International Journal of Computer Networks and Applications (IJCNA)
DOI: 10.22247/ijcna/2024/30 Volume 11, Issue 4, July – August (2024)

RESEARCH ARTICLE

Congestion Control System Optimization with the Use of Vehicle Edge Computing in VANET Powered by Machine Learning

V. M. Niaz Ahamed
Department of Computer Science and Engineering, Bharath Institute of Higher Education and Research, Chennai, Tamil Nadu, India.
msajce.niazahamed@gmail.com

K. Sivaraman
Department of Computer Science and Engineering, Bharath Institute of Higher Education and Research, Chennai, Tamil Nadu, India.
sivaraman2006@gmail.com

Received: 18 May 2024 / Revised: 07 July 2024 / Accepted: 20 July 2024 / Published: 31 August 2024

Abstract – Vehicular Ad Hoc Networks (VANETs) have recently given rise to a wide range of applications for security, infotainment, rescue, and safety-related reasons. The future of V2V communication systems and related applications relies heavily on VANET. Communication channel congestion concerns have had a negative influence on safety applications, which are a result of a range of network uses. Vehicle traffic is negatively impacted by channel congestion, which causes packet loss, delays, and unreliability. This in turn leads to traffic accidents, traffic bottlenecks, and incorrect traffic decisions. This paper introduces a new idea for VANET forwarding of packets and congestion control that is based on utilities. Therefore, an Optimization for Congestion Control System using Machine Learning [OCCS-ML] is proposed based on packet forwarding is introduced to solve the issues by the method for the secure and prompt transfer of data, as it pertains to security projects. A communication channel is the intended target of the proposed scheme, which aims to guarantee the timely and dependable delivery of messages to all network neighbors and serve as a medium for broadcasting safety alerts. Vehicles to vehicle communication is the intended use of the proposed scheme, which does not rely on any permanent infrastructure. Each data packet that is transferred contains quantitative utility information in a visible manner for all users in a local environment. This information is encoded using an application-specific utility function. There has been a substantial improvement in the accuracy and efficiency of information distribution.

Index Terms – Congestion Control, Data Packets, Vehicle Communication, VANET, Traffic.

1. INTRODUCTION

These days, smart vehicles are essential to the idea of ITS, or intelligent traffic systems, and they help make roads safer and more enjoyable to drive in general. When smart cars are networked with one another and with roadside units (RSUs), the road infrastructure of a smart city can rely on ICTs [1]. Communication of data among vehicle nodes is the main function of Vehicular Ad hoc Networks (VANETs), which operate mostly in the absence of infrastructure and a centralized management of communication [2]. By enhancing data transmission procedures and the functioning of wireless communication channels, these networks primarily aim at helping traffic monitoring systems and maintain network efficiency [3].

Vehicles that have an ad hoc capable air interface share data in a VANET to make everyone's journey safer and more comfortable [4]. Communication is provided at no cost in VANETs since no communication infrastructure is required [5]. Several safety and entertainment apps have been developed for VANETs, such as those that notify of emergencies, accidents, curves, file-sharing, the internet, and commercials [6]. Typically, vehicle nodes transmit two kinds of data: traffic event-driven data and traffic management messages. Hello messages (beacons) are disseminated frequently throughout the network and contain location, speed, and direction information for vehicle nodes [7]. These messages are used for traffic control. In contrast, traffic situations like accidents, road surface collapses, and congestion trigger the broadcasting of event-driven or safety warnings [8]. Traffic information systems are one common use case for VANETs; in these systems, the cars themselves serve as sensors to determine the current traffic situation [9]. VANETs have several potential safety and comfort uses. All vehicles in the VANET are able to monitor the current traffic conditions to the data that is collected, processed, and shared across the network [10].

Safe and efficient transportation systems are the goal of VANETs, which aim to lessen the likelihood of accidents involving drivers, passengers, and pedestrians [11]. Two types of units are standard on VANETs; these are the Road-Side Unit (RSU) and the On-Board Unit (OBU). The former is stationary on the side of the road, whereas the latter is moving from one location to another [12]. These devices provide wireless communications in two directions: first, between vehicles themselves (V2V communications), and second, between vehicles and the infrastructure along the roadside (V2I communications) [13]. For the purpose of sharing data between vehicles in the communication networks, ITS employ VANET. This lessens the frequency of traffic accidents while simultaneously increasing traffic mobility. Some communication systems, such as V2I and V2V have made use of VANETs [14]. Therefore, to facilitate communication between vehicle-to-vehicle and vehicle-to-infrastructure communication systems [15], VANETs have made use of the Wireless Access of the Vehicular Environment (WAVE). There are primarily two uses for VANETs:

1) safety-related apps that use the Control Channel (CCH) to transmit beacon signals and event-driven messages;

2) Non-safety related applications that use the Service Channel (SCH) to transmit notifications about traffic and parking availability.

Because of the open nature of the wireless medium, VANETs are susceptible to several forms of attacks. The assaults severely hinder VANET performance and cause major issues for authorized drivers [16]. Consequently, securing VANET traffic against tampering, interception, and message deletion has been an enormous task and a major focus for both academics and businesses [17]. There are distinguishing features that characterize each type of VANET assault. In VANET, machine learning (ML) methods have become popular for processing massive datasets to derive actionable rules for event detection, categorization, and prediction [18].

The movement pattern of VANETs is regular and easier to control. When thinking about how to improve the ITS to make drivers' lives easier and safer, VANET is one potential area of influence [19]. Because of the current changes in traffic density and sparsity, safety applications have become more popular. Reliable and fast data transmission is essential for event-driven messaging in the network to deliver emergency notification messages [20]. Accidents, traffic congestion, and poor traffic judgments could occur if these communications take too long to reach the network [21].

The research’s key findings are as follows:

- Here, we provide an Optimization for Congestion Control System utilizing Machine Learning [OCCS-ML] with the goal of reducing the negative impacts of channel congestion on traffic flow.
- Consequently, packet forwarding is implemented to address the problems with the method for the safe and efficient transfer of data in relation to security initiatives.
- A utility function that is specific to the application is used to encode each data packet. The efficiency and fairness of information distribution have both seen significant improvements.

The outline of the paper is as follows: An introduction to VANET is given in Section 1, and research on comparable situations is covered in Section 2. As mentioned in Section 3, OCCS-ML suggests optimizing the congestion control mechanism between vehicles. In sections 4, the paper provides a summary of the research with figures and discusses the importance of the findings. Section 5 serves as the conclusion.

2. RELATED WORK

When compared to fixed and wired networks, VANETs lack a well-established congestion control function. Thus, there are certain restrictions imposed by these networks by different congestion control systems. When dealing with distributed and self-organizing networks, these systems struggle. The researchers go on to discuss about their work on VANET congestion control in the part that follows.

Issues with communication channel congestion have had a detrimental effect on safety applications. The negative effects of channel congestion on vehicular traffic, such as packet loss, delay, and unreliability, as well as on traffic accidents, congestion, and poor traffic decisions, are substantial. When it came to safety applications, Qureshi, K. N. et al [22]. used Dynamic Congestion Control Scheme (DCCS) to ensure data delivery was reliable and timely. The suggested system is made for communication channels that all neighbors in a network can receive messages reliably and on time, and that safety messages can be broadcasted. For DCCS to work there must be no fixed infrastructure; instead, all communication must take place between vehicles. A suggested scheme's performance is evaluated and compared to existing state-of-the-art schemes using comprehensive simulation.

Quality of Service (QoS) must be considered to ensure dependable communications in Vehicle Ad hoc Networks (VANets). The two primary qualities of service (QoS) metrics taken into account by congestion control schemes are packet loss and delay. To manage congestion in VANets, Taherkhani, N., et al [23]. created the [MOTabu] technique. To minimize latency and jitter, the congestion management component uses a MOTabu algorithm to adjust the

RESEARCH ARTICLE

communication range and rate for safety and non-safety messages. Using five performance metrics—throughput, average delay, number of retransmissions, packet loss ratio, technique outperforms other strategies in comparison, according to the simulation data.

Nodes in a vehicle ad hoc network channel act like selfish players desiring high data transmission rates; to control congestion, Amer, H. et al [24]. suggested a non-cooperative game method [NCGM]. To top it all off, we have demonstrated that every vehicle achieves its optimal data transmission rate by meeting the Nash equilibrium requirement. Data transmission rates, vehicle priority, and contention delay form the basis of a utility function that is used to find the best rates. Over two testing scenarios involving highway and urban traffic, the suggested method's performance was compared to three other alternatives and validated. On average, there was a 35% improvement in network speed and efficiency, a 30% improvement in channel busy time, and a 37.17% improvement in the number of congestion messages.

The paper's authors, Alsarhan et al. [25], use support vector machines (SVMs) to detect intrusions in VANETs. The structure of support vector machines (SVMs) offers numerous computational benefits, such as a lack of correlation between algorithm complexity and sample dimension and a focus on a limited number of samples. Finding intrusions in VANETs is a combinatorial and nonconvex challenge. To maximize the SVM classifier's accuracy, three intelligence optimization strategies are employed. Among these optimization techniques are ant colony optimization (ACO), genetic algorithm (GA), and particle swarm optimization (PSO). Based on our findings, GA is the superior optimization algorithm.

The current congestion management systems [CCA] were developed by Sattari, M. R. J. et al [26]. and are based on many factors such as the rate of packet production, control of transmit power, utility functions, carrier sense thresholds, or a mix of these. Additionally, we provide and execute a method that allows for the dynamic assignment of carrier sense (CS) threshold or Max Beaconing Load (MBL) values for the purpose of fine-tuning the Distributed Fair broadcasts. This and number of packet loss—the suggested technique is then tested with highway and urban settings. The MOTabu

algorithm The D-FPAV congestion control method for power adjustment in VANETs. Optimal channel bandwidth usage is just one of many possible applications of the suggested technique, which takes both traffic and non-traffic scenarios into account.

One way to make VANETs more secure and dependable is to include congestion control. Beyond simple routing assistance, vehicles have many more uses, such as detecting congestion, creating entertainment apps, and spreading information. To enhance the achievement ratio and other criteria, information on energy use is provided and traditional methods such DCCS, MOTabu, NCGM, SVM, and CCA have been suggested as safe and effective approaches. An overview of the proposed model is given in this research.

Mengqi Wang et al. [27] recommended the VANET Edge Computing Model to Minimize Latency and Delay Utilizing 5G Network. Using 5G localized Multi-Access Edge Computing (MEC) servers further reduced wait times and latency, enhancing edge technology resources and achieving latency and QoS goals. With the experiment, the author reduced data latency by 20% compared to an experiment that used just cloud computing. The processing time was also cut by 35% compared to the architecture used by cloud computing. By reducing communication costs and improving energy usage, the WDFO-VANET approach is suggested to enhance VANET.

Alshimaa H. Ismail et al. [28] suggested the K-means approach for Congestion Management in Mobile Edge Computing 5G Systems. The suggested model improves throughput, energy usage, and delay. The proposed model uses the K-means technique and the improved random early detection strategy. In addition, a virtual list is created to store packet data and accommodate more packets. The NS2 green cloud simulator is used to realize the suggested model. The simulation results show that the suggested model significantly improves the conventional cloud and fog computing models regarding latency, throughput, and energy usage. The summary of the previous works is listed in table 1.

Table 1 Comparison Between the Existing Methods

Authors	Methods	Advantages	Disadvantages
Qureshi, K. N. et al [22]	For DCCS to work there must be no fixed infrastructure; instead, all communication must take place between vehicles.	The proposed system uses communication channels to broadcast safety alerts and reliably deliver messages to network neighbors.	Comprehensive simulation compares a proposed scheme's performance to state-of-the-art schemes.

Taherkhani, N., et al [23]	For DCCS to work there must be no fixed infrastructure; instead, all communication must take place between vehicles	Simulations show that MOTabu outperforms other techniques.	The congestion management component adjusts safety and non-safety message range and rate using a MOTabu algorithm.
Amer, H. et al [24]	To minimize latency and jitter, the congestion management component uses a MOTabu algorithm to adjust the communication range and rate for safety and non-safety messages.	Finally, people showed that every vehicle meets the Nash equilibrium criteria for optimum data transmission.	The proposed strategy was verified against three additional options in highway and urban traffic situations.
Alsarhan et al. [25]	The structure of SVMs offers numerous computational benefits, such as a lack of correlation between algorithm complexity and sample dimension and a focus on a limited number of samples	To maximize the SVM classifier's accuracy, three intelligence optimization strategies are employed.	SVMs provide multiple computational advantages, including a lack of connection between algorithm complexity and sample size and a concentration on a few samples.
Sattari, M. R. J. et al [26]	The D-FPAV congestion control method for power adjustment in VANETs.	Rate of packet creation, transmit power control, utility functions, carrier sense thresholds	They further include a mechanism for dynamically assigning carrier sense (CS) threshold or Max Beaconing Load (MBL) values to fine-tune Distributed Fair broadcasts.
Mengqi Wang et al. [27]	Edge Computing Model	Reducing communication costs and improving energy savings	Increased computational cost
Alshimaa H. Ismail et al. [28]	K-means approach	Less latency, throughput, and energy usage	High computational time

3. PORPOSED MODELLING

3.1. Problem Statement

- Context: VANETs are ad-hoc networks formed by vehicles with wireless communication equipment, such as cars and buses.
- Safety applications in VANETs aim to reduce road accidents. Traffic information transmission between cars is critical for effective traffic management.

Congestion Control Challenges:

- Congestion: When traffic arises, controlling the load on the communication channel is critical.
- Beacon Messages: These carry time-critical information (e.g., safety alarms) and necessitate a suitable bandwidth.
- Problem: Providing timely and reliable message transmission while avoiding congestion

3.2. Optimization for Congestion Control System using Machine Learning [OCCS-ML]

In the context of traffic, several plans have been proposed in the literature for managing congestion. Adaptation of contention windows, control rates, and transmission power regulation were among the congestion control strategies employed by these designs. The efficiency of communication networks degrades when the number of wireless channels grows in response to a rise in broadcast power. Conversely, in sparse areas in particular, modest transmit power leads have a direct impact on next hop selection due to dynamically changing topologies. Due to the substantial mobility of connections in networks and the frequent changes in topologies, these strategies isolate vehicle nodes in congested circumstances. There have been a number of problems with these systems, including inefficient bandwidth usage, communication overhead, and transmission delays.

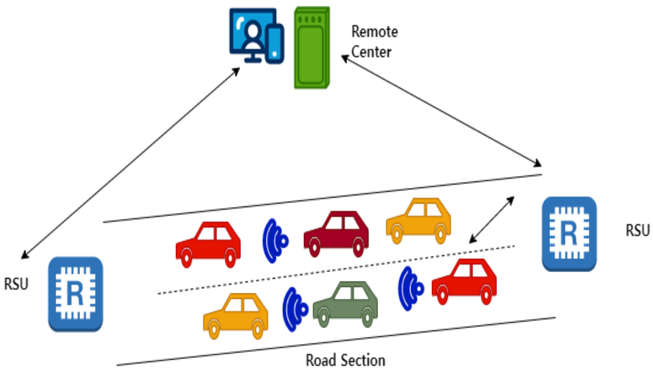

Figure 1 The Back End Architectural Design of Remote Sensor Unit

Figure 1 shows the schematic for the back end's architectural design. Vehicles that have onboard positioning units (OBUs) communicate with remote sensor units (RSUs) on a periodic basis to share location and other real-time data. Continuously updating the current alarm level, the convolutional neural network takes in data and uses it to make predictions totally by hand, somewhat by hand, conditional automated, fully automated, and totally automated are the ways the standards classify different levels of autopilot. An essential component of autopilot technology is the backup warning system. Applying current warning systems to large-scale real-world settings presents a number of challenges. Not all approaches provide adequate cautions; some don't even bother to warn.

$$p_y^n = k_1 P_y^n + K_2^n\left(L_y^{max} - V_y^n\right) + K_3^n\left(L_y^{max} - V_y^n\right) \quad (1)$$

P_y^n is the notation for the detection of precision vectors, while V_y^n is the notation for the velocity vector in equation (1). $k_1, k_2\ K_3^n$ denotes the constants for each vehicle. Therefore, to streamline energy management, lessen the likelihood of accidents, and cut down on maintenance and repair times, power systems can be automated thanks to the exponential growth of automation. Because of the critical nature of the power system and the low fault tolerance rate that must be met, it is essential to monitor the system in real-time.

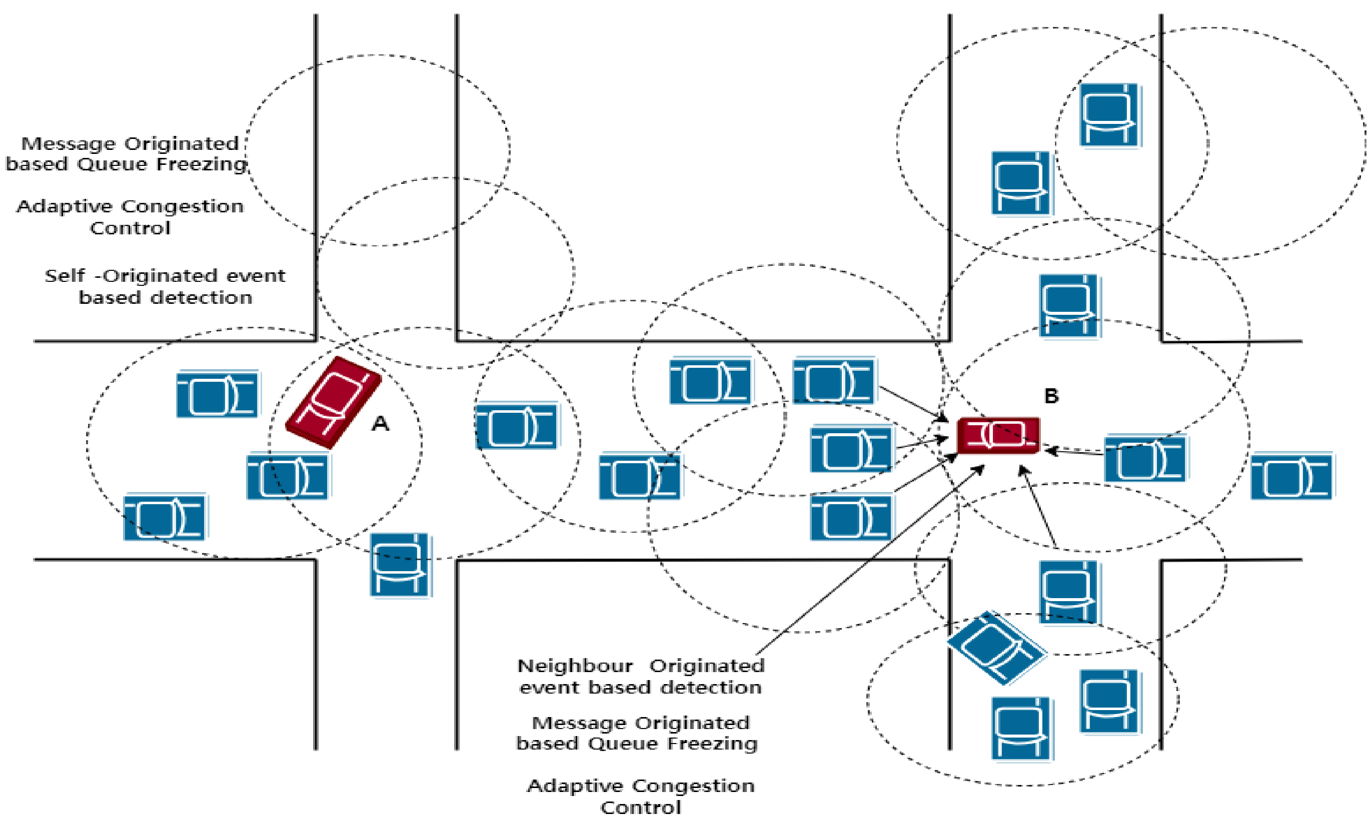

Figure 2 Congestion Control System

International Journal of Computer Networks and Applications (IJCNA)
DOI: 10.22247/ijcna/2024/30 Volume 11, Issue 4, July – August (2024)

The Congestion Control System is depicted in Figure 2 as shown above. The congestion control in a vehicle environment proposes a number of strategies. Transmitter control of power, congestion window adaptation, and management rate adaptation were some of the congestion control strategies used by these schemes. The efficiency of communication networks degrades when the number of wireless channels grows in response to an increase in broadcast power. However, in sparse areas in particular, modest transmit power leads have a direct impact on next hop selection due to dynamically changing topologies. Due to the wide range of mobility of nodes in networks and the frequent changes in topologies, these strategies isolate vehicle nodes in congested circumstances. There have been a number of problems with these systems, including inefficient bandwidth usage, communication overhead, and transmission delays. A wide range of applications have been customized to enhance security and ease in VANETs. Because they rely on vital data, such as identifying accidents and emergency communications, safety applications are given top attention in networks. Due to the high volume of safety warnings transmitted by roadside units, access points, and nearby vehicles, communication channels are often overloaded. It is still a challenge for VANETs to ensure the prompt transmission of safety application messages due to the broadcast of different application messages. The increasing congestion on the exchange of information channels is leading to problems with networking overhead, loss of packets, and delays. This paper suggests a Congestion Control Scheme (CCS) to enhance the delivery of safety messages and alleviate network congestion.

$$AT = C + \frac{\sum_{k=1}^{N} S_{ij}([f - y_j]^{2/})}{\sum_{k=1}^{N} ([f - y_j]^{2/})} - N \qquad (2)$$

$k = 1, 2, \ldots\ldots N$ and $j = 1, 2 \ldots\ldots\ldots N$

AT indicates the automation technology C and N indicate the total number of groups and links between groups, respectively, from the aforementioned equation (2) which clearly helps in robustness in dynamic environments.

Vehicle node A in figure 2, initiates congestion control by utilizing adaptive congestion control and queue freezing techniques when it identifies self-originated event-based congestion, such as accidents. Congestion control is implemented in vehicle B using adaptive approaches, time stamp-based queue freezing, and neighbor-originating event-based detection.

An up-and-coming technology, Vehicular Edge Computing (VEC) provides a platform for in-vehicle applications to increase service availability via the compute offloading idea. Through computational offloading to an edge infrastructure optimized for vehicle applications, VEC enhances the user experience by shifting some of the work load away from the core network. Due of this, it is capable of performing delay-intolerant complex procedures. The most promising areas of use for VEC-based systems are in the areas of improved driver assistance, e-horizon, autonomous driving, and accident prevention. Machine learning (ML) and artificial intelligence (AI) applications use algorithms that process data in real time and demand a lot of processing power.

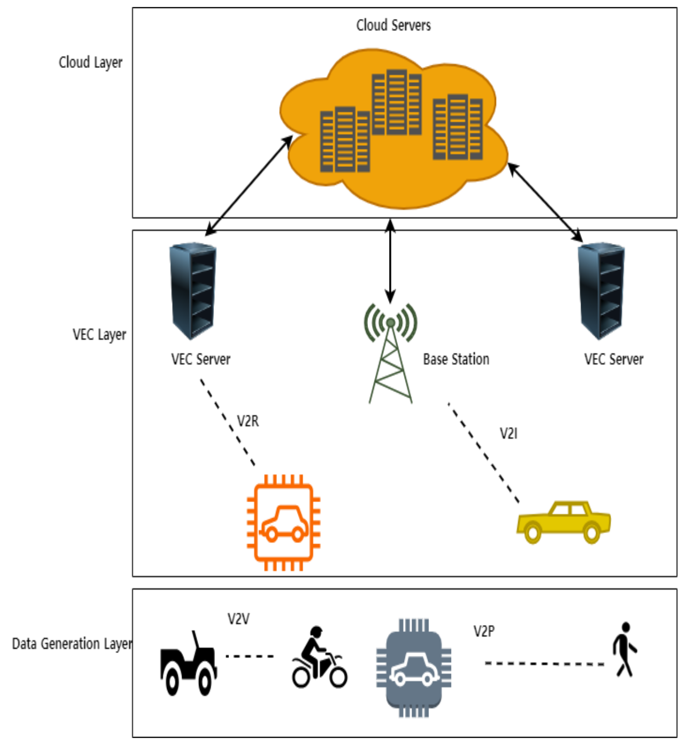

Figure 3 Autonomous Vehicle Networks Built on Machine Learning Framework

Figure 3 shows the self-driving car networks that were built using the Machine Learning framework. Figure depicts offloading of computation over a multi-tier architecture that includes connected automobiles, Road Side Units, and cloud computing components. This can improve the IoV concept, its groundbreaking applications, and the amenities for future smart roads. The vehicles themselves are embedded in the lowest layer, which may be referred to as the "data generation" layer.

$$OE_N = \frac{\frac{1}{n}\sum_{x=0}^{n}\left(DL_{n_n - n_r}\right)^2 + \log\left(IL_{n_n - n_r}\right)^2}{S_N} \qquad (3)$$

In equation (3), the quantity represented by OE_N is the operational efficiency which can be thought of as the Transmitter function used to assess the proposed modification. The number n represented the nodes of the proponent. The notation for expressing direct link (DL) and indirect link (IL) respectively. S_N be the sensor nodes.

The OBUs do not provide computing power or storage space. At this level, the OBUs can do some operations locally if needed. The secondary form of remuneration is RSUs, which may be rapidly turned into cash. This tier is where will find the edge servers. Third and lastly, we have traditional cloud servers. Despite the potential benefits to vehicle processing from the idea of work offloading.

The following are the mathematical formulations of the OCCS-ML viewpoint model. The factor space is developed by integrating {D (O) C} with the CCS features used with important element factors such as distance computation, a collision factor, and an output factor.

$$c_j(d) = [c_1(d), c_2(d), \dots, c(d)], \quad d \in i, \ j \in x \qquad (4)$$

It is seen in equation (4) that the critical element factors are compared sequentially. The sequential comparison is denoted by$c_j(d)$, the non-dimensional element is represented by c, and the polarization component for key element factors is denoted by d.

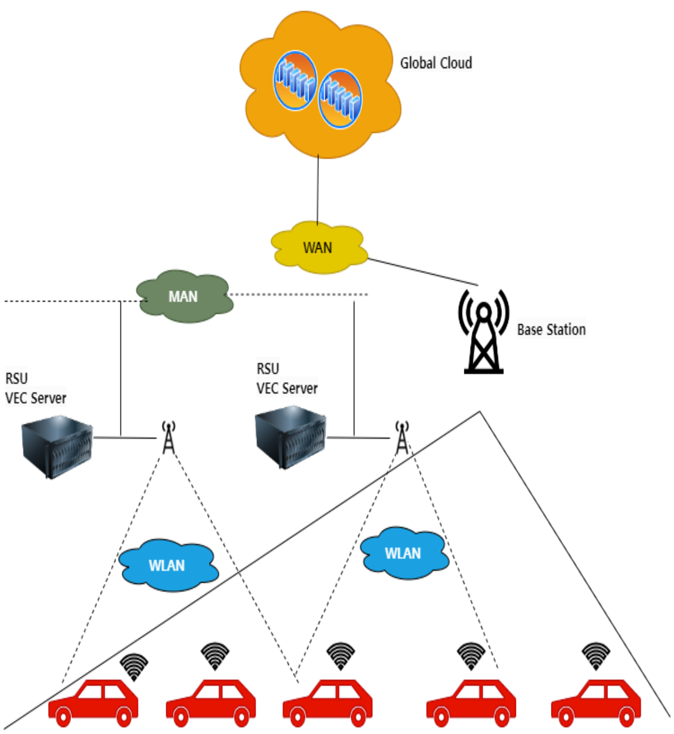

Figure 4 Collaborative Computing at the Vehicle Edge with Various Access Layers

Figure 4 depicts the aforementioned scenario of collaborative computing at the vehicle edge with many access layers. In the hope that drivers will modify their actions to prevent real accidents, we classify alert intensities into three categories based on people's actual behavior behind the wheel. To avoid fatal or serious injury, a vehicle must come to a complete stop in Level 1 congestion. Vehicle damage and crew injuries are both kept to a minimum in a level 2 event. The goal of the second level is to have drivers consider reducing their speed. When operating in its default setting, Level 3 does not interrupt the driver. Figure 4 shows that we expect smart highways will use state-of-the-art applications that operate on multi-tier, multi-access VEC designs in the near future. The cars in our architecture are able to assign tasks to the servers located at the edge using the WLAN interface. The underlying technology for short-range wireless access is known as a WLAN, which stands for local area network.

$$C_{0j} == \frac{\emptyset_{min.} + \emptyset_{max.}}{\partial_{max.}} + c_j(d) + D_{(c_0,c)} \qquad (5)$$

In equation (5) C_{0j} denotes the Car in motion, $\emptyset_{min}$ be the angle of deviation in which the car is moving minimum, $\emptyset_{max}$ be the angle of deviation in which the car is moving maximum, $\partial_{max.}$ be the coefficient of VEC interface. $D_{(c_0,c)}$ be the distance till which the car is congested.

By substituting equation (4) in equation (5) we get equation (6)

$$C_{0j} = \frac{\emptyset_{min.} + \emptyset_{max.}}{\partial_{max.}} + [c_1(d), c_2(d), \dots, c(d)] + D_{(c_0,c)} \qquad (6)$$

The ability to offload tasks to remote servers in the cloud is made possible through the Internet connection (WAN), which opens the door to potentially more flexible network architecture. In the suggested design, the broadband connection may originate from a cellular network or an RSU. The concept states that RSUs can, via the cellular base station, hop to the resources of the cloud. This approach will produce a significant backlog at the base stations. Based on our concept, RSUs could provide Internet access through a fiber communication link.

$$\mathrm{RSU} = \mathrm{C_m} + \mathrm{bs_m}(\mathrm{cl} - e^{CC-UCV}) \qquad (7)$$

As shown in equation (7), $\mathrm{C_m}$ indicates the cellular station , $\mathrm{bs_m}$ is a base station , cl denotes exposure of the developing cars to cloud through machine learning, e^{CC-UCV} represents the beginning portion clarifies an exponential mechanism where CC be the congested vehicle and UCV be the uncongested vehicle.

$$\mathrm{DR(C)} = \frac{1 + \mathrm{e}^{-\mathrm{CC}} + \mathrm{m}(\mathrm{c_{ij}}) - \mathrm{m}(CC)}{e^{CC-UCV}} \qquad (8)$$

In equation (8) DR(C) be the data rate of the vehicle which is moving at constant speed, $\mathrm{m}(\mathrm{c_{ij}})$ be the mean of the cars travelling in particular area, $\mathrm{m}(CC)$ be the mean of the congested vehicle which is affected through collision. UCV be the uncongested car.

$$\left.\begin{aligned} \text{Efficiency} &= \frac{\mathrm{DR(C)}}{\mathrm{RSU}} \\ \text{Efficiency} &= \frac{\frac{1+\mathrm{e}^{-\mathrm{CC}}+\mathrm{m}(\mathrm{c_{ij}})-\mathrm{m(CC)}}{\mathrm{e}^{\mathrm{CC-UCV}}}}{\mathrm{C_m}+\mathrm{bs_m}(\mathrm{cl}-\mathrm{e}^{\mathrm{CC-UCV}})} \end{aligned}\right] \qquad (9)$$

RESEARCH ARTICLE

As per equation (9) efficiency is the ratio of data rate and road side unit constant which is then solved by substituting equation (7) and (8).

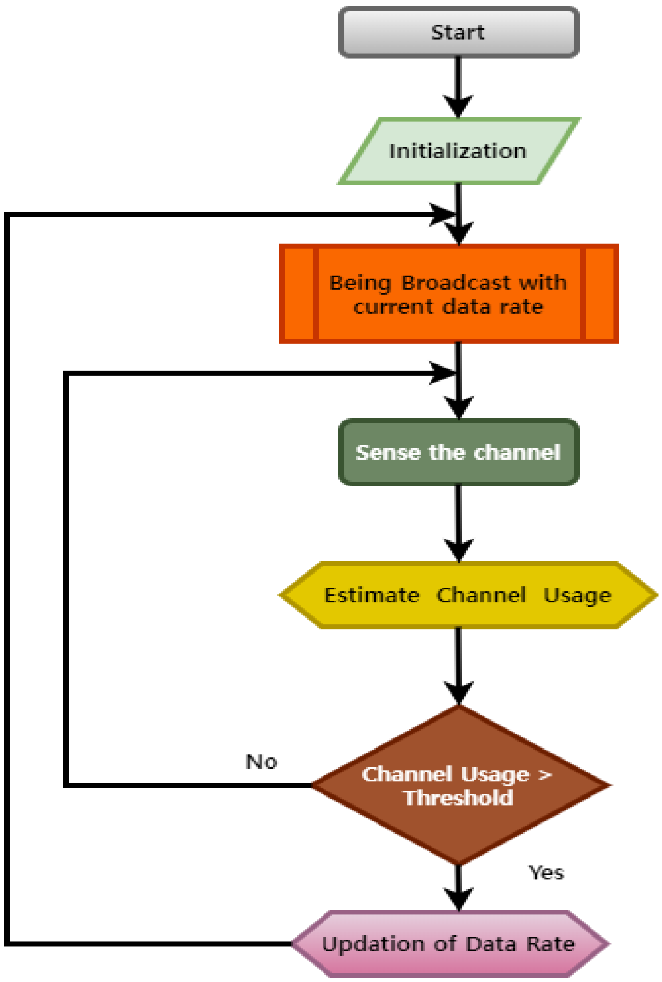

Figure 5 A schematic of VANET Congestion Control

When participating in a VANET system, cars or RSUs disseminate information to other nodes in the network that are within communication range. One issue that can arise with VANET channels is data congestion, which happens when a vehicle broadcasts a lot of traffic data or when multiple nodes start spreading their information at once without thinking about the channel capacity or traffic flow conditions. Here, by measuring the degree of channel utilization and comparing it to a predetermined threshold, every vehicle or RSU will periodically assess the congestion circumstances.

This research assumes a channel usage level threshold of 70%. To that end, it is considered that communication channels are congested if their usage level is higher than the threshold. The second part of the plan is to find the source of the congestion and then remove it. The cars adjust the data rate when they detect congestion as shown in figure 5 flowchart.

Input: Input all the nodes

Output: The process of giving a power, PA(i) for node ui , in such a way that the final power is optimal

Step 1: Consideration of the nodes' status

Step 2: Find the highest amount of common transmitter power

Step 3: Distribute Pi to every node in traffic and non-traffic areas

Step 4: Get the messages based on your degree of power from nodes

Step 5: Compute the final power level in traffic

Step 6: Finish the execution

Algorithm 1 Structural Optimization Method

Algorithm 1 represents the structural optimization and all the steps are executed in manner based on the node's transmission and reception. Controlling the amount of electricity transmitted and the rate of message creation form the basis of the implementation. There are two primary methods to describe the state of roads and highways: when traffic is heavy and when it is light. Information from beacons and the speed of vehicles can indicate when there is heavy traffic on streets and roads. Four distinct states are produced according to the circumstances indicated above: non-traffic and event-driven, traffic and event-driven, non-traffic and non-event-driven, and traffic and non-event-driven.

The high delay caused by data travelling to and from a central server is a common problem with traditional techniques of congestion management that depend on centralized systems. The Genetic Algorithm (GA) optimization technique drastically reduces latency by processing data locally at the edge nodes by generating fast, localized decisions. Better real-time performance and faster responses are the results of this. Optimal solutions may be evolved via generations, allowing GA to allocate resources dynamically. Even during heavy traffic, this guarantees the network's resources are used effectively, increasing throughput.

The table 2 shows the comparison of different existing methods against the proposed model.

The paper compares various criteria to the proposed technique. This research uses OCCS-ML to show how it works. In settings with a lower range of congestion, the suggested technique drastically cut down on network overhead. Network area, node density, transmission distance, efficiency and host of other parameters were varied in the experiments.

Table 2 Comparison of Different Methods

Number of Nodes	DCCS (Dynamic Congestion Control Scheme) (2018)	MOTabu (Multi-Objective Tabu Search) (2015)	NCGM (non-cooperative game method) (2020)	SVM (Support vector machines) (2021)	CCA (Congestion Control Approaches) (2013)	OCCS-ML (Optimization for Congestion Control System using Machine Learning)
10	22.7	28.7	15.1	15.9	55.3	15.5
20	25.3	41	30.2	42.2	59	17.3
30	27.6	41.1	50.4	63.7	63.5	74.4
40	30.7	48.6	57.8	69.1	67.3	81.3
50	30.8	66.7	72.4	70.4	69.1	93.9
60	32.6	70.1	72.4	73.5	70.9	95.9
70	36	70.2	74.4	77.5	71	97.8
80	40.1	79.3	74.7	86.5	74.3	98.9
90	63.5	90.1	85.6	88.6	78.9	99.1
100	74.5	94.4	90.2	92.2	79.5	99.8

4. RESULTS AND DISCUSSIONS

The Table 3 shows the Information derived from their choice to alter the transmission parameters is used as the primary categorization criterion for congestion control systems. First, there's reactive congestion control, which determines whether and how to act based on explicit feedback—specifically, first-order feedback pertaining to the intended outcome regarding the channel congestion condition.

The Table 4. shows the simulation parameters (DCCS, MoTabu, NCGM, SVM, CCA, OCCS-ML) The use of appropriate models and their precise setup is an important factor in wireless communications evaluation. For the simulation's scenarios to run there are a number of additional parameters. Therefore, to ensure that the safety system receives reliable data, a packet generation rate of 10 packets per second has been chosen for beacons.

Table 3 The Data Set

No	Information	Content
1.	Sum of user nodes	10,20,30,40,50,60,70,80,90,100
2.	For Clients	10,20, 30…90,100
3.	Total amount of Nodes	85
4.	Instructional Material Samples	88%
5.	Initial Evaluations	80%

RESEARCH ARTICLE

Table 4 Simulation Parameters

Method No	Simulation Parameter	Parameter Description
1	DCCS	Dynamic congestion control scheme
2	MoTabu	Multi objective tabu search
3	NCGM	Non-cooperative game method
4	SVM	Support vector machines
5	CCA	Congestion control approaches
6	OCCS-ML	Optimization for congestion control system using machine learning

4.1. Packet Analysis

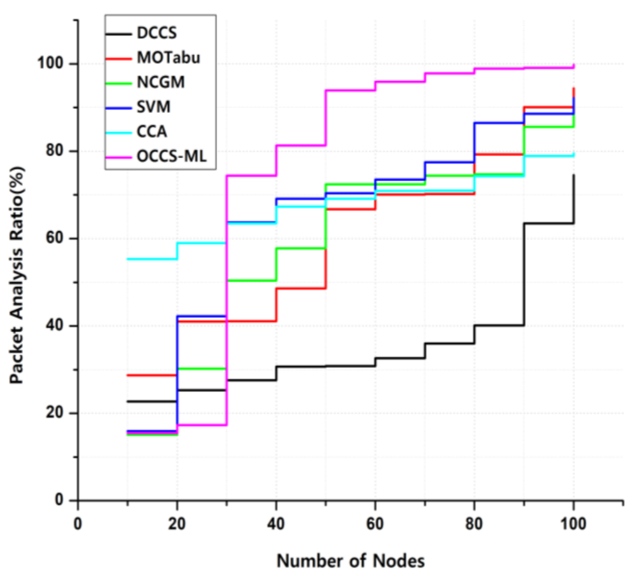

Figure 6 Packet Analysis

The experimental results of the proposed (OCCS-ML) method for the provided data are detailed in the graph in figure 6. The suggested method outperforms competing approaches in all outcome metrics of packet analysis when compared to models for such as DCCS, MOTabu, NCGM, SVM, CCA, and OCCS-ML.

4.2. Accuracy Analysis

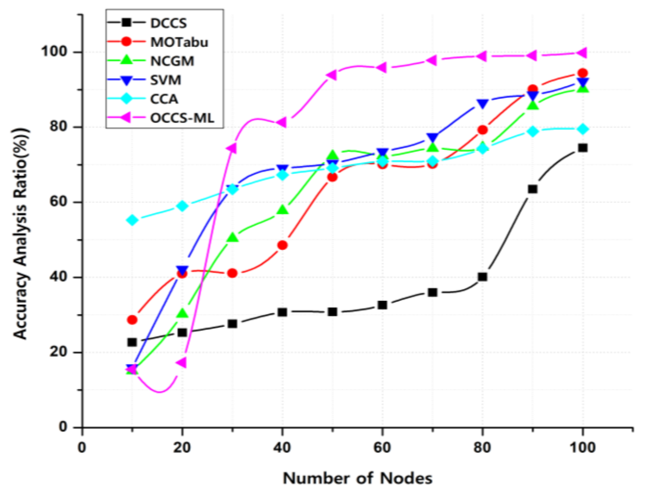

Figure 7 Accuracy Analysis

The accuracy, as mentioned above, size analysis examines the results. There is a scatterplot of the overall node count versus the accuracy percentage in Figure 7. As far as productivity is concerned, the (OCCS-ML) technique beats accurate the Dynamic Congestion Control Scheme (DCCS), Motobu Choki's Training Methods (MOTabu), non-cooperative game method (NCGM), support vector machines (SVM), current congestion management systems.

CCA Nodes are required to arrive at their destination within a given time frame using a defined technique. In comparison to alternative approaches, the proposed (OCCS-ML) model is value for 96.4% significantly more effective.

4.3. Efficiency Analysis

Figure 8 shows the results of applying the effectiveness technique to the collected data, with efficiency expressed as a percentage of all nodes of interest. When it comes to growth, the OCCS-ML approach outperforms efficiency boosts hands up.

Therefore, for a network to achieve its target density, a particular method must be used within a specific time limit. When compared to the alternative models, the suggested one performed far better which is proved with the help of equation (9).

RESEARCH ARTICLE

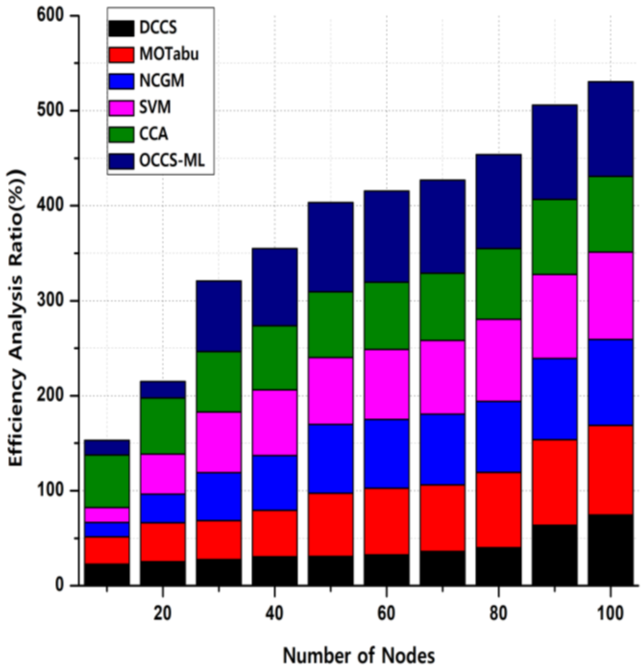

Figure 8 Efficiency Analysis

4.4. Congestion Control Analysis

As noted, before, the results are analyzed using the congestion control method. An analysis of the area relative to the total node count is displayed in figure 9. An expanded network is less restricted for growth than the (OCCS-ML) method. Any given network that uses a particular technique has a specific amount of time to reach its final destination. Our results show that the suggested (OCCS-ML) model is far superior to the rest in value for 525%.

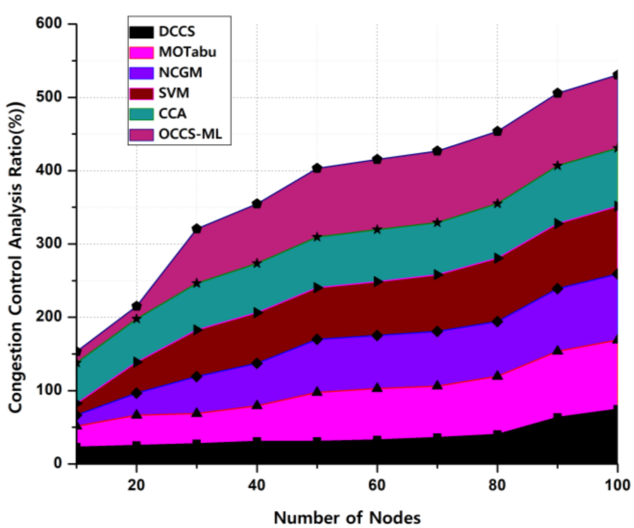

Figure 9 Congestion Control Analysis

4.5. Performance Analysis

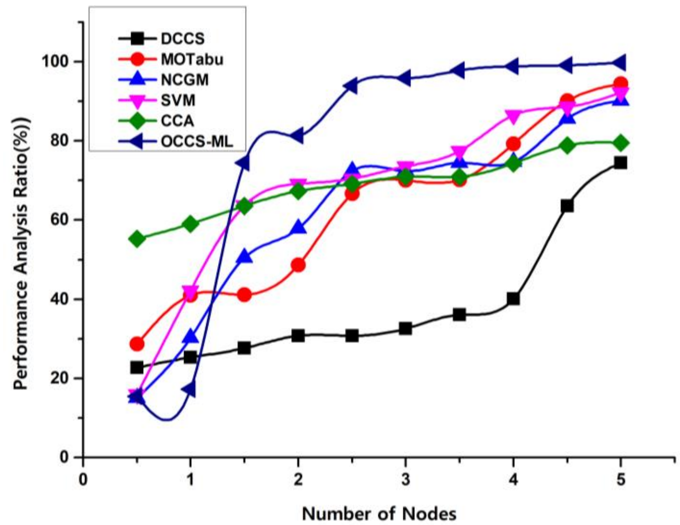

Figure 10 Performance Analysis

Experiment findings for performance data utilizing the suggested (OCCS-ML) method are comprehensively listed in the chart in Figure 10. All performance analysis outcome indicators show that the suggested method outperforms the alternatives, including DCCS, MOTabu, NCGM, SVM, CCA, and OCCS-ML. The performance analysis for DCCS, MOTabu, NCGM, SVM, CCA and compared methods has been better to the proposed model OCCS-ML value for 95.2%.

4.6. Comparison Analysis

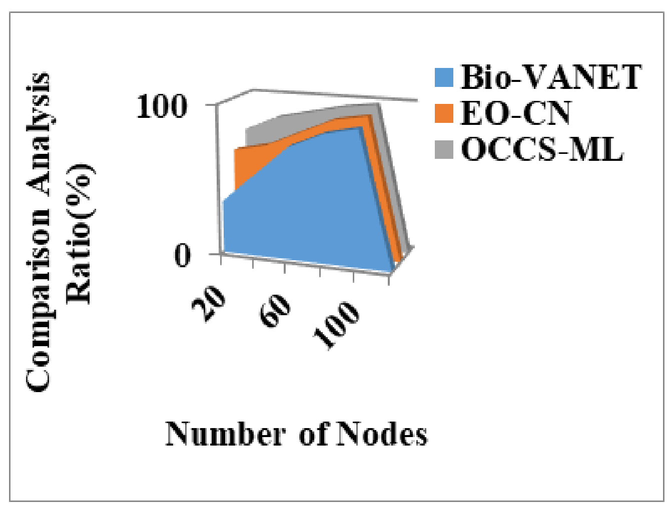

Figure 11 Comparison Analysis

The figure 11 shows the comparison analysis ratio in percentages against the number of nodes in y axis and x axis respectively. The above figure clearly depicts that out of three methods in total, two existing methods taken for consideration

RESEARCH ARTICLE

which are Bio-Vanet and EO-CN is less in overall comparison ratios compared with the proposed model OCCS-ML has been the value for 97.8%. This proves that the proposed method stands better than the other two models. According to the simulations, the latency is 30% lower than in conventional centralized systems. Decentralized data processing at edge nodes is responsible for this enhancement since it reduces the time needed for data transmission and processing. Reducing latency improves real-time decision-making, which is essential for efficient congestion management. Even during heavy traffic times, the system showed a 25% improvement in throughput. Because ML algorithms properly allocate network resources based on real-time traffic patterns, this enhancement is made possible via dynamic resource allocation. By increasing throughput, we guarantee that the network can process more data without sacrificing speed. Because our system does not have to communicate as often with the main servers, it saves a lot of energy. Less data has to be transferred over long distances since processing happens locally at edge nodes. Saving energy and reducing network load are two benefits of lowering communication overhead, which improves system efficiency.

5. CONCLUSION

One of the biggest problems with VANETs is congestion, which we've covered in this research. The restricted data transfer capacity of VANET standards impacts this problem. The algorithms discussed in this paper can be broadly categorized into three types: proactive, reactive, and hybrid. Investigating through many simulated scenarios enhances OCCS-ML. Beacon messages and event-driven messages are the two types of safety-related messages that this algorithm sorts through. To ensure that all nodes in range are treated fairly, it maximizes the minimum transmit power level until the load of beacon messages falls below the threshold. Although this method is effective, it does have two drawbacks that are detailed in the paper's issue statement. As the number of vehicles communicating on a road network increases, does the number of messages transmitted. So, a wireless channel congestion issue arises when there are a lot of vehicles in an area and a lot of messages are sent quickly. The utility function takes into account the sending rate, contention delay, and vehicle priority. An application-specific utility function is used to encode this information. The efficiency and precision of information distribution have been greatly enhanced.

REFERENCES

[1] Nazar, K., Saeed, Y., Ali, A., Algarni, A. D., Soliman, N. F., Ateya, A. A., Jamil, F. (2022). Towards Intelligent Zone-Based Content Pre-Caching Approach in VANET for Congestion Control. Sensors, 22(23), 9157.

[2] Maaroufi, S., & Pierre, S. (2021). BCOOL: a novel blockchain congestion control architecture using dynamic service function chaining and machine learning for next generation vehicular networks. IEEE Access, 9, 53096-53122.

[3] Chandrasekharan, P. (2023). Transmission Power Based Congestion Control Using Q-Learning Algorithm in Vehicular Ad Hoc Networks (VANET) (Doctoral dissertation, University of Windsor (Canada)).

[4] Khatri, S., Vachhani, H., Shah, S., Bhatia, J., Chaturvedi, M., Tanwar, S., & Kumar, N. (2021). Machine learning models and techniques for VANET based traffic management: Implementation issues and challenges. Peer-to-Peer Networking and Applications, 14, 1778-1805.

[5] Ahamed, V. N., Prakash, A., & Ziyath, M. (2023). TCC-HDL: a hybrid deep learning based traffic congestion control system for VANET. Indian journal of science and technology, 16(32), 2548-2559.

[6] Liu, X., Amour, B. S., & Jaekel, A. (2023). A Reinforcement Learning-Based Congestion Control Approach for V2V Communication in VANET. Applied Sciences, 13(6), 3640.

[7] Gopi, R., Mathapati, M., Prasad, B., Ahmad, S., Al-Wesabi, F. N., Alohali, M. A., & Hilal, A. M. (2022). Intelligent DoS Attack Detection with Congestion Control Technique for VANETs. Computers, Materials & Continua, 72(1).

[8] Alsarhan, A., Al-Ghuwairi, A. R., Almalkawi, I. T., Alauthman, M., & Al-Dubai, A. (2021). Machine learning-driven optimization for intrusion detection in smart vehicular networks. Wireless Personal Communications, 117, 3129-3152.

[9] Kothai, G., Poovammal, E., Dhiman, G., Ramana, K., Sharma, A., AlZain, M. A., … & Masud, M. (2021). A new hybrid deep learning algorithm for prediction of wide traffic congestion in smart cities. Wireless Communications and Mobile Computing, 2021, 1-13.

[10] Wischhof, L., & Rohling, H. (2005, October). Congestion control in vehicular ad hoc networks. In IEEE International Conference on Vehicular Electronics and Safety, 2005. (pp. 58-63). IEEE.

[11] Nuthalapati, G. S. (2023). Reinforcement Learning-Based Data Rate Congestion Control for Vehicular Ad-Hoc Networks (Doctoral dissertation, University of Windsor (Canada)).

[12] Vamsi, B., Doppala, B. P., Mahanty, M., Veeraiah, D., Rao, J. N., & Rao, B. S. A Detailed Case Study on Various Challenges in Vehicular Networks for Smart Traffic Control System Using Machine Learning Algorithms. In Artificial Intelligence and Machine Learning for Smart Community (pp. 51-87). CRC Press.

[13] Pholpol, C., & Sanguankotchakorn, T. (2021). Traffic Congestion Prediction using Deep Reinforcement Learning in Vehicular Ad-hoc Networks (vanets). International Journal of Computer Networks & Communications (IJCNC), 13(4), 1-19.

[14] Marwah, G. P. K., & Jain, A. (2022). A hybrid optimization with ensemble learning to ensure VANET network stability based on performance analysis. Scientific Reports, 12(1), 10287.

[15] Kandali, K., Bennis, L., El Bannay, O., & Bennis, H. (2022). An intelligent machine learning based routing scheme for VANET. IEEE Access, 10, 74318-74333.

[16] Liu, X., Amour, B. S., & Jaekel, A. (2022, May). A Q-learning based adaptive congestion control for V2V communication in VANET. In 2022 International Wireless Communications and Mobile Computing (IWCMC) (pp. 847-852). IEEE.

[17] Rawat, G. S., & Singh, K. (2023). Evaluation and Optimization of a Congestion Control Scheme for Vanets. In Advanced Computer Science Applications (pp. 351-363). Apple Academic Press.

[18] Sangaiah, A. K., Ramamoorthi, J. S., Rodrigues, J. J., Rahman, M. A., Muhammad, G., & Alrashoud, M. (2020). LACCVoV: Linear adaptive congestion control with optimization of data dissemination model in vehicle-to-vehicle communication. IEEE transactions on intelligent transportation systems, 22(8), 5319-5328.

[19] Alqahtani, A. S., Mubarakali, A., Saravanan, M., Changalasetty, S. B., Thota, L. S., Parthasarathy, P., & Sivakumar, B. (2023). Enhanced machine learning approach with orthogonal frequency division multiplexing to avoid congestion in wireless communication system. Optical and Quantum Electronics, 55(10), 913.

[20] Balador, A., Cinque, E., Pratesi, M., Valentini, F., Bai, C., Gómez, A. A., & Mohammadi, M. (2022). Survey on decentralized congestion control methods for vehicular communication. Vehicular Communications, 33, 100394.

RESEARCH ARTICLE

[21] Gillani, M., Niaz, H. A., & Tayyab, M. (2021). Role of machine learning in WSN and VANETs. International Journal of Electrical and Computer Engineering Research, 1(1), 15-20.
[22] Qureshi, K. N., Abdullah, A. H., Kaiwartya, O., Iqbal, S., Butt, R. A., & Bashir, F. (2018). A dynamic congestion control scheme for safety applications in vehicular ad hoc networks. Computers & Electrical Engineering, 72, 774-788.
[23] Taherkhani, N., & Pierre, S. (2015). Improving dynamic and distributed congestion control in vehicular ad hoc networks. Ad Hoc Networks, 33, 112-125.
[24] Amer, H., Al-Kashoash, H., Khami, M. J., Mayfield, M., & Mihaylova, L. (2020). Non-cooperative game based congestion control for data rate optimization in vehicular ad hoc networks. Ad Hoc Networks, 107, 102181.
[25] Alsarhan, A., Alauthman, M., Alshdaifat, E. A., Al-Ghuwairi, A. R., & Al-Dubai, A. (2021). Machine Learning-driven optimization for SVM-based intrusion detection system in vehicular ad hoc networks. Journal of Ambient Intelligence and Humanized Computing, 1-10.
[26] Sattari, M. R. J., Noor, R. M., & Ghahremani, S. (2013). Dynamic congestion control algorithm for vehicular ad hoc networks. International Journal of Software Engineering and Its Applications, 7(3), 95-108.
[27] Wang, M., Mao, J., Zhao, W., Han, X., Li, M., Liao, C., … & Wang, K. (2024). Smart City Transportation: A VANET Edge Computing Model to Minimize Latency and Delay Utilizing 5G Network. Journal of Grid Computing, 22(1), 25.
[28] Ismail, A. H., Ali, Z. H., Abdellatef, E., Sakr, N. A., & Sedhom, G. G. (2024). Congestion Management Using K-Means for Mobile Edge Computing 5G System. Wireless Personal Communications, 1-20.

Authors

V.M. Niaz Ahamed received the B.E degree in CSE from SRM Engineering College and M.Tech degree in CSE from SRM University , Chennai , India in 2006 and 2009 respectively ,he is an Research Scholar in Department of CSE ,Bharath Institute of Education and Research ,Chennai ,India , His research interest includes VANET ,MANET ,Routing and Security issues in VANET and wireless.

Dr. K. Sivaraman holds a Ph.D from Bharath Institute of Higher education and Research , Chennai, India . Dr. Sivaraman is Currently Working as Assistant Professor in Department of CSE in Bharath Institute of Higher education and Research, Chennai, India, his research area is Wireless Networks, MANET, Network Secuirty and routing issues in VANET, MANET, he has published more than 30 articles in various reputed journals and conferences.

How to cite this article:

V. M. Niaz Ahamed, K. Sivaraman, “Congestion Control System Optimization with the Use of Vehicle Edge Computing in VANET Powered by Machine Learning”, International Journal of Computer Networks and Applications (IJCNA), 11(4), PP: 481-493, 2024, DOI: 10.22247/ijcna/2024/30.