned to the higher Vel value. In equation (6), one unit is added to the number of neighbors so that if there are no neighbors, the denominator is not zero and the results are not shown vaguely.

$$SNR(d) = \frac{T_p}{I + N} \tag{4}$$

$$Vel = \frac{\pi \times R^2 + 2 \times R \times v \times dt}{\pi \times R^2} \tag{5}$$

$$Dynamic_{Factor} = \frac{Vel \times SNR(d)}{N + 1} \tag{6}$$

To better understand the proposed method, the flowchart of the DCCV method is shown in fig. 3.

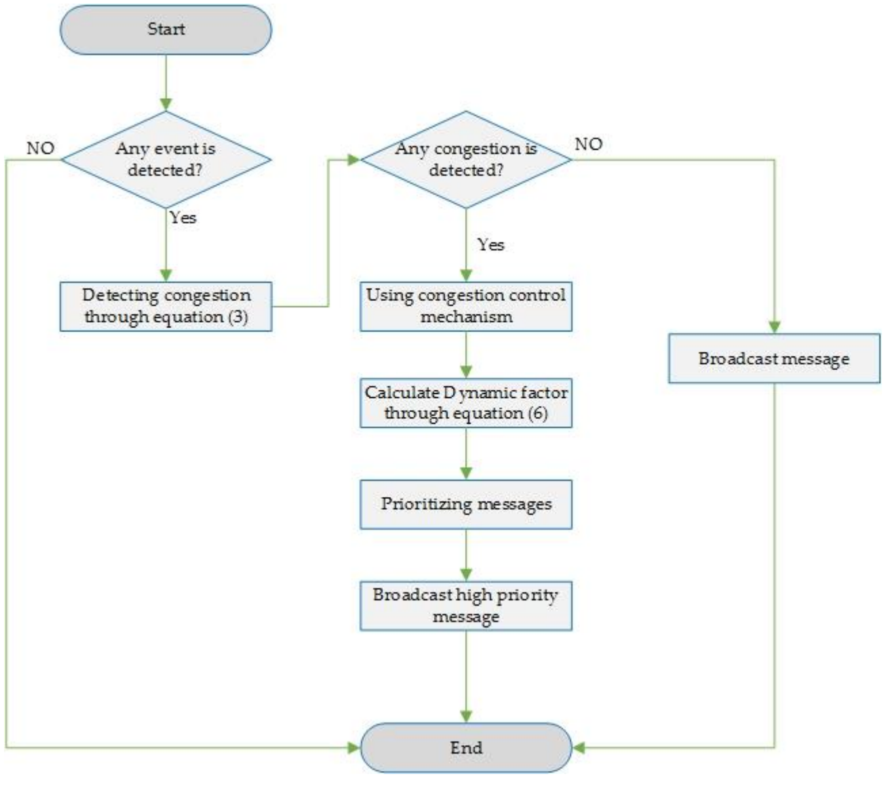

Fig.3. DCCV Flowchart

4. Simulation

The proposed method was implemented using the NS-2 simulator. The simulation was conducted on a 64-bit system with 8 GB of RAM and an Intel® Core™ i7-2670QM CPU running at 2.20 GHz, featuring 4 cores and 8 logical processors.

Several input parameters were configured to define the network protocol stack, including the operating environment, the MAC layer standard, the propagation model, the simulation scenario, the number of nodes, the traffic type, and the transmission rates. A detailed explanation of each parameter is provided below. Additionally, Table 2 summarizes the NS-2 simulation parameters used in this study.

TABLE 2- SIMULATION PARAMETERS

PARAMETER	**Value**
Number of Vehicles	50, 100, 150, 200,250,300,350
Transmission Range	300 meters
Transmission Power	0.98 mw
Simulation Area (m*m)	2000 * 2000
Mobility Generator	C4R
Routing Protocol	ADDP, DRCC, TDCCA & DCCV
MAC/PHY	IEEE 802.11p
Packet Rate	1 packet per second
Minimum speed	30 Km/h
Maximum speed	100 Km/h
Bit Rate	3 Mbps
Beacon Size	32 Byte
Data Packet Size	512 Byte
Buffer size	50 Packets
Propagation Model	Nakagami
Connection Type	CBR
Simulation Time	450 s
Number of Repetition	15
Channel frequency	5.9 GHz
T_{min}	1 seconds
ΔT	20 illiseconds

4.1.Physical layer model

In the simulation design, we have used the Nakagami model.

4.2.Motion and traffic model

In order to create a real simulator, SUMO software has been used. The considered scenario has dimensions of 2000 meters by 2000 meters.

4.3.Network layer and access control

The contention window size was set between 10 and 1523, and the data rate for broadcast packets was configured at 3 Mbps. Lower data rates provide higher reliability in the presence of network noise and channel distortions. The transmission range was set to 300 meters, and the IEEE 802.11p standard was employed for the MAC layer, with a channel bandwidth of 10 MHz.

4.4.Simulation time

The total simulation duration was set to 450 seconds, with the first 50 seconds excluded to eliminate the effects of transient behavior. A total of 15 simulation runs were conducted, and results were reported with a 95% confidence interval.

4.5.Urban environment with different number of nodes

Scalability is a critical aspect in vehicular networks, and it is essential for proposed methods to assess their performance under varying network conditions. In the proposed approach, different numbers of nodes were considered to evaluate the scalability and robustness of the network.

5. Results and Discussion

This section provides a comprehensive comparative evaluation of the proposed DCCV protocol against three existing schemes: ADDP, DRCC, and TDCCA. The assessment is performed using six performance metrics across varying vehicle densities, ranging from 50 to 350 nodes.

1. **Packet Loss Ratio (PLR):** As shown in Figure 4, DCCV consistently achieves the lowest PLR across all network densities. For example, at 350 vehicles, DCCV exhibits a PLR of approximately 12%, whereas ADDP, DRCC, and TDCCA report around 14%, 23%, and 13%, respectively. The significant reduction in PLR highlights DCCV's ability to manage channel congestion and adaptively regulate beacon transmissions, thereby minimizing packet collisions.
2. **Throughput:** Figure 5 demonstrates that DCCV outperforms other protocols in terms of throughput, particularly under high-density scenarios. At 350 vehicles, DCCV achieves approximately 30 Mbps, compared to TDCCA (22 Mbps), DRCC (29 Mbps), and ADDP (23 Mbps). This improvement is attributed to DCCV's congestion-aware transmission scheduling and prioritized channel access.
3. **Control Rate (CR):** As depicted in Figure 6, DCCV maintains the lowest congestion rate across all network densities. At 350 vehicles, DCCV records a CR of about 38%, whereas ADDP, DRCC, and TDCCA report 47%, 50%, and 41%, respectively. This reduction underscores the effectiveness of DCCV in dynamically managing traffic load and mitigating channel contention, thereby reducing congestion under heavy network conditions.
4. **End-to-End Delay:** Figure 7 illustrates the superior delay performance of DCCV. At 350 vehicles, the average E2E delay for DCCV remains below 80 ms, while DRCC, TDCCA, and ADDP exhibit approximately 100 ms, 82 ms, and 90 ms, respectively. The dynamic congestion control in DCCV facilitates faster route convergence and timely packet forwarding, which is critical for real-time vehicular applications.
5. **Routing Overhead:** As shown in Figure 8, DCCV maintains a routing overhead of around 15%, the lowest among all compared protocols. In high-density conditions, TDCCA and ADDP increase to 17% and 24%, respectively. The cluster-based architecture and efficient control mechanisms of DCCV contribute to reduced routing load and enhanced scalability.
6. **Packet Delivery Ratio (PDR):** Figure 9 indicates that DCCV achieves the highest PDR across nearly all vehicle densities. At 350 vehicles, DCCV reaches a PDR of approximately 26%, compared to TDCCA (20%) and both DRCC and ADDP (20% and

23%). The higher PDR confirms the robustness of DCCV in maintaining network connectivity and reliability, especially under congested conditions.

Table 3 provides a comparative summary of all evaluated protocols at a network density of 350 vehicles, highlighting the efficiency and superiority of the proposed DCCV approach in mitigating congestion and enhancing overall network performance.

TABLE 3- PROTOCOL COMPARISON AT 350 VEHICLES

Metric	DCCV	TDCCA	DRCC	ADDP
Packet Loss Ratio (%)	12	13	23	14
Throughput (Mbps)	29	21	29	23
Congestion Ratio (%)	38	41	50	47
E2E Delay (ms)	78	82	100	90
Routing Overhead (%)	15	17	24	16
Packet Delivery Ratio (%)	26	20	20	23

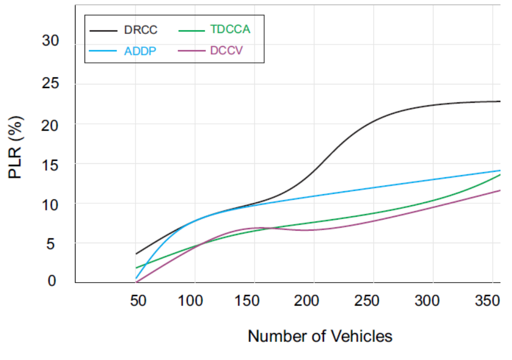

Fig.4. Packet loss Rate in different number of nodes

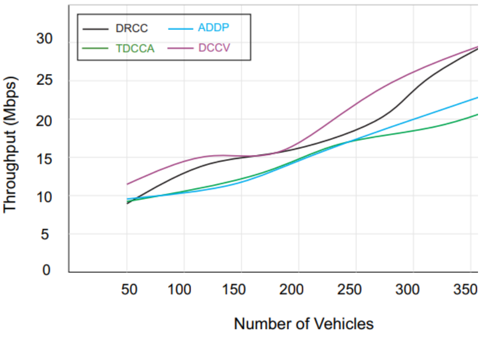

Fig.5. Throughput in different number of nodes

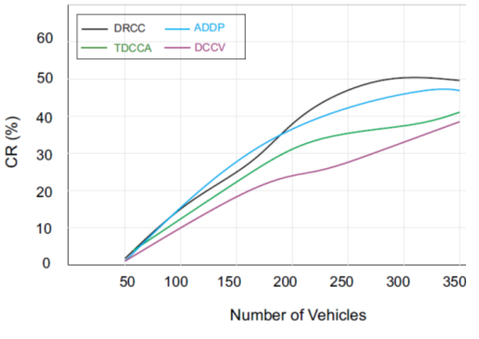

Fig.6. Collision Rate in different number of nodes

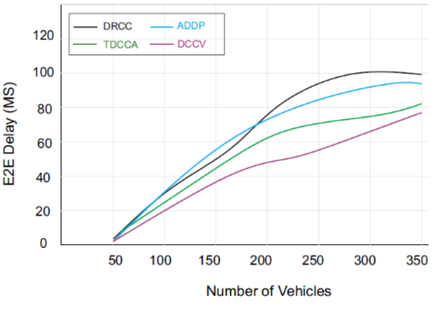

Fig.7. End-to-End delay in different number of nodes

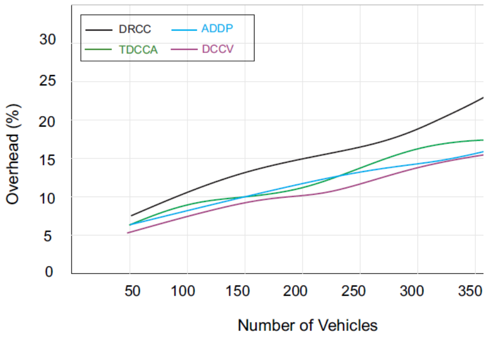

Fig.8. Beacon overhead in different number of nodes

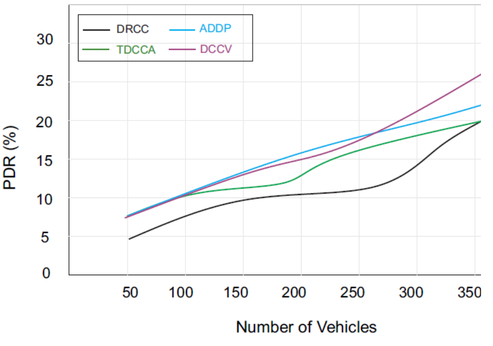

Fig.9. Packet delivery Rate in different number of nodes

The analysis confirms that the proposed DCCV protocol delivers substantial improvements across all key performance metrics, particularly in high-density network scenarios. It achieves higher packet delivery ratios and throughput, while reducing end-to-end delay, packet loss, and control overhead. These enhancements demonstrate that DCCV is well-suited for reliable and efficient communication in VANET environments.

6. Conclusion and Future Work

In this study, we propose a hybrid and intelligent framework, termed Dynamic Congestion Control for VANETs (DCCV), for dynamic congestion management and message scheduling in Vehicular Ad Hoc Networks (VANETs). The framework is designed to tackle major challenges in vehicular communications, particularly under high-density conditions, including channel congestion, delays in delivering critical messages, and degraded Quality of Service (QoS).

The first phase of DCCV involves an adaptive beacon rate control mechanism that dynamically adjusts beacon transmission rates based on real-time traffic density analysis, thereby preventing congestion and enhancing bandwidth utilization. In the second phase, a two-stage message scheduling mechanism is implemented, considering both intrinsic message characteristics (e.g., type and priority) and current network conditions (e.g., emergency situations and traffic load levels).

Simulation results obtained in the NS-3 environment under realistic scenarios demonstrate that DCCV significantly improves key performance metrics, including packet delivery ratio, end-to-end delay, throughput, and control overhead, compared to existing approaches. These results indicate that the proposed framework is an effective solution for enhancing VANET performance, especially for time-critical applications such as collision warnings and emergency notifications.

For future work, reinforcement learning algorithms could be employed to automatically optimize DCCV settings. Such an approach would allow the framework to learn optimal strategies for beacon rate adjustment and message prioritization dynamically and adaptively by analyzing network and environmental conditions, thereby providing more intelligent and stable performance in complex and variable scenarios.

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