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Mitigating Intermittent Connectivity Problems in Vehicle-to-Vehicle Communication (V2VC): A Sparse Network Computational Model (SNCM)

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Abstract

INTRODUCTION: Wireless communication has made remarkable progress, by the rapid development of wireless technology in Artificial Intelligence (AI). Intelligent Transportation Systems (ITS), and Vehicular Ad Hoc Networks (VANETs) have received significant attention to ensure safety. However, V2V communication in VANETs faces uncontrollable challenges due to frequent intermittent connectivity issues in infrastructure-less networks. Addressing these problems in both safety and non-safety applications is a complex task.
OBJECTIVES: To mitigate the intermittent connectivity problems, a novel Sparse Network Computational Model (SNCM) was proposed.
METHODS: Extensive simulations using MATLAB to analyze the impact of spatial-temporal variations under different traffic flow densities. We varied the sensitivity factor (λ) at different time intervals while maintaining a constant traffic density.
RESULTS: The findings indicate that there is no need to increase λ beyond certain thresholds for each level of service. The simulation results provide valuable guidelines for designing sparse networks, effectively mitigating frequent intermittent disconnections. Simulation experiments revealed an optimal threshold for the sensitivity factor λ for each level of service. Increasing λ beyond certain thresholds did not yield significant improvements in mitigating disconnections in V2V communication.
CONCLUSION: The results provide valuable insights and guidelines for designing sparse networks to enhance connectivity and address intermittent disconnection issues. This paper presents a groundbreaking endeavor, and therefore, direct comparisons with existing protocols to evaluate its overall performance are beyond the scope of this paper. Instead, the SNCM protocol is intended to set a standard for future researchers to benchmark their research contributions against.

Keywords: Intelligent Transportation Systems, V2V Communications, Road Accident Prevention, Vehicular Ad Hoc Networks, Frequent Intermittent Connectivity, Safety Message Dissemination.

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1. Introduction

Vehicle communication is a highly researched topic that has gained international attention [1]. Vehicle-to-vehicle (V2V) communication in Vehicular Ad Hoc Networks (VANETs) has the potential to introduce innovative applications in vehicular networks, particularly in enhancing safety [1] [2]. However, certain technical

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difficulties and security concerns are associated with these applications and the VANET protocol. Consequently, the research focus on VANETs and Inter-Vehicle Communication (IVC) systems has increased, drawing significant attention from both the research community and the automotive industry. Annually, over six million crashes occur worldwide, resulting in millions of deaths and fatal injuries. Intelligent Transportation Systems (ITS) based on V2V and Vehicle-2-Infrastructure (V2I) communication in VANETs can contribute to improving road safety [3] [4] [5]. By using wireless communication technology, these systems can provide drivers with warning signs in hazardous situations like accident scenes [4] [6]. To enhance V2V communication protocols, it is very necessary to examine new system concepts that are capable of addressing the dynamic features of VANETs. Hence, the need to propose a novel Sparse Network Computational Model (SNCM) to overcome the inherent challenges of sparse networks. This paper represents a pioneering effort, and as such, there is no need for direct comparisons with existing protocols to assess its overall performance. Instead, the SNCM protocol is intended to set a standard for future researchers to benchmark their research contributions against. This wireless V2V communication standard ensures the dissemination of safety messages under varying network conditions [5] [6]. This approach provides drivers in motion an unlimited supply of alert messages to help reduce fatalities on the roads.

The article discusses the challenges and methodologies associated with traffic alert message exchanges in sparse network conditions. The SNCM emphasizes the need for decentralized controllers to implement novel applications in Vehicular Ad Hoc Networks (VANETs) and highlights the importance of determining threshold parameter trajectories for effective communication [7]. The traffic flow characteristics involve volume, density, and speed which are interconnected, and used to compute unknown flow parameters [8] [9] . While there is no specific theory to explain traffic flow complexities, the proposed Sparse Network Computational Model (SNCM) traffic flow models provide insights into the relationships between flow parameters and vehicle interactions on the road [8] [9].

The traffic flow theory is based on two main relations: conservation law involving vehicles and the assumed relationship between traffic flow and traffic density. The SNCM presents an equation expressing the traffic flow movement and density changes within a specific location on the road. The density increases when the incoming traffic flow exceeds the outgoing flow. The speed is considered a function of density, and drivers adjust their speed based on traffic density to maintain safe headway. The SNCM introduces an equation that describes the traffic flow density as a function of traffic density alone [10]. The flow condition necessitates obtaining one-dimensional measurements, where the flow conditions, denoted as “q”, are assessed at two distinct points, namely, x =a and x =b, with an arbitrary separation distance between them. The sole variable subject to arbitrary alterations within the vehicular traffic flow pertains to the number of cars passing through the intersection at x =a and x =b. This computational expression is detailed as per preference [9] [10].

$$\frac{\partial \kappa}{\partial t} + \frac{\partial \mathrm{q}}{\partial \chi} = 0 \tag{1}$$

Equation (1) asserts that at any given location on the road, the flow of traffic to the left should be less than the flow to the right, resulting in a reduction in density at that specific location within a defined time frame, denoted as 't.' As a consequence, traffic density increases when incoming traffic flow surpasses outgoing traffic flow. This assumption necessitates further computational analysis to tackle challenges in situations of limited network traffic flow [9] [10]. To meet the prerequisites of this assumption, it is crucial to stipulate that speed is a function of density, represented as v =u(k). While this is a reasonable assumption, it may be more applicable in scenarios of dense traffic. Consequently, the assumption put forward is that drivers can adjust their speed based on traffic density; as traffic density rises, speed must decrease to ensure safe following distances. Furthermore, 'q' should be defined based solely on the assumption as a function of traffic density, i.e., q = ku(k) [10]. The specific form of 'u(k)' can encompass any function. Subsequently, Equation (1) can be expressed as follows:

$$\frac{\partial k}{\partial t} + \frac{\partial \mathrm{q}}{\partial \chi} = 0 \tag{2}$$

When ∂q/∂k = u(k) + ku_1(k) = 0, the solution to equation (2) reveals that the density 'k' remains constant along a set of curves known as characteristics or waves. These waves represent variations in traffic flow and density along the roadway. The velocity of the wave is denoted as 'c,' (see Figure 3), which signifies a constant and represents the slope of the flow concerning density, evaluated at a fixed density. It has been demonstrated in references [9] [10] that the value of 'c' should be negative only if the road is unquestionably operating beyond critical traffic density limits.

The shockwave signifies a mathematical discontinuity where alterations occur in the relationships between 'q' and 'k' or 'u' and 'k' (see Figure 1). This shockwave serves as a computational model, separating the boundary between congested areas and free-flow traffic situations. It manifests when vehicular traffic decelerates, indicating congested traffic conditions, or accelerates spontaneously, indicating free-flow traffic situations. The direction of this shockwave, depending on the traffic conditions on the road, may propagate either forward or backward, contingent upon computational parameters. The characteristics of the shockwave’s speed, denoted as 'μw,' are detailed in references [9] [10]:

$$\mu_w = \frac{q_d - q_u}{k_d - k_u} \tag{3}$$

In the context of downstream and upstream traffic parameters, denoted as k_d, q_d, and k_u , q_u respectively, the diagram presented below illustrates the connection between conditions of free flow and congestion and their relationship to shockwave speed. The slope of the dashed line serves as an indicator distinguishing between these two traffic states, as depicted in Figure 1, Figure 2 and Figure 3.

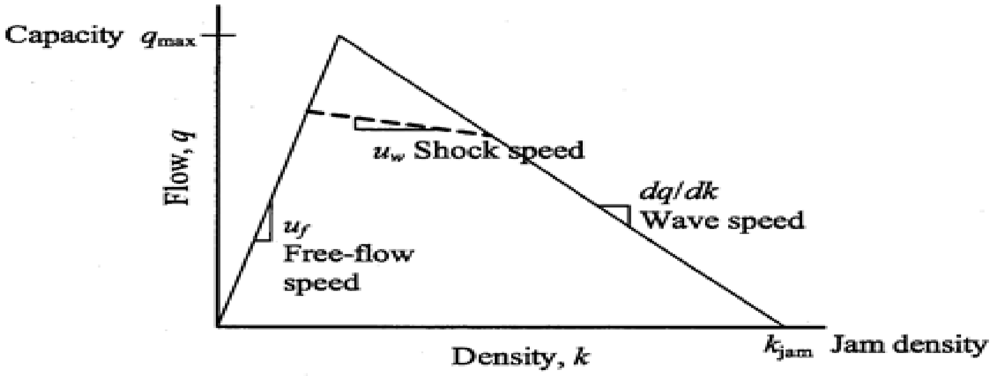

Figure 1. Fundamental Traffic Flow Conditions on the Roadway [11]

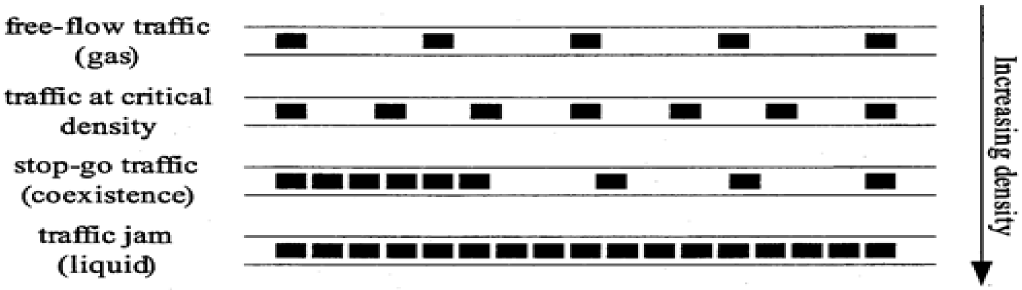

Figure 2. Traffic Flow Phase Transition [11]

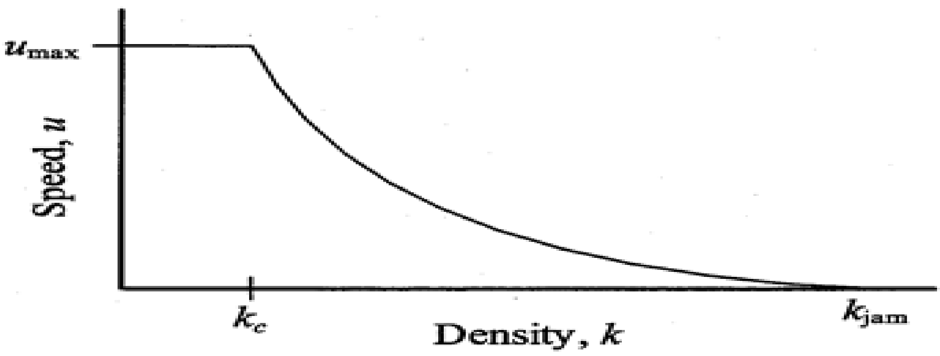

Figure 3. Speed-Density Relationship in Traffic Flow Scenarios [11]

Recent times have seen a significant focus on addressing traffic flow challenges using the Cellular Automata (CA) model [12]. This dynamic model comprises space, time, and discrete states. The discrete space is represented by a grid of cells, with each cell having a finite number of states that are updated based on predetermined local rules [13]. This study adopts a CA approach that aligns with the macroscopic traffic flow model, where the sensitivity factor (λ) increases over time. This time-dependent change allows for parallel updates of all grid paths within discrete time intervals. The CA approach considers various factors such as complex turns, lane changing, and intersection configurations, with each driver having a specific destination [12] [13].

While several approaches have been explored to address traffic flow issues, some challenges persist and continue to be the subject of intense research to enhance Intelligent Transportation Systems (ITS). This study focuses on analytically investigating the proposed Sparse Network Computational Model (SNCM) traffic flow model as a groundbreaking endeavor, and therefore, direct comparisons with existing protocols to evaluate its overall performance are out of scope. Instead, the SNCM protocol is designed to establish a benchmark against which future researchers can measure their research contributions.

The subsequent section will provide a detailed explanation of the materials and methods employed to study sparse network traffic flow conditions.

2. Related work

In this comprehensive literature review, we will discuss the findings and contributions of the following research papers related to wireless communication and connectivity in vehicular networks. Connectivity in mobile networks can be highly variable due to factors like mobility and network conditions. In environments where intermittent connectivity is unavoidable, it becomes crucial to estimate data transfer capacity accurately. This systematic literature review aims to provide an overview of research articles addressing the estimation of data transfer capacity for intermittent connectivity in mobile networks. We analyze and synthesize findings from these selected papers to gain insights into the models, methods, and advancements in these fields. Vehicular Ad Hoc Networks (VANETs) have gained significant attention due to their potential to enhance road safety, traffic management, and infotainment services. However, VANETs face unique challenges, primarily due to the intermittent connectivity arising from the mobility of vehicles. This literature review aims to explore various models and strategies proposed to address intermittent connectivity issues in VANETs. We examine key research papers and their contributions to understanding and improving connectivity in the context of intermittent connectivity problems in V2V Communications are discussed as follows.

The author [14], proposes a modular access gateway to address intermittent connectivity issues in vehicular communications. They focus on the Drive-thru Internet architecture, where vehicles connect to IEEE 802.11 WLAN access points at the roadside. The gateway efficiently manages short periods of connectivity, reduces disconnection times, and handles varying transmission characteristics. This research emphasizes the importance of seamless connectivity for mobile users and provides a solution to enhance user experience in vehicular networks. The investigator [15], analyzes the challenges of vehicle-to-vehicle (V2V) communication in VANETs, emphasizing the inherent instability due to high vehicle mobility. They employ mathematical models to investigate connectivity factors such as headway distance, acceleration, connection setup time, relative speed, transmission range, and message size. The study offers valuable insights into the factors affecting V2V wireless connectivity and provides a foundation for improving communication reliability in VANETs. Another author did a similar work [16], to address the challenge of providing internet access in sparse WiFi deployment along roads. They develop an analytical model to estimate session completion, considering parameters like vehicle density, bandwidth, transmission range, and data volume. This research aids in optimizing sparse WiFi deployment, ensuring that vehicles can complete data transmission within access points' coverage areas. The findings contribute to improving internet access in vehicular environments. The Author [17], focuses on the potential of WiFi-based vehicle-to-vehicle networks for disseminating traffic information. It addresses the issue of traffic congestion and explores the idea of using peer-to-peer architecture for traffic information dissemination. The authors examine the characteristics of such networks and their effectiveness in supporting traffic information dissemination. However, they noted that the large geographical extent of transportation networks can hinder network connectivity. This paper highlights the importance of exploring alternative solutions to improve traffic information dissemination. In [18], the author analyzes connectivity and capacity in vehicle-to-vehicle (V2V) networks using geometric probability. Their model considers factors like vehicle density, transmission range, and random vehicle arrivals. They find that network capacity increases linearly with the number of vehicles. This research offers insights into the performance of V2V networks, highlighting the potential for scalability and improved capacity through geometric modeling. This author [19], focuses on vehicular ad hoc networks (VANETs) in signalized city roads. They consider factors like traffic signals and vehicle speed, analyzing inter-vehicle connectivity while waiting at intersections. The study reveals that vehicles with lower speeds perform better in terms of packet forwarding. This research informs VANET design and optimization in urban environments, where traffic signals play a crucial role. In [17] [20], the authors introduce a generalized framework for connectivity analysis in vehicle-to-vehicle (V2V) communications. They consider headway distance and communication channel characteristics in highway vehicular networks. The framework is derived under the Nakagami-m fading model and is valuable for analyzing and simulating V2V communication systems. This research contributes to understanding the connectivity dynamics in V2V networks and assists in system design.

The Author [21], addresses challenges in mobile ad hoc networks, particularly in providing ubiquitous connectivity for modern applications. They highlight the need for improved performance metrics in terms of bandwidth, packet loss, delay, and reliability. Although the paper lacks specific findings, it underscores the importance of meeting the requirements of emerging applications in mobile environments. In [22], the author introduces a metric called available connectivity to address the challenges of connectivity in VANETs. Their approach combines direct and indirect connectivity, considering factors such as vehicle density, bandwidth, transmission range, and data volume. This research provides a statistical framework for connectivity analysis in vehicular environments, aiding in protocol design and performance improvements for different applications. The Authors [20, 23], investigate the challenge of network connectivity in Vehicular Ad hoc Networks (VANETs) during high-speed and sparse traffic conditions. They analyze network connectivity behavior concerning transmission range, particularly focusing on communicated vehicles equipped with wireless devices. The paper explores an equivalent traffic model based on queuing theory to study network connectivity in VANETs and investigates how roadside units (RSUs) impact network connectivity and performance. The paper offers insights into optimizing transmission range for achieving a required degree of network connectivity in vehicular environments. In [24], the author focuses on intermittent-connectivity networks, where there is rarely a connected path between a source and a destination. Redundancy, where nodes replicate data when in proximity, helps mitigate connectivity issues but increases energy and storage usage. The paper quantifies the resource-delay trade-off and throughput capacity for intermittent-connectivity networks with quality-of-service constraints and offers insights into the design and performance trade-offs for routing protocols in such networks.

The Author [25], proposes a resource allocation framework for vehicle-to-vehicle (V2V) communication that minimizes transmission power while meeting reliability and queuing latency constraints. The scheme incorporates physical proximity and traffic demands of vehicles to optimize resource allocation. A virtual clustering mechanism is introduced to group vehicles into zones based on mutual interference. The proposed scheme improves latency and reliability for V2V communication, with significant reductions in queuing latency and improvements in reliability compared to existing approaches. In [26], the author analyzes the minimum transmit power required for network connectivity in vehicular ad hoc networks with random communication ranges. The paper adopts a physical layer perspective to address network connectivity, accounting for channel fading and random communication range. The model provides insights into the relationship between transmit power and network connectivity in the presence of channel fading and variable communication links. The paper validates the theoretical analysis, providing practical insights into ensuring network connectivity in vehicular environments. The author [27], introduces a system that takes advantage of intermittent network connections while leveraging parallel networks. It emphasizes the challenges posed by intermittent connectivity in mobile environments and presents a system that optimizes data transfer by exploiting multiple heterogeneous networks in parallel. The study provides insights into improving network efficiency and data delivery rates by bundling data for intermittent connections. It highlights the significance of considering parallel networks in intermittently connected mobile environments.

In [28], the paper analyzes network connectivity in vehicular networks with slight traffic interference, such as small-scale traffic accidents. It develops an analytical model for scenarios where traffic interference temporarily slows down vehicles. The paper examines the impact of various parameters on connectivity probability, providing deep insights into how factors like vehicle arrival rate, communication range, and road length affect network connectivity. The Author [29], addresses the challenges of maintaining network connectivity in sparse vehicular networks, where classical ad-hoc network algorithms become impractical. It proposes a delay-tolerant approach using the store-carry-forward method to ensure data delivery. The paper focuses on determining data lifetime based on vehicle density and throughput requirements, contributing to the fulfillment of Quality of Service (QoS) requirements in vehicular ad hoc networks. The author [30], investigates the impact of various parameters on communication delays in sparse infrastructure-less vehicular networks. It specifically examines factors like vehicle deceleration and transmission power. The study shows that adjusting these parameters can substantially improve network connectivity in scenarios where Road Side Units (RSUs) are not widely deployed, offering cost-effective solutions to enhance communication in such environments. In [31], the author focuses on intermittent connectivity in vehicular ad hoc networks (VANETs) in sparse scenarios. It evaluates average delay and maximum stable throughput for packet forwarding along a typical two-way street in VANETs. The research uses queueing network models to analyze network performance, considering vehicle velocities and opportunistic relaying. The paper provides insights into optimizing VANETs for reliable communication in sparse situations.

The author [32], addresses the tradeoff between network coverage area and connectivity in vehicular networks. It proposes a relay-based coverage area model that uses connected vehicles as relays to improve connectivity without extending the transmission range or deploying additional RSUs. The research emphasizes the efficiency and cost-effectiveness of this approach, offering a solution to enhance connectivity in urban areas. In [33], explores vehicle-to-vehicle connectivity in scenarios involving parallel roadways with varying headway distributions. Unfortunately, the provided information does not offer specific findings or contributions from the paper. The gap identified in this research paper is the direction of the proposed Sparse Network Computational Model (SNCM) Approach which is a novel alternative methodology to address the weaknesses in an unprecedented manner and does not warrant any comparison with the existing paper due to its approach.

In [16], the author addresses the challenge of providing internet access in sparse WiFi deployment along roads. They develop an analytical model to estimate session completion, considering parameters like vehicle density, bandwidth, transmission range, and data volume. This research aids in optimizing sparse WiFi deployment, ensuring that vehicles can complete data transmission within access points' coverage areas. The findings contribute to improving internet access in vehicular environments. The author [34], emphasizes the role of vehicle-to-infrastructure (V2I) communications in mitigating network fragmentation within VANETs. It provides insights into how infrastructure elements can act as anchor points to improve connectivity, The author [35], explores the concept of using mobile base stations to enhance connectivity in VANETs. It offers analytical insights into how varying the number of mobile base stations can influence connectivity levels. In [36] , the author introduces the concept of the critical transmitting range, applicable to both dense and sparse ad hoc networks. It sheds light on the importance of transmission range in achieving and maintaining connectivity. The author [37], proposes a connectivity model designed to ensure effective and reliable connectivity in the challenging urban road environment. It offers valuable concepts for urban VANET deployment.

Intermittent connectivity remains a significant challenge in VANETs, given the mobility of vehicles. The reviewed literature provides valuable insights into various approaches and models aimed at improving connectivity. The alternative methodology is leveraging the infrastructure, mobile base stations, transmission range optimization, and RSU deployments in order to propose the novel Sparse Network Computational Model (SNCM) Approach. As far as I am aware, the SNCM is the pioneering methodology applied in this context to tackle the connectivity challenges observed in V2V Communication. These research efforts jointly contribute significantly to the advancement of the reliability and efficiency of VANETs, which are of paramount importance for the advancement of future intelligent transportation systems.

3. Methodology

In this study, we focus on addressing the intermittent network problems in vehicular traffic flow within sparse networks using the Sparse Network Computational Model (SNCM). Previous research in [33] [30] [15] has explored various techniques to investigate these issues, but the problem persists, necessitating further rigorous research to improve Intelligent Transportation Systems (ITS). To address the traffic flow problems, we employ traffic simulations, which are commonly used to mitigate such issues. However, there is no single theory currently used to effectively tackle the frequent intermittent disconnections in sparse network traffic flow. This study aims to investigate and mitigate these challenges using the proposed SNCM approach.

Macroscopic flow characteristics are determined based on the rate of flow (volume) and are defined as the movement of vehicles passing through a point in each time interval, typically expressed as an hourly flow rate. In low-traffic density situations, vehicle interaction is minimal due to free-flow conditions, where vehicles move independently without any restrictions on the roads. On the other hand, under dense network conditions, traffic experiences a phenomenon known as stop-and-go movement (see Figure 2). To model the arrival process of vehicles under high-density highway conditions, a computational model [38] [39] [40] is employed, utilizing the Poisson process with an arrival rate of λt.

3.1. Computational model based on vehicle speed

In a simulation setup, it is crucial to use vehicle speed as the initial input. There are different approaches for assigning speeds to vehicles. Some studies [41] [7] [42] [43], propose using a speed distribution that corresponds to real measurements on German highways. Others [43] [41] suggest assigning speeds using a normal distribution, which we adopt for our proposed SNCM to ensure the novelty of its kind. Another option is to use the "85th percentile speed," which sets a speed limit for the highways [44] [45] [46]. This speed represents the speed at which 85% of drivers are moving at or below, and it is typically close to the average speed limit. The remaining 15% of drivers consist of both slower and higher-speed drivers.

Previous studies [46] [44] also support the use of speed sampling based on the Normal distribution, with the standard deviation indicating the relationship between slow, average, and high-speed thresholds. In our simulations, we varied the speed and time headway to achieve the best results [42], since these parameters change in real traffic scenarios. The choice of average speed may vary depending on the environment under consideration. For highway simulations, the average speed is typically set to 100-130 km/hr [42] [43], while simulations in city street grids use an average speed of 40-80 km/hr either randomly or based on street types [43].

3.2. Vehicular Mobility under sparse network conditions

The challenges posed by sparse network conditions in inter-vehicle communication have motivated researchers to investigate the complexities of maintaining connectivity. Analyzing and simulating traffic parameters such as flow, speed, and density under low-density environments offers flexibility for analytical analysis. However, it is essential to recognize that frequent intermittent disconnections in sparse networks make assumptions about independent parameters valid only under free-flow traffic conditions in SNCM, and this novelty makes a substantial contribution which is a shift from the previous research papers. As a result, the outcomes of this study may not directly apply to dense traffic flow conditions. Nevertheless, this study places significant focus on sparse traffic conditions due to their crucial applications in VANETs, considering that:

- Vehicle density can influence message dissemination [43] [40].
- Vehicle traffic flow undergoes rapid changes during free-flow conditions.
- Traffic flow can swiftly transition between free-flow and congested traffic due to traffic controls and road constraints, such as accidents.

3.3. The sparse network computational model (SNCM)simulation procedures

The following tables in this section outline the simulation parameters. These parameters are detailed in Table 1 and Table 2, respectively.

Density (veh/mile/lane)	Level of Services	Flow Conditions	
0-12	A	Free-flow operations	
12-20	B	Reasonable free-flow operations	Uncongested Flow conditions
20-30	C	Stable operations	
30-42	D	Borders on unstable Operations	
42-67	E	Extremely unstable flow operations	Near-capacity flow conditions
67-100	F	Force or breakdown operations	
>100	F	Incident situation operations	Congested flow conditions

Table 1. Traffic Flow Density Conditions at Different Levels

List of Symbols (Parameters)					
Variable	Description		Variable	Description
λ	Sensitivity factor representing two-vehicle interaction in the car-following model.		q	Traffic flow, representing the number of vehicles passing a point on the road per unit of time.
d	Distance between two consecutive vehicles		u_T	Time-mean speed, which is the average speed of vehicles over a specified time period.
n	Number of nodes in the network or system.		h	Headway, referring to the time gap or distance between two consecutive vehicles.
nl	The total number of traffic lanes on the road.		η	Traffic quality of service factor, describing the level of service quality experienced by drivers.
N	Total count of vehicles present on a specific highway segment.		f_s	Fraction of vehicles that are stationary or stopped at a given moment.
L	Length of the highway segment under consideration.		T_s	Total time a vehicle spends in a stopped or stationary state.
T	The duration for which spot measurements are taken for observations.		T_t	The average time taken by a vehicle to complete its journey.
t	A variable representing time in various traffic-related calculations.		x	The number of vehicles entering a highway segment or migrating to it.
k	Traffic density, which refers to the number of vehicles per unit length of road.		D	Traffic density measured in vehicles per mile per lane (veh/mile/lane).
υ	Space mean speed, indicating the average speed of vehicles on the road.		V	Traffic volume, measured in vehicles per hour (veh/hr).
ui	The speed of a specific vehicle within the traffic flow.		v	Space mean speed measured in miles per hour (mile/hr).

Table 2. List of Symbols for Simulation Parameters

Step 1: The initial phase involves identifying and clearly articulating the objectives and problems to be addressed analytically. This step requires thorough consideration of several questions, including: What inputs are necessary to achieve the desired outputs? What are the study's boundaries, limitations, and time constraints? Should selected parameters be modeled as a whole or individually? Once these crucial questions are answered, we proceed to the subsequent steps.

Step 2: In this step, we address the questions raised in Step 1 explicitly and affirm that simulation is the most appropriate methodology to analytically tackle the research problem. We also assess the feasibility of the simulation, considering the availability of resources and the solvability of the problem. The study is confident in its ability to solve the problem using the proposed Spare Network Computational Model (SNCM). MATLAB is chosen as the simulation tool due to its simplicity, user-friendly environment, and wide adoption by researchers for complex simulations.

Step 3: Formulation of the problem begins by creating a flowchart with assigned inputs, emphasizing their impact on the desired output. Analytical simulations are conducted to understand the proposed SNCM better. The input variables include design elements, traffic demand patterns, operational rules, and control conditions.

Step 4: Traffic models are formulated through an intermediate flowchart, aiming to deepen the understanding of the model's basic logic. This stage involves an iterative process until the desired results are achieved.

Step 5: The stage involves estimating the required parameters and their associated variables in the model. Some parameters are deterministic, remaining constant in all situations or varying over a continuous range as needed. Other parameters are probabilistic (stochastic), allowing variations to meet specific objectives.

Step 6: Evaluations of the current state of the model are performed at this stage. Outcomes are assessed, and decisions are made to add, change, or delete unrealistic variables for further testing. The iterative nature of this stage continues until the desired solution to the problem is accomplished, leading to the formulation of computer code. MATLAB is then utilized for various simulations to validate the computer codes and achieve the desired solution.

3.4. The proposed sparse network computational model (SNCM)

Vehicles experiencing low traffic density exhibit minimal interaction on the road, resulting in free traffic flow. This realistic independent movement occurs without significant restrictions on the roads. In contrast, dense network conditions lead to stop-and-go movement (see Figure 2). The arrival process of vehicles with highway density can be modeled using a Poisson process with an arrival rate denoted as λt. Our focus is on a free-flow traffic situation known as a sparse network condition.

$$p(\chi = n) = \frac{(\chi\lambda t)^n}{n!} e^{-\lambda t\chi} \tag{4}$$

The symbol χ signifies the initial movement of a vehicle onto a highway within a specific time interval denoted as 'χ.'

$$f_T(t) = \begin{Bmatrix} -\lambda t e^{-\lambda t(t-\tau)}, & t < 0 \\ 0, & t < \tau \end{Bmatrix} \tag{5}$$

$$D = \frac{V}{\upsilon} \tag{6}$$

In this context, the time headway distribution, as described [16, 40], follows an exponential distribution characterized by Parameter $\frac{1}{\lambda t}$. The probability density function (PDF) $f_T(t) = \lambda t e^{-\lambda t\chi}$, *where* $t \geq 0$. PDF allows for the possibility of a time headway approaching zero, indicating the highest relative likelihood of events occurring that are not practically equal to zero under the specified conditions. To achieve reasonable results, it is important to increment the minimum allowable time headway. The time headway distribution follows an exponential distribution with parameter λt, allowing for a non-zero likelihood of occurrences under the set conditions. The relationship between traffic volume (V), density (D), and space mean speed (υ) is given in equation (6). Different traffic flow conditions corresponding to each density level are classified in table 2 [40].

In equation (6), 'V' represents traffic volume, measured in vehicles per hour (veh/hr), 'D' denotes density, measured in vehicles per mile per lane (veh/mile/lane), and 'υ' stands for the space mean speed, measured in miles per hour (mph). The traffic flow conditions associated with different density levels are categorized in Table 1.

Service Levels	Traffic flow conditions	v/c limit	Service volume (veh/hr)	Speed (mph)	Density (veh/mile/lane)
A	Free	0.350	700.00	60.00	12.00
B	Stable	0.540	1100.00	57.00	20.00
C	Stable	0.770	1550.00	54.00	30.00
D	High Density	0.930	1850.00	46.00	40.00
E	Near Capacity	1.000	2000.00	30.00	67.00
F	Breakdown	Unstable	Unstable	<30.00	<67.00

Table 3. Speed-Density Relationship in Traffic Flow Scenarios [1]

3.4.1. Simulation of system parameters in sparse network conditions

This emphasizes the dynamics of traffic flow in sparse vehicular ad-hoc networks (VANETs). The study examines how the network behaves across a range of traffic densities, specifically from 10 vehicles per mile per lane (veh/mile/lane) to 30 vehicles per mile per lane, along a 60-mile road section with four lanes. The aim is to analyze network behavior analytically and understand the interactions between vehicles in terms of traffic flow density.

To achieve this objective, we vary the value of λ from 1 to 10, considering traffic densities of 0, 5, 10, 15, 20, 25, and 30 veh/mile/lane. This investigation seeks to determine the network transmission range under different λ values, where λ represents the sensitivity factor in car-following models, crucial for establishing network connectivity in a sparse network with four lanes, as illustrated in Table 3.

The trajectory of network connectivity is observed within specific ranges: A) $1 \leq \lambda \leq 3$, B) $1 \leq \lambda \leq 4$, and C) $1 \leq \lambda \leq 5$, where absolute connectivity is achieved. Beyond these ranges, particularly within $7 \leq \lambda \leq 12$, the network connectivity is not sustained, as indicated in Figure 1.

Item Number	Parameters	Descriptions
1	The platform	MATLAB
2	The speed of vehicles	54-60 m/hr
3	No. of Vehicles on the road	700-1550
4	The type of road (Capacity)	Highways, Urban, Semi-urban
5	The number of lanes in each direction	4
6	The average percentage of vehicles	15%
7	The expected threshold changes	10%
8	Speed Limit	60 mile/hr

Table 4. Parameters Simulating Spare Networks

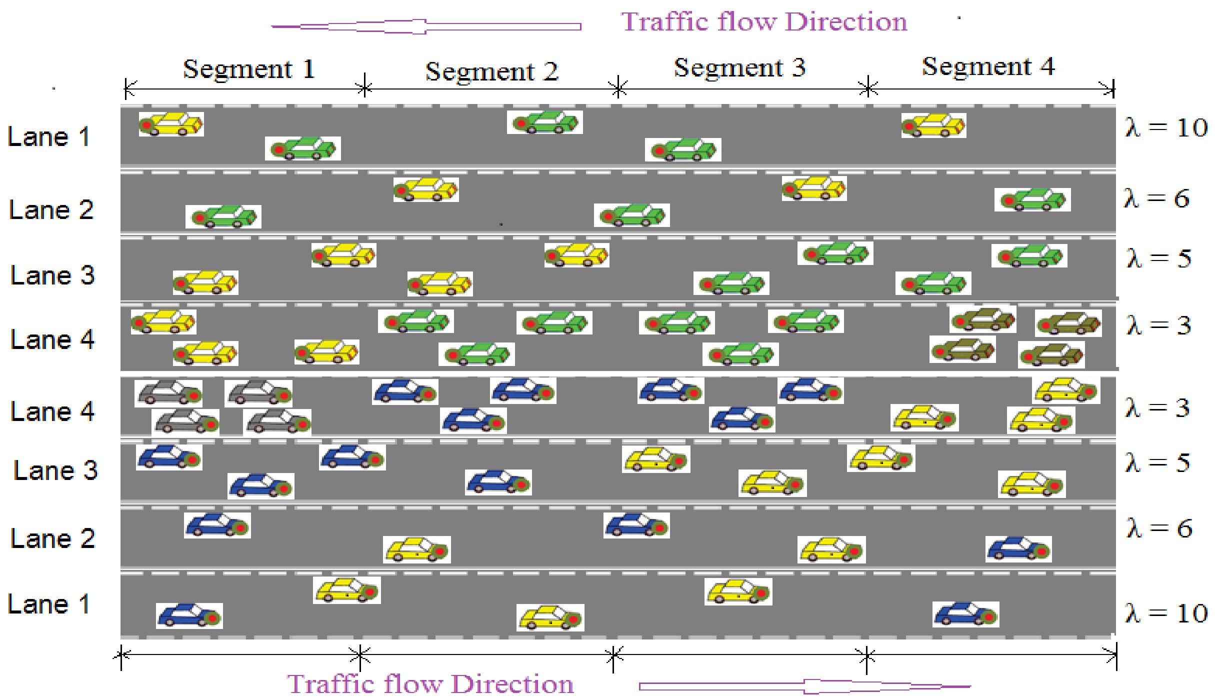

Figure 4. Two-Way Traffic Flow Across Different λ Thresholds

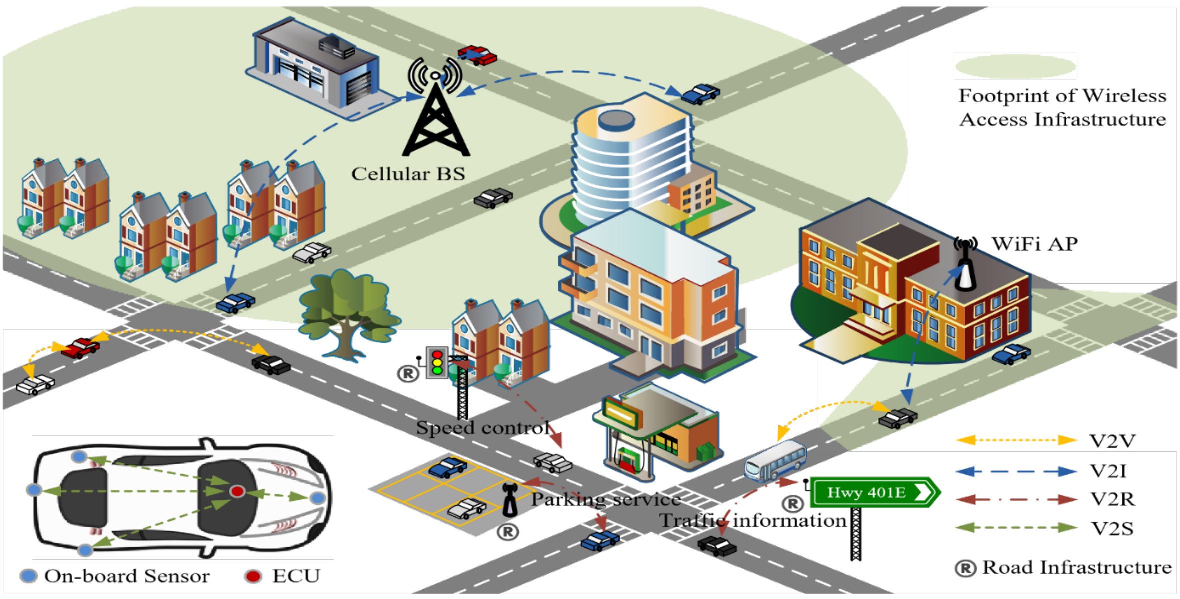

Figure 5. VANETs Connected Vehicles Overview

4. Experimental evaluation of sparse network computational model (SNCM)

The model consists of four lanes, and the study focuses on measuring the outcomes of vehicular traffic flow in terms of traffic alert dissemination. We estimate the transmission connectivity range under each lane as a percentage, using the sensitivity factor λ in the car-following model. This computational estimation helps understand the spatial-temporal variation of λ. The simulation results, based on different values of λ for each lane (1, 2, 3, and 4), indicate a reasonable range of connectivity distribution considering vehicle speed and distances.

Currently, the acceptable transmission range is known to be 1000 meters. We analyze the actual connectivity range of vehicles moving under each lane, to the effective network transmission values of λ. We present the simulation results for different values of λ and their corresponding network transmission ranges for each lane. For example, when λ is 1, the network transmission range is 79.6% for lane 1, 80% for lane 2, 81% for lane 3, and 82.4% for lane 4. The values of the network transmission range vary for different values of λ in each lane.

We observe the network connectivity patterns based on the transmission range between vehicles in different lanes. We noted that when λ is 1, 2, 3, and 4, lane 4 exhibits higher connectivity than lane 3. Similarly, Lane 3 has higher connectivity than Lane 2, and Lane 2 has higher connectivity than Lane 1. However, this pattern changes when λ is 5 and beyond. The simulation trajectories demonstrate the network conditions for individual lanes, but with certain limitations when λ exceeds 5. Furthermore, the study analyzes the traffic flow conditions under sparse network connectivity at different values of λ. Analytical graphs explain the nature of traffic flow when λ increases while the time remains constant for each lane during vehicle motion under spare network conditions.

4.1. Network performance analysis within sparse network connectivity at different values of λ=1

Concerning the analytical graphs depicted below. It demonstrates the traffic flow conditions characteristics as the value of λ increases, while the time remains constant for each lane, with vehicles in motion under sparse network conditions.

4.1.1. Traffic flow conditions in a sparse network with four lanes at λ=1

Regarding the effective network transmission range for vehicles moving in each lane with the sensitivity factor λ: The simulation results for λ=1 indicate that the network transmission range between two or more vehicles on each lane is as follows - Lane 1: 79.6%, Lane 2: 80%, Lane 3: 81%, and Lane 4: 82.4%. Lane 1 represents a scenario of free-flowing traffic with a packet penetration rate of 79.6%, while Lane 2 has a penetration rate of 80%. On the other hand, Lane 3 and Lane 4 exhibit 81% and 82.4% penetration rates respectively, owing to the proximity of vehicles in these lanes. It is noteworthy that Lane 4 boasts a higher packet penetration rate compared to Lane 3, and Lane 3 outperforms Lane 2, while Lane 2 surpasses Lane 1, as demonstrated in Figures 6a and 6b. The simulation results further illustrate vehicle trajectories under different λ values, showing that as λ increases, so does traffic density.

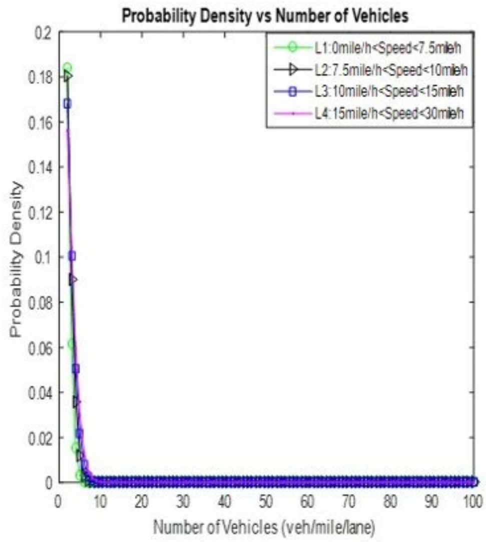

Figure 6a. Impact on Traffic Flow at λ = 1

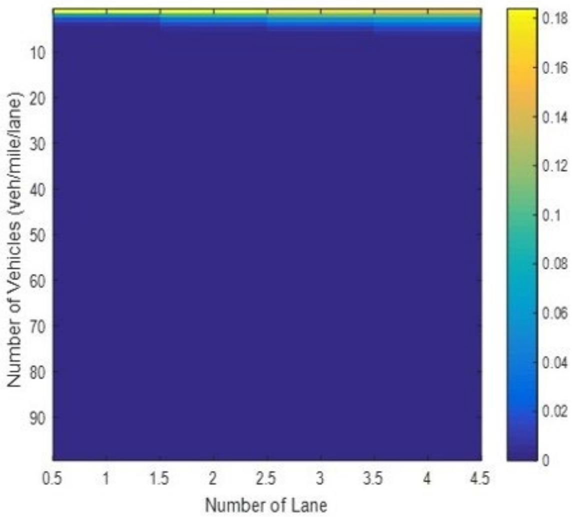

Figure 6b. Vehicle Trajectories in Each Lane

4.1.2. Traffic flow conditions in a sparse network with four lanes at λ=2

In this section, we focus on the traffic flow conditions under a sparse network using four lanes when the value of λ is set to 2. The simulation results reveal the network transmission range between two or more vehicles on each lane for this specific value of λ. When λ is 2, the network transmission ranges for the four lanes are as follows: Lane 1 has a range of 70.9%, Lane 2 has 78.5%, lane 3 has 82%, and lane 4 has 84%. Lane 1 represents a relatively free flow of traffic with a packet penetration of 70.9%, while lane 2 exhibits a higher transmission range at 78.5%. Lanes 3 and 4 have even higher packet penetration with ranges of 82% and 84%, respectively, due to the closer proximity of vehicles in these lanes. Notably, Lane 4 demonstrates higher packet penetration than Lane 3, and similarly, Lane 3 has higher packet penetration than Lane 2. Additionally, Lane 2 has higher packet penetration than Lane 1, as illustrated in Figures 7a and 7b. These simulation results offer insights into the behavior of network connectivity and traffic flow as the value of λ increases, along with an increase in traffic density. By examining the vehicle trajectories, the study further shows the relationship between λ and the resulting density, highlighting the impact on network transmission range and packet penetration. In brief, the findings underscore the specific traffic flow conditions observed under a sparse network configuration with four lanes when λ is set to 2. The varying transmission ranges and packet penetration across the lanes provide valuable information about network connectivity and traffic patterns in relation to the sensitivity factor λ.

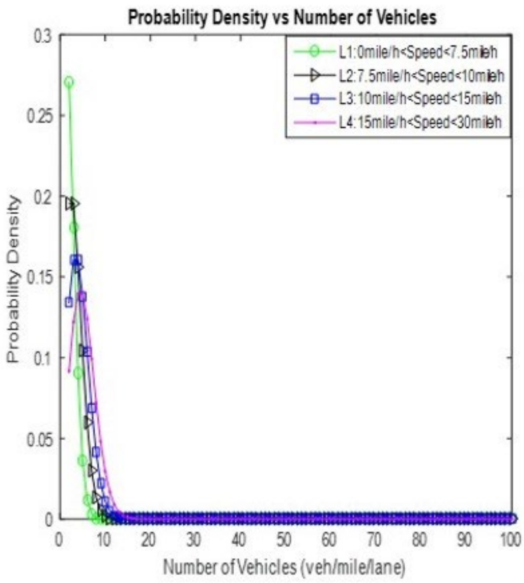

Figure 7a. Impact on Traffic Flow at λ = 1

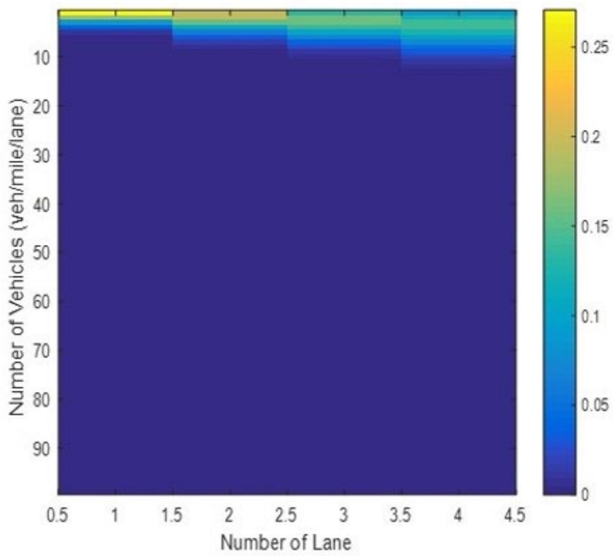

Figure 7b. Vehicle Trajectories in Each Lane

4.1.3. Traffic flow conditions in a sparse network with four lanes at λ=3

Here, we examine the traffic flow conditions under a sparse network configuration using four lanes when the value of λ is set to 3. The simulation results shed light on the network transmission range between two or more vehicles on each lane for this specific value of λ. When λ is 3, the network transmission ranges for the four lanes are as follows: Lane 1 has a range of 75.6%, Lane 2 has 82%, Lane 3 has 85%, and Lane 4 has 87%. Lane 1 represents a relatively free flow of traffic with a packet penetration of 75.6%, while lane 2 exhibits a higher transmission range at 82%. Lanes 3 and 4 demonstrate even higher packet penetration with ranges of 85% and 87%, respectively, due to the closer proximity of vehicles in these lanes. Notably, Lane 4 exhibits higher packet penetration than Lane 3, and similarly, Lane 3 has higher packet penetration than Lane 2. Additionally, Lane 2 has higher packet penetration than Lane 1, as indicated in Figures 8a and 8b. These simulation results provide concepts into the network connectivity and traffic flow patterns when λ is set to 3. By analyzing the vehicle trajectories, the study reveals the relationship between λ and the resulting density, illustrating the impact on network transmission range and packet penetration. Thus, the findings highlight the specific traffic flow conditions observed under a sparse network configuration with four lanes when λ is set to 3. The varying transmission ranges and packet penetration across the lanes offer valuable information about network connectivity and traffic patterns in relation to the sensitivity factor λ.

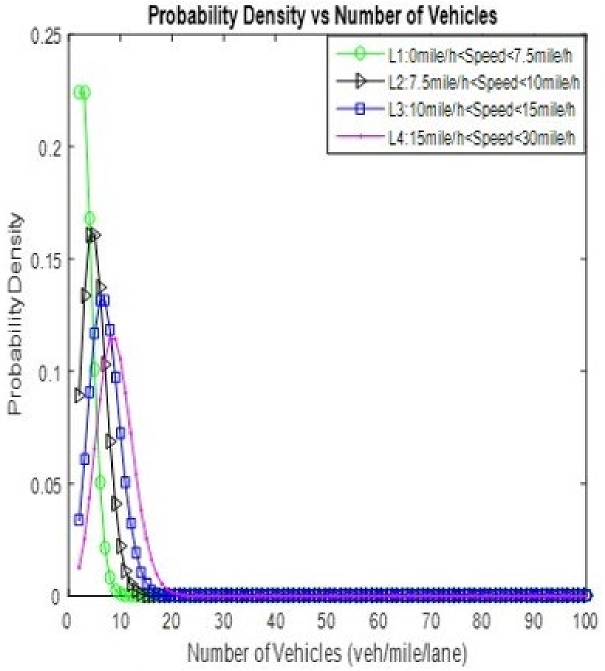

Figure 8a. Impact on Traffic Flow at λ = 1

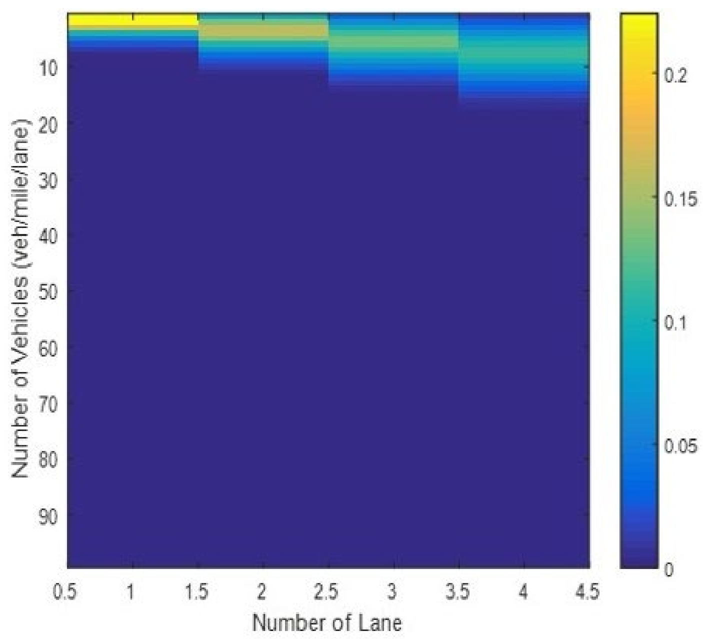

Figure 8b. Vehicle Trajectories in Each Lane

4.1.4. Traffic flow conditions in a sparse network with four lanes at λ=4

Also, this section focuses on examining the traffic flow conditions under a sparse network configuration using four lanes when the value of λ is set to 4. The simulation results provide an understanding of the network transmission range between two or more vehicles on each lane for this particular value of λ. When λ is set to 4, the network transmission ranges for the four lanes are as follows: Lane 1 has a range of 78.3%, Lane 2 has 84%, Lane 3 has 87%, and Lane 4 has 88%. Lane 1 represents a relatively free flow of traffic with a packet penetration of 78.3%, while Lane 2 exhibits a higher transmission range at 84%. Lanes 3 and 4 demonstrate even higher packet penetration with ranges of 87% and 88%, respectively, due to the closer proximity of vehicles in these lanes. Notably, lane 4 exhibits higher packet penetration than lane 3, and similarly, Lane 3 has higher packet penetration than Lane 2. Additionally, Lane 2 has higher packet penetration than Lane 1, as indicated in Figures 8a and 8b. These simulation results offer valuable backgrounds into the network connectivity and traffic flow patterns when λ is set to 4. By analyzing the vehicle trajectories, the study reveals the relationship between λ, increasing density, and its impact on network transmission range and packet penetration. Hence, the findings provide a comprehensive understanding of the traffic flow conditions under a sparse network configuration with four lanes when λ is set to 4. The observed variations in transmission ranges and packet penetration across the lanes contribute to the overall understanding of network connectivity and traffic patterns in relation to the sensitivity factor λ.

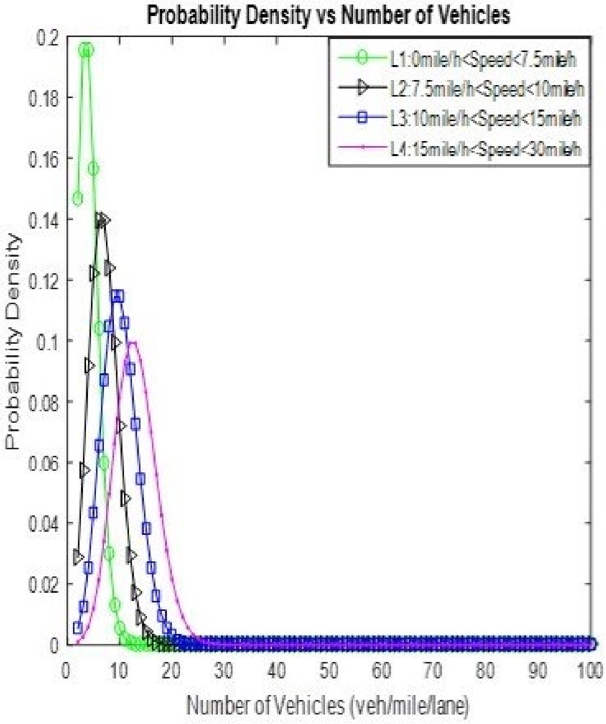

Figure 9a. Impact on Traffic Flow at λ = 1

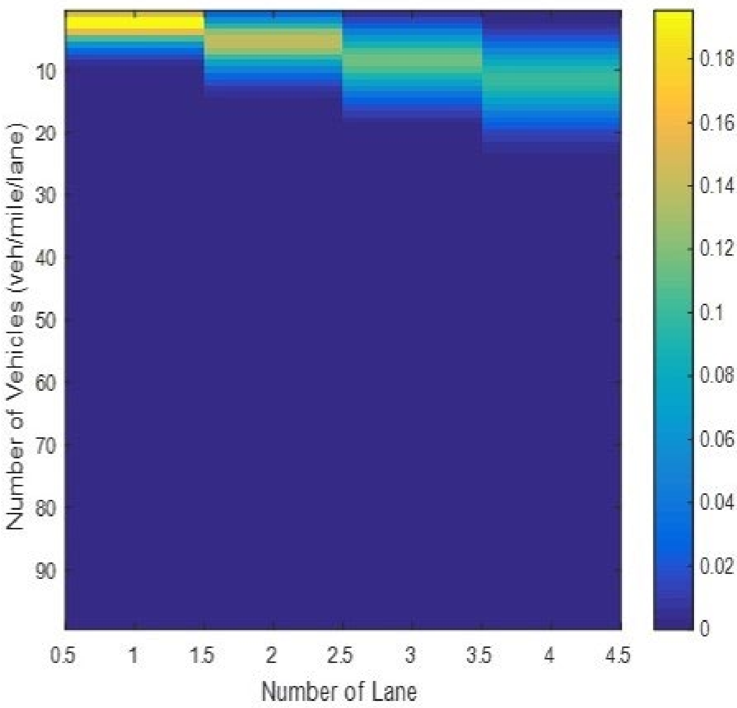

Figure 9b. Vehicle Trajectories in Each Lane

4.1.5. Traffic flow conditions in a sparse network with four lanes at λ=5

Similarly, this section examines the traffic flow conditions under a sparse network configuration using four lanes when the value of λ is set to 5. The simulation results provide deep insights into the network transmission range between two or more vehicles on each lane for this particular value of λ. When λ is set to 5, the network transmission ranges for the four lanes are as follows: Lane 1 has a range of 80.4%, Lane 2 has 85.4%, Lane 3 has 97.4%, and Lane 4 has 88%. Lane 1 represents a relatively free flow of traffic with a packet penetration of 80.4%, while Lane 2 exhibits a higher transmission range at 85.4%. Notably, Lanes 3 and 4 demonstrate significantly higher packet penetration with ranges of 97.4% and 88%, respectively, due to the closer proximity of vehicles in these lanes. Lane 4 exhibits higher packet penetration than lane 3, while lane 3 has higher packet penetration than lane 2. Additionally, Lane 2 has higher packet penetration than Lane 1, as indicated in Figures 10a and 10b. These simulation results provide valuable insights into the network connectivity and traffic flow patterns when λ is set to 5. The observed variations in transmission ranges and packet penetration across the lanes contribute to a better understanding of network connectivity and traffic patterns to the sensitivity factor λ. Hence, the findings reveal the traffic flow conditions under a sparse network configuration with four Lanes when λ is set to 5. The varying transmission ranges and packet penetration across the lanes highlight the influence of λ and increasing density on network connectivity and traffic behavior. These insights contribute to the overall understanding of traffic dynamics in a sparse network environment.

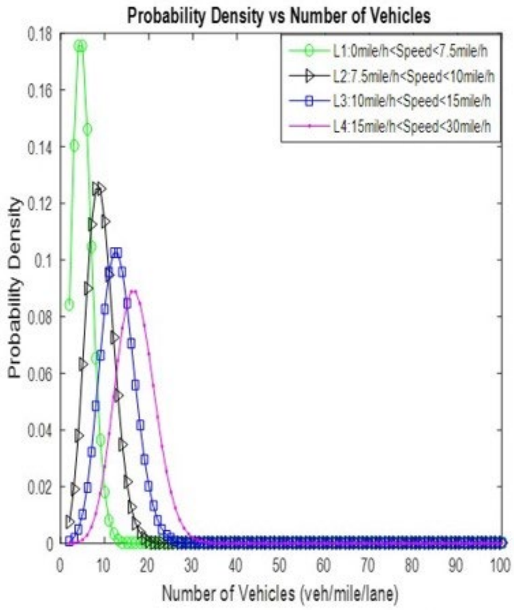

Figure 10a. Impact on Traffic Flow at λ = 1

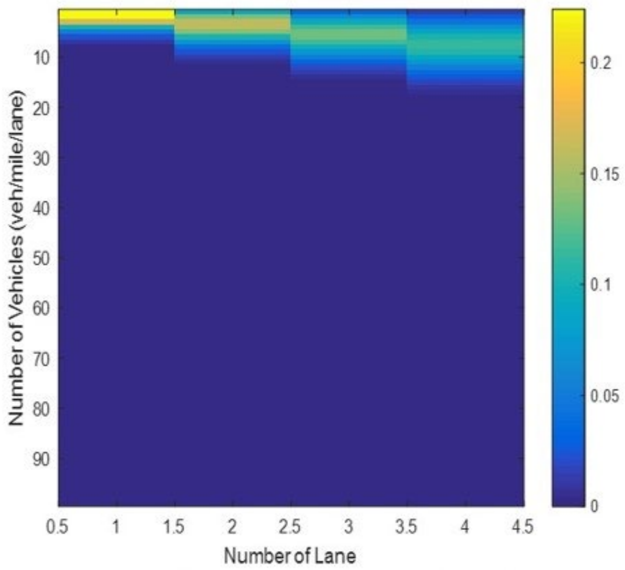

Figure 10b. Vehicle Trajectories in Each Lane

4.1.6. Traffic flow conditions in a sparse network with four lanes at λ=6

Finally, this section examines the traffic flow conditions under a sparse network configuration using four lanes when the value of λ is set to 6. The simulation results provide the basis for the network transmission range between two or more vehicles on each lane for this specific value of λ. When λ is set to 6, the network transmission ranges for the four lanes are as follows:

Lane 1 has a range of 83.4%, Lane 2 has 87.4%, Lane 3 has 96.4%, and Lane 4 has 86%. Lane 1 represents a relatively free flow of traffic with a packet penetration of 83.4%, while lane 2 exhibits a higher transmission range at 87.4%. Lanes 3 and 4 demonstrate higher packet penetration with ranges of 96.4% and 86%, respectively, due to the closer proximity of vehicles in these lanes. Lane 4 exhibits higher packet penetration than Lane 3, while Lane 3 has higher packet penetration than Lane 2. Additionally, Lane 2 has higher packet penetration than Lane 1, as indicated in Figures 10a and 11.

These simulation results provide valuable trajectory into the network connectivity and traffic flow patterns when λ is set to 6. The observed variations in transmission ranges and packet penetration across the lanes contribute to a better understanding of network connectivity and traffic patterns to the sensitivity factor λ. Therefore, the findings reveal the traffic flow conditions under a sparse network configuration with four lanes when λ is set to 6.

The varying transmission ranges and packet penetration across the lanes highlight the influence of λ and increasing density on network connectivity and traffic behavior. These insights contribute to the overall understanding of traffic dynamics in a sparse network environment.

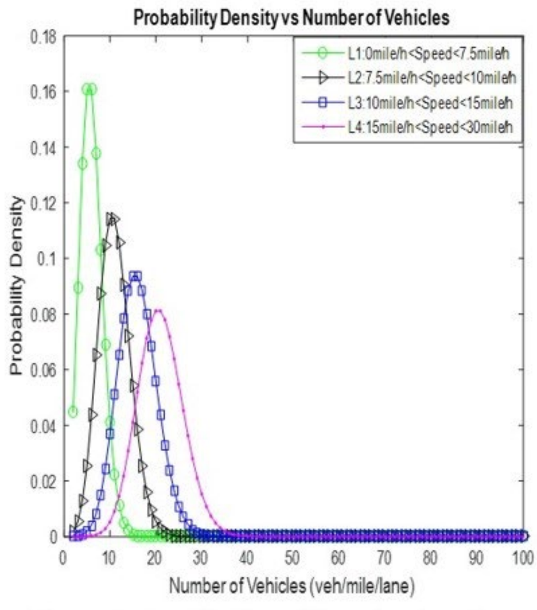

Figure 11a. Impact on Traffic Flow at λ = 1

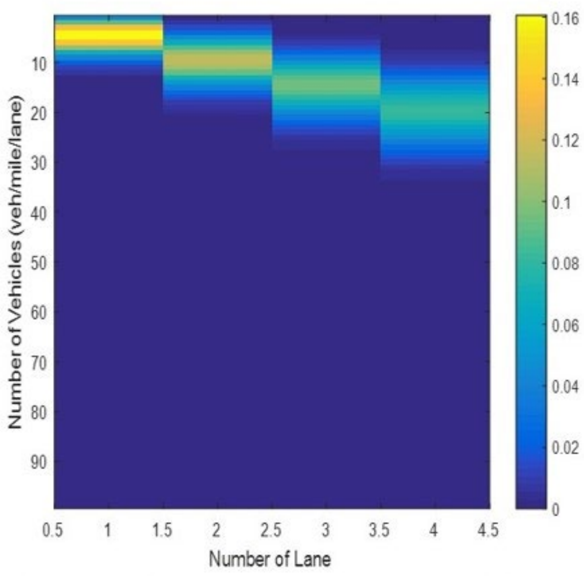

Figure 11b. Vehicle Trajectories in Each Lane

In brief, the findings from the graphs above highlight the behavior of network connectivity and traffic flow under different values of λ in a sparse network, emphasizing the variations in transmission range and packet penetration among the lanes.

5. Results of the sparse network computational model (SNCM)

This paper introduces an innovative protocol named the Sparse Network Computational Model (SNCM), which is based on a probability density function. In this section, we present the simulation results obtained from the performance evaluation of the SNCM protocol.

The SNCM protocol effectively models the intricate relationship among traffic volume (V), density (D), and space mean speed (υ). Various traffic flow conditions are examined, each corresponding to specific density levels. This approach ensures that the time headway distribution adheres to an exponential distribution characterized by the parameter λt. This characteristic allows for the occurrence of non-zero likelihood events under predefined conditions, especially as the values of λt increase to time headway while maintaining constant density. This adjustment is particularly valuable for mitigating intermittent disconnections. In addition, this section demonstrates the significance of the proposed SNCM protocol.

The results of the Sparse Network Computational Model (SNCM) provide valuable backgrounds into the traffic flow conditions and packet penetration rates across different lanes under varying values of λ. The findings shed light on the behavior of the network and the influence of λ and density on traffic patterns.

When λ is set to 1, Lane 1 exhibits a free flow of traffic with a packet penetration of 79.6%. Lane 2 follows closely with a packet penetration of 80%. Lanes 3 and 4 show slightly higher packet penetrations of 81% and 82.4%, respectively, due to the proximity of vehicles in these lanes. The results indicate that Lane 4 has higher packet penetration than Lane 3, while Lane 3 surpasses Lane 2, and Lane 2 surpasses Lane 1, in Figures 6a and 6b. Increasing the value of λ to 2 leads to changes in packet penetration rates. Lane 1 now has a packet penetration of 70.9%, while Lane 2 experiences an increase of 78.5%. Lanes 3 and 4 further exhibit higher packet penetrations of 82% and 84% due to the closer distances between vehicles. Similar to the previous scenario, Lane 4 surpasses Lane 3 in packet penetration, Lane 3 surpasses Lane 2, and Lane 2 surpasses Lane 1 (see Figures 7a and 7b).

When λ is set to 3, the packet penetration rates continue to evolve. Lane 1 now achieves a penetration of 75.6%, Lane 2 reaches 82%, Lane 3 increases to 85%, and Lane 4 shows the highest penetration of 87%. These results indicate that as λ increases, the packet penetration improves across all lanes, with Lane 4 exhibiting the highest connectivity. The packet penetration hierarchy remains consistent, with Lane 4 surpassing Lane 3, Lane 3 surpassing Lane 2, and Lane 2 surpassing Lane 1 (refer to Figures 8a and 8b). A similar pattern emerges when λ is set to 4. Lane 1 experiences a packet penetration of 78.3%, Lane 2 achieves 84%, Lane 3 increases to 87%, and Lane 4 exhibits the highest penetration of 88%. The hierarchy of packet penetration remains intact, with Lane 4 leading, followed by Lane 3, Lane 2, and Lane 1 (see Figures 9a and 9b).

Furthermore, at λ = 5, Lane 1 reaches a packet penetration of 80.4%, Lane 2 achieves 85.4%, Lane 3 experiences a significant increase to 97.4%, and Lane 4 maintains a penetration rate of 88%. The hierarchy of packet penetration is consistent, with Lane 3 surpassing all other lanes in connectivity. However, Lane 4 maintains higher penetration than Lane 1 and Lane 2 (refer to Figures 10a and 10b). Lastly, at λ = 6, Lane 1 shows a packet penetration of 83.4%, Lane 2 increases to 87.4%, Lane 3 reaches 96.4%, and Lane 4 maintains a penetration rate of 86%. The hierarchy remains consistent, with Lane 3 achieving the highest connectivity, followed by Lane 2, Lane 1, and Lane 4 (see Figures 11a and 11b). The results indicate that as the value of λ increases, the packet penetration rates improve across all lanes, demonstrating the influence of λ on network connectivity and traffic behavior. Additionally, the proximity of vehicles within lanes contributes to higher packet penetration rates.

It is very essential to emphasize that this paper represents a pioneering effort, and as such, there is no need for direct comparisons with existing protocols to assess its overall performance. Instead, the SNCM protocol is intended to set a standard for future researchers to benchmark their research contributions against.

6. Conclusion and future work

Vehicular accidents are a leading cause of global fatalities today. To mitigate these tragedies on the road, the SNCM protocol was developed to infuse intelligence into the network, reducing accidents. VANETs empower Intelligent Transportation Systems (ITS) with various applications capable of predicting nearby nodes and implementing preventative measures. Due to their time-sensitive nature, existing literature provides valuable insights into numerous protocols. However, some of these protocols struggle to cope with the dynamic changes in VANET topologies and ineffective traffic load management, resulting in reduced performance.

To address these challenges, we introduce a novel SNCM protocol that employs a probability density function approach to select transmission ranges for identifying the best packet forwarder. SNCM utilizes the relative speeds of vehicles and packet rates, determined by sensitivity factor λ values, to forecast vehicle trajectories on the road. Relative speeds help mitigate frequent topological changes, while packet penetration rates enhance efficient load management. Moreover, this work introduces a novel method to prioritize time-critical safety messages over non-safety messages.

The simulation results demonstrate that the SNCM protocol enhances end-to-end delays, minimizes packet loss rates, enhances network throughput, and improves link lifetime in a four-lane network. This paper represents a pioneering effort, and as such, direct comparisons with existing protocols to assess overall performance are outside its scope. Instead, the SNCM protocol aims to establish a benchmark for future researchers to measure their contributions against.

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