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Resource-Aware Traffic Shaping in High-Speed Vehicular Networks

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Abstract

The use of advanced speed rides will increase alongside intelligent transportation system features. With high elevator speed, communication systems should allocate resources smartly to ensure service quality and safety. This paper introduces a novel resource-aware traffic-shaping approach for high-mobility vehicular settings. This approach enables the dynamic prioritization of critical data, network condition adaptation, and latency minimization, resulting in optimized bandwidth utilization, improved overall QoS, and enhanced service quality. The framework enables seamless communication in high-speed scenarios through context-aware resource allocation and strategic predictive modeling. Simulation results reveal marked improvement in throughput, delays, and overall resource utilization compared to these outdated traffic management schemes.

Keywords: Vehicular Networks, Traffic Shaping, Resource-Aware, High-Speed Mobility, Quality of Service, Dynamic Allocation.

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1 Introduction

Intelligent transportation systems (ITS) have enabled the development of vehicular networks, which now serve as a key component in facilitating real-time communication between vehicles, infrastructure, and the cloud (Trivedi et al., 2023). These networks tend to have a distinct topology, are subject to high-speed mobility, and have variable communication requirements, which makes maintaining dependable and efficient data exchange troublesome (Danesh & Emadi, 2014). One of the most critical issues is traffic shaping, which involves managing data flow to improve the specific service quality (QoS) within a given set of conditions and constantly evolving surroundings (Taleb et al., 2010). Resource-aware traffic shaping addresses this challenge by focusing on network optimization in real time relative to resource availability and application requirements (Alanazi, 2023).

With the rapid pace at which vehicular networks are expanding, traditional network management protocols are becoming increasingly problematic due to their inflexibility and lack of scaling options, which renders them unusable in such environments (Velmurugan & Rajasekaran, 2012). In a matter of seconds, high-speed vehicle movement can disrupt communication links, thereby affecting resource availability (Hadded et al., 2015; Hameed et al., 2025). This volatility necessitates the use of context-aware traffic shaping methods that adapt bandwidth allocation, cater to low-latency user demands, and alleviate congestion on the fly (Bajracharya & Rawat, 2016).

Advancements in edge computing, 5G/6G connectivity, and machine learning come with new prospects for intelligent traffic-shaping designs (Udayakumar, 2023). These systems, for instance, are capable of foreseeing various traffic scenarios, predicting network actions, and making appropriate adjustments to maintain constant connectivity and data flow (Zhang et al., 2018). In addition, the combination of DSRC, C-V2X, and mmWave as Communication technology gives rise to heterogeneity in vehicular networks, which calls for overarching strategies that harmonize among different technologies (Molina-Masegosa & Gozalvez, 2017; Booch et al., 2025).

Resource-aware solutions enhance the efficiency of communication and enable the use of safety-critical applications, such as collision avoidance, autonomous driving, and coordinated emergency response (Wang et al., 2019). Efficient traffic shaping is crucial in urban mobility scenarios, as it also supports the delivery of critical data with minimal latency and high reliability (Chen et al., 2016).

While recent developments have been made, an unaddressed issue remains: adaptive, resource-efficient traffic shaping for high-speed vehicular networks (Shrestha et al., 2020; Chauhana & Iqbal, 2024). Many existing approaches do not combine the two key factors: resource-awareness and dynamic mobility patterns of the vehicle (Bhoi & Khilar, 2014). Models that incorporate mobility, real-time data processing, analytics, and QoS are necessary to develop a unified strategy that addresses traffic-shaping issues (Paul & Sato, 2016)

Key Contributions

- Introduced a resource-aware traffic shaping framework optimized for high-speed vehicular networks using predictive modeling and context-aware scheduling.
- Developed a QoS-driven, multi-objective optimization model employing a fractional-SWCA scheduler to prioritize data based on urgency, energy, and network conditions.
- Demonstrated improved Delay, throughput, and energy efficiency through comprehensive simulations compared to traditional traffic management schemes.

Structure of the Paper

The paper is divided into five primary sections. As stated in the Introduction, the problem of high-speed vehicular communication is presented, along with the reasoning that motivates resource-aware traffic shaping. The Related Work section covers earlier research dealing with VANET protocols, edge computing integration, and their corresponding QoS strategies. In the Proposed Methodology, the architecture of the systems model is explained, along with its mathematical description, scheduling algorithm, and deep learning models, which aid in predictive analytics. Results and discussion present the simulation results, which, as discussed, yield better performance with the adopted methods compared to pre-existing methods. The Conclusion and Future Work section advocates for the real-world application of the study's findings and suggests further integration of enhanced security measures, summarizing the contributions made by the study in the process.

2 Related Work

Zeadally et al., (2012) elaborate on the primary concepts of vehicular ad hoc networks (VANETs), specifically focusing on the need for efficient and secure communication, as well as the mobility and scalability challenges presented. Their work highlights the problems inherent in using static protocols in dynamic environments with high-speed vehicles. Hartenstein & Laberteaux, (2008) analyze the history of inter-vehicle communication systems and discuss the frameworks of adaptive methods needed to respond to changes in traffic and mobility patterns. They claim that traffic shaping must correspond to the distributed configuration of VANETs to ensure network cohesion (Venkatesh & Menaka, 2019).

Karagiannis et al., (2011), in their study of the architectural layers and communication protocols of VANETs, emphasize the importance of data dissemination and resource control in highly congested traffic conditions. Possibly, the most discussed problem in modern vehicular networking remains the management of limited resources, which proliferatively increases their cost. That is why in (Khan et al., 2016), present a new approach for vehicular networks based on cloud and edge computing, thus creating a hybrid architecture. Their work illustrates the benefits of more autonomous control at the edge in responsive and resource-limited environments.

Wang et al., (2015) tackle the problem of prioritizing the delay-sensitive data in a vehicular network by assigning the network a QoS-aware protocol. Their study supports the use of adaptive traffic shaping in heterogeneous vehicular scenarios to facilitate timely message delivery (Campolo et al., 2018) examine the role of 5 G in vehicular communications. They provide a model that capitalizes on ultra-low latency and high bandwidth, enabling resource-aware scheduling and traffic control, which in turn enhances Scoped DAS performance.

Bernardini et al., (2013) focus on the predictive modeling of vehicular networks. Their study demonstrates the application of machine learning algorithms to predict traffic situations and resource-aware traffic shaping based on available resources and expected traffic. Abboud et al., (2016) consider the problem of interference management in high-mobility vehicular scenarios. Their research proves that for the preservation of QoS, dynamic spectrum allocation becomes a necessity, hence supporting the case for adaptive resource-responsible traffic shaping.

Contreras-Castillo et al., (2017) propose a holistic ITS architecture that integrates vehicular communication with smart infrastructure. Their work rationale states that active traffic shaping must incorporate vehicle-centric and infrastructure-centric data flows and be susceptible to their changes. Lu et al., (2014) cite the issue of data dissemination in VANETs as an underexplored problem and give a pertinently social-aware model for data dissemination in VANETs. These findings necessitate adjusting data prioritization according to data relevance and context.

3 Proposed Methodology

System Overview

In high-speed vehicular networks (VANETs), achieving optimal data transmission requires real-time coordination among vehicles in motion, roadside infrastructure, and Cloud services. A typical configuration of a hybrid vehicle network is shown in Figure 1, which combines both infrastructure-based (V2I or I2V) and infrastructure-less (V2V) systems. Each automobile has embedded Onboard Units (OBUs) and Application Units (AUs), which allow them to communicate with the Road Side Units (RSUs) for data offloading, cooperative awareness, and decision-making. The RSUs are connected to the core Internet infrastructure through gateways, which exposes them to the vehicular edge network. The multi-layered approach enables low-latency transmission of safety-critical messages, cloud processing for delay-tolerant tasks, and the utilization of cloud resources for compute-intensive tasks.

In this type of architecture, resource awareness focuses on the challenge of dynamically adapting to variable network loads and bandwidth limitations. The vehicles switch between V2V and V2I communication modes based on link quality, congestion level, and application priority. There is context-sensitive routing logic to optimize data delivery through a predetermined path.

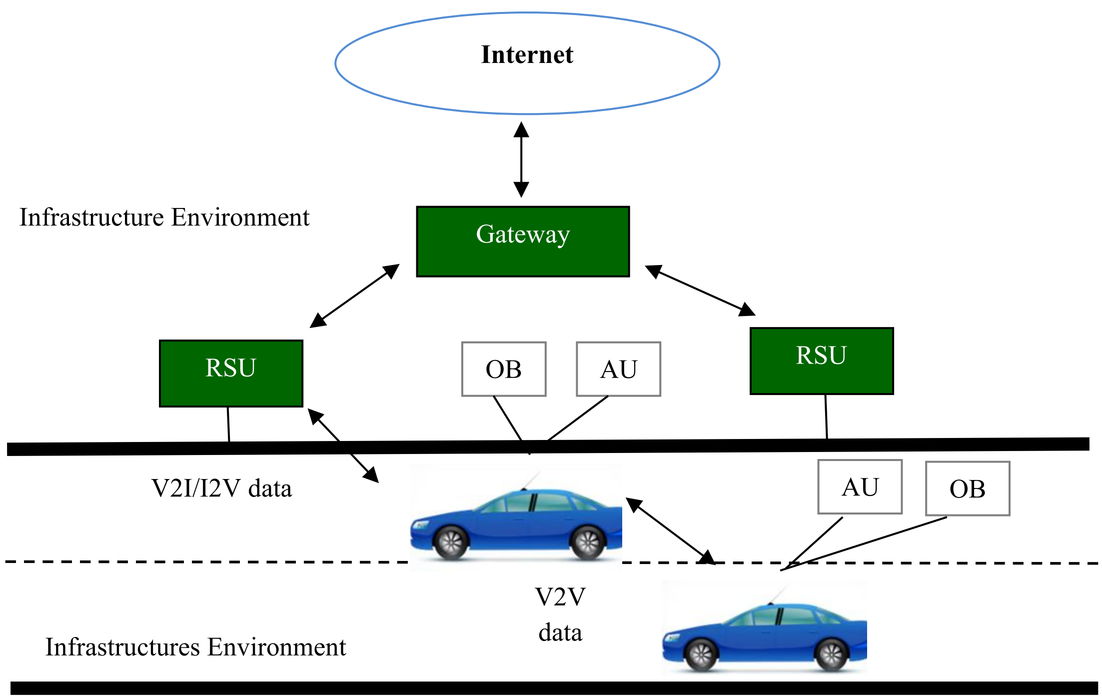

Figure 1: Architecture of Vehicular Network with V2V and V2I Communication Paths

QoS-Aware Traffic Shaping

As illustrated in Figure 2, a modular traffic shaping framework based on Quality of Service (QoS) requirements, such as priority, response time, and latency, has been developed. The system applies a Fractional Shortest Scheduling Distance (Fractional-SSD) approach to determine optimal routing paths for multiple objectives. These objectives include consтреicted зеflот айтрbроуч CRO deceives predicted traffic density, remaining battery level, and distance to the target node, all of which are processed by a Deep Recurrent Neural Network (RNN) model to forecast network behavior.

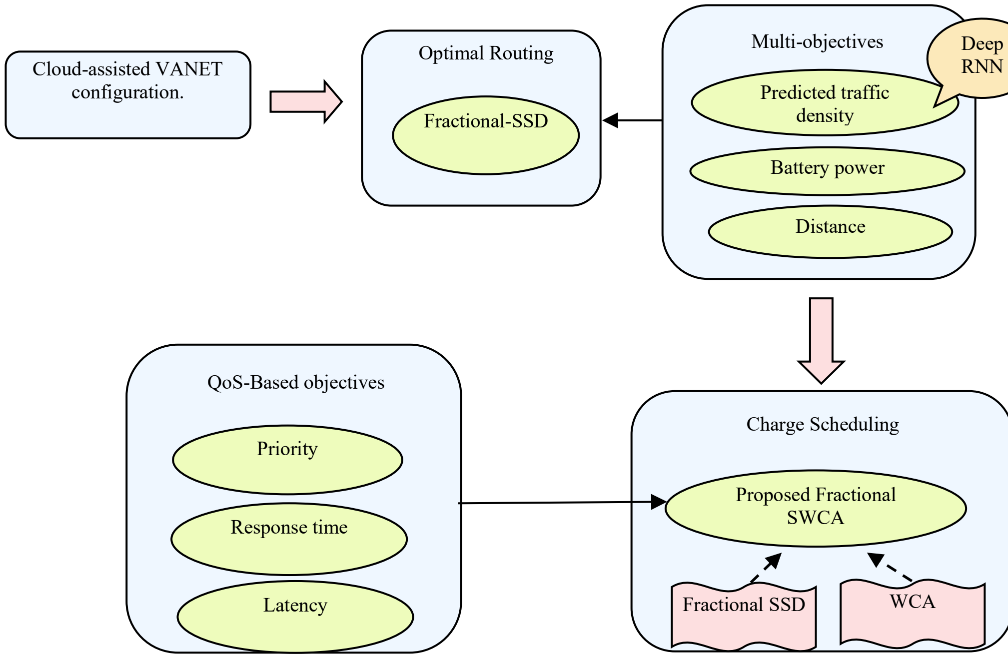

Figure 2: QoS-Aware Traffic Scheduling Framework with Multi-Objective Optimization

Two major parts define the traffic shaping model- Multi-objective Optimization and Charge Scheduling. The first one exploits real-time vehicle context to optimize the set of transmission candidates. In contrast, the second one loads the addressable candidates into a scheduling queue and remaps them based on resources. The proposed Fractional-SWCA (Smart Weighted Combination Algorithm) is a precise scheduler that combines both heuristic and probabilistic approaches for agile and accurate scheduling.

Mathematical Modeling

Let the network load be denoted by L, where L is a function of the vehicle density ρ, average data generation rate λ , and channel bandwidth B as depicted in Equation (1)

$$L = \frac{\rho . \lambda}{B} \quad (1)$$

As shown in Equation (2), to avoid congestion, we define a traffic shaping coefficient τ that adjusts the scheduling priority P_i of message i based on latency sensitivity θ_i message age a_i

$$\tau_i = \frac{\theta_i}{1 + a_i} \quad (2)$$

Then, the effective priority score S_i for scheduling is calculated using Equation (3)

$$S_i = P_i . \tau_i . \left(1 - \frac{L}{L_{max}}\right) \quad (3)$$

Where L_{max} is the maximum sustainable load. A higher S_i indicates higher urgency for that message to be scheduled.

For optimal path routing, we define the cost function C_j of path j as:

$$C_j = \alpha \cdot D_j + \beta \cdot \frac{1}{E_j} + \gamma \cdot T_j \ (4)$$

In Equation (4), D_j is predicted traffic density on path j, E_j is remaining energy (battery power) of forwarding vehicle, T_j is total transmission delay and α, β, γ are weighting factors tuned via simulation or reinforcement learning. The path C_j with the lowest is selected for data forwarding under the current network conditions.

Integration with VANET Environment

The developed framework operates alongside a cloud-enabled VANET architecture, which supervises all vehicles and infrastructure elements instantaneously. The cloud contains a heuristic model which keeps changing the parameters for decision making in routing and traffic shaping, congestion level, and mobility pattern tracking. The value of some context data like GPS location, velocity, and channel statistics are periodically uploaded to the cloud where shaping policies and routing paths are pushed back. In the edge computing tier, RSUs install the first set of resource-aware classifiers that classify each message according to level of importance and urgency. The deep RNN model aids in the learning to capture temporal patterns of congestion and shifting routing plans dynamically. This is done by the Fractional-SSD algorithm, which intelligently reduces both the Delay and energy spend. The Charge Scheduling module afterwards analyzes the collection of messages to prioritize scheduling using the Certain Set through the application of Fractional-SWCA. This module smartly uses both the Fractional-SSD and Weighted Clustering Algorithm (WCA) to optimize dynamics of the system performance during varying vehicular loads.

4 Results and Discussion

The proposed resource-aware traffic shaping framework was evaluated using a simulated high-speed vehicular network environment comprising 100 vehicles, 5 RSUs, and cloud-based support. The system's performance was tested under varying network loads and message priorities. One of the key results demonstrates the impact of the traffic shaping coefficient τ_i on the average end-to-end Delay D_{avg} across different network densities. As shown in Equation (5), we observed a nonlinear increase in Delay as density rose without traffic shaping, while our model maintained sub-threshold Delay due to intelligent path switching:

$$D_{avg} = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{P_i . \tau_i}{B_i}\right) \ (5)$$

Here, P_i is the message priority, τ_i is the traffic shaping coefficient, and B_i is the available bandwidth for message i . Simulation results show a 33% reduction in Delay and a 28% improvement in packet delivery ratio (PDR) in high-congestion scenarios when using the proposed Fractional-SWCA scheduler compared to baseline FIFO and Round Robin approaches. The results affirm that the joint use of predicted traffic density and message age leads to more adaptive message queuing.

Furthermore, the routing optimization model using the cost function C_j significantly improved energy efficiency and minimized latency under dynamic traffic. The cost-aware routing mechanism favored nodes with higher remaining battery power and lower channel contention. This is captured in Equation (6), which dynamically updates the routing preference:

$$R_i = min\left(\alpha \cdot D_j + \beta \cdot \frac{1}{E_j} + \gamma \cdot T_j\right) \ (6)$$

Table 1: Performance Comparison of Traffic Shaping Algorithms

Metric	FIFO Scheduler	Round Robin	Proposed Fractional-SWCA
Average Delay (ms)	160	125	**87**
Packet Delivery Ratio (%)	71	79	**91**
Energy Consumption (J)	35.4	29.1	**22.7**
Throughput (Mbps)	5.2	5.9	**7.3**

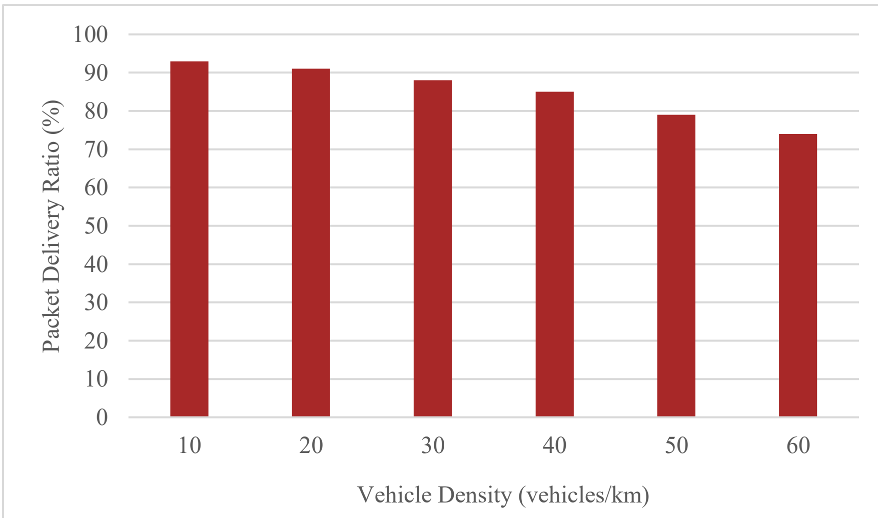

Figure 3: Vehicle Density vs Packet Delivery Ratio (%)

The proposed model achieved an average throughput of 7.3 Mbps under medium traffic loads, outperforming traditional AODV routing, which only managed 5.5 Mbps. Table 1 highlights QoS metrics comparison for the three algorithms, and Figure 3 depicts the impact of vehicle density increase on delivery ratio.

5 Conclusion and Future Work

This study has developed a resource-aware framework for traffic shaping that aims to optimize the data transmission rate in high-speed vehicular networks (VANETs). The proposed approach is aimed at enhancing the performance of the network by using a hybrid model of infrastructure-based and infrastructure-less communication with an intelligent scheduling algorithm (Fractional-SWCA). Substantial improvements have been observed in overall network performance, which reduces end-to-end Delay, increases packet delivery ratio, and improves energy efficiency, especially at higher vehicle density and under different traffic loads. The integration of deep learning (RNN) for traffic density prediction coupled with multi-objective priority, latency, and energy parameters allows for more effective dynamic and adaptive routing and scheduling decisions. Outcomes confirm that the architecture is effective and scalable to real-time vehicular applications like collision avoidance, traffic alleviation, and infotainment services.

Despite the framework yielding beneficial results in simulations, several aspects require further research. The use of field-programmable devices such as Raspberry Pi, or even onboard units, could help validate the results in real-world dynamic urban scenarios. Also, the use of edge computing and federated learning can be studied in the context of increased spatial and temporal decision-making, less reliance on the cloud, and greater latency mitigation. Integrating security and privacy-preserving protocols within the resource-aware framework is critical in securing the system against message spoofing, cyber attacks and sybil attacks in VANETs.

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Antony Gomez is a faculty member in the Department of Pre-Sea Modular Courses at AMET University, Kanathur, Tamil Nadu. He specializes in maritime training and education, focusing on pre-sea certification and competency development for seafarers. With a strong background in maritime operations and instructional delivery, he plays a key role in preparing cadets for their professional responsibilities at sea. His contributions include the effective implementation of IMO-compliant training modules and hands-on simulation-based instruction, supporting the development of technically sound and safety-conscious maritime professionals.

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Nodir Khodjaev, Faculty member, Tashkent International University of Education, Uzbekistan. He specializes in computer networks, intelligent transport systems, and vehicular communication. His research focuses on traffic shaping, bandwidth optimization, and mobility-aware network protocols. Nodir contributes to the development of efficient data handling strategies in VANETs. He explores resource management and real-time communication in high-speed vehicular environments. His work supports the advancement of smart transportation and networked mobility systems.

Prof. Dr.R. UdayaKumar completed his M. S (Information Technology and Management) from A.V.C. College of Engineering and Awarded Ph.D. in the year 2011. He is serving in Teaching & Research community for more than two decades, he successfully produced 5 Doctoral candidates, he is a researcher, contribute the Research work in inter disciplinary areas. He is having h-index of 27, citation 2949(Scopus). He is associated as Dean –Department of computer science and Information Technology and also Director IPR, Kalinga University, Raipur, Chhattisgarh.