COMPREHENSIVE SURVEY ON CONGESTION REDUCTION IN VEHICULAR COMMUNICATION NETWORKS

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***Abstract* —** Research delves into the comprehensive integration of Software-Defined Networking (SDN), Fog Computing, and Deep Reinforcement Learning (DRL) into Vehicular Ad-hoc Networks (VANETs) to enhance communication efficiency, resource management, and data optimization. SDN controllers analyze traffic patterns to guide intelligent data routing between VANETs and the internet, vehicle to vehicle, streamlining network operations and optimizing resource allocation. Meanwhile, Fog Computing decentralizes processing and storage resources, enabling low-latency data processing essential for real-time applications. The study elucidates the intricacies of the network model, SDN processing, device management, and routing mechanisms within an SDN-enabled VANET environment, highlighting dynamic resource allocation and adaptive routing strategies. Additionally, it incorporates congestion reduction mechanisms, empowering autonomous decision-making for data scheduling and resource optimization, and implements parked vehicle routing to manage communication in remote areas. The DRL process, encompassing policy creation, reward computation, and learning, plays a pivotal role in augmenting network efficiency and scalability. Ultimately, the synergistic integration of SDN, Fog Computing, parked vehicle routing, and DRL into VANETs emerges as a transformative force poised to revolutionize transportation systems, offering safer, more efficient, and seamlessly connected mobility experiences.
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1. INTRODUCTION

Vehicular ad hoc networks (VANETs), an exciting research field, thrive on the continuous development of vehicular wireless communication technology. In this context, vehicles act as mobile nodes within mobile ad hoc networks (MANETs), a specific category of VANETs, fostering communication among neighboring vehicles and roadside equipment. Notably, VANETs stand out by having vehicles as their nodes, constrained by the road topology while in motion. The ability to predict a vehicle's future position relies on available road information. Consequently, the significance of in-vehicle processing, networking, and sensor capabilities cannot be overstated, as they ensure continuous transmission power to support these critical operations [1].

VANETs represent a specialized category of Mobile Ad Hoc Networks (MANETs) designed to facilitate communication among vehicles and roadside infrastructure. VANETs leverage the wireless communication capabilities of vehicles to enable a variety of applications, ranging from safety-critical tasks like collision avoidance and traffic management to non-safety applications such as infotainment and internet access. These networks rely on vehicles equipped with onboard communication devices, such as Dedicated Short-Range Communication (DSRC) units or cellular modems, to exchange information with neighbouring vehicles and roadside units.

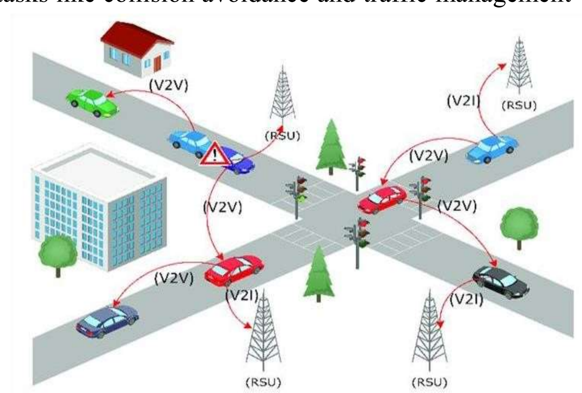


Fig. 1. VANET Communication Architecture

These two VANET communication methods, V2V and V2I, exhibit limitations that vary depending on the situation. V2V communication on highways relies on the sparse distribution and speed of cars to transmit time-critical information, such as traffic collision alerts, leading to challenges in implementing safety applications due to inconsistent connectivity. Moreover, the periodic broadcast of beacons or welcome messages between vehicles consumes a significant amount of bandwidth from the limited VANET spectrum (75 MHz). In contrast, the success of V2I communication in urban and highway settings heavily relies on the viability of roadside infrastructures. Addressing these limitations requires the development of elegant solutions that seamlessly integrate with existing constraints [2 &3].

II. VANETS FEATURES

Topic covered in this section Features of VANETs, Applications and Challenges. Towards the conclusion of this section, we also analyze into various performance metrics related to congestion control.

A. CHARACTERISTICS OF VANETS

VANETs are a specific function of Mobile Ad- hoc Networks (MANETs), distinguished by their mobile and dynamic in nature. Unique features of VANETs include dynamic topology, high mobility, predictable mobility patterns, energy constraints, unbounded network size, and wireless communication.

- Dynamic topology - High-speed and continuously changing directions as well as speeds of vehicles make predicting their positions challenging, leading to abrupt changes in vehicular density in specific regions. As vehicular dense increases, congestion control will occur. [10].
- Time criticality - A crucial characteristic of information in VANETs is their time criticality, emphasizing the need for timely delivery to facilitate prompt actions. For instance, delivering medical emergency messages promptly can save lives. To avoid congestion increasing throughput and reducing network latency is essential [11], [12].
- No energy constraints –MANETs, VANETs benefit from ample power supplied by vehicle batteries, enabling the deployment of computationally intensive schemes and solutions. However, the time-sensitive nature of information presents a challenge in striking a balance between efficiency and complexity. Moreover, ensuring reliable communication is crucial for delivering essential assistance to drivers, although continuous message acknowledgment may contribute to congestion [15].
- Unbounded network size – VANET can be implemented with varying sizes, surrounding towns, multiple cities, and even entire countries. Designing routing protocols ineffective the simple flooding principle, to encourage their scalability mean while it allows for the development of a scalable version of VANET. The challenge arises due to high vehicular density and increased mobility. Bandwidth limitations necessitate the effective utilization of available resources [16].
- In VANETs, wireless communication facilitates frequent information exchange among vehicles and nodes through periodic messages, ensuring awareness of their surroundings. However, the wireless nature of VANETs introduces several security challenges that must be addressed to ensure efficient communication. Another critical use-case emerging from the convergence of Internet of Things (IoT). VANETs are the concept of smart cities communication, promising transformative interactions among machines. Moreover, handover management becomes crucial in these dynamically changing environments [17], [18].
- Enhanced physical protection in VANET nodes enhances overall security by making it difficult for unauthorized access. Each vehicle's acts as a central hub, integrating sensors, resources, storage, user interfaces and easy communication between On-board Unit (OBUs) and Roadside Units (RSUs) [19].

B. VANETS APPLICATIONS

VANET applications are divided into two key categories: safety and efficiency, each serving distinct purposes. These applications gather data from the environment and interact with other nodes to make informed decisions. They encompass safety-related functions, efficiency enhancements, comfort features, interactive tools, entertainment options, urban sensing capabilities, and more. Tailoring specific applications to meet particular needs is common within this dynamic and interconnected network topology. Safety and non-safety applications are predominant, with other categories often being variations or extensions of these fundamental types [20].

- Safety applications – Safety applications in VANETs aim to reduce the likelihood of accidents by providing timely alerts to vehicles, thereby preventing potential collisions. These warnings have the potential to prevent over 60 percent of accidents by guiding drivers to safer routes, consequently reducing both accidents and congestion at intersections. However, effectively managing traffic flow at intersections remains challenging due to the merging of different traffic streams. Upcoming technology of protection messages are disseminated as Co-operative Awareness Messages (CAM) through Co-operative Intelligent Transport Systems (C-ITS). [21], [22].

- Efficiency applications – These applications enable vehicles to share their location with others, promoting enhanced communication and interaction among vehicles. By utilizing data from neighboring vehicles, including acceleration, position, velocity and other parameters, they improve traffic awareness and facilitate better mobility for vehicles. [23].
- Comfort or customization applications – These applications aim to improve the driving experience by offering convenience and entertainment. They provide information on nearby amenities like restaurants, gas stations, and weather forecasts. In case of health emergencies, drivers can send a message to a vehicular cloud for the nearest health center location. These applications also assist in emergencies like accidents. Furthermore, they help locate social venues like bars or meeting points with friends. Some applications may include crowd sourcing features to encourage collective interaction for mutual benefit [24].
- Interactive applications – Entertainment applications provide passengers with a range of services, including chats, internet access, music, games and web browsing. They can automatically download information about local attractions and advertisements enhancing the experience for both passengers and drivers. The incorporation of multimedia content and diverse entertainment options makes these applications more appealing. [25], [26].
- Urban sensing – Sensing and communication are vital components of a traffic management system (TMS), enabling efficient interactions and control [27]. Equipped with various sensors, used for measuring environmental parameters like monitoring traffic conditions, conducting video/audio surveillance and On-board unit (OBU), sensors are utilized for sensing the urban environment and sharing relevant data among vehicles. Urban sensing also encompasses monitoring social activities [28], [29]. Moreover, VANETs applications are categorized into several types, namely Congestion Road Notification (CRN), Co-operative Collision Warning (CCW) and Lane Change Assistance (LCA) [30].

III. BACKGROUND OF THE WORK

A comprehensive survey on traffic prediction using graph neural networks (GNN) encompassing various challenges such as traffic speed, flow, and demand prediction, as well as parking availability prediction. The survey includes numerous datasets and codes, aiding researchers in replicating works and delving into more intricate prediction tasks. We specifically highlight three works focusing on parking availability prediction using GNN. Our research incorporates statistical methods, machine learning, and deep learning to provide a comprehensive overview.

Communication provides a comprehensive background on the evolution of Vehicular Ad-Hoc Networks (VANETs) and their significance in enhancing safety and productivity in Intelligent Transportation Systems (ITS). It discusses the historical context of radio transmissions among vehicles and the advancements in ITS technologies for improving vehicular safety. The background section also introduces the concept of Time-To-Collision (TTC) as a common approach for analyzing safety applications in VANETs. By providing this background information, the paper effectively contextualizes the importance of congestion control in vehicle-to-vehicle communication within the broader evolution of VANETs and ITS technologies.

Vehicle-to-Vehicle Communication identifies two types of security messages:

1. Periodical Messages: These messages, Basic Safety Messages (BSMs) and Co-operative Awareness Messages (CAMs) are broadcast frequently to convey the status of the nearby vehicle.
2. Event-Driven Messages: These messages are transmitted as a result of a traffic conflict or roadway accident, providing critical information in response to specific events.

The distinction between these two types of messages is essential for understanding the communication protocols and strategies employed in vehicle-to-vehicle communication systems.

We Discusses the use of open access tools for simulating Vehicular Ad-Hoc Networks (VANETs). It categorizes three distinct classes with existing software for VANET simulation:

1. Vehicular Mobility Generators: These tools are used to generate vehicular mobility scenarios and simulate the movement of vehicles within the network. Examples of such tools include MOVE, STRAW, and SUMO.

2. Network Simulators: These simulators provide package-level simulation of the source, targets, data traffic broadcast, response, layout, links, and channels. Examples of network simulators include GloMoSim, GTNetS, NS-2,5, NS 3.5 and SNS.
3. VANET Simulators: These simulators offer both network simulation and traffic movement simulation. Examples of VANET simulators include MobiREAL, NCTUns, and TraNS. The use of these open access tools is crucial for researchers and practitioners to simulate and evaluate the performance of congestion control algorithms and communication protocols in VANETs.

IV. STRATEGIES FOR CONGESTION CONTROL IN VANETS

In VANETs, messages are distributed by broadcasting them to all vehicles in the network, with each vehicle duplicating and transmitting the message. To manage congestion, three approaches are utilized: proactive, reactive, and hybrid congestion control [49], [50]. These approaches categorize congestion control strategies into six main types based on their functional mechanisms and techniques. These types include clustering-based, CSMA/CA-based, hybrid, power-based, prioritizing rate-based strategies [51], [52].

Hybrid approaches in VANETs integrate both rate-based and power-based techniques, concurrently adapting them to manage network congestion efficiently. MAC-based strategies, commonly used in VANETs to handle congestion, function within a CSMA/CA framework. Here, nodes assess the channel's status before transmitting data, ensuring transmission occurs only when the channel is clear. These protocols regulate channel access by modifying parameters like the contention window size [55].

Power-based approaches in VANETs focus on alleviating congestion by reducing the transmission power of nodes. This reduction decreases the likelihood of packet collisions, particularly in scenarios with high concurrent packet transmission, thereby easing congestion and reducing packet loss [53]. Conversely, rate-based strategies adapt the data transmission rate according to network conditions. In congested situations where packet loss is likely, this strategy lowers the data rate to minimize collisions and mitigate packet loss in the network [54].

Priority-based approaches in VANETs allocate different priorities to messages depending on their significance [56]. Critical messages, such as emergency or safety-related data, are prioritized for prompt delivery compared to safety messages. Emergency information typically includes details about accidents or congestion vital for optimizing network performance. This section presents diverse strategies for mitigating congestion are summarized in the Fig 2.

A. POWER-BASED STRATEGIES

Power-based strategies in network management involve dynamically adjusting transmission power based on the prevailing network conditions. Upon detecting congestion, vehicles modify their transmission power to mitigate the congestion effectively [57 &58**].**

- ✓ **Multi-metric tx-power Control Protocol (MPC)**

The approach outlined in [59] effectively maintains an acceptable channel saturation level and transmission power across varied coverage ranges. Nodes achieve this by dynamically adjusting their transmission power, considering factors such as the quality of the control channel and the specific requirements of the application. Control channel quality and application needs play crucial roles in tailoring transmission power to the specific requirements of each node. To prevent channel saturation and collisions, it is essential to assess both the current and anticipated channel quality for transmissions.
The protocol utilizes a beaconing load metric to assess the quality of the channel for upcoming beacons. Denda et al. [60] explain about the estimates beaconing and anticipated load on the control channel, factoring in the estimated density of vehicles. It calculates the beacon load for all vehicles under the assumption of a consistent frequency and packet size.
Transmission power is adapted according to application requirements, Let us considering the desired transmission range and priority levels assigned9, as illustrated in Figure 3. Messages triggered by events, prioritized at level 1, utilize the highest transmission power, while general safety messages, prioritized at level 0, employ the lowest transmission power, particularly during congestion. When congestion is absent, event-specific messages are transmitted with the highest power, showcasing flexibility to changing network conditions. However, some drawbacks exist. The method calculates vehicular density based on vehicular advertisement, but the threshold for congestion detection remains unspecified. Furthermore, the passage expresses

concerns regarding how vehicles will receive beacons amidst existing network congestion.

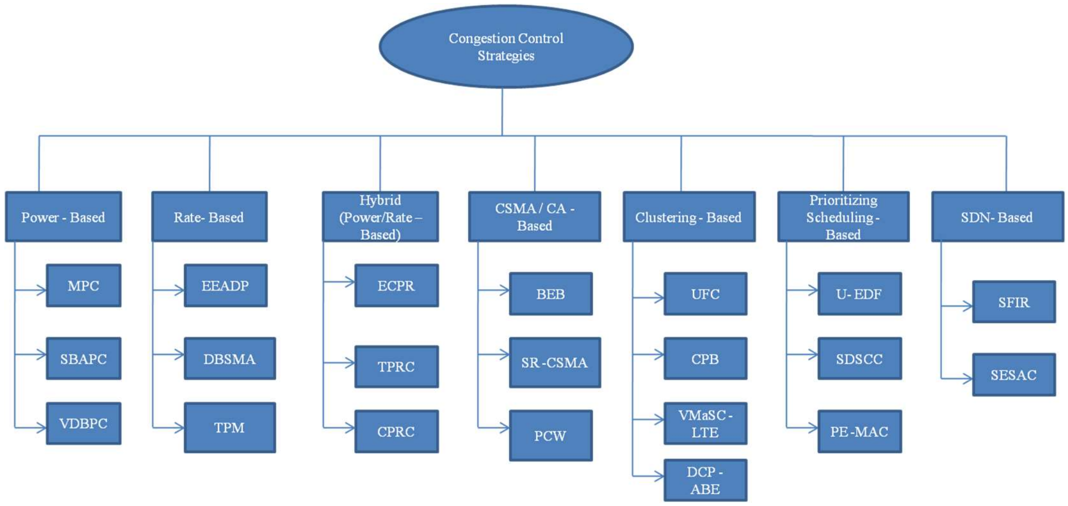
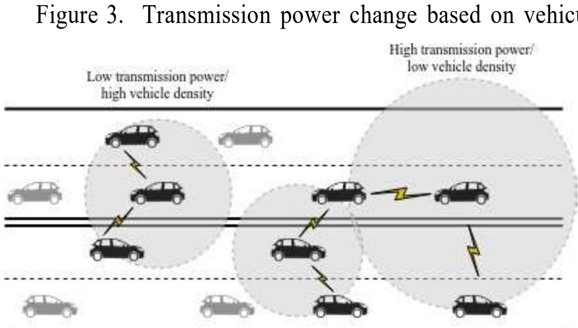


Figure 2: Taxonomy of congestion control protocols

- ✓ **Speed-Based Adaptive Power Control (SBAPC)**

Denda et al. [60], they propose reducing network congestion by dynamically modifying the power transmission based on the vehicle's speed. This adjustment is rooted in the inverse correlation between a vehicle's speed and the Time to Collision (TTC) with neighboring vehicles. Essentially, higher speeds lead to shorter TTC, demanding increased awareness from distant vehicles to receive BSMs. This protocol involves an initialization phase where maximum transmission power and cycle length to be established, followed by a power control phase.
The protocol sets the maximum transmission power at 10mw; allowing BSM to reach up to 360m and it will establish a packets size length 7/cycle use to regulate transmission power factor and length.

Figure 3. Transmission power change based on vehicular



densities.

Subsequently, the vehicle's transmission power is adjusted incrementally after each BSM transmission according to this power factor. Final maximum power transmission sent by BSM, even though for vehicle's speed. Aim of expanding the vehicle's awareness circle by boosting transmission power, particularly noticeable at higher speeds. However, a drawback is observed: in regions with high vehicular density, transmission power decreases, thereby limiting awareness of neighboring vehicles.

- ✓ **Vehicle density-based power control (VDBPC)**

In this method described [61], the MAC layer transmission power is controlled according to the vehicle density in a specific area. It begins by setting a maximum transmission range of 1000m, with packets transmitted steadily at a constant maximum rate of 10Hz, which equates to an average of 10 packets per second.. Vehicular density is determined by counting the number of vehicles in the region, categorizing it as dense (if the count exceeds 100), moderately dense (if the count is between 50 and 100), or sparse (if the count is less than 50).
In congested environments, the transmission rate is reduced to minimize the higher likelihood of close proximity and collisions, thus preventing congestion. In moderately dense scenarios, transmission power is adjusted to a medium level to accommodate space between the vehicles. Conversely, in sparse conditions maximum transmission power is set to vehicles are more widely dispersed to reducing congestion.

However, drawbacks include the unaddressed congestion effects on event-driven messages and the reliance on arbitrary assumptions regarding vehicular count or density.

- ✓ **Discussion**

Congestion control techniques aim to improve awareness of far-away vehicles, primarily achieved through power-based methods that extend the transmission range. This extension improves a remote vehicle's understanding of its environment. However, a drawback of power-based approaches arises in scenarios with higher transmission power, where issues like hidden nodes and channel fading become more prominent. These challenges result in a decreased channel sensing range, potentially causing power control methods to prioritize awareness of nearby vehicles over distant ones [62].

B. RATE-BASED STRATEGIES

This handles congestion by modifying either the transmission rate or the rate at which packets are generated. Augmenting the transmission rate significantly impacts VANET performance, enhancing the transmission of safety messages and increasing vehicle awareness of their surroundings. However, this increase in transmission rate incurs costs, potentially resulting in network congestion. In high-density scenarios, numerous vehicles transmitting substantial data elevate the channel load, leading to collisions. [63&64].

- ✓ **Effective and Efficient Adaptive probabilistic Data dissemination Protocol (EEADP)**

It Aim’s to improve broadcast storm problem and data delivery rates. By adjusting the waiting period based on distance and evaluating each node's suitability for rebroadcasting, it ensures optimal transmission scheduling. Increasing two or more alternative direction helps to reduce vehicle density. To address transmit problem, different segments are assigned varying waiting times, designating the final slot as the unique forwarder node. In regions with high vehicle numbers, rebroadcast probability is determined based on preceding redundancy, prioritizing slots with lower vehicles and redundancy ratios. This approach is particularly suitable for safety message exchange.

Drawbacks include the proposal's cost-efficiency and the suggestion that introducing more road segments can address network congestion when vehicular density surpasses a certain threshold. This approach may be inefficient in specific scenarios, considering alternative solutions such as adjusting transmission power or prioritizing event-driven safety messages to effectively alleviate network congestion.

- ✓ **Dynamic Broadcast Storm Mitigation Approach (DBSMA)**

The system swiftly detects hazards and responds promptly, with perception and reaction times varying from 1/4 - 1/2 and 1/4 - 3/4 of seconds, respectively. To ensure safety, a minimum distance of 200m at a speed rate of 120 km/h is maintained, often adhering to the 3-second rule for vehicles under normal conditions. According to the WAVE standard, vehicle-to-vehicle communication operates within a maximum range of 1000m.

In the event of a faulty vehicle on the roadside, awareness messages are transmitted at a reduced rate, with faster-moving vehicles broadcasting more frequently than slower ones. The tolerance range, set at 20%, equates to 800m in this context, requiring slow or parked vehicles to send at least two messages within an 800m range. This approach prompts fast-approaching vehicles to adjust their speed upon receiving messages, effectively mitigating congestion by adapting to the situation.

However, a drawback of this method is the potential unavailability of critical information. Safety-related messages, like accident or congestion alerts, are essential and must reach approaching vehicles within a specific timeframe. Lowering the data rate may result in occasional information unavailability during critical moments [65].

- ✓ **Trajectory Predicted Mechanism (TPM)**

The Trajectory Prediction Mechanism (TPM) was devised to alleviate congestion in V2I communication by reducing beaconing rates, thereby minimizing unnecessary messages in the network. Vehicles utilize sensed and previously predicted data to construct future trajectory models. Instead of uniformly transmitting data, each vehicle sends messages based on its anticipated trajectory. As the network topology evolves, these models expire, prompting the transmission of updated models with refreshed predict positions. TPM operates on a linear model, triggering new transmissions when vehicles turn, brake or accelerate. For calculating error position vector new model transmission threshold are Initiate, which compares received GPS positions with predicted positions. Discrepancies between these vectors dictate the error threshold, determining when new model transmissions occur. Additionally, TPM mandates periodic new model transmissions, regardless of whether the error falls within the threshold. However, a potential drawback is the risk of inaccuracies in predicted trajectories due to malicious behavior by certain vehicles [66].

- ✓ **Discussion**

Data rate approaches provide a partial remedy for congestion by dynamically adjusting data rates according to network conditions. These schemes effectively alleviate congestion by reducing data rates during significant collisions. However, adapting data rates in VANETs presents challenges. Unlike conventional networks, which broadcast at the lowest supported data rate, efficient management of interference levels across channels. As vehicular density increases, the hidden node terminal effect becomes more pronounced, posing challenges in achieving optimal channel utilization and minimizing interference. [67 & 68].

C. HYBRID STRATEGIES

This strategy employs a combined approach, adjusting both transmission power and rate concurrently to better manage congestion. Rather than modifying power or rate separately, this method provides an improved means of congestion management by synchronizing the transmission rate with the transmission range [69 & 70].

- ✓ **Environmental and Context-aware Combined Power and Rate distributed congestion control (ECPR)**

The objective of congestion control is to enhance awareness among vehicles, ensuring timely dissemination of safety messages to prevent potential hazards. Power adjustments address awareness issues and reduce channel load, while data rate control optimizes resource utilization to achieve the desired load. Power adaptation is determined by the transmit power level conveyed in transmitted packets, estimating channel path loss for all vehicles using the Path Loss Exponent (PLE). For data rate adjustment, the Linear Message Rate Integrated Control (LIMERIC) algorithm utilizes the channel busy ratio and current beacon rate to maintain the channel busy ratio below a set threshold.

However, challenges arise in tracking dynamic and mobile nodes, quality of awareness that affects topology changes. Hence, during congestion control implementation tracking errors must be considered [71].

- ✓ **Transmission Power Rate Control (TPRC)**

This method to enhance Power/rate approach vehicular safety communication performance by computing the kth percentile of Inter-Reception Time (IRT) at a specified distance, preventing channel saturation. Unlike transmission rate, transmission power has an optimal value irrespective of vehicular density. Spatial and temporal characteristics, crucial for safety application packet reception, are examined. Spatial aspects ensure beacon audibility at the target distance, between sender and receiver packets. Performance enhancement transmission selection power is based on distance, with channel load guiding data rate determination to minimize interference. The algorithm verifies if the channel loads within limits; if not, it adjusts transmission power or lowers the data rate. Drawback is focused on beacons, overlooking critical event-driven safety messages is essential for VANET [72].

- ✓ **Combined Power and Rate Control (CPRC)**

This approach tackles network congestion in a unified loop, adjusting both power and rate simultaneously. When a node encounters a hazardous situation, like turning at an intersection, it reduces transmission power to alert other nodes. Simultaneously, the transmission rate increases based on contextual factors such as collision probability and speed, staying below a predefined reliability threshold. Two algorithms operate in succession, offering flexibility. The first algorithm calculates transmission rate and data rates for each power level based on vehicular density, ensuring fairness within a specific transmission range. In the subsequent phase, nodes calculate inter-packet arrival times for neighboring nodes and their own packet generation rates. The choice of transmission rate is coordinated with transmission power to ensure the overall traffic load remains below a predefined threshold. However, a limitation arises from employing the same data rate for fairness, which might not correspond to real-world situations where factors like vehicle speed warrant different data rates for individual vehicles.

- ✓ **Discussion**

These strategies mainly concentrate on adjusting power & data rates to mitigate network congestion but neglect crucial factors such as traffic dynamics and vehicular movement states, like speed. Moreover, they overlook the significance of position errors computed by nearby vehicles, which are vital for ensuring high accuracy in the vehicular network, especially for precise parking and navigation.

D. CSMA/CA-BASED STRATEGIES

Ensuring efficient medium access is vital for vehicles to deliver services reliably. MAC strategies define how vehicles access the channel, optimizing the utilization of both safety and non-safety applications is shown in the Figure 4. [73– 76].

- ✓ **Binary Exponential Back-off (BEB)**

The proposed strategy adopts a decremental exponential back-off approach to balance collisions and expired beacons, addressing ghost nodes in the process. It seeks to improve communication quality on the control channel by reducing the contention window for consecutive messages upon expiration. Recognizing the limitations of RTS/CTS and BEB strategies in VANET broadcast environments, particularly concerning the short lifespan of CAM messages, the strategy aims to ensure timely availability to neighboring vehicles [77].

In VANETs, especially concerning CAM, the primary objective isn't merely data transmission or throughput increase but rather enhancing awareness among nearby vehicles. The approach underscores the need to balance collision prevention with handling expired beacons. It acknowledges that waiting based on a contention window before sending critical messages risks rendering the information outdated, posing hazards to the network.

Initially, the strategy introduces a large contention window (CW), halving it with each expired message to prioritize event-based crucial messages. This tradeoff aims to minimize collisions and control ghost node occurrences. However, reducing the congestion window by half may not sufficiently prevent vehicles from sending packets more frequently without causing collisions.

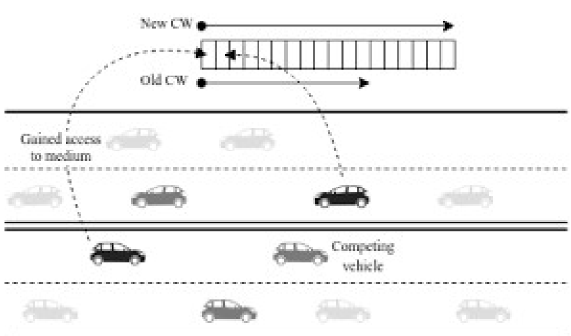


Figure 4: CSMA/CA-Based Strategies.

- ✓ **Safety Range-Carrier Sense Multiple Access (SR-CSMA)**

A proposed channel access technique enhances message reception within the safety range, extending beyond the vehicles' transmission range to alleviate congestion. This mechanism, inspired by conventional CSMA principles, initiates beacon transmission when the channel is clear, employing an exponential back-off timer upon channel occupancy.

Incorporating an additional step, SR-CSMA evaluates to transmit safe nodes and message significance. If the safety range is not empty and messages are critical, the channel is considered busy. In such cases, the Signal-to-Interference Ratio (SIR) is computed to gauge interference at the safety range border, permitting transmission if the SIR exceeds a set threshold. This approach aims to boost reception probability. However, inefficiency arises when safety messages require transmission during busy channel periods, as the random back-off timer introduces delays [78].

- ✓ **Predictive Contention Window (PCW)**

In this mechanism, prompt other vehicle to transmit traffic information and control channel to adjust their window size. Hidden Markov Model (HMM) enhances real-time capabilities by predicting vehicular states for future movement based on attribute sets, while Predictive contention Window (PCW) dynamically adjusts window size facilitated by the MAC layer.

Limitation is noted as the predictive contention window primarily focuses on predicting window size and does not explicitly address the handling of safety messages [79]

- ✓ **Discussion**

These methods aim to assess the communication medium before commencing transmission. It elevated vehicular density within a region due to constrained channel bandwidth. Conversely, environments characterized by lower density to improved their performance.

E. CLUSTER-BASED STRATEGIES

Clustering is widely utilized in VANETs to enhance network reliability and scalability. Vehicles are grouped into clusters, enabling decentralized communication. Each cluster autonomously handles its tasks, improving information sharing and incident detection. Cluster-based routing enhances scalability by transitioning the network from a flat to a hierarchical structure. Various techniques are employed for clustering.

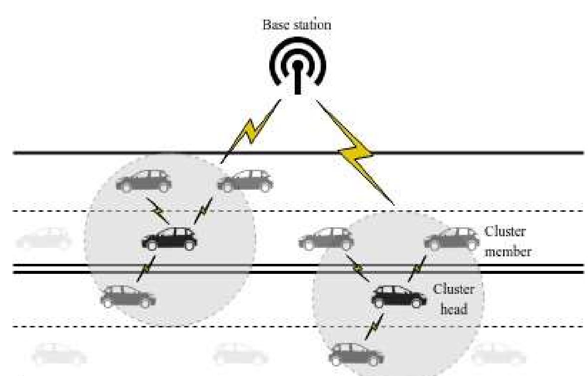


Figure 5: Clustering-based approaches

- ✓ **Unified Framework of Clustering (UFC)**

Enhance cluster efficiency mobility-based metrics are used. Initially, it identifies stable neighbors capable of connecting with the cluster head (CH). Potential stable neighbors are chosen based on similarities in mobility patterns, including shared direction and a speed difference below a defined threshold. To reduce clustering management overhead, each vehicle computes a random back-off timer to assist in CH selection. Vehicles with a higher chance of becoming a CH set a shorter back-off timer. CH selection and back-off timer computation consider three parameters: Average relative speed, Distance and Link life time [82]

- ✓ **Clustering-based Probabilistic Broadcasting (CPB)**

The objective is to effectively distribute safety messages while reducing collisions. Cluster head (CH) selection relies on factors like vehicle direction and geographic location, ensuring continuous communication between vehicles. For data broadcasting, a probability assignment function, considering vehicular density or network conditions, is employed. A probabilistic forwarding algorithm, derived from this function, decides data forwarding based on calculated probabilities. If the packet receiver is within the dissemination range of the CH, it broadcasts the packet. Otherwise, if another node receives the packet and the CH is out of its transmission range, it probabilistically forwards the packet. If the CH is within the transmission range, the vehicle discards the packet to reduce latency and packet loss. However, a challenge lies in determining an efficient density threshold for packet forwarding on a probabilistic basis [83]

- ✓ **Vehicular Multi-hop algorithm for Stable Clustering - Long Term Evolution (VMaSC-LTE)**

This system aims to reduce end-to-end delay and improve packet delivery ratio. Vehicles select a Cluster Head (CH) based on average speed. It employs two interfaces: 802.11p for V2V communication and LTE for CH communication with vehicles and infrastructure. To address interference between clusters, which can cause contention and collisions, the system optimizes cluster size and count. Vehicles prioritize connecting to existing clusters and only announce themselves as new CH when necessary. Clusters within each other's transmission range try to merge into a single cluster if the vehicle count is below a specified threshold. Vehicles either connect to existing clusters or send multi-hop requests to join a cluster if the CH is unreachable directly or indirectly. VMaSC-LTE suggests merging neighboring clusters in the same direction, selecting the slow-moving CH from previous clusters as the new CH. However, a drawback is the lack of clarity regarding the threshold or vehicular count for a cluster and its impact on contention [84].

- ✓ **A Cluster of CP-ABE Micro services for VANET**

This strategy effectively allocates encryption tasks across vehicle clusters organized by Kubernetes, thereby decreasing CP-ABE processing time. Task distribution takes into account the computational capacities and resource details of each vehicle, gathered by Kubernetes. Encryption operations are conducted in V2V connections, eliminating the need for infrastructure elements such as RSUs, which reduces computational expenses and minimizes delays. However, a drawback is the potential for increased inter-cluster interference as the number of clusters grows, without specifying methods to maintain an optimal interference level with cluster expansion [85]

F. PRIORITY-BASED STRATEGIES

Critical in vehicular networks are event-driven safety messages, pivotal for timely adaptation of other vehicles and networks to the network's behavior is given in Figure 6. Messages vary in priority, with certain ones carrying vital information such as accident or congestion details. The network prioritizes these messages, emphasizing their importance. Several protocols, as discussed below, aim to manage congestion by prioritizing certain messages over others [86 & 87].

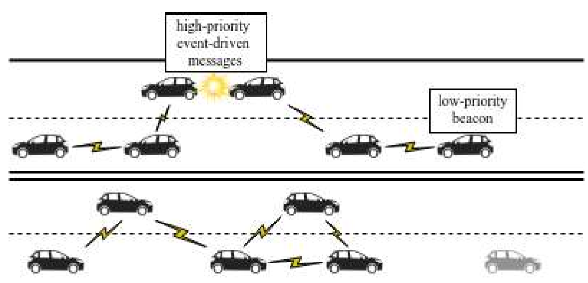


Figure 6: Priority and scheduling based strategy.

- ✓ **Uni-priority safety messages dissemination using Earliest Deadline First (U-EDF) [88]**

Measurement-based detection entails monitoring queues and discarding incoming messages if they surpass a predefined threshold, while event-driven detection prioritizes critical messages over regular packets. Upon identifying event-driven messages, the protocol suspends all MAC transmissions, allocating sufficient resources for their efficient dissemination. Leveraging the Earliest Deadline First (EDF) scheduling algorithm, EDF prioritizes messages with the shortest deadlines, ensuring effective transmission. However, a limitation is noted as the scheme exclusively handles uni-priority messages, lacking mechanisms for managing messages with varying priorities.

- ✓ **Static and Dynamic Scheduling for Congestion Control (SDSCC)**

This approach alleviates network congestion by prioritizing packets within the IEEE 1609.2 multi-channel MAC framework. It enhances the static scheduling scheme by making packet sending decisions based on predefined parameters in the priority assignment unit. For dynamic scheduling, two methods are employed. The first method involves recalculating initial priority transmission unit and the second method addresses the NP-hard problem of dynamic topology constraints, using a meta-heuristic algorithm known as the tabu search algorithm. This algorithm provides a near-optimal solution for scheduling control and service queues, effectively reducing end-to-end delay and jitter. However, one drawback is that under normal circumstances, service channels often handle high traffic, primarily consisting of low-priority or general safety messages. During congestion, if service channels become overloaded, addressing the routing becomes challenging.

- ✓ **Power Efficient Media Access Control (PE-MAC)**

This modification employs the PE-MAC protocol, a variation of the 802.11p protocol, to manage congestion windows and random back-off timers, reducing delays for emergency messages. Emergency data, particularly ambulance data is assigned a shorter back-off period compared to other types. For the first three types following normal distributions, mean values are strategically chosen to create smaller back-off timers with higher probabilities for lower mean values. The mean values are arranged such that mean1 > mean2 > mean3, ensuring back-off timers are selected in increasing order. One drawback is that retransmission may not effectively address low-latency network issues like VANETs, potentially leading to increased delay and packet loss as vehicular density [89].

G. SDN-BASED STRATEGIES

- ✓ **SDN and Fog-based Intersection Routing (SFIR)**

This section introduces V2V communication within coverage holes in VANETs. It occurs without RSUs, where vehicles relay data packets to maintain coverage. The routing method at intersections aims to find the most efficient path from source to destination. However, lacking a comprehensive system overview can lead to suboptimal routing paths. To tackle this issue, software-defined networking (SDN) is utilized. By Euclidean distance method Fog coverage area nodes vehicle density and street lengths are calculated. The SDN controller uses this data to determine the best transmission paths, and data is then sent on the V2V channel following these paths. An issue arises with the abundance of metrics available for consideration, posing a challenge in determining the optimal solution based on multiple parameters or features [90].

- ✓ **SDN-Enabled Social-Aware Clustering algorithm (SESAC)**

The proposal suggests employing clustering methods enhanced by software-defined Access network in 5G to address packet loss and congestion. SDN's adaptability aids in maintaining stable clusters within the dynamic VANET setting. Stability is further bolster by integrating future route predictions and observed social behaviors in VANET. It represented by dwell times on road segments and their frequencies are analyzed by using a discrete time-homogeneous Semi-Markov model. This model generates social patterns for every vehicle, aiding in the formation of clusters with shared routes among vehicles. Cluster head (CH) selection considers metrics like relative speed and vehicle distance. Nonetheless, a significant drawback is that optimal cluster performance relies on various factors, and with an increase in cluster numbers, inter-cluster interference rises. Thus, determining the ideal cluster count becomes essential for efficient operation [91].
Table 1 represents the comprehensive summary approach of congestion control. The extensive exploration and study of SDN have garnered considerable interest, and its progress is shaped by various technologies. Simultaneously, the impact of SDN architecture extends to both wired and wireless networks, including vehicular, cellular and sensor networks (such as 4G and 5G).

A. Software Defined Network Function Virtualization

Network Function Virtualization (NFV) stands out as a promising technology, offering a flexible and open network architecture by virtualizing network functions and decoupling them from specialized hardware. This approach facilitates swift network reconfiguration and has the potential to reduce capital expenditures for Internet Service Providers (ISPs) scaling up their networks. NFV and Software-Defined Networking (SDN) are closely intertwined technologies that enhance network control and management. While SDN controls network resources, NFV concentrates on the software-based transformation of network functions through virtualization.

B. Software Defined Edge Computing

The rise of smart phones and wearable devices, such as smart glasses, watches, and bracelets, has brought significant attention to Edge Computing as an innovative paradigm. Edge Computing plays a crucial role in addressing computation-intensive tasks by offloading them from less capable devices to powerful edge servers. This practice not only extends device battery life but also accelerates the execution of computation-intensive tasks.

C. Software Defined Optical Networks

Optical networks, with their high transmission capacities, play a crucial role in modern information systems. However, the unique characteristics of optical transmission, including burst, circuit, and packet switching on wavelength channels, pose challenges in network control. To address this, the concept of Software Defined Optical Network (SDON) has been introduced, allowing networking applications to dynamically and efficiently utilize the underlying optical network infrastructure through logically centralized control in SDN.

Unlike other networks, optical networks rely on the optical physical layer where light paths are established for data transmission. The Quality of Transmission (QoT) of a light path is influenced by various parameters such as baud rate, code rate, and modulation format. Predicting QoT before deploying a new light path is crucial for designing and planning optical networks. Supervised learning algorithms, such as k-NN, random forest, and neural networks, prove effective in QoT prediction. For instance, in [92], KNN and random forest predict QoT based on parameters like light path length, traffic volume, and modulation format, while uses a neural network for QoT prediction.

Fault management is another critical aspect of optical networks due to their high data transmission capacities. The failure of light paths can lead to significant data losses, making supervised learning algorithms valuable for fault management based on historical failure incidents. Techniques like statistical machine learning in predict failure probabilities for individual links, and employs neural networks to assess network performance by predicting blocking probabilities.

Additionally, Reinforcement Learning (RL) is frequently employed to optimize the allocation of resources in optical network infrastructure components, enabling flexible, reconfigurable, and cost-effective end-to-end services.

D. Software Defined Internet of Things

The Internet of Things (IoT) is poised to connect various devices, from traditional communication tools to household appliances, enabling applications like intelligent transportation, smart healthcare, and energy systems. A proposed software-defined IoT architecture allows remote control by network operators and users, leveraging real-time information for intelligent services

Due to substantial data generated by IoT devices, Machine Learning (ML) techniques are utilized for data processing. However, ML algorithms often require significant storage and computing resources. To tackle this challenge, a centralized approach is typically adopted for ML model training. Yet, transmitting large raw data volumes to the centralized SDN controller consumes considerable network bandwidth. Edge computing addresses this by preprocessing raw data, reducing data transferred to the controller and accelerating ML model training. Deploying trained ML models on edge servers enhances IoT service response times

Security is a major concern in IoT, prompting the use of supervised learning algorithms to bolster edge computing-based IoT systems. Techniques like deep neural networks and Support Vector Machines (SVM) aid in anomaly detection and sensor data analysis, strengthening IoT network security against cyber-attacks.

In summary, the integrated approach of Software-Defined Networking (SDN), edge computing, and ML techniques streamlines IoT system deployment and advances IoT services.

E. Software Defined Vehicular Networks

The emergence of smart vehicles highlights the importance of establishing internet access and communication within vehicular networks. These networks aim to improve comfort, convenience, traffic efficiency, and road safety by enabling real-time exchange of vital traffic information, including conditions, accidents, and obstacles, among vehicles. However, vehicular networks encounter inherent challenges such as varying vehicle densities, limited RSU distribution, high vehicle mobility, dynamic traffic conditions, and diverse application needs.

Routing in vehicular networks involves unicast, multicast, and broadcast approaches. While multicast and broadcast may not be energy-efficient due to redundant transmissions, unicast routing directs traffic to the intended destination through a specific path. Unicast routing includes topology-based and position-based routing methods. Topology-based routing decisions rely on link information among vehicles, considering factors such as link quality, available bandwidth, and vehicle mobility. In contrast, position-based routing makes decisions based on vehicles' position information.

Topology-based routing can select neighbor vehicles with better link conditions but may lack destination vehicles' position information, leading to local optimal decisions. Conversely, position-based routing minimizes communication hops by selecting the closest neighbor vehicle to the destination but may be less stable due to weak signal strength. To improve routing decisions, both link and position information should be considered.

The introduction of the Software-Defined Vehicular Network (SDVN) aims to streamline network information collection and analysis, reducing communication costs and enhancing network performance. ML techniques like Long Short-Term Memory (LSTM) and Reinforcement Learning (RL) are utilized in SDVN to predict vehicle movement and changes in vehicular network topology. These predictions guide SDN controller decisions for data forwarding, illustrating how ML techniques contribute to building an intelligent, safe, and efficient vehicular network.

F. Software Defined Mobile Networks

Mobile networks have transitioned into the 5G era after decades of progress, aiming to support a growing number of connected devices, higher user data rates, increased mobile data traffic, and reduced transmission delay and energy consumption. Besides these performance goals, 5G networks must also accommodate diverse services, devices, and access networks. However, they face challenges such as heterogeneous wireless environments, complex network management, escalating mobile traffic demands, and varied service requirements.

To address these challenges, Machine Learning (ML) techniques are integrated into 5G networks to infuse intelligence. ML algorithms enable self-configuration, self-optimization, and self-healing functionalities. Self-configuration involves automatically setting network parameters for operational readiness, including operational and radio-related parameters. Self-optimization continually monitors the network environment to enhance performance, optimizing aspects like mobility management, handover parameters, load balancing, and resource allocation. Self-healing detects failures, analyzes faults, and expedites recovery, primarily using ML for fault detection, classification, and cell outage management. A detailed overview of ML algorithms for these functions can be found in Reference [95].

The global network perspective provided by SDN controllers facilitates efficient collection and analysis of network information. Consequently, the Software Defined Mobile Network (SDMN) has been introduced to implement intelligent mobile networks, leveraging a software-oriented design approach.

G. Software Defined Wireless Sensor Networks

The evolution of smart sensors in recent years has propelled the advancement of Wireless Sensor Networks (WSN). These networks comprise numerous small, cost-effective sensor nodes capable of monitoring environmental data like temperature, pressure, humidity, and movement. However, smart sensors encounter limitations in storage, energy, computational capacity, and communication bandwidth, posing challenges in managing diverse nodes and configuring network settings.To address these challenges, Software-Defined Networking (SDN) has emerged as a paradigm to streamline network management and configuration. There's a growing trend of integrating WSN with SDN to improve efficiency and sustainability, as seen in the Software-Defined WSN (SDWSN) model.

Machine learning (ML) algorithms play a pivotal role in SDWSN by effectively managing sensor nodes, optimizing resource utilization, and scheduling communication links flexibly. ML techniques are widely employed to tackle various WSN challenges, including routing optimization, node clustering, data aggregation, event detection, query processing, localization, intrusion detection, fault detection, and more. Reference [9] offers a comprehensive survey of ML algorithms and their applications in resolving these WSN issues.

TABLE 1. Summary table of congestion strategies with relevant attributes.

	Simulator	Dataset	Density	Delay	Throughput	Loss	Coverage	Nodes / Devices	Internode Communication	Communication Protocol
Powder- Based Strategies										
Ishtiaq Wahid et.al(2022)	NS-2.34, MOVE, and SUMO	D / U /M	✓	✓	✓	✓	1000m	✓	✓	DSRC / WAVE
Akinland et.al (2018)	OMNET ++ / Veins / SUMO	D / U /M	✓	✓	✓	×	1000m	×	✓	DSRC / WAVE
Joseph et.al. (2018)	OMNET ++ / Veins / SUMO	D / U /M	✓	✓	✓	×	1000m	×	✓	DSRC / WAVE
Shah et.al. (2016)	OMNET ++ / Veins	U /L	✓	✓	✓	×	750m	×	✓	DSRC
Rate – Based Strategies										
Sospeter et.al. (2018)	NS2 / SUMO	U / ML	✓	✓	✓	×	700m	×	✓	IEEE 802.11p
Feuken et.al (2018)	MATLAB	D / U /ML	✓	✓	✓	×	1000m	×	✓	IEEE 802.11p / IEEE.1609
Boquet et.al. (2017)	NS3 / SUMO	D / U /ML	✓	✓	✓	×	20mW	✓	✓	IEEE 802.11p
CSMA / CA – Based Strategies										
Y.L.G et.al. (2016)	NA	D /U	✓	✓	✓	×	NA	×	✓	IEEE 802.11p
Stanica et.al. (2012)	NA	U	✓	✓	✓	×	100m	×	✓	IEEE 802.11p
Stanica et.al. (2011)	JIST SWANS / STRAW	D / HW	✓	✓	✓	✓	200m	×	✓	IEEE 802.11p
Clustering – Based Strategies										
Taha et.al. (2019)	NA	NA	×	✓	×	×	NA	✓	✓	NA
Ren et.al.(2018)	NS3 / SUMO	HW / M	×	✓	✓	×	300 m	×	✓	IEEE 802.11p
Liu et.al. (2018)	NS2 / VANET MobiSim	HW / H	✓	✓	✓	×	250 m	×	✓	IEEE 802.11DCF
Ucar et..al. (2016)	NS3 / SUMO	U / H	✓	✓	✓	×	200 m	×	✓	IEEE 802.11p - LTE
Priority – Based Strategies										
Nellore et.al. (2016)	NS2 / MAT	NA	✓	✓	✓	×	NA	×	✓	IEEE 802.11p

	Lab									
Taherkhani et.al. (2016)	NS2 / SUMO / MOVE	U/ H	✓	✓	✓	×	10 packets	×	✓	IEEE 802.11p
Darus et.al. (2013)	OMNeT ++ / SWANS /STRAW	H	✓	✓	✓	×	400m	×	✓	IEEE 802.11p
SDN – Based Strategies										
Noorani et.al. (2018)	NS2 / SUMO	U/ M	×	✓	✓	×	200 m	×	✓	IEEE 802.11p
Qi et.al. (2018)	NA	U/ M	✓	✓	×	×	350 m	×	✓	IEEE 802.11p
Hybrid Strategies										
Baldessari et.al. (2019)	NS2	HW / H	✓	✓	✓	×	500m	✓	✓	IEEE 802.11 MAC
Aygun et.al. (2016)	NS2/GEM v2 V2V/ SUMO	U	✓	✓	✓	×	500m	×	✓	DCC / IEEE 802.11p
Tielert et.al. (2013)	NS3	U	✓	✓	✓	×	600m	×	✓	NA

Note: D- Dense, U- Urban, HW- Highway, ML- Multilane, L- Low speed, M- Medium Speed, H- High Speed and NA- Not Available.

Table 2: Comparison of Simulation software

	Written in	Language Support	Multi Language Support	802.11p Support	Scalability	Network Delay	Availability	Learning Curve	Virtualization Support	Parallel Support
NS3 [104]	Python / C^{++}	C^{++}	✓	✓	Limited	Low	✓	Hard	✓	✓
NS2 [103]	C^{++}	C^{++} / OTCL	✓	✓	Low	High	✓	Easy	×	×
OMNET ++ [105]	C^{++}	C^{++}	×	✓	Medium	Medium	✓	Easy	×	✓
Mininet [106]	Python	Python	×	✓	Medium	NA	✓	Hard	✓	✓
JIST / SWANS [106]	Java	Java	×	×	High	Low	✓	Hard	✓	✓
OPNET [107]	C^{++}	C^{++} / OTCL	✓	✓	Large	Low	×	Easy	✓	✓

Table 3: Evaluation measures used.

Author (Year)	Delay	Throughput	Loss	Contention	Energy	Clustering Overhead	Coverage
Abdul Hameed et.al (2022)	✓	✓	✓	×	✓	×	✓
Aboud et.al. (2021)	✓	✓	✓	✓	×	×	✓
Maan Chaba et.al. (2021)	✓	✓	×	×	×	×	✓
Bhavani et.al. (2020)	✓	✓	✓	✓	✓	×	✓
Adbed et.al. (2020)	✓	✓	×	×	×	×	✓
Arif et.al. (2020)	✓	✓	✓	×	×	✓	✓
Benalia et.al. (2020)	✓	✓	×	✓	✓	×	✓
Jaballahet.al. (2019)	✓	✓	✓	✓	✓	×	✓
Akinlade et.al. (2019)	✓	✓	✓	✓	×	×	×
M.B. Taha et.al. (2019)	✓	×	×	×	✓	×	×
Baldessari et.al. (2019)	✓	✓	×	✓	×	×	×
Joseph et.al. (2018)	✓	✓	×	✓	×	×	×
Sospeter et.al. (2018)	✓	✓	×	✓	×	×	×
Feuken et.al (2018)	✓	✓	×	×	×	×	×
Ren et.al (2018)	✓	✓	×	×	×	×	×
Liuet.al. (2018)	✓	✓	×	×	×	×	×
W.Qiet.al. (2018)	✓	×	×	×	×	×	✓
N.Noorani et.al. (2018)	✓	✓	×	×	×	×	✓
Boquet et.al. (2017)	✓	✓	×	✓	×	×	×
Shah et.al.(2016)	✓	✓	×	×	×	×	×
Y.L.U et.al. (2016)	✓	✓	×	×	×	×	×
Taherhhani et.al. (2016)	✓	✓	✓	×	×	×	×
Aygun et.al. (2016)	✓	✓	×	✓	×	×	✓
Ucar et.al. (2016)	✓	✓	×	×	×	✓	×
Tielert et.al. (2013)	✓	✓	×	×	×	×	×
Nellore et.al. (2013)	✓	✓	×	×	✓	×	✓
Darus et.al. (2013)	✓	✓	×	✓	×	×	✓
Stanica et.al. (2012)	✓	✓	×	×	×	×	×
Stanica et.al. (2011)	✓	✓	✓	✓	×	×	×

Table 4: Structure of Congestion Control Algorithms [21]-[23]

Algorithms	Features			
	Metric Applied	Type of Messages	Rate Power Control	Simulator Used
Adaptive Transmission control	Cut off error (app 95%)	Beacon	Hybrid	OPNET
CPRC	Channel Busy Time (CBT)	Beacon	Hybrid	NS-2 Version 2.31
EMBARC	Tracking Error	Beacon	Rate	NS - 2
LIMERIC	CBE	Beacon	Rate	NS - 2
MD - DCC	CBT	Beacon	Hybrid	Sumo & NS- 2
NOPC	CBR	Beacon	Power	Omenet ++ & Sumo
OSC	Beacon Error Rate	Beacon	Power	Veins & Omenet ++
PULSAR	CBR	Beacon	Rate	NS- 2
RTPC	CBR & Rate of Packet Collision	Beacon	Power	NS - 3
SBAPC	CBR & Beacon Error Rate	Beacon	Power	Veins & Omenet ++
SPAV	Beacon Load	Beacon	Power	NS - 2
TPRC	CBR	Beacon	Hybrid	NS - 3

V. PERFORMANCE PARAMETERS AND SIMULATION METRICS

Discusses various performance parameters and simulation metrics used to evaluate congestion control algorithms in vehicle-to-vehicle communication. Some of the key parameters and metrics highlighted in the paper include: Performance Parameters: 1. Channel Busy Ratio (CBR) 2. Packet Loss Rate (PLR) 3. Inter-Packet Delay (IPD) 4. Additional Metrics such as Elapsed Time Simulation Metrics: 1. Traffic Situations: Deterministic and randomly located vehicles 2. Channel Fading Model: Models for simulating practical channel fading, such as Rayleigh model, deterministic Two-Ray Ground model, and Nakagami model These parameters and metrics are essential for evaluating the performance of congestion control algorithms and simulating the impact of various traffic scenarios and channel conditions on vehicle-to-vehicle communication systems.

A. Performance Parameters

We discuss several performance parameters used for evaluating congestion control algorithms in vehicle-to-vehicle communication. Some of the key performance parameters highlighted in the paper include:

1. Channel Busy Ratio (CBR): The ratio of time the channel is busy to the total measurement time, used to assess the information advantage of congestion control algorithms.
2. Packet Loss Rate (PLR): Measures the proportion of lost packets due to accidents or expiration of control channel intervals.
3. Inter-Packet Delay (IPD): The average delay between consecutive packets received from neighboring vehicles, providing insight into message age and communication with nearby vehicles.
4. Additional Metrics: Other parameters such as Elapsed Time, which measures the update lag between consecutive Basic Safety Messages (BSMs) or Cooperative Awareness Messages (CAMs) from the same transmitter, contributing to the evaluation of vehicle awareness through communication.

These performance parameters are crucial for assessing the effectiveness of congestion control algorithms and understanding the behavior of vehicle-to-vehicle communication systems in various scenarios.

B. simulation metrics

Discusses about simulation metrics used to evaluate congestion control algorithms in vehicle-to-vehicle communication. Some of the simulation metrics highlighted in the paper include:

1. Traffic Situations: Deterministic and randomly located vehicles, which influence the occurrence of

congestion in the channel.
2. Channel Fading Model: Models for simulating practical channel fading, such as Rayleigh model, deterministic Two-Ray Ground model, and Nakagami model, which impact the reliability and quality of communication in vehicular networks.
These simulation metrics are essential for simulating and evaluating the performance of congestion control algorithms in various traffic scenarios and channel conditions in vehicle-to-vehicle communication systems.

C. Simulation Tools

There are several simulation tools available to researchers to understand the performance and display the networks as well as their protocols in VANETs. Some of the popular and commonly used simulation tools are:
1. Vehicular mobility generators: These are required to improve the authenticity level in vehicular ad-hoc network simulations. Examples of vehicular mobility generators include Vanet Mobi Sim and SUMO.
2. Network simulators: These simulators permit researchers to examine how the system would work under diverse conditions. Examples of network simulators include GloMoSim and ns-3.
3. VANET simulators: These simulators present both network simulation as well as traffic movement simulation. Examples of VANET simulators include MobiREAL, NCTUns, and TranS.

VI. FURTHER DESIGN TO CONTROLLING CONGESTION FOR V2V

Two additional design considerations are implemented to manage congestion in vehicle-to-vehicle communication.

A. Fairness:

In vehicular networks, fairness is crucial to ensure equitable interaction among nearby nodes [34]. It aims to allocate resources equally among vehicles, avoiding resource disparity. However, there exists a trade-off between fairness and efficiency: prioritizing fairness often leads to less effective resource utilization. While many congestion control strategies prioritize fairness, there is no universally accepted standard for measuring it, making it challenging to evaluate and compare different fairness strategies.

B. Control of Awareness

So far, the strategies discussed have focused on reducing channel capacity to manage congestion. However, the ultimate goal of congestion control is to improve overall awareness among vehicles, thus ensuring their safety and security.

VII. CONCLUSION

Improving vehicular safety involves enhancing vehicle-to-vehicle communication to increase awareness on roadways. However, as vehicle density rises, the available 10 MHz channel may not reliably transmit security messages without latency or failure, especially given the dynamic nature of vehicular channels. This paper addresses congestion in vehicle-to-vehicle communication, reviewing existing congestion control strategies from literature. It explores the causes of congestion and examines commonly used parameters and metrics for assessing channel performance. Additionally, it organizes and analyzes major congestion control strategies based on various key measures such as applied metrics, message types, rate/power control, and simulation tools. While several effective approaches have been proposed, congestion control remains a challenging research problem in VANETs, with many open analysis questions. Our study evaluates diverse parameters and strategies for secure V2V communication. While a centralized solution for congestion may not be feasible, standardizing the parameters used in strategies is crucial for fair and consistent evaluation. Thus, there's a need for standardized technology and methodology to ensure unbiased assessment of different congestion control strategies.

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