A MONTE-CARLO ANALYSIS BETWEEN A MICROSCOPIC MODEL AND A MESOSCOPIC MODEL FOR VEHICULAR AD-HOC NETWORKS

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ABSTRACT

Vehicular Ad-hoc Networks (VANETs) are crucial for advancing intelligent transportation systems, enhancing road safety, and enabling efficient vehicle-to-vehicle and vehicle-to-infrastructure communications. However, accurately simulating vehicular environments' dynamic and complex nature remains a significant challenge. This study addresses this gap by benchmarking the performance of a mesoscopic model, which incorporates a lane-changing technique, against a microscopic model using Monte Carlo simulations. The microscopic model focuses on individual vehicle movements, considering driver behaviour and interactions, while the mesoscopic model captures traffic flow at the road segment or neighbourhood level. The updated mesoscopic model incorporates a lane change technique to better reflect realistic vehicle movements. The updated mesoscopic model generated approximately 350 to 400 vehicles in the simulations, with a narrow distribution and a peak frequency of about 120 vehicles. In contrast, the original microscopic model produced around 800 vehicles and had a wider distribution but exhibited a similar peak frequency. The revised model demonstrated a slight negative skewness of -0.1019, while the original model showed a slight positive skewness of 0.0618. Both models displayed negative kurtosis values, indicating lighter tails than a normal distribution. Notably, the original model had a more negative kurtosis of -0.2931, compared to -0.1742 for the revised model. These findings suggest that the microscopic model is more adept at capturing the variability of traffic flow, making it a more accurate reflection of real-world scenarios where vehicle interactions significantly impact vehicle dynamics during data transmissions.

KEYWORDS

VANET; mobility model; microscopic; mesoscopic; Monte-Carlo

1. INTRODUCTION

Vehicular Ad-Hoc Networks (VANETs) have become increasingly important in advancing intelligent transportation systems, improving road safety, and establishing effective means for vehicle-to-vehicle and vehicle-to-infrastructure communications [1, 2]. Given the dynamic nature of vehicular environments with high mobility and diverse traffic conditions, simulations are essential to develop efficient network protocols for VANETs [2]. These simulations rely on mobility models to accurately represent real-world vehicle movements within the network. The movement patterns of vehicles have a significant impact on VANET simulations, influencing network protocol performance metrics such as throughput, delay, and packet delivery ratios [3]. These models aim to capture the dynamic behaviour of vehicles on roads, encompassing aspects like acceleration, deceleration, lane changes, and route variations. Therefore, comprehensive mobility models must consider numerous factors, from basic vehicle motions to complex interactions with road systems and traffic conditions.

The selection of an appropriate mobility model is crucial for accurately representing real-world simulation scenarios [2]. Researchers have developed various mobility models, each designed for specific simulation requirements and levels of realism. These models can be broadly classified into three categories: microscopic, mesoscopic, and macroscopic, based on their level of complexity and the scale at which they operate [2, 4-6]. Microscopic models focus on the intricate details of individual vehicle movements, considering factors such as driver behaviour, vehicle acceleration, and interactions with other vehicles [2, 4-6]. In contrast, mesoscopic models offer a moderate level of detail, suitable for simulating traffic flow and vehicle movements at the level of road segments or neighbourhoods [7]. On the other hand, macroscopic models abstract individual vehicle movements to concentrate on the overall traffic flow patterns across larger areas, such as cities or regions [6, 8].

Each type of mobility model offers unique advantages and is suitable for different kinds of VANET simulations. By carefully selecting and applying these models, researchers and engineers can derive meaningful insights into the performance and behaviour of VANETs under a wide range of conditions. Ultimately, the insights gained from simulations using accurate mobility models are instrumental in designing and optimizing VANET protocols and applications for real-world deployment, paving the way for smarter, safer, and more efficient transportation systems.
The mobility model presented in this paper has been adapted from a prior model developed by [9] by incorporating a lane change technique to better capture the realistic movements of vehicles in VANET environments. The formulation of this adapted model has been thoroughly described in references [10, 11]. The current study aims to benchmark the performance of this revised model, which is a mesoscopic mobility model against the original mobility model from [9] that is based on a microscopic mobility model.

2. Literature Survey on VANETs Mobility Models

In VANETs, the dynamic vehicular movements trigger variations in the network architecture, directly impacting key performance metrics such as throughput, transmission latency, and packet loss rate [2, 3, 6]. Accurately reproducing realistic traffic flow in the simulation environment is crucial for advancing research on VANET topology and routing protocols. Consequently, the vehicular mobility model has become the primary focus in VANET simulation research, concentrating on identifying the movement patterns of vehicle nodes to enhance the realism of the simulations. This ensures that the conclusions drawn from the research are applicable to real-world implementations. Therefore, researchers employ various methods to accurately simulate vehicle mobility [3, 6].

One of the early influential works is by Wisitpongphan et al. [12]., which is still highly cited. In this research, the authors developed an analytical framework based on an extended car-following model, which falls under the category of the microscopic mobility model. The authors utilized empirical data collected from the dual-loop detector on the eastbound I-80, a 5-lane highway immediately east of the San Francisco-Oakland Bay Bridge between Emeryville, CA, and Berkeley, CA. From the realistic mobility trace, the authors were able to approximate the probability distribution of inter-arrival times and inter-vehicle spacing as exponential distribution, and vehicle arrival as a Poisson distribution. The study conducted by Wisitpongphan et al. [12] formed the basis for our revised mobility model, which incorporates Poisson distribution to represent vehicle arrival rate and exponential distribution to account for vehicle inter-arrival times.

Table 1 presents a summary of research conducted between 2019 and 2024 on empirical mobility trace and mobility models. These works aim to accurately represent the dynamic nature of vehicle movements in both highway and urban areas.

Table 1: Literature review on common approaches for generating vehicles' mobility for year 2019-2024

Vehicle Mobility Approach	**Reference**	**Dataset/Model/ Technique**	**Objectives**
Mobility Trace	[13]	Beijing taxi traces, Singapore and Jakarta e-hailing vehicle traces	This study examines data dissemination in a vehicular network using empirical mobility traces and incorporates the method of index coding to minimize the number and size of transmissions.
	[14]	Public transportation mobility using General Transit Feed Specification (GTFS) data for Dublin, Rome, Seattle and Washington	The study reveals key characteristics of bus-based networks and examines their network topology and spatiotemporal impacts. The data is further used to assess the design of routing protocols in bus-based networks.
	[15]	Two sets of GPS traces. 1) over 4000 taxis and buses in Shanghai, 2) over 7000 taxis in Shenzhen	The mobility trace is incorporated into the proposed Dynamically Evolving Networking model, which simulates the evolution of VANETs. This model enables a more accurate representation of how VANETs function in real-world scenarios. The proposed model allows the network to evolve into a scale-free network as it grows, self-organizes, and even decreases in size. Additionally, it can ensure good network connectivity and survivability.
	[16]	Datasets of GPS traces from 320 taxis in Rome and 551 taxis in San Francisco	The study employs three distinct approaches - instantaneous, aggregated, and time-varying analysis - to model vehicular ad-hoc networks using graph theory. The authors analyze two large-scale traces, which enables them to ground the theoretical models in real-world data, thereby enhancing the validity and applicability of the findings.
Microscopic Mobility Mode	[17]	Microscopic Mechanism based on Intersection Records (MMIR)	The proposed mechanism aims to enhance the accuracy of connectivity probability or estimated delivery delay for street selection in VANETs using a microscopic approach that leverages individual vehicle data.
	[18]	A microscopic traffic modelling for road networks	In this research, the authors use microscopic modelling to focus on vehicle behaviour and interactions rather than on aggregate traffic flow analysis. A new formalism has been introduced to describe the dynamics of vehicle traffic, particularly in unidirectional traffic scenarios. This model effectively captures vehicle interactions, including acceleration, deceleration, and the maintenance of safe distances. It reveals the behaviour of individual vehicles and is adaptable to various road networks, making it a valuable tool for analyzing traffic systems and urban environments. This approach benefits both scholars and practitioners who are studying complex traffic situations due to its detailed examination and broad applicability.

	[19]	the Adaptive Driver Model (ADM) and Adaptive Lane Changing Model (ALC)	This study develops microscopic simulations that can accurately represent realistic traffic configurations and support large-scale applications in cyber-physical systems
	[20]	A Variable Speed Limit (VSL) control algorithm with the Model Predictive Control (MPC) framework	This study examines Variable Speed Limit control strategies that leverage microscopic traffic flow data to enhance traffic flow predictions.
Mesoscopic Mobility Model	[21]	A mesoscopic model of vehicular mobility on a multilane highway with steady-state traffic flow conditions	This study presents the mathematical modelling of 1) the expected number of hops in a communication link, 2) the distribution of successful multi-hop forwarding, 3) the expected time delay, and 4) the expected connectivity distance. The accuracy of the proposed model is validated through simulations conducted using an event-based network simulator and a road traffic simulator
	[22]	Probability-based theoretical approaches, including the Poisson process, uniform distribution, and exponential distribution, are applied to deduce the connectivity probabilities of cognitive vehicular networks (CVNs)	The authors develop a robust analytical framework using probability theory to analyze the connectivity of cognitive vehicular networks under different scenarios, including single-hop and multi-hop clustering. By examining these scenarios independently, the authors gain insights into how connectivity varies with distinct communication structures, namely the inter-cluster integration process and the intra-cluster communication process.
	[23]	The study uses a stochastic geometry model to characterize the vehicular network's spatial features. It integrates the Poisson Line Process to model the distribution of roadside infrastructure and the 1D Poisson Point Process to represent vehicle locations within the network.	The paper proposes a comprehensive analytical framework for investigating multi-hop relaying in vehicular networks. The framework analyzes how various network parameters, such as the number of hops, impact the coverage provided by road-side units (RSUs) to vehicles. This analysis provides insights into the optimal RSU density required for effective network-wide communication. Additionally, the study assesses the delivery delays introduced by multi-hop relaying.
	[24]	The paper uses the M/M/1 queuing model to assess the VANET system's performance, assuming a Poisson arrival process and exponential service times to understand vehicle flow and service dynamics on highways.	The paper presents a mathematical model that captures the dynamic nature of traffic and service in VANETs. It includes the calculation of the average number of vehicles in the queue and the distribution of waiting times. The authors analyze the queuing system's performance by measuring traffic flow in highway lanes, with a specific focus on the impact of vehicle collisions. The simulation helps understand how vehicles interact within the network and their overall impact on communication efficiency.

Macroscopic Mobility Model	[25]	A new macroscopic model for Variable Speed Limits (VSLs).	This study investigates the impact of variable speed limits on the fundamental diagram of traffic flow. The research reveals that the fundamental diagram induced by VSLs does not conform to the traditional triangular assumption, challenging the conventional understanding of traffic flow under speed restrictions. The authors aim to demonstrate how changes in speed limits can alter the characteristics of this diagram, particularly in terms of capacity and density. Their findings indicate that reducing the speed limit from 120 to 90 km/h leads to a decrease in freeway capacity and an increase in critical density for the studied segment of the A12 freeway in The Netherlands. Furthermore, the proposed model is rigorously compared with two well-established macroscopic models for VSLs
	[26]	The authors have modified the original Greenberg model to improve its accuracy and applicability in real-world scenarios.	The authors employed a modified Greenberg model to simulate traffic variables across different scenarios, incorporating intermediate inputs/outputs as well as a viscosity term in the motion equation. The primary goal of this work was to investigate the impact of viscosity on traffic variables by conducting simulations using the modified model and leveraging measured traffic data as the initial and boundary conditions.
	[27]	The authors adopt the macroscopic first-order Lighthill-Whitham-Richards model to describe the overall dynamics of the traffic flow, coupled with two ordinary differential equations that characterize the trajectories of the front and back endpoints of the platoon.	The model effectively captures the interaction between a platoon of vehicles and the surrounding traffic flow, representing a novel approach in this research area. The paper highlights the dynamics of how slow-moving vehicles, depicted as a platoon, can create point-moving bottlenecks in traffic. Additionally, the authors have developed a finite volume scheme to compute approximate solutions to the coupled partial differential equation and ordinary differential equation system. This computational method is evaluated within the paper, demonstrating its effectiveness in simulating the dynamics of vehicle platooning.
	[28]	This work improves the established Lighthill-Whitham-Richards model by incorporating vehicle spacing in both time and distance domains.	This paper introduces a novel model that focuses on the analysis of inhomogeneous traffic flow during transitional periods. The proposed model is designed to more effectively characterize the evolution of traffic dynamics and provide deeper insights into the behavior of traffic under varying conditions. The authors employ the Godunov numerical technique to evaluate both the established LWR model and their newly developed model, ensuring numerical stability and reliability through adherence to the Courant-Friedrichs-Lewy condition. The performance of the proposed model is rigorously assessed and compared to the LWR model using Greenshields and Underwood target velocity distributions

2.1. Real-World Mobility Trace

Based on a survey done by Clayson et al. [29], a mobility trace is a dataset that records vehicle positions over time using Global Navigation Satellite System (GPS) and cellular networks. Real-world traces provide accurate vehicle movement data, aiding in creating realistic simulations and improving vehicular network solutions. As a result, these traces offer advantages that range from creating more realistic simulation scenarios to identifying information that improves solutions for vehicular networks.

According to Clayson et al. [29], most vehicular mobility traces originate from academic research or are provided by traffic control organizations. In their survey, the authors identified three types of mobility traces that contain vehicle movement data from real-world scenarios: bus mobility traces, taxi mobility traces, and private car mobility traces. The authors present several vehicular motion traces and conducts a qualitative comparison among them. All of the traces are publicly accessible and can be categorized as either real-world or synthetic. Real-world traces comprise positioning data captured by location devices such as GPS receivers. However, due to privacy and security concerns, the majority of these traces are of the movements of anonymous taxis or buses.

The literature review presented in Table 1 clearly shows that researchers are likely using mobility trace data from public transportation due to significant concerns about security and privacy.

2.2. Mobility Models

As mentioned in Section 1, VANET mobility models are typically classified into three main categories: 1) microscopic, 2) mesoscopic, and 3) macroscopic.

2.2.1. Microscopic Mobility Models

The microscopic mobility model focuses on individual vehicle motion, typically at the level of a single road segment. Several models have been developed under this category, including the Car Following Model, Intelligent Driver Model, Krauss Model, Wiedemann Model, and Cellular Automata Model [6].

2.2.2. Mesoscopic Mobility Models

Mesoscopic traffic models represent an intermediate level of abstraction, capturing the overall properties of traffic flows through probability distributions while still accounting for individual vehicle interactions [6, 21]. For instance, these models may employ a uniform distribution to characterize the velocity distribution at a given time and location or an exponential distribution for the vehicular arrival rate.

The mesoscopic mobility model is commonly used in VANET research for simulating vehicular communication networks. It captures steady-state traffic flow conditions and predicts connectivity metrics, essential for designing efficient VANET applications [6, 21]. While mesoscopic models are practical, there's a growing interest in more detailed microscopic models that capture finer-grained mobility patterns, providing insights into individual vehicle behaviours' impact on network performance for specific applications like autonomous driving and pedestrian safety.

2.2.3. Macroscopic Mobility Models

This model takes into account more than just vehicles. It considers the flow of a large number of vehicles from a global perspective, taking into account road topology, features and conditions, traffic density and distribution, traffic signals, and traffic flow [6]. This approach allows for the calculation of road capacity and traffic distribution in the road network.

3. MOBILITY MODELS ANALYSIS

This section provides an overview of how the behavioural characteristics in the mobility model from [9] and [10, 11] influence the overall traffic flow and patterns. Comprehensive documentation of both the original and revised mobility models can be found in the references cited. Table 2 listed the summary on the analysis of both mobility models.

Table 2: Analysis on mobility models by [9] and [10, 11]

Assumption	Mobility Model by [9]	Mobility Model by [10, 11]
Vehicle Arrival Rate	Traffic flow based on microscopic approach	Poisson process
Inter-Arrival Rate between vehicle batches	Not stated	Exponential distribution
Vehicles Speed Distribution	Vehicles' speed in both model use an equation that is influenced by acceleration factor. The factor is determined by a set of equations involving several random variables and an aggressiveness (AGG) parameter	
Aggressiveness of Vehicle Mobility Behaviour (AGG)	The AGG parameter affects the predictability of vehicle movements, thereby influencing the performance of the routing protocol proposed by the authors. The parameter AGG is represented by the single value of 0.2.	The impact of the parameter in a traffic scenario is illustrated using three different AGG values: 0.2, 0.5, and 0.8.

The revised mobility model utilizes a batch arrival process to simulate vehicle arrivals, with vehicles being generated in groups according to a Poisson process, as stated in Table 2. The parameters of the Poisson distribution, including the mean and standard deviation, are employed to manage the expected batch size and its variability. From the definition given in Section 2, we can confidently categorize our revised model as a mesoscopic mobility model.

Conversely, the mobility model in [9] does not explicitly mention batch generation for vehicle arrival. Instead, it uses traffic flow that is based on a microscopic approach to focus on maintaining a continuous flow of vehicles on the highway.

As shown in Table 2, the revised model in [10, 11] employs an exponential distribution to represent the inter-arrival rate between vehicle batches. This probabilistic distribution effectively captures the randomness and variability in the time intervals between successive vehicle arrivals, mirroring the stochastic nature of traffic flow. The rate parameter of the exponential distribution determines the expected time interval between batches, allowing for flexibility in simulating diverse traffic conditions.

On the other hand, the authors in [9] does not explicitly define an inter-arrival rate distribution. Instead, the authors use a discrete-time model where vehicles continuously recalculate their acceleration at regular intervals. This approach focuses on the uninterrupted movement of vehicles rather than discrete arrival events, aligning with the model's emphasis on maintaining prescribed speed limits and lane dynamics.

Both models employ a similar approach to modelling speed distribution, drawing from the methodology outlined in [9]. For each time interval, the models calculate each vehicle's speed by incorporating an acceleration factor to determine whether vehicles should accelerate or decelerate. Additionally, the models leverage random variables and aggressiveness (AGG) factors to simulate realistic speed variations among vehicles, capturing the dynamic nature of highway traffic.

As both mobility models employ the same approach to determine vehicle speeds, they also utilize the same definition for the aggressiveness parameter [10, 11]. The AGG parameter, as defined by Kesting et al. [30], is used to control and simulate the aggressive driving behavior of vehicles in the proposed model. Higher values of AGG indicate more aggressive driving, which significantly affects the overall mobility pattern of vehicles on the highway. Therefore, AGG parameter has a direct impact on the performance of the proposed routing protocol in [9], influencing its ability to accurately predict route lifetimes and proactively create new routes before existing ones fail. The authors for the revised mobility model in [10, 11] investigated the impacts of varying the AGG parameter, which represents driver aggressiveness, at specific values of 0.2 (low), 0.5 (medium), and 0.8 (high), on the performance of the proposed clustering algorithm.

3.1. The Lane Changing Technique

In our revised mobility model, we incorporate a lane-changing technique to enhance the performance of the clustering algorithm proposed in [9]. This technique involves the introduction of two key probabilities:

p_1: The probability of a vehicle maintaining its current lane when the relative distance between the vehicle and its preceding vehicle is lower than a specific threshold, known as the “safety distance.”

p_2: The probability of a vehicle preserving its lane when the relative distance between the vehicle and its preceding vehicle exceeds a certain value, denoted as the d_{th} parameter

The lane-changing technique divides the complementary probabilities p_1 and p_2 into two equal probabilities. For vehicles not in the border lanes, p_1: represents the probability of a lane change to the right, while p_2: represents the probability of a lane change to the left. However, for vehicles in the border lanes, there is only one lane change option, either to the right or to the left. The mathematical expressions for the two key probabilities, p_1 and p_2 are presented in Equation 1. Equation 1 formalizes the lane change decision-making process, where the vehicle's lateral position y is updated based on the probabilities of executing a lane change to the right or left. These probabilities are determined by the distance d between the vehicle and its leading vehicle, as well as the values of the probabilities p_1 and p_2.

$$y_{i,t+1} = \begin{cases} y_{i,t+1} \; if \left(\varepsilon \geq p_1 \& \, \varepsilon < p_1 + \dfrac{1-p_1}{2} \& \, d < d_{th}\right) or \left(\varepsilon \geq p_1 \& \, \varepsilon < p_2 + \dfrac{1-p_2}{2} \& \, d \geq d_{th}\right) \\ y_{i,t-1} \; if \left(\varepsilon < 1 \; \& \, \varepsilon \geq p_1 + \dfrac{1-p_1}{2} \& \, d < d_{th}\right) or \left(\varepsilon \; < 1 \; \& \, \varepsilon \; \geq p_2 + \dfrac{1-p_2}{2} \& \, d \geq d_{th}\right) \\ y_{i,t} \; if(\varepsilon < p_1 \; \& \, d < d_{th}) or(\varepsilon \; < p_2 \; \& \, d \geq d_{th}) \end{cases} \tag{1}$$

With

$d = |x_{i+1,t} - x_{i,t}|$

Where

$y_{i,t+1}$: the updated position of vehicle i at time $t + 1$

ε: a random number generated between 0 and 1

d: denotes the distance separating the vehicle of interest and its preceding vehicle

d_{th}: denotes a distance threshold between the vehicle i and the lead vehicle that triggers a lane change for probability p_1.

4. MOBILITY MODELS BENCHMARK

A Monte Carlo simulation, comprising 1000 iterations, was conducted to assess the performance of the two mobility models. The simulated scenario involved a 6-lane unidirectional highway spanning 10 kilometres. Communication configuration and delay factors were excluded from this simulation. The purpose of the Monte Carlo simulation was to evaluate and analyse the differences between the two mobility models based on the discussion presented in the preceding section.

4.1. Results on Vehicles' Generation

The first step in the Monte Carlo simulation for both mobility models is to analyze the characteristics and the distribution for the vehicle generation.

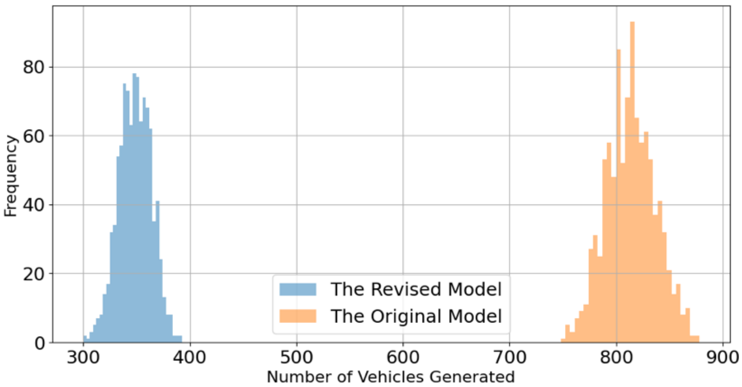

Figure 1. Comparison between two models on number of vehicles generated

Figure 1 presents the histograms depicting the frequency distributions of the number of vehicles generated by the two modelling approaches. The histogram on the left represents the distribution of the number of vehicles generated by the revised model, while the histogram on the right represents the distribution of the number of vehicles generated by the original model. A histogram is a graphical representation of the frequency distribution of a quantitative variable. The x-axis depicts the variable values, with each bar representing a discrete value or a class of continuous values arranged in ascending order. The height of the bars on the y-axis corresponds to the frequency distribution of the respective variable values.

The revised model, as indicated in Table 2 and referenced in [10, 11], employs a Poisson process for generating the number of vehicles and an Exponential distribution for inter-arrival time. In contrast, the original model described in [9] adopts a microscopic approach to determine the number of vehicles. As depicted in Figure 1, the distribution for the revised model is centred around 350-400 vehicles with a relatively narrow spread and a higher peak frequency of approximately 120 vehicles. On the other hand, the distribution of the original model is centred around 800 vehicles with a wider spread but a similar peak frequency, highlighting greater variability in vehicle generation. This aligns with the model's emphasis on individual vehicle behaviours and dynamic routing. In summary, the revised model assumes a random arrival of vehicles based on an average rate, making it more suitable for modelling traffic flow at a macro level or for less congested scenarios. Conversely, the original model accounts for individual vehicle behaviours and interactions, allowing for more densely packed vehicles and potentially providing a more realistic representation of congested highway scenarios.

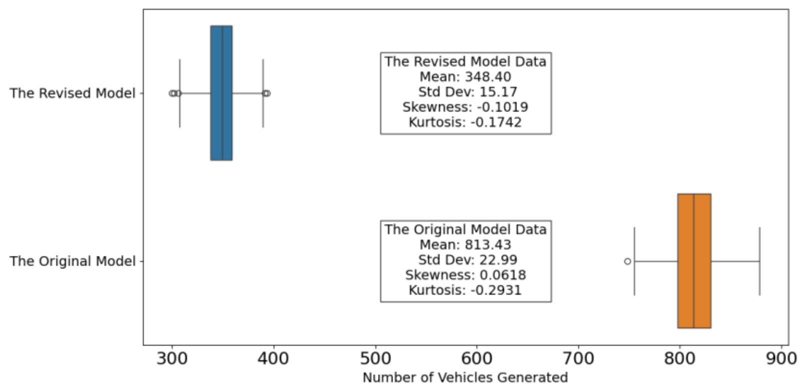

Figure 2. Number of vehicles generated statistical comparison between the two models

Furthermore, Figure 2 presents the findings on skewness and kurtosis. Skewness is a measure used to assess the symmetry, or lack thereof, in a distribution or dataset [31]. An asymmetric distribution appears the same on both sides of its central point. Both models exhibit relatively small skewness values, indicating that their distributions are nearly symmetrical. The revised model has a slightly negative skewness of -0.1019, suggesting a subtle leftward asymmetry, whereas the original model demonstrates a slightly positive skewness of 0.0618, indicating a mild rightward asymmetry.

Kurtosis is a statistical measure that indicates whether the data exhibits a heavy-tailed or light-tailed distribution relative to a normal distribution [31]. A kurtosis value of 0 corresponds to a distribution with a peak and tails similar to a normal distribution. Both models exhibit negative kurtosis values, indicating that their distributions have lighter tails and are more platykurtic (flatter) compared to a normal distribution. The original model has a slightly more negative kurtosis value of -0.2931 compared to the revised model's -0.1742, suggesting an even flatter distribution with fewer extreme values in the tails than the revised model. This implies a slightly flatter peak and lighter tails for the original model.

4.2. Impact on the AGG Parameters on the Traffic Flow

This section examines the impact of the aggressiveness behaviour parameter on traffic flow using the Monte Carlo simulation. Figure 3 illustrates the relationship between the aggressiveness (AGG) parameter and different vehicle traffic flows in the network. The AGG parameter is used to control and simulate the aggressive driving behaviour of vehicles in the network. As described in Section 3, this parameter influences the acceleration and deceleration dynamics of vehicles, where higher AGG values correspond to more aggressive driving. This parameter has a significant impact on the overall mobility patterns exhibited by vehicles on the highway.

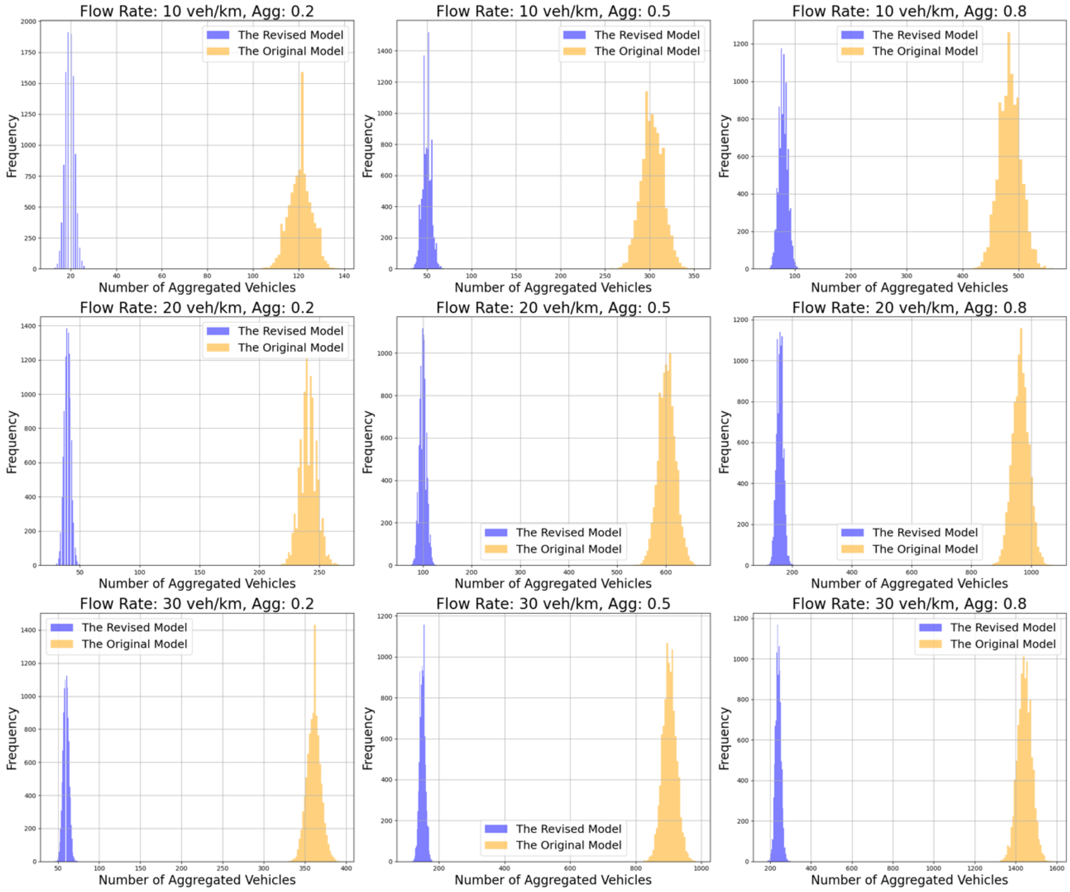

Figure 3. Comparison of Two Models Examining the Impact of Aggressiveness Parameters on Different Traffic Flows

In terms of the distribution shape, the revised model exhibits a more symmetric and narrower distribution, which is consistent with the Poisson distribution used for vehicle arrivals. In contrast, the original model displays a wider range of vehicle counts, reflecting a more complex, microscopic approach to vehicle movement. As we progress through the rows in Figure 3, both models demonstrate an increase in vehicle count as the AGG parameter rises. However, this effect is more pronounced in the original model, indicating that the microscopic approach is more sensitive to changes in driver aggressiveness.

As the traffic flow increases as we move right across the columns of Figure 3, both models demonstrate a rise in vehicle generation. The original model exhibits a wider spread of vehicle counts at higher flow rates, indicating that the microscopic approach is able to capture a greater degree of variability in traffic patterns. Conversely, the revised model's narrower distribution suggests that it may be more adept at predicting average traffic conditions, but could underestimate extreme scenarios. The wider distribution seen in the original model implies that it encompasses a wider range of traffic scenarios, potentially making it more suitable for the study of edge cases or unusual traffic patterns.

The findings illustrated in Figure 3 suggest that the original model displays higher peak densities, particularly at elevated AGG values and flow rates. This implies that the original model's microscopic approach may be more effective in capturing traffic clustering or congestion effects. Additionally, both models exhibit sensitivity to changes in AGG and flow rate, but the original model appears to be more responsive. This indicates that the original model's microscopic approach may be better equipped to adapt to diverse traffic conditions and driver behaviours.

In summary, both models exhibit the expected behaviour as flow rates and aggregation parameters increase. The original model, which utilizes a microscopic approach, consistently yields higher vehicle counts, possibly due to its more detailed representation of vehicle interactions. In contrast, the revised model, which employs a Poisson process, demonstrates slightly more right-skewed distributions compared to the original model.

While both models produce distributions that closely resemble a normal distribution, they still significantly differ from a perfectly normal distribution. These results emphasize the distinctions between the two modelling approaches and their implications for traffic flow simulation. The original model appears to capture more variability in traffic flow, potentially making it more representative of real-world scenarios where vehicle interactions play a significant role. On the other hand, the revised model, although simpler, still captures the general trends of increasing traffic density and the effects of the AGG parameter.

4.3. Results on Lane Changing Technique

This section presents the findings from the extended version of the Monte Carlo simulation conducted in the previous section. The extended simulation incorporated a lane-changing technique for both the original and revised models. For the revised model, the lane-changing technique was based on Equation 1. However, the authors in [9]. did not specifically mention the model or technique for lane changing in the original model. Therefore, it is assumed that the authors of the original model employed a microscopic approach to model lane-changing behaviour. The scenario for this extended simulation remains consistent with the previous section, featuring a 10 km highway with six unidirectional lanes.

Table 3: List of parameters used in the extended Monte-Carlo simulation

Parameter	Value
v_{min}	5.56 m/s (20 km/h)
v_{max}	33.33 m/s (120 km/h)
d_{th}	52 meter
a_{max}	2.0 m/s^2
d_{max}	-2.0 m/s^2

Table 3 presents the parameter values employed in the extended Monte-Carlo simulation. The parameters v_{min} and v_{max} correspond to the speed ranges observed for vehicles on a highway setting. Similarly, v_{min} and v_{max} reflect the acceleration and deceleration limits typically exhibited by highway vehicles. The parameter d_{th} represents the distance threshold used to trigger lane-changing decisions, and its value is based on the commonly used 3-second rule for safe following distances on highways [32].

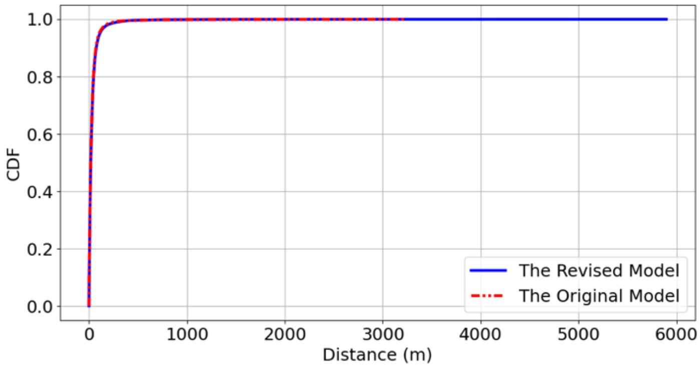

Figure 4. CDF of Distances Between Vehicles

Figure 4 presents the cumulative distribution functions of the inter-vehicle distances for both models. The x-axis in Figure 4 indicates that the distances between vehicles range from very small (close to 0 meters) to quite large (over 5000 meters), reflecting the variability in traffic density along the highway. The relatively smooth curve suggests a continuous distribution of distances with no sharp jumps at any particular distance, indicating that vehicles are spread out along the highway rather than clustering at specific intervals.

A notable feature is the relatively steep increase in the CDF for short distances (0-100 meters), suggesting that a significant portion of vehicles are quite close to each other, potentially representing areas of higher traffic density or potential congestion. Furthermore, the curve flattens out for larger distances (beyond 500 meters), indicating fewer instances of very large gaps between vehicles. From this CDF, it is evident that only a small fraction of vehicle pairs (less than 5%) is within the threshold distance (67 meters) of each other

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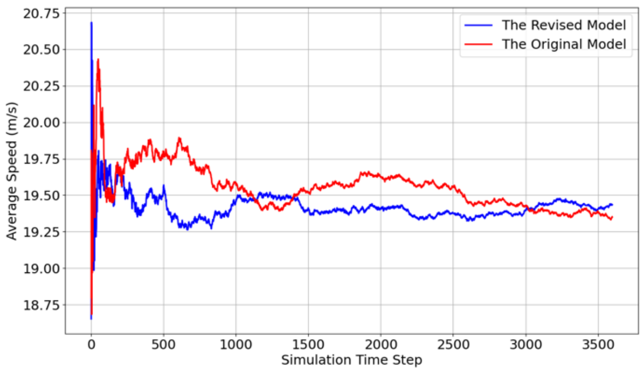

Figure 5. Average Vehicles Speed over Simulation Time

In Figure 5, the average speeds of both models throughout the simulation period are illustrated. The revised model starts with a slightly lower average speed compared to the original model. However, both models rapidly stabilize and maintain consistent average speeds throughout the simulation. The revised model demonstrates minor fluctuations in speed, suggesting a more controlled traffic flow with a gradual decline in average speed over time, but within a consistent range. In contrast, the original model starts with a higher average speed than the revised model but then experiences a sharp drop in average speed early in the simulation. The output for the original model in Figure 5 shows more pronounced variations in speed throughout the simulation, with a decreasing trend in average speed over time and greater variability.

5. CONCLUSION

This study compares a microscopic model and a mesoscopic model for vehicular ad hoc networks (VANETs), highlighting their respective strengths and applications. The microscopic model offers a detailed representation of individual vehicle behaviours, making it suitable for scenarios that require high accuracy in vehicle interactions and driver behaviour. In contrast, the mesoscopic model captures broader traffic flow patterns, making it better suited for simulations at the level of road segments or neighbourhoods. Including a lane-changing technique in the revised mesoscopic model enhances its realism and applicability.

While the microscopic model excels in reflecting the variability of traffic flow and is more responsive to changes in driver aggressiveness, it also presents higher computational complexity, which may limit its use in certain situations. On the other hand, although less detailed, the mesoscopic model provides a practical approach for macro-level traffic flow modelling; however, it may need to fully address extreme traffic scenarios or the sensitivity to driver behaviour.

The Monte Carlo simulations show that the microscopic model provides a more accurate representation of vehicle movements, which is crucial for developing effective VANET protocols. Future work could further investigate these models' performance in more complex scenarios, such as urban environments with traffic signals, intersections, and pedestrian interactions. Insights gained from simulations using accurate mobility models are essential for designing and optimizing VANET protocols and applications for real-world deployment, paving the way for smarter, safer, and more efficient transportation systems.

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