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A Developed Modeling Approach to Simulate the Mobility Patterns of the Vehicular Networks

A Dissertation

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بِسْمِ اللَّهِ الرَّحْمَنِ الرَّحِيمِ

﴿فَتَعَالَى اللَّهُ الْمَلِكُ الْحَقُّ وَلَا تَعْجَلْ بِالْقُرْآنِ مِنْ قَبْلِ أَنْ يُقْضَىٰ إِلَيْكَ وَ
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Dedications

To My Parents

To My Husband

To My Husband's Mother

And To the Candles Glowing: My Sons

{MOHAMMED AND RAWAN}

With All My Respect and Love...

Roaa Sabah Naser

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First of all, I would like to thank God, without divine providence, I would not have even considered all the work involved in this study.

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Abstract

The most important feature of vehicular networks is their high mobility. This feature makes the mobility model the most important factor that should be wisely selected when implementing any simulation scenario. The development of modeling approaches to simulate mobility patterns in vehicular networks has become increasingly important in recent years. Mobility models should accurately reflect the real movement of vehicles on roads. These models take into consideration different factors such as velocity, acceleration, deceleration, lane changes, and interactions between vehicles. This dissertation considers two Car-following mobility models (Safety distance and General Motor models). An in-depth study is created to analyse these models and find a requirement to improve them as well as develop ways to estimate their parameters based on real datasets. Two real datasets are utilized in this dissertation (HighD and NGSIM). Datasets statistics are utilized in estimating these models parameters as well as in creating the simulation setups. Sampling from different probability distributions is also used in generating vehicle mobility and traffic parameters to suit real case applications. Adding a certain new variable to the safety distance model will make it more accurate and suitable to predict the next velocities and accelerations. This added variable values are proposed and indicated as (0, 1, and -1). Also, a developed mathematical approach is developed to estimate the constant term (α) in the General Motor model based on analysing the collected datasets. In General Motor model, relative velocity (ΔV) is the main factor that must be estimated correctly. Three proposed approaches are created and implemented in this dissertation to

estimate the suitable value of the relative velocity. These three values are based on the (max, min, and mean) velocity collected after analysing datasets. One of these three values will be selected in implementing the models calculation based on vehicle and street data behavior. A developed lane change mathematical model is also proposed in a mathematical manner using the fundamentals of the Binomial probability distribution and the theory of the Markov models. All these proposed models are simulated and their results are observed. A comparison with related works shows the superiority of the developed models over the related works. Simulation results are implemented to show the impact of vehicle traffic on data dissemination and network performance is also evaluated. Acceptable results were recorded in different simulation scenarios which reflects the reliability of the proposed approaches.

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List of Abbreviations

Abbreviation	Description
DSRC	Dedicated Short-Range Communications
E2E	End-to-end Delay
GM	General Motor
ITS	Intelligent Transportation System
OBU	On-Board Unit
PDR	Packet Delivery Ratio
RSU	Road Side Unit
V2I	Vehicle to Infrastructure
V2V	Vehicle to Vehicle
VANET	Vehicular Ad hoc Network

CHAPTER ONE

GENERAL INTRODUCTION

1.1 Introduction

The rapid advancement of wireless communication technologies and the proliferation of connected vehicles have led to increased interest in Vehicular ad-hoc Networks (VANETs) (Ali et al., 2018). Vehicular networks facilitate communication among vehicles and between vehicles and infrastructure, enabling various applications such as traffic management, safety, and infotainment (Hartenstein & Laberteaux, 2008).

VANET, in its initial establishment, represents a self-organizing wireless network to connect vehicles without any infrastructure. It connects to other devices wirelessly using an On-Board Unit (OBU) to achieve low cost and availability. There are different categories of VANET: Vehicle to Infrastructure (V2I), Infrastructure to Vehicle (I2V), Vehicle to Vehicle (V2V), and Infrastructure to Infrastructure (I2I) (Lee and Atkison, 2021).

A critical aspect of VANET research is understanding and modeling mobility patterns, as they directly influence the network's performance, topology dynamics, and routing protocols (Rawat et al., 2016). Mobility models play a crucial role in simulating and evaluating the performance of VANETs, facilitating the development of advanced communication protocols and V2V applications (Abdelgadir, et al, 2017)

The dynamic mobility in VANET causes frequent changes in topology and link disconnection. The prediction of future movement in VANET is a very important issue due to the constraints of environments, traffic conditions, and urban layout. Therefore, prediction plays a crucial role in building an efficient VANET communication system. Most prediction studies which are about 65% were focused on urban scenarios and only 10% focused on Highways (Abdel-Halim and Fahmy, 2018).

Traditionally, researchers have employed various mobility models, such as random waypoint, Gauss-Markov, and intelligent driver models, to simulate VANET scenarios (Camp et al., 2002) and (Treiber et al., 2000). However, these models often fail to capture real-world complexities, leading to discrepancies between simulated and actual vehicular behaviors (Djahel et al., 2015). To address these limitations, recent studies have focused on incorporating real-world datasets and developing more accurate mobility models (Akhtar et al., 2015).

For developing these transportation systems connectivity is the most important thing in them. It will allow them to collect a big amount of data for designing strong monitoring ways and different mechanisms to be able to fully control the traffic flow and improve driving and road conditions and maintain safety (Yeferny and Hamad, 2021).

Intelligent Transportation System (ITS) supports wireless communication by utilizing the VANET (Hasan and Sarker, 2020). VANET can interact with the Internet of Vehicles (IoV) to create suitable and useful wireless vehicular network communication. Over the last few years, VANET has been considered an important field in wireless vehicular network communication (Yeferny and Hamad, 2021). Three familiar scenarios exist in simulating VANET environments; urban, rural, and highway (Abdel-Halim and Fahmy, 2018).

Every environment presents unique difficulties that must be solved. For instance, low vehicle density is still the key concern in a sparse network like motorways. Low penetration ratios and low traffic volumes at night might result in significant network delays even in urban areas. Under the VANET paradigm, the mobility model must take into account how moving vehicles behave both singly and collectively to ensure error-free, effective packet transmission (Singh and Er, 2023).

Numerous challenges in the VANET mobility field have not been completely overcome yet. These challenges make it difficult to develop effective and reliable VANET systems, but researchers and engineers continue to work on addressing these issues to improve the overall performance and usefulness of VANETs (Hussain, et al, 2019)

Moreover, most VANETs' Car following models and lane change models are essential components in understanding and simulating traffic flow, particularly in the context of VANETs.

Car following models describe the behavior of a vehicle in response to the motion of the vehicle directly in front of it. These models focus on factors such as reaction time, sensitivity, stability, and comfort, taking into account the velocity, acceleration, and distance between vehicles. Some popular car following models include Gipps' Model, Pipes' Model, Intelligent Driver Model (IDM), Krauss' Model, and Optimal Velocity Model (OVM).

Lane change models, on the other hand, focus on the decision-making process and actions taken by a driver when changing lanes. These models consider factors such as the driver's motivation to change lanes (e.g., to overtake slower vehicles or to exit the road), the available gap between vehicles in the target lane, and the driver's aggressiveness or willingness to accept smaller gaps.

Combining car following and lane change models allow researchers and engineers to simulate realistic traffic flow scenarios and study the impact of various factors on traffic efficiency, safety, and the performance of Vehicular Ad Hoc Networks.

Data dissemination in VANETs faces several challenges, such as high node mobility, network partitioning, and varying communication quality (Yeferny

and Hamad, 2021). Data can be disseminated among vehicles to inform drivers about traffic, predicted weather conditions, and expected risks (Yeferny, et al, 2013). To overcome these challenges, researchers have developed various protocols and techniques that consider factors like network topology, vehicle density, and communication range to optimize data dissemination, ensuring timely and reliable information exchange among vehicles and infrastructure components.

1.2 Motivations

The driver behaviors and interactions with nearby vehicles, which impact variations in distance headway over time, are unpredictable. Furthermore, a mesoscopic model does not reflect the relationship between a distance headway and its variations over time. As a result, a microscopic mobility model should be utilized to precisely simulate the temporal fluctuations in VANET architecture. As a result, the chosen mobility model parameter must appropriately describe the temporal fluctuations in VANET architecture. In the literature, microscopic mobility models comprise a collection of deterministic and/or probabilistic rules that explain how a vehicle on the road adjusts its lane change, velocity, and/or acceleration in response to the behaviors of its neighbors.

1.3 Problem statement

The main features of the Vehicular Networks are their dynamic topology, Mobility models, infinite energy supply, and localization functionality. The essential applications of Vehicular Networks are in traffic safety, traffic management services, and in traffic information systems. The future of vehicular communications applications aims to improve the ITSs by incorporating various advanced technologies. These technologies will make the

ITS safer, smarter, and appropriate, and reduce its congestion. Future vehicles will have equipped with radios capable of communicating with roadside infrastructure or with other vehicles at certain distances. Such new applications will provide the driver with everything from instant and update experience.

One of the VANET environments is the highway, in simulating a VANET environment, a traffic simulator (mobility model) can be used to generate the movement of vehicles. Driver behavior on a road is very complex and plays a significant role in traffic tracking and control. Drivers must continuously react to changing road conditions (congestions) and other situations. Selecting a suitable mobility model will influence the relevance and viability of the results. Selecting an appropriate mobility model can have a significant effect on network performance. Simulation analysis using a realistic mobility model for the VANET environment is greatly affected by the mobility model. The performance of a VANET and its data dissemination can vary significantly with different mobility models. The mobility models for VANET should most closely match the expected real-world scenario. Developing a suitable mobility model and depicting the most really important factors in its creation represents a significant approach to improving the VANET performance in different simulations and real applications.

1.4 The Aim of the Dissertation

The aim of this dissertation is to develop Modeling approaches to simulate the Mobility Patterns of Vehicular Networks and observe their association with wireless data dissemination. This aim can be achieved by the following objectives:

- Study, analyze, and develop the available car-following mobility models to make them applicable in simulating or predicting the movement of the vehicle.
- Propose methods to estimate the mobility model parameters values in a practical manner based on collected real datasets.
- Propose mathematical foundations to create and simulate the vehicular network environment. Propose methods to randomly generate the vehicle's variable velocity and acceleration close to the real application.
- Propose methods to generate the vehicles entrance (flow rate) to the road segment. Based on this method, the number of vehicles in each area and their density level can be generated. These generated values must be similar to their associated values in real datasets.
- Model the driver behavior (reaction time) as a Probability value in a practical random manner considering the vehicle's flow rate, velocities, and the number of lanes by making use of real datasets.
- Perform simulation scenarios with the proposed prediction models to and show their effects on wireless data dissemination.

1.5 Research Questions

In order to achieve the aim of this dissertation, the following research questions must be addressed:

- 1- How to create a specific number of vehicles with their variable velocities and acceleration in a simulation environment?
- 2- How to adapt the car-following mobility model be reliably used in predicting long-term velocities?
- 3- How to estimate the suitable values for GM model parameters?
- 4- How to expect the driver's behaviors?
- 5- How to predict the lane change probability?

1.6 The Contributions

In this dissertation, a modeling and simulation process was applied to show the effects of the mobility models on the Vehicular network performance metrics. The contributions in this dissertation abstract are as follows:

1. Propose mathematical models to create and simulate the vehicle's arrival (flow) rate (vehicle entrance to road segment), velocities, and accelerations from specific random probability distributions that well-matched real datasets.
2. Improve the available car-following mobility model (by adding a new variable) to be used in predicting long-time vehicles velocities and their acceleration.
3. Develop a mathematical model (Markov model with a Binomial Probability distribution) to propose a lane change process during each simulation scenario based on road lanes and driver's behavior.
4. Propose a Random method to estimate the driver behavior (reaction time).
5. Compare the possible approaches to estimate the Relative Velocity values in implementing a Car following models and select the best suitable one.

1.7 Related Works

In this section related works are divided into two categories: Clustering related works and Data dissemination-related works.

Zhang, et al, suggested a proposed method for simulating the connected and automated vehicles' decision-making behavior when changing lanes. They adopted a molecular interaction potential model which advances their comprehension of CAVs in a variety of traffic conditions. Their study

examined the variables that influence CAVs' decisions to change lanes, including vehicle velocity, the volume of nearby traffic, and the final destination. These elements can be taken into account by the MIP model to more correctly mimic and forecast CAV behavior, resulting in safer and more effective traffic systems (Zhang, et al, 2022).

Anderson, et al, 2021 presented a kinematic model that predicts the trajectories of vehicles on highways. The model took into account the vehicle's initial position, speed, and acceleration, as well as road geometry, and the behavior of other vehicles on the road. The model was tested on real-world data and shows promising results in accurately predicting the trajectories of vehicles on highways. The authors believed that this model can be used in various applications such as driver assistance systems and autonomous vehicles to improve safety and efficiency on highways (Anderson, et al, 2021).

Kurtc presented an analysis of car-following behavior using the HighD dataset at 2021. HighD is a large-scale naturalistic driving dataset that captures the behavior of drivers in real-world traffic situations. The analysis revealed that the car-following behavior of drivers was influenced by a variety of factors, including traffic density, speed, and the presence of other vehicles. The authors used statistical modeling techniques to quantify the impact of these factors on car-following behavior and showed that the models can predict the behavior of drivers in different traffic scenarios (Kurtc, 2021).

Srisurin and Kondyli proposed a model approach and simulated mixed traffic environments with both connected automated vehicles (CAVs) and conventional manually-driven vehicles (MDVs) in 2021. They took into their consideration both the car-following and lane-changing behaviors. Understanding how these vehicles interact and how it affects overall traffic

flow and safety represents their study goal. They claimed that they can more accurately forecast vehicle trajectories and examine the behavior of both CAVs and MDVs in a mixed-traffic scenario by merging car-following and lane-changing models (Srisurin and Kondyli, 2021).

A brand-new car-following model was presented by Bingmei Jia, et al, in 2020, which took into account the effect of preventing lane change. The final velocity of the car in front of it combines a safe velocity with a velocity that prevents lane changes. Using numerical simulation, the model's stability condition was derived, validated, and the various factors that affect stability were examined. The outcomes show that the stability requirement agrees with the outcomes of the simulation. The proportion and lane-changing time headway have optimal values that can produce the best level of traffic flow stability (Bingmei Jia, et al, 2020).

Rehman, et al, analyzed the influence of variations in vehicle velocity on the performance of two messaging techniques, the furthest distance, and connection quality-based schemes, which are often used in VANETs. Their study focused on message reachability and end-to-end (E2E) communication delay as crucial performance indicators for VANETs. The important understanding of how network density and mobility velocity impact communication dependability in VANETs was investigated (Rehman, et al, 2020).

Farooq and Juhasz look into how different traffic characteristics affect lane-changing behavior for a "cautious" driving stance on highways at 2019. Their goal is to comprehend how variables like velocity variance and the frequency of vehicles going over the velocity limit affect lane-changing decisions. They offered important insights to improve traffic safety and

efficiency on motorways by examining these elements. The study also made an effort to create a regression model to calculate how often lanes change as a result of the parameters that were observed. In contrast to other traffic characteristics, the regression model's findings indicated that intended velocity distribution had the greatest impact on the frequency of lane changes. They indicated the most important traffic factors that affect the frequency of lane changes (Farooq and Juhasz, 2019).

Li and Sun examined the relationship between lane-changing behavior and its effects on traffic flow, safety, and environmental factors. They used various models and simulations to assess the effects of various lane-changing tactics on traffic characteristics. Their study provided useful insights for traffic management, infrastructure design, and policy-making to increase traffic efficiency, and safety, and reduce environmental impacts by investigating the interaction between lane-changing actions and their effects (Li and Sun, 2017).

"A Game Theory Approach" was presented by Talebpour, et. al, in 2015. They presented a lane-changing model that accounts for the flow of information between connected vehicles and used game theory to capture the strategic interactions between drivers. The suggested model categorizes lane-changing maneuvers as either mandatory or discretionary. Based on this work, a proposal is created in this dissertation study to study the possibility of implementing the principle of the binomial distribution as the driver has two options either to change the lane or to stay in the original lane (Talebpour, et al, 2015).

No	Reference	Models	Result	Data	Parameters
1	(Zhang, et al, 2022)	suggested a proposed method for simulating the connected and automated vehicles' decision-making behavior when changing lanes	the MIP model to more correctly mimic and forecast CAV behavior, resulting in safer and more effective traffic systems		Vehicle velocity, the volume of nearby traffic, and the final destination.
2	(Anderson, et al, 2021).	presented a kinematic model that predicts the trajectories of vehicles on highways			vehicle's initial position, speed, and acceleration,
3	(Kurtc, 2021).	analysis of car-following behavior	The analysis revealed that the car-following behavior of drivers was influenced by a variety of factors, including traffic density, speed, and the presence of other vehicles	HighD dataset	
4	(Srisurin and Kondyli, 2021).	Car-following and lane-changing behaviors.	They claimed that they can more accurately forecast vehicle trajectories and examine the behavior of both CAVs and MDVs in a mixed-traffic scenario		
5	(Bingmei Jia, et al, 2020).	car-following model and lane change	The proportion and lane-changing time headway have optimal values that can produce the best level of traffic flow stability. The drivers' car-following behavior is not only affected by the preceding vehicle on the same lane but also be affected by the vehicles on the adjacent lanes.	NGSIM	lane-changing time headway, safe velocity and lane-changing prevention velocity.

6	(Farooq and Juhasz, 2019).	lane-changing	The drivers' car-following behavior is not only affected by the preceding vehicle on the same lane but also be affected by the vehicles on the adjacent lanes.		velocity variance and frequency of vehicle
7	(Li and Sun, 2017).	lane-changing behavior	Their study provided useful insights for traffic management, infrastructure design, and policy-making to increase traffic efficiency, and safety, and reduce environmental impacts by investigating the interaction between lane-changing actions and their effects		Traffic flow, safety, and environmental factors
8	(Talebpour, et al, 2015)	lane-changing model	The suggested model categorizes lane-changing maneuvers as either mandatory or discretionary	NGSIM	

1.8 Dissertation Organization

In addition to the first chapter, this dissertation contains the following chapters:

Chapter Two: is entitled Theoretical Background. In this chapter, VANETs are clarified with challenges and applications. Mobility models in the VANET approach are discussed with criteria and types. Prediction is explained especially prediction using Markov. Many probability distributions are explained. As well, Data Dissemination in VANET is explained. The performance metrics for data dissemination are discussed.

Chapter Three: In this chapter, the developed modeling approach is clarified as well as the method of applying the developed models in the proposed environment. Car-following mobility models are analyzed, modified, and applied based on certain reliable improvements. The data dissemination is also clarified in this chapter.

Chapter Four: The results are discussions were presented in this chapter. The most affected performance metrics and evaluations and their relations were also presented and listed as graphs and tables. All the models and data dissemination calculations for each data dissemination model were listed and discussed. A comparison among many cases for different scenarios was also performed.

Chapter Five: Conclusions And Future Works were presented in this chapter.

CHAPTER TWO
THEORETICAL BACKGROUND

2.1 Introduction

In the last few years, Vehicular Networks opens wide new research directions. It represents the core of the ITS. VANET helps in providing users with safety and infotainment. These goals require stable communication. This is not compatible with VANET's dynamic topology and frequent communication disconnections.

2.2 Vehicular Ad hoc Networks

VANETs are the result of advanced improvements in wireless technology, ITS, and car engineering. They are regarded as a particular class of Mobile Ad hoc networks (MANETs), with nodes acting as vehicles and having needs and characteristics. A VANET is a network of vehicular nodes and fixed roadside units as entities that cooperate to communicate and exchange vital data based on traffic patterns and other vehicles (Liang et al., 2019)

One of the primary driving forces behind the development of VANETs is the increasing demand for ITS that harness advanced communication technologies to enhance road safety, traffic efficiency, and driver comfort (Shinde and Tarchiet, 2021).

By enabling the real-time exchange of information, such as traffic updates, accident warnings, and route guidance, VANETs have the potential to significantly reduce the number of road accidents, alleviate traffic congestion, and minimize fuel consumption (Menouar et al. 2017)

People utilize vehicles extensively on a daily basis. Sharing information among vehicles is crucial and supportive of ITS since there are numerous road incidents that vehicles cause that result in human fatalities. This data is based on two categories: both safety-related and unrelated information (Aldegheishem, et al, 2018). VANETs facilitate direct communication between vehicles V2V and

between vehicles and the infrastructure of V2I in a decentralized, self-organizing manner (Al-Sultan et al. 2014).

There are three environments in VANET (rural, urban, and highway environment) and each type of them have different characteristics and different road conditions (Najafzadeh, et al, 2014):

2.2.1 Communication in VANET

Vehicular Ad-Hoc Networks (VANETs) enable communication among vehicles and between vehicles and infrastructure. Communication in VANETs is typically based on wireless technologies, such as Wi-Fi and Dedicated Short Range Communications (DSRC), which enable data exchange between vehicles and infrastructure units (Arena et al, 2020).

In vehicular networks, communication can be classified into two categories: V2V and V2I. V2V communication allows direct communication between vehicles, while V2I communication enables communication between vehicles and roadside infrastructure such as traffic lights, road signs, and toll gates (Li, 2014), (Jantošová et al, 2019), (Arena et al, 2020).

Figure 1.1 shows the different communication modes used by vehicles to exchange information with each other and with the infrastructure.

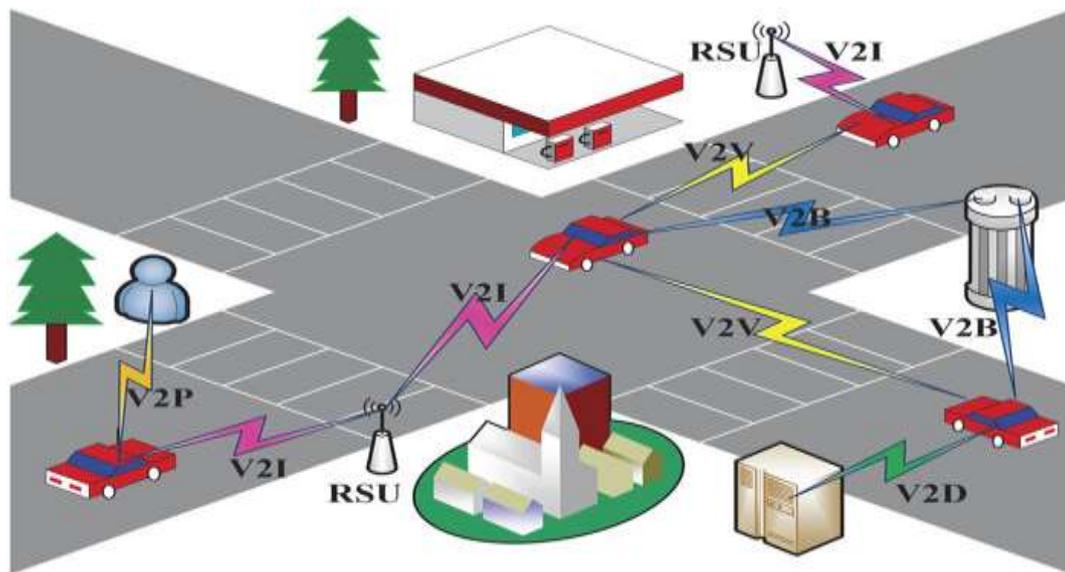


Figure 1.1 Communication type in the vehicular networks (Zhang and Wei, 2021)

2.2.2 VANET applications

The VANETs offer an opportunity for the development of applications that allow for the improvement of transportation and vehicular traffic conditions through collaborative systems built on v2x communications. Based on their purpose, vehicle applications are categorized into three groups: road effectiveness, traffic safety, informational services, and commercial services (Hamdi, et al, 2020).

A. Safety Applications

These applications aim to prevent accidents, damage, and save human lives on the road, also deliver safety-related information to the vehicle's drivers. In this type, an alarm message was associated with road events to notify the driver. The information contains incident management and nearby vehicles (Rasheed *et al.*, 2017). Most of these applications are collision avoidance and incident management (Hamdi *et al.*, 2020).

B. Unsafety Applications (Infotainment)

This application provides passengers with suitable information and entertainment to achieve people's comfort and improve traffic efficiency. It provides the drivers with Internet connectivity, and the location of shopping malls, restaurants, etc. (Ahmad *et al.*, 2018). This application contains two types: entertainment and background information (Hamdi *et al.*, 2020).

2.2.3 VANET Characteristics

Here are some of the most important characteristics of the VANET (Hamdi *et al.*, 2020):

1. **Dynamic Topology:** Because of the great mobility of the vehicles, the topology of the VANET environment is continually changing. The link between two cars going in opposing directions at suburban average speeds is only sustained for a very little period of time. In a motorway or highway setting, this connection time is significantly shorter as the speed of the cars rises.
2. **Disconnections:** Because of the rapid node mobility and frequent environmental changes, the connection of links between the VANETs vehicles is frequently disconnected.
3. **Mobility Modeling:** For this extremely dynamic environment of VANET, a realistic mobility model is necessary in order to implement VANET effectively and accurately.
4. **Mobility Patterns prediction:** In a VANET system, the majority of vehicles travel on routes that have already been established. This makes it possible to employ predictable mobility patterns when designing networks.
5. **Unlimited Power:** VANET nodes enjoy the benefit of having longer battery lives than other Mobile Ad-hoc Network (MANET) devices.

This may be used to handle complicated routing and security methods in the network that are computationally intensive.(Hamdi *et al.*, 2020).

2.2.4 VANET Challenges

Some of the most recognizable characteristics of a VANET are its dynamic architecture, rapid speed, driver behavior, and mobility limits. Since these characteristics have a substantial effect on networks' evaluations, some of the difficulties can be overcome. (Misener, Biswas, and Larson, 2011)(Fernandes and Nunes, 2007):

- **Node velocity**

In a VANET, nodes can be RSUs (remote sensing units) or vehicles (reaching speeds of up to 200 km/h on the highway). Given the unusual difficulty of maintaining connectivity in this scenario, speed will play a significant role in VANET (Hamdi *et al.*, 2020). RSUs have a range of around 1 kilometer, but vehicles moving at high speeds quickly leave that range and are no longer within range of the RSUs. When dealing with accelerated speeds, especially on the highway, the clustering method is the best option (Bao *et al.*, 2020).

- **Movement Patterns**

A VANET is potentially distinguished by a large number of mobile nodes (such as the speed of a vehicle). This high mobility can be crucial to the character of roadways (highways RSUs small streets) (Soleymani, *et al.*, 2020). Automobiles do not drive in a random manner; in reality, they probably move in two directions on highways that have been established. Typically, irregular shifts in vehicle direction only occur at road crossings. There are three distinct sorts of roadways (Contreras and Games, 2020), including freeways, rural roads, and urban roads.

- **Node Density**

Node density refers to the number of vehicles (nodes) present within a specific area of the network. The density of nodes is an important factor that influences the performance and characteristics of VANETs. It significantly affects network connectivity, routing protocols, communication overhead, and the effectiveness of safety applications. Numerous research has focused on node density. The writers (Hamdi, et al., 2020) rely on trust to evaluate the reliability and collect information such as the vehicle's location.

- **Scalability and availability**

Scalability indicates that a network's performance is unaffected by its expansion in size. Despite the strength of the channel, it is nevertheless susceptible to attack and network disruption. Availability is a crucial characteristic of VANET since the availability of the network is relevant to security, for example, when attackers bring the network down (denial of service) (Bakhtiari, et al., 2020).

- **Frequent disconnection:**

High node velocity leads to frequent changes in network topology, making it challenging to maintain stable connections between vehicles. This can result in reduced network performance and increased packet loss (Bakhtiari, et al., 2020).

2.3 Mobility of Vehicle

Mobility in VANETs plays a crucial role in ensuring efficient communication among vehicles and infrastructure.

VANETs are wireless networks formed by vehicles communicating with each other and with infrastructure components, such as roadside units (RSUs). In VANETs, vehicles are constantly moving and changing their positions, which can affect the quality of communication and the performance of network protocols (Benrhaïem and Hafid, 2020)

The vehicles mobility affects the network in different ways. For example, it affects the topology of the network, the routing paths between vehicles, the signal strength of the wireless transmissions, and the availability of communication links. Therefore, it is important to consider the mobility patterns of vehicles when designing VANETs (Gillani, et al, 2022)

To address the challenges posed by vehicle mobility in VANETs, researchers have proposed various protocols and techniques. These include mobility models to simulate the movement of vehicles, routing protocols that take into account the mobility of vehicles, and handover mechanisms to manage the transition of communication links between vehicles and RSUs (Wahid, et al, 2022)

2.4 Mobility Models for VANETs

Mobility models for vehicular ad hoc networks are essential for simulations and performance analysis of such networks. A popular model used in such simulations is the car-following model, which focuses on the pattern and reaction of vehicles while they follow a leader vehicle. This model can be used to analyze the interactions between vehicles and predict traffic density in vehicular ad hoc networks. It also helps to determine the effect of speed, acceleration, and deceleration on traffic flow. A car-following model is an

effective tool that helps to understand and improve mobility models for vehicular ad hoc networks (S, Pradeep Kumar T, 2023)

Since actual vehicle tracks are not accessible, the movement of vehicles can be generated using a traffic simulator. On the road, however, driver conduct is quite complicated. In order to safely navigate the road, drivers must interact with the environment. Road conditions (e.g., congestion) depend in turn on the drivers' plans and conduct.

The motions of vehicles during a simulation of VANETS are defined by the mobility model in a given area (real map, road platform, etc.). Depending on the level of description, mobility models are split into three groups. Therefore, the choice of the traffic simulator affects the final relevance and practicality of the data obtained (Gillani, et al, 2022). The two main types of vehicular traffic simulators are microscopic and macroscopic simulators.

These models can specify free or constrained movement such as constrained speed, the existence of impediments, and realism-related restrictions due to mobility restrictions. They are defined as follows (Zong, et al, 2021):

1. **Macro mobility:** When attempting to analyze the amount of traffic, macroscopic models are employed. In addition to its structure (unidirectional, multidirectional, one or more channels, etc.), this sort of model considers the topology of the road (street, lane, intersections), traffic density, type of traffic, initial distribution of vehicles on the various tracks, etc.
2. **Micro mobility:** in this type of model, the vehicle movement as well as any interactions it may have with its surroundings such as lane changes, overtaking, signaling, and driving at junctions are analyzed.

2.5 Car Following Models

Car-following mobility models play a crucial role in the study and analysis of traffic flow dynamics, enabling researchers and engineers to simulate and predict the behavior of individual vehicles on roadways (Cui, et al, 2022). The primary objective of these models is to describe how drivers adjust their speed and following distance in response to the movements of preceding vehicles, thereby capturing the fundamental interactions between vehicles in traffic streams (Ahmed, et al, 2021).

Over the years, various car-following models have been proposed, each with distinct assumptions and characteristics that address different aspects of driver behavior and traffic flow (Treiber and Kesting 2013). Early models, such as the General Motors (GM) model and the optimal velocity model, were based on simple mathematical formulations that focused on the relationship between vehicle speeds, distances, and accelerations (Ahmed, et al, 2021). In recent years, significant advancements have been made in car-following models, with researchers focusing on the development and refinement of these models to better represent real-world vehicle interactions and to accommodate emerging technologies (Cui, et al, 2022).

The micro-simulation tool defines the acceleration/deceleration (maximum, minimum, and desirable values), speed (minimum, maximum, and desired values), and other vehicle parameters for any car following the model using a variety of statistical distributions and functions, so there are some examples of the car following models such as The General Motors (GM) model, the Safety distance or collision avoidance model, the psychophysical Wiedemann model, the optimal velocity model (OVM), the intelligent driver model (IDM), the adaptive cruise control (ACC) and cooperative adaptive cruise control (CACC) models (Ahmed, et al, 2021).

1. Safety Distance Model

The safety distance model is one of the car-following models. It is also known as the Gipps model and it was widely used in avoiding the collision class. This class of car-following models attempts to determine a safe following distance behind the leading vehicle. These models contain two parts: acceleration and deceleration sub-models. This acceleration sub-model is equivalent to the empirical formulations displayed by Eq. (2.1) (Ahmed, et al, 2021).

$$v_n^{acc}(t + \Delta t) = v_n(t) + 2.5 \cdot a_n \cdot \Delta t \left[1 - \frac{v_n(t)}{\text{desired speed}} \right] \sqrt{0.025 + \frac{v_n(t)}{\text{desired speed}}} \dots \dots (2.1)$$

Where the acceleration of the vehicle is $v_n^{acc}(t + \Delta t)$, Δt is the reaction time, $v_n(t)$ is the speeds of vehicles n at time t , *desired speed* is the desired speed that the following vehicle wants to reach, and a_n is the maximum acceleration for a vehicle n .

2. General Motor Model

In traffic engineering, the General Motors (GM) car-following mobility model is a well-known and often used model. This model describes the behavior of a vehicle driver as they follow another vehicle, based on their relative speed and distance. (Chen, et al, 2022).

The assumption the GM makes is that a car traveling in a specific direction never exceeds another car or changes lanes, this is the linearity of the models and a constant sensitivity value is the General Motors Model (GMM) (Ahmed, et al, 2021).

It is derived from driving dynamics theory, and its basic formula for acceleration can be indicated as (Ahmed, et al, 2021).

$$a_n(t) = \alpha \cdot \Delta V_n^{front}(t - \Delta t_n) \quad \dots\dots\dots (2. 2)$$

Where the acceleration of driver “n” at time t is $a_n(t)$, $\Delta V_n^{front}(t - \Delta t)$ is the relative speed of the leader vehicle recorded at the time $(t - \Delta t)$, Δt is reaction time, and α is a constant term it is explain in more details in section 3.2.3

2.6 Probability Distributions

Probability distributions play a central role in the analysis of data and the modeling of uncertain events, providing the foundation for statistical inference and decision-making (Mastrogiacomo and Gianin, 2019). In recent years, researchers have been developing novel probability distributions and refining existing ones to better capture the complexities and nuances of real-world phenomena.

A random process is frequently described by one or more variables or features, and its outputs by numerical values or classifications. These variables or qualities are known as random variables or random attributes (Carraway and Jenkins, 2017).

There are several probability distribution types, such as:

1. Poisson probability distribution

The number (count) of statistically independent events taking place within a unit of time or space is a discrete random variable that is subject to the Poisson distribution, which is a probability distribution of discrete random variables. The probability function, when applied to the variable X, is defined as (Poisson) (Haenggi, 2021):

$$f(n) = P(X = n) = \frac{e^{-\mu} \mu^n}{n!} \quad (2. 3)$$

2. Normal probability distribution

The normal probability distribution, also known as the Gaussian distribution or bell curve, is a continuous probability distribution characterized by its symmetric bell shape. It is widely used in statistics and various fields due to its properties and the central limit theorem, which states that the sum of many independent and identically distributed random variables approaches a normal distribution as the number of variables increases.

The probability density function (PDF) of the normal distribution is given by:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} \quad \dots (2.4)$$

Where x is variable, μ is the mean of the distribution, representing the center of the bell curve, σ is the standard deviation, which indicates the spread or dispersion of the distribution

3. Binomial probability distribution

The binomial probability distribution is a discrete probability distribution that describes the number of successes in a fixed number of independent Bernoulli trials, each with the same probability of success. It is commonly used to model situations where there are only two possible outcomes, such as coin tosses or pass/fail tests.

The probability mass function (PMF) of the binomial distribution is given by:

$$P_x = \binom{n}{x} p^x q^{n-x} \quad \dots (2.5)$$

Where x is the number of the specific outcome within n trials, n is the number of trials, p is the number of successes, and q is the probability of failure in each trial

4. Uniform probability distribution

The Uniform or Rectangular distribution has random variable X restricted to a finite interval $[a, b]$ and has $f(x)$ has constant density over the interval. An illustration is [uniform-dis]:

$$f(x) = \begin{cases} \frac{1}{b-a}, & a \leq x \leq b \\ 0 & \text{otherwise} \end{cases} \quad \dots (2.6)$$

2.7 Stochastic Process

Mathematical models can be divided into probability models and deterministic models. Through this division, probabilistic models are more appropriate to represent most life phenomena. The use of probabilistic models is more used than their specific counterparts, as they are given in the form of groups or families of random variables instead of a single value for the random variable. Random variables are grouped using a parameter such as time. These are known as stochastic processes (or random/chance processes (Ge, Gao, and Quan, 2018)).

The theory of stochastic processes plays an important role in the investigation of the stochastic phenomenon depending on time. The first results were achieved in this field with research on Brownian motion, telephone calls, and traffic accidents. The basis for the mathematical theory of stochastic processes was given by A. N. Kolmogorov (1931) and since then the theory and practice of stochastic processes in it have not undergone significant development (Vvedenskaya *et al.*, 2018).

The birth-death process is a continuous Markov process in which only two ways are stated: birth, which increases the state variable by one, and death, which decreases the state by one. The name of the model is derived from a population representation where transitions are literal births and deaths. The process of birth and death can be used to observe the number of vehicles in a cluster. When birth occurs, the process goes from state n to state $n+1$. When a death occurs, the process goes from state n to state $n-1$ (Rasheed *et al.*, 2017).

2.7.1 Continuous Markov Model

Markov chains and processes represent stochastic processes with a special property. This special property states that the current value depends only on the previous value, and the next future value can be estimated from the current value. A birth-death process (as a Markov process) is commonly used to analyze, describe and evaluate the process of estimating the changes in arriving or departing entities' number through time. This makes Markov processes memoryless. (Steel, Hordijk, and Kauffman, 2020).

Markov processes are used in a wide range of applications, including physics, chemistry, economics, finance, and computer science. They are especially useful for modeling systems that exhibit stochastic behavior, such as the stock market or weather patterns (Soukarieh and Bouzebda, 2022).

2.8 Lane change Modeling

Lane change modeling is a crucial aspect of traffic flow simulation and management, and it has been the subject of extensive research in recent years. Various approaches have been proposed to model lane-changing behavior, such as car-following models, cellular automata, and game theory-based models (Shen, et al, 2023) and (Ali, et al, 2019).

Recent studies have focused on enhancing the accuracy and realism of lane change models by incorporating a broader range of factors and parameters. For instance, researchers have explored the impact of driver characteristics, such as age, gender, and experience, on lane-changing decisions (Zhang, et al, 2022).

Moreover, with the advent of connected and autonomous vehicles, new challenges and opportunities have emerged for lane change modeling (Ahmed, et al, 2022). Some studies have proposed integrating vehicle-to-vehicle and vehicle-to-infrastructure communication to improve the accuracy and safety of lane-change predictions (Shen, et al, 2023). Others have explored the potential of machine learning techniques, such as deep reinforcement learning, to model complex and dynamic lane-changing behavior.

Overall, the latest research in lane change modeling has contributed to a better understanding of the complex dynamics of traffic flow and provided valuable insights for traffic management and infrastructure planning. As such, incorporating the latest findings in lane change modeling into traffic flow simulations can help improve traffic efficiency, safety, and reduce environmental impacts.

2.9 Data Dissemination

Lots of people lose their lives or infect with deformities due to accidents or sad sudden events on roads, as well as losing fuel and time in traffic jams. Providing vehicles with timely and frequent information about traffic conditions and unexpected occurrences of dangerous events can improve human safety, ITS efficiency, and reduce fuel loss and time (Sutariya and Pradhan, 2010). In VANET, Information can spread among vehicles that contain communication equipment. Each vehicle plays the role of the sender, router, or receiver. Warning messages can propagate among vehicles to inform about traffic,

weather conditions, unexpected events, etc. This process can be done through DSRC which has a low to medium range, which can connect V2V and V2I (Lochert *et al.*, 2007).

2.9.1 Data Dissemination Classification

Data dissemination in VANETs refers to the process of distributing information among vehicles and infrastructure components, such as roadside units (RSUs). This process is crucial for various applications, including traffic safety, traffic management, and infotainment services (Azzaoui, et al, 2022).

In VANETs, data dissemination can be classified into three main categories:

- 1. Broadcast-based dissemination:** This approach involves transmitting data to all neighboring vehicles or nodes without considering specific target recipients. It is useful for safety-related messages, such as emergency warnings or collision avoidance alerts. Flooding and probabilistic broadcasting are two common techniques in this category.
- 2. Geocast-based dissemination:** In this approach, data is disseminated to vehicles within a specific geographic region or area of interest. Geocasting is particularly effective for location-based services and applications, such as traffic signal coordination, traffic jam notifications, and parking availability updates. Various geocasting protocols, such as GeoNet and DG-Cast, have been proposed to optimize data dissemination in VANETs.
- 3. Unicast-based dissemination:** This method involves transmitting data between two specific nodes, typically a sender and a receiver. Unicast-based dissemination is useful for point-to-point communication and applications that require reliable and secure data transfer, such as

electronic toll collection or vehicle diagnostics. Routing protocols, such as AODV, DSR, and GPSR, can be employed for efficient unicast communication in VANETs.

2.5.2 Evaluation Metrics

The effective proposed mobility model that is based on different performance evaluation metrics that ensure the model. (Talib *et al.*, 2020). Following are some of the important metrics that can be used in evaluating the data dissemination of the proposed VANET mobility model (Rathore, et al, 2020)

1. Throughput:

It can be measured by dividing the total number of packets that transfer by total times. This can be estimated by Eq. (2.7) (Hasson and Abbas, 2021):

$$\text{Throughput} = \frac{(\text{number of received packets} \times \text{size of packet})}{\text{total time}} \quad \dots\dots (2.7)$$

2. End-to-End (E2E) Delay:

It is an important factor in data dissemination. It can be calculated by dividing the total time of transfer of the message from the source to another node until it reaches the destination by the summation of received packets. As shown in Eq. (2.8) (Hasson and Abbas, 2021):

$$\text{E2E Delay} = (\text{Time of receive} - \text{Time of sending}) \quad \dots\dots (2.8)$$

3. Message Loss:

It can be calculated by subtracting the summation of received packets from the total created packet as shown in Eq. (2.9).

$$\text{Message loss} = \text{No. of sent messages} - \text{No. of received messages} \quad \dots (2.9)$$

4. Packet Delivery Ratio (PDR):

It can be calculated by dividing the received message's summation by the created message's summation as shown in Eq. (2.10).

$$\text{Packet Delivery Ratio (PDR)} = \frac{\sum \text{number of recieved messages}}{\text{number of sending messages}} * 100 \quad \dots (2.10)$$

2.10 VANET Simulation

Vehicular network simulations involve modeling and analyzing the behavior of communication networks specifically designed for vehicles, known as vehicular communication systems (VCS). Vehicular network simulations are computer-based models that replicate the behavior and characteristics of vehicular communication systems. These simulations allow researchers, engineers, and developers to study various aspects of vehicular networks, such as traffic management, safety applications, mobility patterns, communication protocols, and network scalability. By simulating vehicular networks, it becomes possible to assess the impact of different factors on network performance and devise strategies for optimizing vehicular communication systems.

Several simulation tools have been developed to facilitate the analysis and evaluation of vehicular network systems. These tools provide capabilities for modeling the physical environment, vehicle movements, wireless communication links, and network protocols. Such as SUMO (Simulation of Urban MObility), ns-3 (network simulator 3), OMNeT++, Veins, MATLAB and Simulink, and NetLogo simulation.

These are just a few examples of the simulation tools available for studying vehicular networks. Each tool has its strengths and focuses on different aspects of vehicular communication systems, allowing researchers and developers to

choose the most suitable tool based on their specific simulation requirements and objectives.

2.10.1 Netlogo Simulation

NetLogo is a powerful, open-source agent-based modeling and simulation platform developed by the Center for Connected Learning and Computer-Based Modeling at Northwestern University. It provides a versatile environment for simulating complex systems and processes, making it well-suited for modeling traffic flow and lane-changing behavior (Ramli and Rawi, 2020).

As VANETs are systems that contain many vehicles (agents) that behave in a self-organized manner, Agent-Based Modeling can model such systems no matter how difficult they are. (Hiroki Sayama, 2015) has defined Agent-Based Modeling as “computational simulation models that involve many discrete agents.”

In this dissertation, the application of NetLogo is used for simulating lane-changing dynamics and outlining the key components of our simulation model. By utilizing the NetLogo simulation platform, researchers can gain valuable insights into the complex dynamics of traffic flow and lane-changing behavior. This, in turn, can inform traffic management strategies and infrastructure planning to improve overall traffic efficiency and safety.

2.11 Datasets Description

In order to implement, model, and evaluate the safety distance and general motor (GM) car-following models, two datasets are utilized.

The first dataset is highD. In this dataset, vehicle trajectories recorded on the German highways dataset (highD) are downloaded from ([The highD Dataset \(highd-dataset.com\)](http://highd-dataset.com)). A highD dataset is utilized in this dissertation. It represents a collection of accurate vehicle trajectories. A highD dataset contains more than

110 500 vehicles, the total driven distance is 44 500 kilometers, and 147 driven hours in traffic at six distinct sites. The trajectory of each vehicle, including its size, type, and maneuvers, is automatically extracted. The placement inaccuracy is often less than 10 centimeters when using cutting-edge computer vision techniques. Enriched Data Pre-extracted information includes surrounding vehicle metrics like Time Headway (THW) or Time-to-Collision (TTC), and Driven maneuvers (e.g. lane changes).

In this dissertation, a subset of the highD dataset (0_1 trucks) was considered. This file contains all time-dependent values for each vehicle (car and truck). Information such as current velocity, viewing ranges, and information about surrounding vehicles are included.

The next step is to split the file into two files each one representing one direction. Each direction file also divides into two files based on the vehicle type (car or truck). Each file contains the vehicle's ID, direction with its velocity, and acceleration in different frames for each period of time. Figure (4.1) shows a screen view of a sample from the presented highD dataset.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
1	frame	id	x	y	width	height	xVelocity	yVelocity	xAccelerat	yAccelerat	frontSight	backSight	L_dhw	thw	ttc	preceding	preceding
2	1	1	362.26	21.68	4.85	2.12	40.85	0	0.3	0	48.05	363.77	0	0	0	0	0
3	2	1	363.73	21.68	4.85	2.12	40.87	0	0.3	0	46.54	365.28	0	0	0	0	0
4	3	1	365.27	21.68	4.85	2.12	40.88	0	0.31	0	44.87	366.95	0	0	0	0	0
5	4	1	366.83	21.68	4.85	2.12	40.89	0	0.32	0	43.25	368.57	0	0	0	0	0
6	5	1	368.42	21.68	4.85	2.12	40.9	0.01	0.32	0	41.64	370.18	0	0	0	0	0
7	1	2	162.75	9.39	4.24	1.92	-32.04	0	-0.26	0	164.63	247.19	0	0	0	0	0
8	2	2	161.58	9.39	4.24	1.92	-32.06	0	-0.27	0	163.41	248.41	112.62	3.51	-17.38	-38.53	13
9	3	2	160.36	9.39	4.24	1.92	-32.07	0	-0.27	0	162.05	249.77	112.73	3.51	-17.36	-38.55	13
10	4	2	159.13	9.39	4.24	1.92	-32.08	0	-0.27	-0.01	160.84	250.98	112.91	3.52	-17.36	-38.58	13
11	5	2	157.86	9.39	4.24	1.92	-32.09	0	-0.27	-0.01	159.47	252.35	113.11	3.52	-17.36	-38.6	13
12	6	2	156.59	9.39	4.24	1.92	-32.1	0	-0.27	-0.01	158.16	253.66	113.36	3.53	-17.36	-38.62	13
13	7	2	155.31	9.39	4.24	1.92	-32.11	0	-0.28	-0.01	156.95	254.87	113.57	3.53	-17.36	-38.65	13
14	1	3	182.08	21.64	3.94	1.92	35.69	0	0.17	0	228.7	183.12	176.24	4.94	-34.08	40.85	1
15	2	3	183.39	21.64	3.94	1.92	35.69	0	0.17	0	227.28	184.54	90.31	2.53	-15.56	41.49	14
16	3	3	184.75	21.64	3.94	1.92	35.7	0	0.18	-0.01	225.82	186	90.47	2.53	-15.57	41.5	14
17	4	3	186.13	21.64	3.94	1.92	35.71	0	0.18	-0.01	224.35	187.47	90.66	2.54	-15.59	41.51	14
18	5	3	187.53	21.64	3.94	1.92	35.71	0	0.19	-0.01	222.94	188.88	90.86	2.54	-15.62	41.53	14
19	6	3	188.95	21.64	3.94	1.92	35.72	-0.01	0.19	-0.01	221.52	190.3	91.08	2.55	-15.64	41.54	14
20	7	3	190.37	21.64	3.94	1.92	35.73	-0.01	0.19	-0.01	220.01	191.81	91.3	2.55	-15.67	41.55	14
21	8	3	191.79	21.64	3.94	1.92	35.74	-0.01	0.2	-0.01	218.59	193.23	91.53	2.56	-15.7	41.56	14
22	9	3	193.21	21.64	3.94	1.92	35.75	-0.01	0.2	-0.01	217.28	194.54	91.76	2.56	-15.72	41.58	14

Figure (4.1) Screen view of a sample from a highD dataset.

In highD records, the velocities and accelerations for each vehicle are recorded in different frames for each period of time. The total number of records is 348,756. These records are summarized into 1047 records by estimating the average and standard deviation values for each vehicle from its recorded frames.

The second dataset is the Vehicle Trajectories for Next Generation Simulation (NGSIM) and Related Information ([Next Generation Simulation \(NGSIM\) Vehicle Trajectories and Supporting Data | Department of Transportation - Data Portal](#)). On June 15, 2005, in Los Angeles, California, researchers for the NGSIM program gathered thorough vehicle trajectory data on southbound US 101, often known as the Hollywood Freeway. Five mainline lanes made up the research area, which was about 640 meters (2,100 feet) long and had five of them. Between the on-ramp at Ventura Boulevard and the off-ramp at Cahuenga Boulevard, a

section of the corridor has an extra lane. Vehicles traveling through the study area were captured on video by eight synchronized digital video cameras positioned on the top of a 36-story structure close to the motorway. The vehicle trajectory information was extracted from the video using NG-VIDEO, a specially designed software program created for the NGSIM initiative. Figure (4.2) shows a screen view of a sample from the presented NGSIM dataset.

Vehicle_ID	Frame_ID	Total_Far	Global_T	Local_X	Local_Y	Global_X	Global_Y	v_Length	v_Width	v_Class	v_Vel	v_Acc	Lane_ID	O_Zone	D_Zone	Int_ID	Section_ID	Direction	Movement	Preceding	Following	Space_Hes
515	2300	1,123	1.12E+12	30.084	188.062	6451204	1873293	13	6.9	2	23.31	2.05	3	NA	NA	NA	NA	NA	NA	500	523	119.1
515	2300	1,123	1.12E+12	30.084	188.062	6451204	1873293	13	6.9	2	23.31	2.05	3	NA	NA	NA	NA	NA	NA	500	523	119.1
2224	6548	1,902	1.11E+12	41.429	472.901	6042814	2133542	14.3	6.9	2	26.54	-0.76	4							2,206	2,211	53.34
2127	6459	567	1.12E+12	19.632	1,775.61	6452425	1872172	13.5	6.9	2	37.52	11.2	2	NA	NA	NA	NA	NA	NA	2,124	2,132	48.92
1033	4827	592	1.12E+12	6.202	1,701.14	6452348	1872258	13.5	4.4	2	41.99	0.1	1	NA	NA	NA	NA	NA	NA	1,019	1,040	38.81
1033	4827	592	1.12E+12	6.202	1,701.14	6452348	1872258	13.5	4.4	2	41.99	0.1	1	NA	NA	NA	NA	NA	NA	1,019	1,040	38.81
1890	9157	628	1.12E+12	53.514	817.521	6451655	1872801	24	8.5	3	45.12	-0.55	5							1,882	1,897	102.65
744	3392	996	1.12E+12	28.878	490.086	6451422	1873041	15	5.9	2	24.54	-0.04	3	NA	NA	NA	NA	NA	NA	740	752	37.8
744	3392	996	1.12E+12	28.878	490.086	6451422	1873041	15	5.9	2	24.54	-0.04	3	NA	NA	NA	NA	NA	NA	740	752	37.8
879	6336	811	1.12E+12	-24.046	513.096	6452106	1873272	15	7	2	0	0	1	108	201	0	3	4	1	869	881	22.92
2283	8002	1,821	1.11E+12	55.072	1,124.71	6042739	2134191	15.9	5.9	2	6.57	3.93	5							2,330	2,344	46.38
1503	8609	1,130	1.12E+12	-6.564	996.874	6452314	1873715	16.2	7.4	2	47.47	5.98	1	108	201	0	3	4	1	1,502	1,509	46.1
2252	6364	2,150	1.11E+12	54.277	174.602	6042864	2133248	15.3	6.9	2	7.33	0	5							2,117	2,266	35.98
2388	7958	1,318	1.11E+12	63.707	1,655.65	6042758	2134124	13.3	7.8	2	25.78	7.44	6							2,381	2,394	39.17
1919	8338	1,856	1.11E+12	40.935	1,368.25	6042686	2134430	14.3	6.9	2	4.79	0.3	4							1,910	1,925	25.03
496	2766	771	1.12E+12	52.141	1,656.45	6452284	1872253	15	4.9	2	32.59	-6.93	5	NA	NA	NA	NA	NA	NA	510	502	68.21
496	2766	771	1.12E+12	52.141	1,656.45	6452284	1872253	15	4.9	2	32.59	-6.93	5	NA	NA	NA	NA	NA	NA	510	502	68.21
946	4104	676	1.12E+12	5.373	365.819	6451347	1873143	13	4.4	2	22.67	0	1	NA	NA	NA	NA	NA	NA	936	951	60.94
946	4104	676	1.12E+12	5.373	365.819	6451347	1873143	13	4.4	2	22.67	0	1	NA	NA	NA	NA	NA	NA	936	951	60.94
633	3318	275	1.12E+12	-51.513	399.214	6452032	1873196	12.5	7	2	21.8	0	1	111	205	2	0	1	2	0	0	0
1779	5317	490	1.12E+12	31.09	713.063	6451633	1872850	28	7.9	3	49.92	1.69	3	NA	NA	NA	NA	NA	NA	1,769	1,784	189.54
2780	8340	828	1.12E+12	17.385	858.349	6451736	1872778	10	5	2	0	0	2	NA	NA	NA	NA	NA	NA	2,768	2,792	24
1528	8866	404	1.12E+12	-24.053	452.041	6452083	1873225	19	8	2	43.39	0	1	108	201	2	0	4	1	0	1,541	0
1212	6655	1,176	1.12E+12	20.177	2,136.35	6452675	1873962	14.5	6.4	2	30.63	0.24	2	NA	NA	NA	NA	NA	NA	0	1,218	EM
1350	10267	925	1.12E+12	-14.416	520.815	6452118	1873275	18	7	2	0	0	12	108	203	0	3	4	1	1,338	1,353	28.07
204	1029	160	1.12E+12	36.966	241.56	6452034	1873008	13.5	6.5	2	43.85	11.25	3	102	203	0	2	2	1	162	0	64.15
2182	8334	787	1.12E+12	29.735	1,112.95	6451889	1872628	14.5	5.9	2	35.34	-3.27	3							2,177	2,193	69.99
2032	9204	2,019	1.11E+12	41.993	1,486.78	6042968	2134547	13.3	6.8	2	9.68	0	4							2,024	2,044	49.94

Figure (4.2) Screen view of a sample from an NGSIM dataset.

The second dataset (NGSIM) also contains different numbers of frames for each vehicle. This data was analyzed and processed to extract the velocity and acceleration averages for each vehicle and implement the developed mobility models.

CHAPTER THREE

THE PROPOSED SYSTEM

3.1 Introduction

Vehicular Network is one of the important solutions to Improve the ITS. There are two main challenges in modeling and simulating the vehicular network (VANET). These most important challenges are; the topology of VANET is rapidly changing because of the high mobility of the nodes, and secondly, the frequent communication disconnected. Improving a mobility model is significant to control these challenges and make it similar to the real case. On the other hand, these problems' effects on the VANET data dissemination and network performance must be analyzed. In this chapter, a developed car-following mobility model is analyzed, modified and applied based on certain reliable improvements. Developed approaches to estimate the safety distance and GM models parameters based on modeling certain real datasets are proposed. Proposed approaches are created to calculate the relative velocity and a mathematical model is proposed to represent the lane change process. These proposals' validity and effects on data dissemination are tested by different simulation scenarios using NetLogo 6.3.0 as an agent-based modeling approach.

3.2 The Proposed System

The main stages of the proposed system are represented by building the network environment which is composed of designing and creating Highway scenarios with different parameters such as number of vehicles based on variable arrival (flow) rates, road segments with a different number of lanes, models to create variable vehicles velocity, and models for randomly generating acceleration/deceleration of vehicles. All these are created using a NetLogo as a network simulator. Car following models are analyzed and discussed carefully. A certain data set is utilized to estimate these model parameters. One of these

models parameters is the constant term. This constant term was represented by the constant value in related works. In this dissertation model, a constant term in GM model is estimated based on a developed mathematical approach based on real road dataset. A modification is added to the original car-following model to suit the real vehicle's movement on roads. An additional parameter is added to the model to represent the state of the vehicle acceleration at each time. One of the most effective real case on roads is the driver behavior and lane change process. A proposed mathematical model is proposed to represent the lane change process. After modeling these cases, their effects on data transmission and network performance are discussed and observed in different scenarios. Figure (3.1) present the proposed system in this dissertation.

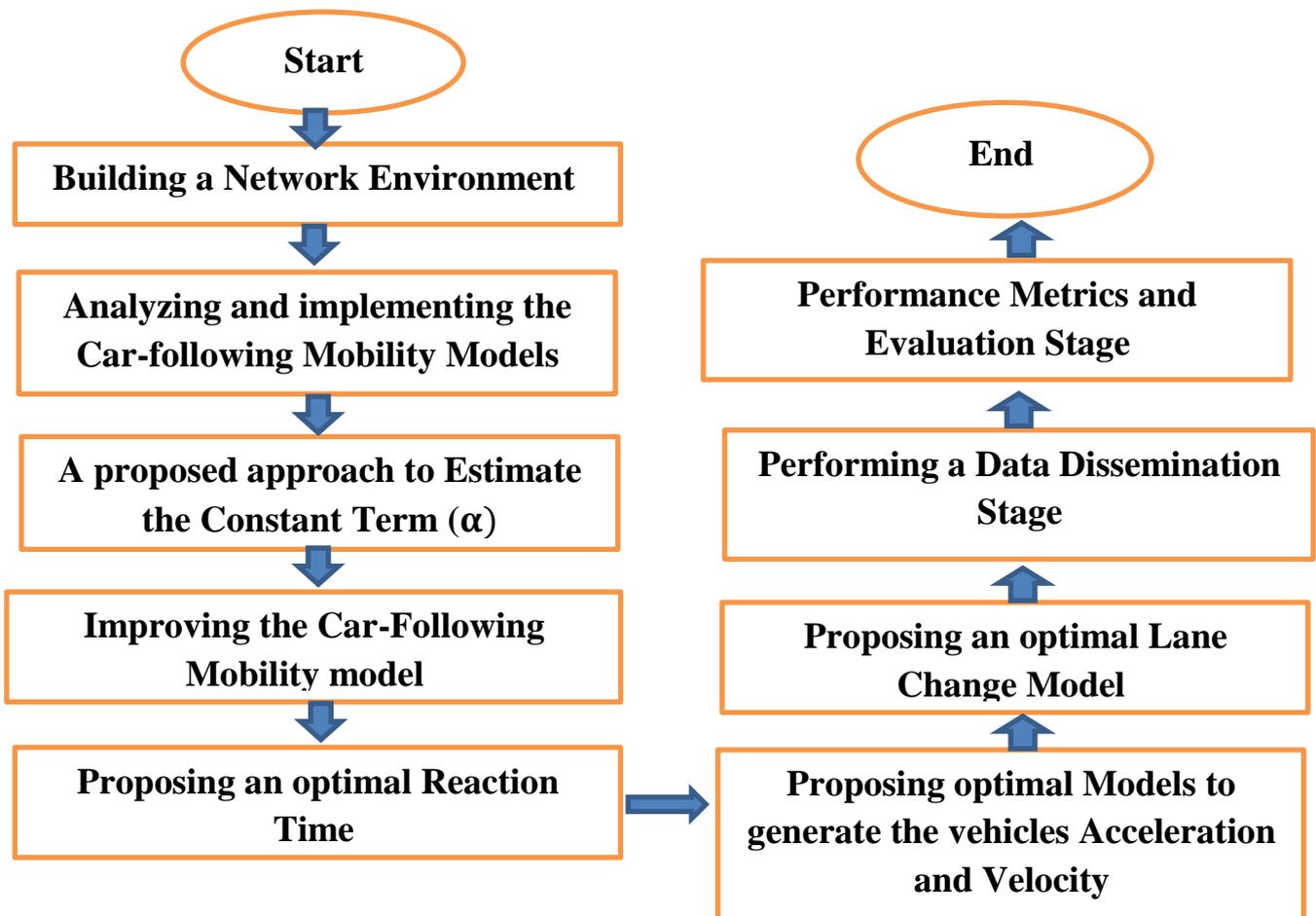


Figure 3.1 The Proposed System Stages

3.2.1 Building a Network Environment

To build a simulation environment to model the VANET, road segments, RSUs, vehicles, and road lanes must be created to model the vehicle's movements and their data dissemination process. For instance, low vehicle density is still the key concern in a sparse network like highway environment. One of the most important challenges in the VANETs environment is the mobility patterns, lane changing, acceleration, and deceleration. A highway environment is created to be suitable for simulation scenarios using an agent-based modeling approach (NetLogo 6.3.0). Following are the steps for creating the highway environment elements:

1. **Road Network Creation:** a road segment with a certain length is proposed and created in a simulation environment. In this dissertation, a road segment of 10 km length is used to test the proposed simulation mobility models. The road is designed with a variable number of lanes.
2. **RSUs Installation:** usually RSUs are located in specific places along the road segment to assist the vehicle's traffics. These RSUs provide centralized reliable communication with vehicles due to their large coverage area (about 1 km radius). A developed Eq. (3.1) is proposed to estimate the number of RSUs required to cover all the road segments' lengths:

$$No_RSU = \left(\frac{L}{RSU\ Coverage\ Diameter} \right) + 1 \dots \dots (3.1)$$

Where L is the length of the road segment, *No_RSU* is the number of required RSUs.

For example:

$L = 10$ Km and *RSU Coverage Distance* = 1 Km then 11 RSUs are required to cover this road segment length.

3. **Road lanes creation:** Each road in the real application is composed of different parts (lanes). Each lane represents a path for one vehicle. The real roads include two, three, four, and more lanes. In this dissertation, a variable slider is created to select the number of lanes in each road segment in each simulation scenario.
4. **Vehicle traffic Creation:** vehicles represent the main nodes in the VANETs environment. A number of vehicles entering the road segment can be created based on a certain arrival rate. The vehicle's arrival rate is proposed based on a certain statistical probability distribution. The entrance of the vehicles to the road segment is also created based on Poisson random probability distribution with three different arrival rates.

Traffic data from the traffic dataset (highD) is utilized to estimate the real vehicle arrival rate. Based on these arrival rates different scenarios are implemented to simulate the high, medium, and low traffic cases. The inter-arrival time can be created as the average period among the arriving vehicles. Eq. (3.2) is proposed to estimate the inter-arrival time base on the arrival rate (λ) observed from the dataset.

$$\text{Inter arrival time} = \left(\frac{1}{\lambda}\right) * 60 \quad \dots\dots\dots (3.2)$$

This random variable (Inter arrival time) is utilized in the simulation scenarios to create the sequence of the vehicle entrance to the road segment.

Based on the vehicles arrival rate (λ), the number of vehicles in each road segment can be estimated based on a developed Eq. (3.3)

$$N = \lambda * t \quad \dots \dots \dots (3.3)$$

Where N represents the total number of vehicles, λ is the expected incoming vehicles per unit time or the arrival rate, and t is the time interval.

Algorithm 3. 1 Moving-vehicles

Input: velocity, max-velocity, min-velocity, acceleration, deceleration

Output: Moving vehicles in a road segment

Begin

1: Vehicles generation on the road

2: **for** each vehicle in the road segment

3: Indicate and save its vehicle ID, velocity, location

4: **for** vehicle_{*i*} ∈ set of vehicles

5: **if** there is other vehicle in front of vehicle_{*i*} **then**

6: Indicate and save the ID, velocity, location of this front vehicle

7: velocity ← velocity of the front vehicle – (deceleration * B * time)

8: **else**

9: velocity ← velocity + (acceleration * B * time)

10: **if** velocity ≥ max-velocity **then**

11: velocity = max-velocity

12: **end_if**

13: **end_if**

14: **end_for**

15: **end_for**

16: **End** Algorithm

3.2.2 Analyzing the Car-following Mobility Models

As indicated in (2.1) and (2.2), these two models represent the essential foundation for vehicle mobility models.

Implementing Eq. (2.1) results in calculating the next vehicle (n) velocity at time ($t + \Delta t$) by adding certain elements to the previous velocity at the time(t). The essential part of these elements is vehicle acceleration(a_n). Utilizing the traffic dataset will result in a continuous increase in vehicle velocity value while the next vehicle velocity can increase, decrease, or stay in the same value after a certain time (Δt). This unusual case is observed and indicated as a gap that must be developed to suit the real case. The proposed development is presented in (3.2.4).

Implementing practical data may help in estimating certain values that can be used in analyzing these mobility model elements. Certain useful datasets are utilized in estimating the vehicle's velocities and accelerations. Each vehicle in this selected dataset file has different velocities and acceleration values in different recording frames. The positive velocity values are assigned to the moving vehicles on the east-direction road and the negative velocities are assigned to the moving vehicles on the west-direction road.

Each vehicle has one velocity and acceleration value in each frame. Summarizing these frames values are performed statistically. Each vehicle's mean velocity ($avg_{v(t)_k}$), acceleration (avg_{acc_k}), and standard deviations ($Stdv_v(t)$) and ($Stdv_{acc}(t)$) respectively.

These estimated values are used as input to the traditional safety distance and collision avoidance model Eq. (2.1). The safety distance and collision avoidance car-following model contains a special variable factor (a_n). The variable a_n represents the vehicle's acceleration. Values from the dataset are

utilized to estimate this value. This equation is used to predict the new vehicle velocity for the next period of time.

Related to Eq. (2.2), a constant term value (α) is used as a multiplier value in calculating the next value acceleration at time (t) based on the previous acceleration at time ($t - \Delta t$). In most related works, the value of this constant term is used as a certain fixed value. This way can be improved by proposing a mathematical model to estimate the feasible value for this constant term. Statement (3.2.3) presents this dissertation proposed approach to estimate the constant term value.

3.2.3 A Proposed Approach to Estimate the Constant Term

In the previous researches, all of the authors used a constant term (α) in applying general motor car-following models as a proposed specific value. In this dissertation proposed model, an approach is created to determine the suitable general motor model parameter values of the constant term (α). The driver behavior observed from the real datasets (highD and NGSIM) plays an important role in estimating this constant term.

Driver behavior can be represented by utilizing vehicle velocity and acceleration. The average values of α are extracted after long calculations. Each vehicle has many acceleration and velocity values (one acceleration and velocity value in each frame). A relative velocity value is calculated for each vehicle between any two successive frames, from each one of them a value for α is estimated. These α values are collected for each vehicle in a datasets and their average value is considered and used for future prediction.

To determine the suitable general motor model parameter values in Eq. (2.2), average, minimum, and maximum values for both parameters (velocity and acceleration) are calculated for each vehicle over different frames as shown

in Eqs. (3.4), (3.5), and (3.6):

$$V_{min_k} = \min_{i=1to n} (v_k) \quad (3.4)$$

$$V_{max_k} = \max_{i=1to n} (v_k) \quad (3.5)$$

$$avg_{v_k} = \frac{\sum_{i=1}^n v_i}{n_i} \quad (3.6)$$

Where V_{min} , V_{max} , and avg_{v_k} are the minimum, maximum, and average velocity for a vehicle k where ($k=1$ to 1047), n is the total number of frames (i) in the dataset. The numbers of frames are different from vehicle to vehicle. The average acceleration parameter as shown in Eq. (3.7):

$$avg_{Acc_k} = \frac{\sum_{i=1}^n acc_i}{n_i} \quad (3.7)$$

Where avg_{Acc_k} is the average acceleration for a vehicle k .

After this calculations, the relative velocity $\Delta V_n^{front}(t - \Delta t)$ is calculated in three different alternative ways. Calculating the relative velocity between any two successive vehicles' velocities at a different time involves determining the difference in their velocities. In this dissertation, the relative velocity is created based on the average, minimum, and maximum values for the velocity. The three values of the relative velocities (ΔV_1 , ΔV_2 , and ΔV_3) are calculated as indicated in Eqs. (3.8), (3.9), and (3.10):

$$\Delta V_1 = V_{max_k} - avg_{v_k} \quad (3.8)$$

$$\Delta V_2 = avg_{v_k} - V_{min_k} \quad (3.9)$$

$$\Delta V_3 = V_{max_k} - V_{min_k} \quad (3.10)$$

Understanding and calculating relative velocity is crucial in designing and improving mobility models, as it helps engineers and planners optimize traffic flow, enhance safety measures, and improve the overall efficiency of

transportation systems. By considering the relative velocity between vehicles, one can develop better traffic management strategies and create more intelligent transportation networks. Observing these three equations' results at different times and frames, a decision is made to implement the suitable one of these three equations.

3.2.4 Improving the Car-following Mobility Model

The main idea behind car-following models is that the movement of a vehicle depends on the behavior of the vehicle immediately in front of it. A car-following model typically considers the main parameters (safety distance, velocity, and acceleration) to evaluate the impact of a leading vehicle on its following vehicle.

A traditional safety distance car-following model was indicated in Eq. (2.1). The value of the velocity and acceleration for the vehicle (n) at the time (t) is used to predict its next velocity at the time ($t + \Delta t$). Usually, the value of the velocity will be adapted to indicate the acceleration value. An increase in acceleration will result in an increase in velocity while a decrease in acceleration (deceleration) will result in a decrease in velocity. The fixed value of acceleration will result in a fixed velocity.

Collected datasets can be used to develop a model based on creating sequenced acceleration values after each short time period and utilizing Eq. (2.1) to create the new velocities. A next-time vehicle velocity at the time ($t + \Delta t$) is estimated after a very short time (Δt) based on its current velocity at time t .

Threshold values are proposed and created to be used in implementing the safety distance mobility model. These threshold values are utilized as probability ranges to predict the next time velocity values in this dissertation.

The next vehicle's velocity and acceleration are usually random in real applications with a certain probability distribution. In the simulation, these random values can be represented by generating random variables from random numbers. A proposed approach is utilized to estimate the threshold ranges. This proposed approach is based on generating random numbers for each step of the prediction process to test the next behavior based on comparing the generated random number and the created threshold.

According to these random values, a new variable (B) is proposed to control the sign of the acceleration factor value in Eq. (2.1) as shown in Eq. (3.11)

$$v_n^{acc}(t + \Delta t) = v_n(t) + 2.5 \cdot B \cdot a_n \cdot \Delta t \left[1 - \frac{v_n(t)}{\text{desired speed}} \right] \sqrt{0.025 + \frac{v_n(t)}{\text{desired speed}}} \quad \dots\dots (3.11)$$

The value of the proposed variable B is (1, -1, or 0). When the acceleration is having a positive value (will result in an increase in the vehicle velocity) so $B = 1$. When the acceleration is having a negative value (which will result in a decrease in the vehicle velocity) so $B = -1$, and $B = 0$ means that acceleration will be zero and will result in fixed velocity. In this model, the value of the velocity and acceleration for the vehicle (n) at the time (t) is used to predict it is next velocity at the time ($t + \Delta t$). Usually, the acceleration value will control the value of the velocity. An increase in acceleration will result in an increase in velocity, a decrease in acceleration (deceleration) will result in a decrease in velocity, and the fixed value of acceleration will result in a fixed velocity.

This modified equation reflects the real situation on the road. It can be used in developing simulation experiments to predict the next future velocity for each vehicle at each time.

3.2.5 Proposing a Reaction Time

Reactivity time is a critical aspect of both vehicular networks and car-following models, as it directly impacts the safety, efficiency, and adaptability of transportation systems. Reactivity time, also known as reaction time, is the time interval between the occurrence of an event (e.g., sudden braking by the leading vehicle) and the moment when the following vehicle responds to that event (e.g., applying brakes or accelerating).

By understanding and optimizing reactivity time, one can create more intelligent, responsive, and safe vehicular networks that provide the needs of modern transportation systems. When the distance between the leading and the following vehicles is less than the safety distance, the reaction time is essential to be considered by the following vehicle. The reaction time value must be inversely proportional to the vehicle's velocity (when the velocity is high, a short time is required to take an action). Otherwise, the reaction time is not critical due to the length of the separation gap and the required time to take action.

A continuous random variable for the reaction time (S) is proposed and fitted to some probability distribution in this dissertation. Reviewing the related works and different traffic datasets, the reaction time can be modeled as a negative exponential distribution. In this dissertation proposal, a sampling technique is utilized from the exponential distribution with a parameter k (arrival rate) to generate the optimum reaction time. To generate each vehicle reactivity time during the simulation run scenario, the following valid model is

proposed, created, and implemented. Based on Eq. (2. 5):

$$f(t) = -\kappa e^{-\kappa S(t)}$$

$$F(t) = \int_0^t f(t) dt$$

$$F(t) = 1 - e^{-\kappa S(t)}$$

$$Rand(t) = 1 - e^{-\kappa S(t)}$$

$$e^{-\kappa S(t)} = 1 - Rand(t)$$

$$e^{-\kappa S(t)} = Rand(t)$$

$$-\kappa S(t) = \ln Rand(t)$$

$$s(t) = -\frac{1}{\kappa} \ln Rand(t) \quad \dots (3.12)$$

Where:

κ is the vehicle's arrival rate, $Rand(t)$ is a pseudo-random number generated at each period of time, and t is a time. This equation is developed to estimate the driver's reaction time at any period of time.

Algorithm 3. 1 Represent the main steps to implement the proposed approach to generate the driver reaction time.

Algorithm 3. 1 Driver Reaction Time

Input: min-dis, arrival-rate, safety distance (sd)

Output: reaction time (s(t))

Begin

1: **for** each vehicle in the road segment

2: $vehicle_i \in$ set of vehicles in one lane

3: Check the min-dis for the $vehicle_i$ with the $vehicle_{i-1}$

 ; Where the $vehicle_i$ is the following vehicle and $vehicle_{i-1}$ is the leading vehicle

4: $t =$ current_time

5: **if** the minimum distance between the following and leading cars

6: min-dis \leq sd **then**

7: Generate a random number according to Eq.(3.12)

8: $s(t) = -\frac{1}{k} * \ln Rand(t)$

9: **end_if**

10: $t = t + \Delta t$

11: **end_for**

12: **end_for**

13: return s (t)

14: **End Algorithm**

3.2.6 Proposed Model to Generate the Velocity and Acceleration of the Vehicle

To simulate the highway environment, the vehicle's velocity, and acceleration must be estimated in an accurate manner to be similar to the practical case during each simulation period. The vehicle velocity and acceleration must be variable and based on the vehicle type and road situation in each simulation scenario.

Certain probability distributions can be used in estimating these variable values. From practical observations, and after reviewing and analyzing the utilized dataset (highD and NGSIM), the suitable distribution to model the velocity and acceleration is the uniform probability distribution with two parameters (max and min) for velocity and the normal distribution for acceleration.

Based on Eqs. (2.6) and (2.5) for the Uniform distribution and the Normal distribution, developed formulas can be created to generate the vehicle's velocity and acceleration values.

$$Velocity(t) = V(t) = A1 + (A2 - A1) * Random \quad (3.13)$$

$$Acc1 = \sqrt{-2 \ln R1} \cos (2\pi R2)$$

$$Acc2 = \sqrt{-2 \ln R1} \sin (2\pi R2)$$

$$Acc(t) = (Acc1, Acc2) \quad (3.14)$$

$$NewVelocity(t + \Delta t) = V(t + \Delta t) = V(t) + Acc(t) * B * \Delta t \quad (3.15)$$

Where:

A1: the minimum velocity

A2: the maximum velocity

Acc1: the minimum velocity

Acc2: the maximum velocity

B: Driver behavior (+ or – Value)

Algorithm 3.2 Represent the essential steps to generate the vehicle velocity and acceleration during the simulation period.

Algorithm 3.2 Vehicles Velocity and Acceleration Generation

Input: max_velocity, min_velocity, a1, a2

Output: vehicle velocities.

Begin

 t ← start time

1: **for** each vehicle in the road segment

2: **for** vehicle_i ∈ set of vehicles

3: velocity_i(t) = (min_velocity)_i + (max_velocity_i – min_velocity_i) * Rand

4: Acc1 = $\sqrt{-2 \ln R1} \cos (2\pi R2)$

 Acc2 = $\sqrt{-2 \ln R1} \sin (2\pi R2)$

 Acc(t) = (Acc1, Acc2)

5: Generate R // where R is a random variable

6: Generate a random number (R)

7: **If** R ≤ a1

8: **Then** B = +1

```

9:           If  $a1 < R \leq a2$ 
10:           Then  $B = -1$ 
11:           If  $R > a2$ 
12:           Then  $B = 0$ 
13:            $velocity_i(t + \Delta t) = velocity_i(t) + Acc_i(t) * B * t$ 
14:            $t = t + \Delta t$ 
15:       end_for
16:       Return  $velocity_i(t + \Delta t)$ 
17: end_for
18: End Algorithm

```

3.2.7 Proposing a Lane Change Model

To perform a reliable simulation environment to model the driver behavior on roads. The lane change process must be considered during the vehicle's journey from its source to its destination. A lane change model is proposed and created by making use of different probabilities based on practical driving behaviors. This dissertation proposes a predictive lane change model based on the fundamentals of Binomial distribution and Markov processes.

The principle of the Binomial probability distribution (as indicated in 2.6) is utilized in this dissertation simulation model to check if the driver can change his/her lane or stay in the same lane.

A certain practical threshold is proposed to indicate whether to change the lane or stay in the same lane. After reviewing the related work and analyzing certain real datasets, a certain probability value can be suggested as a success probability value (p) to indicate the need to change lanes and its complement value ($q = 1 - p$) to represent the waiting action (stay in the same lane). The proposed threshold value is used to control and guide the Binomial probability distribution function. The following assumptions are proposed according to the suggested cases in Figure (3.2):

Assumptions:

Change-lane represents the success process = p

No-change represents the failure process = $q = 1 - p$.

If the success probability is greater or equal to a certain threshold value then the change is considered, otherwise, the vehicle will wait and stay in the same lane. The change can be to the right or left with some constraints. In the case of being on the right lane, the possible change will be to the left lane only. In the case of being on the left lane, the possible change will be to the right lane only.

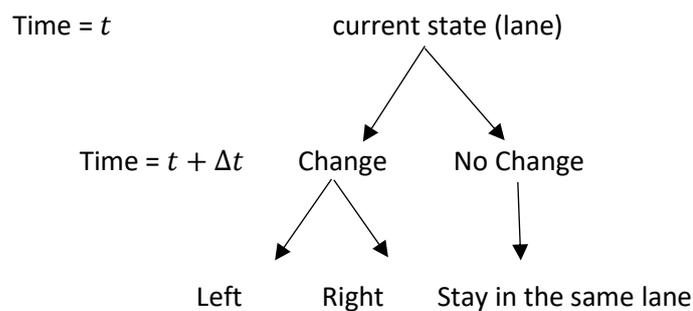
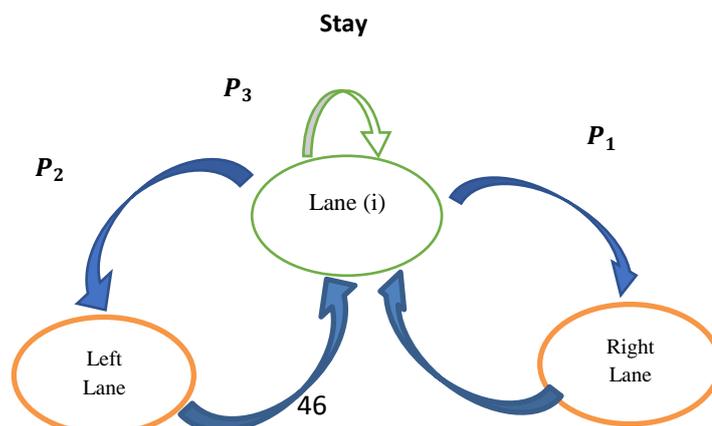


Figure 3.2 The possible states for the lane change process.

Modeling process:

Modeling lane change behavior is an important aspect of simulating traffic flow in the vehicular networks. One approach to modeling lane change behavior is using the binomial probability distribution and the Markov process. (Figure 3.3) present a state diagram to show the possible lane changes.



$$P_5 \quad P_4$$

Figure (3.3) Possible lane changes.

$$P(\text{stay in the same lane}) = 1 - P(\text{change Right}) - P(\text{change Left})$$

$$P_3 = 1 - P_1 - P_2$$

$$P_1 = \begin{cases} 0.5 & \text{middle lane} \\ 0 & \text{Right lane} \\ 1 & \text{Left lane} \end{cases}$$

$$P_2 = \begin{cases} 0.5 & \text{middle lane} \\ 1 & \text{Right lane} \\ 0 & \text{Left lane} \end{cases}$$

$$P(\text{change Right}) = P(\text{Bussy lane}) \text{ and } P(\text{Neighbor Lane empty})$$

$$\begin{aligned} P_1 &= P(\text{Bussy lane}) . P(\text{Right or Left is empty}) \\ &= P(\text{Bussy lane}) . P(\text{Neighbor lanes} > 0) \end{aligned}$$

$$\begin{aligned} P_2 &= P(\text{Bussy lane}) . P(\text{Neighbor lanes} > 0) \\ &= 0 \quad \text{if it in Right \& middle is Bussy} \\ &= 0 \quad \text{if } P(\text{Nighbor} = 0) \end{aligned}$$

In addition, the Markov process is used to model the probability of a vehicle changing lanes based on its current. The Markov process takes into account the current state of the vehicle (e.g. current lane, velocity, and distance to other vehicles) and the probability of transitioning to a new state (e.g. changing lanes, accelerating or decelerating). This probability is based on the current state of the vehicle (middle, right, or left lane) and the probability of observing the surrounding vehicles in the neighboring lanes. (Figure 3.4) present a sample view of a road with three lanes.



Figure (3.4) Sample view of a road with three lanes.

Algorithm 3.3 Presents the lane change states.

Algorithm 3.3 Lane change

Input: Max-V, Min-V, Min-Acc, Min-Acc, Dec, arrival rate

Output: vehicles change lanes in a road segment

Begin

- 1: generate vehicles on the road
 - 2: suggest a certain arrival rate for entering vehicles.
 - 3: **for** each vehicle the in-road segment
 - 4: Indicate and save its vehicle ID and position.
 - 5: generate velocity and acceleration.
 - 6: indicate the current lane.
 - 7: collect its neighbors.
 - 8: if the safety distance \leq th and left or right are empty then
 - 9: accelerate = change lane
 - 10: else
 - 11: deceleration = no-change lane
 - 12: next
 - 13: end
-

3.2.8 Performing a Data Dissemination Stage

A warning message (safety message) is transmitted from the source vehicle to the destination in the Area of Interest in accordance with a specific event. This is how data dissemination is performed (based on the mobility modeling and lane change technique). For instance, a specific cautionary message for all vehicles or RSUs. The suggested method applies data transmission with the assumption that an event will occur at random and that the sender will also be chosen. Regardless of the kind of emergent occurrence, the warning message is transmitted in three formats broadcast and unicast.

With vehicular networks, the infrastructure or the vehicle itself serves as the initial point of data dissemination. The safety applications make the assumption that this principle governs data interchange. Data/information spreading through wireless networks is always referred to as data dissemination. In terms of networking, the ability to broadcast data at the link layer is necessary for the message to reach all the cars within the radio scope.

3.7.1 Select a Sender

Depending on the type of traffic, the message is transmitted from the source to the destination. The source of the message will send a warning message if an accident or collision occurs in the current lane. If the message is unicast, it is sent from the source to the appropriate destination such as near RSU or any vehicle in its area. Then to the relevant bridge (RSU), which disseminates it to all the cars behind the source to alert and warn them of the occurrence. Figure (3.5) represents the flow chart of the data dissemination in the broadcast case. To model the message, this dissertation selects a breed named message (in a simulation tool), then a declaration is made about its variables as local parameter.

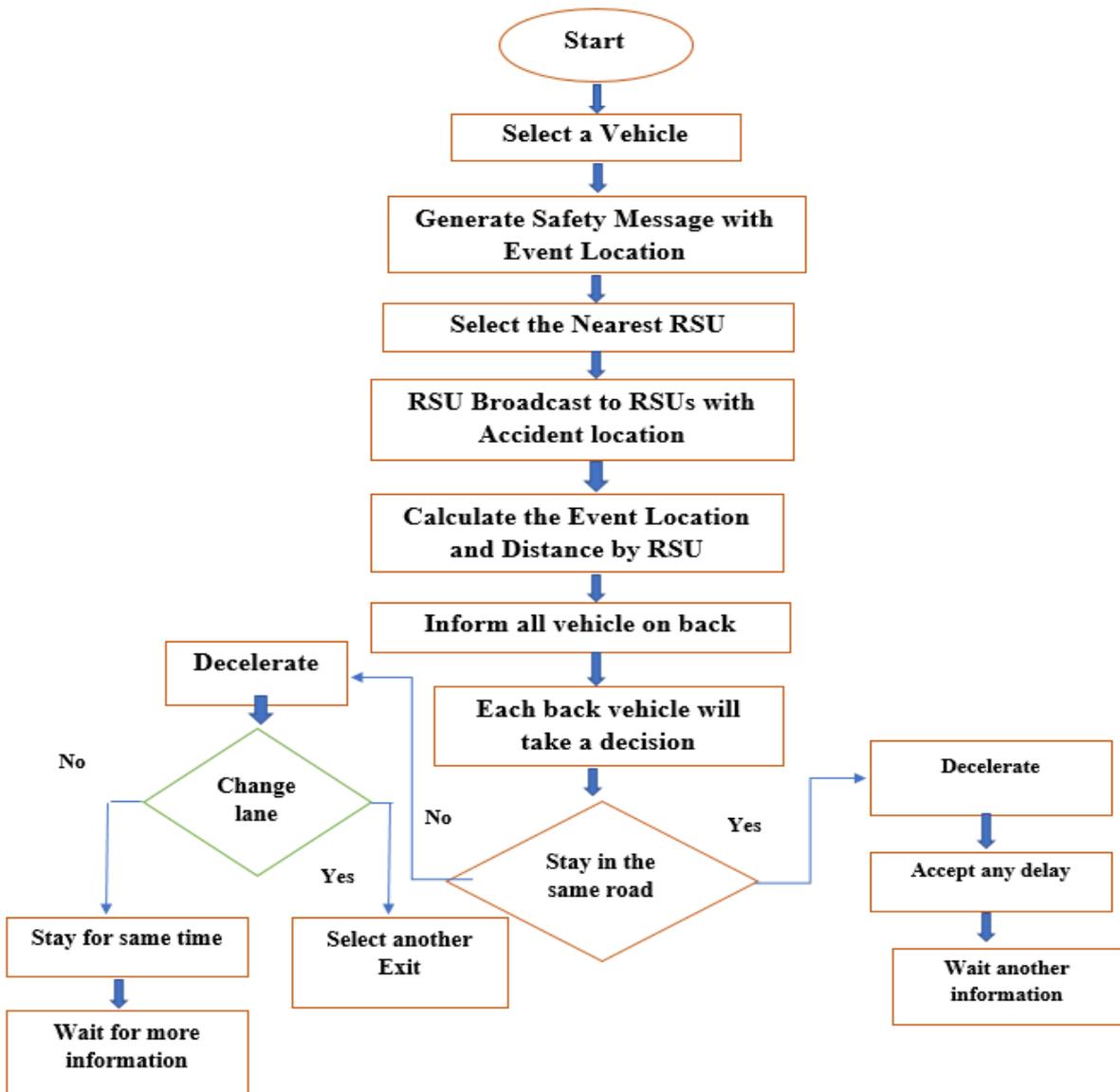


Figure (3.5) The flow chart of the Data dissemination stage.

3.2.9 Data Dissemination Metrics

To evaluate the data dissemination process in all traffic types, the packet loss, delay, packet delivery ratio, and throughput are representing the important metrics. These metrics require calculations. As in the previous sections, the local parameters can be used to calculate these four metrics. Figure (3.6) shows the message properties in NetLogo.

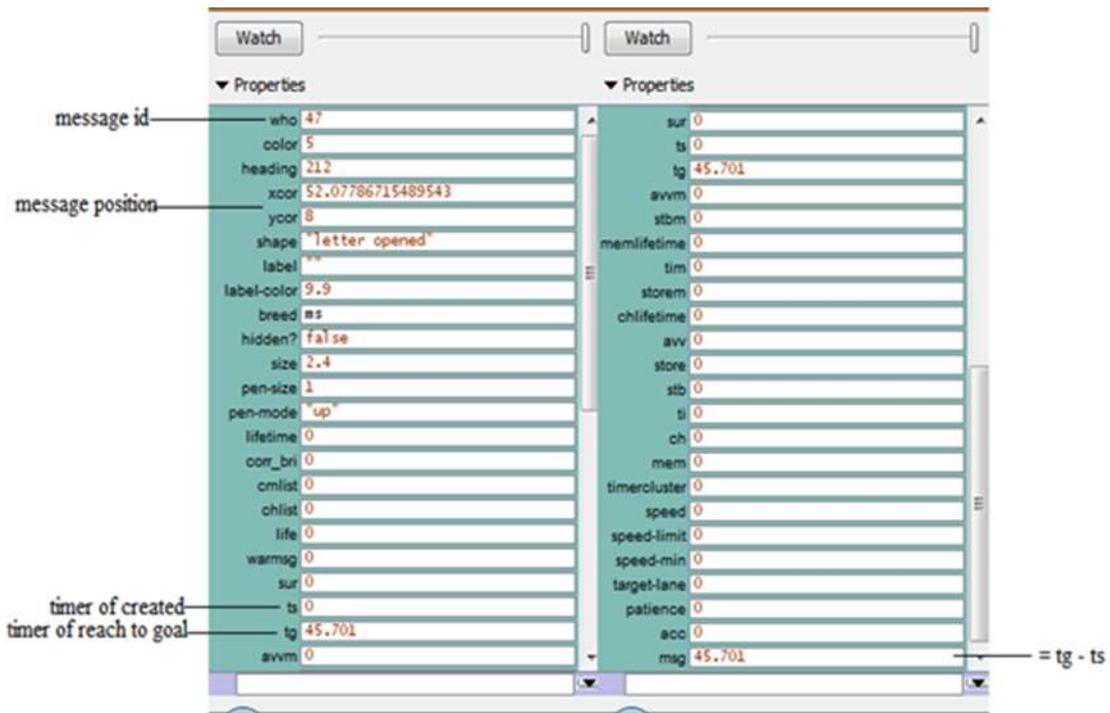


Figure (3.6) Message Properties in NetLogo.

The received and the total created messages were calculated to throw different implementing scenarios. The throughput is calculated according to Eq. (2.7). The message loss can be calculated according to Eq. (2.9) by subtracting the received messages from all created messages. The end-to-end delay is calculated according to Eq. (2.8) by dividing the summation of times consumed in messages transmission by the received messages. The packet delivery ratio is calculated according to Eq. (2.10) by dividing received messages by the total messages.

Performance metrics

The mobility approach should be evaluated using various performance metrics to verify its validity. These metrics are used for comparison between proposed models. Performance metrics are used to measure the effectiveness

and efficiency of data dissemination in VANETs and to evaluate the performance of different communication protocols.

1. **Delivery ratio:** The delivery ratio measures the percentage of messages that are successfully delivered to their intended recipients. A high delivery ratio is essential for ensuring that critical safety messages, such as collision warnings and road hazard alerts, are reliably transmitted and received.
2. **Delay:** The delay measures the time taken for a message to be transmitted from its source to its intended recipient. A low delay is desirable for time-sensitive applications, such as emergency messaging and real-time traffic updates.
3. **Packet loss:** The packet loss measures the percentage of messages that are lost or dropped during transmission. High packet loss can lead to decreased performance and reliability of communication protocols.
4. **The Throughput:** The rate of successful delivery of messages through a network. Moreover, usually, it is measured in bits per second. This is explained in Eq. (2.7).

CHAPTER FOUR

RESULTS AND DISCUSSIONS

4.1 Introduction

This chapter is to investigate how the results of the proposed system achieve a good performance in terms of many performance metrics. Testing any computational model is required to run either by the real-world data, environment, or simulations scenario. The mobility model approach has been designed and implemented using Netlogo 6.3.0 simulation. The obtained results are discussed to show which parameters have an impact on the results of the optimization of the proposed mobility model and performance metrics of the network.

4.2 Simulation Setup

After designing and running the proposed mobility model approach according to the simulation environment, the results were collected and presented using the Netlogo 6.3.0 simulation results viewer. Table (4.1) shows the simulation setup parameters.

Table (4.1) Simulation setup parameters.

Simulator	Netlogo 6.3.0
Number of Simulation Run	10
RSU coverage area	1 km
Arrival rate or Inter-arrival time	Variable
Velocity distribution	Uniform distribution
Acceleration distribution	Normal distribution
Simulation Time	100 s

Environment	Highway
Street length	10 km
Number of lanes	3 and more per side

4.3 Building a Network Environment Results

The suggested simulation environment is presented in Figure (4.3). It presents a simulation snapshot as an implementation sample of the highway topology.

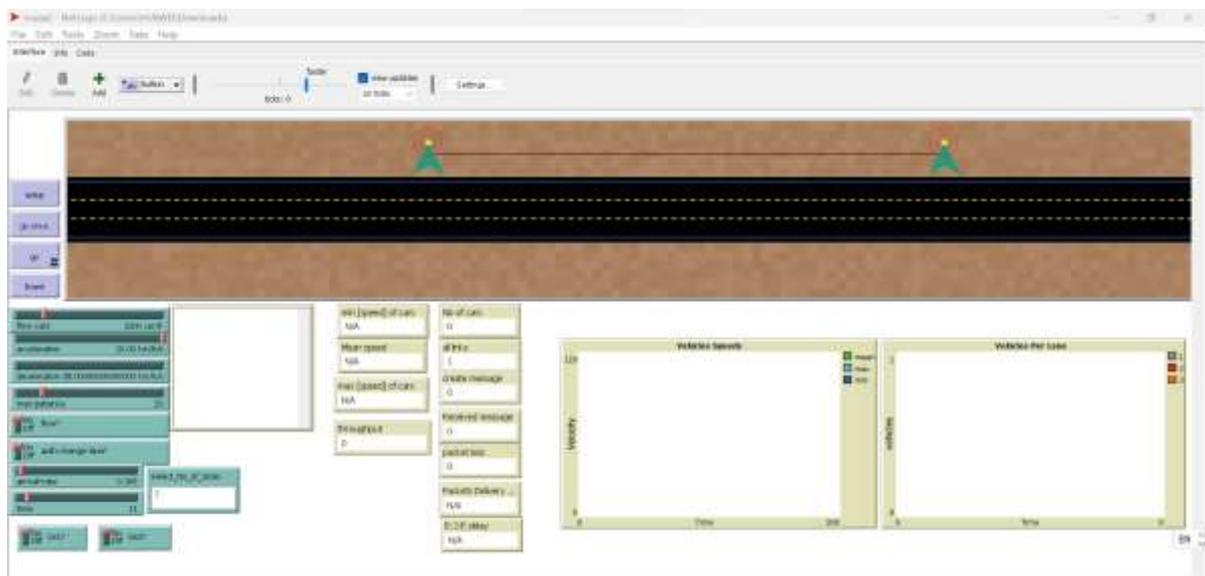


Figure (4.3) Simulation snapshot of the highway topology.

There are two simulation scenarios are tested one with the transient traffic flow scenario and the other with steady-state distribution on the road lanes:

- **Transient Traffic flow scenario:**

Transient traffic flow of vehicles is created with different arrival rates and varying numbers of vehicles at each run time. To achieve this, a procedure that generates vehicles at the start of the road with a given arrival rate. The arrival rate can be defined as the number of vehicles that enter the simulation per unit of

time (e.g., per tick). A slider was used in the simulation user interface to control the suggested arrival rate to generate the number of vehicles arriving during a period of time.

This case is proposed in this dissertation to mimic the real traffic case. It started with an empty road segment and continue by arriving more vehicles with time. After a certain time, the number of vehicles in the road segment will reach a steady state.

- **Steady state distribution:**

Vehicles on highways refer to the pattern of vehicles traveling on the highway at any given time. Also in this scenario different arrival rates and varying numbers of vehicles at each run time. The created vehicles are distributed between the lanes of the road segment before the simulation run. A slider was used in the user interface to control this arrival rate to generate the number of vehicles that are created on the lanes of the road segment.

Building a network of highway environments using NetLogo 6.3.0 simulation can provide valuable insights into how different traffic management strategies affect the performance of the network. By following the steps outlined in (3.2.1), the environment is represented, as a road network, and study its behavior under different scenarios. The results obtained can be used to improve the design and management of real-world highway systems.

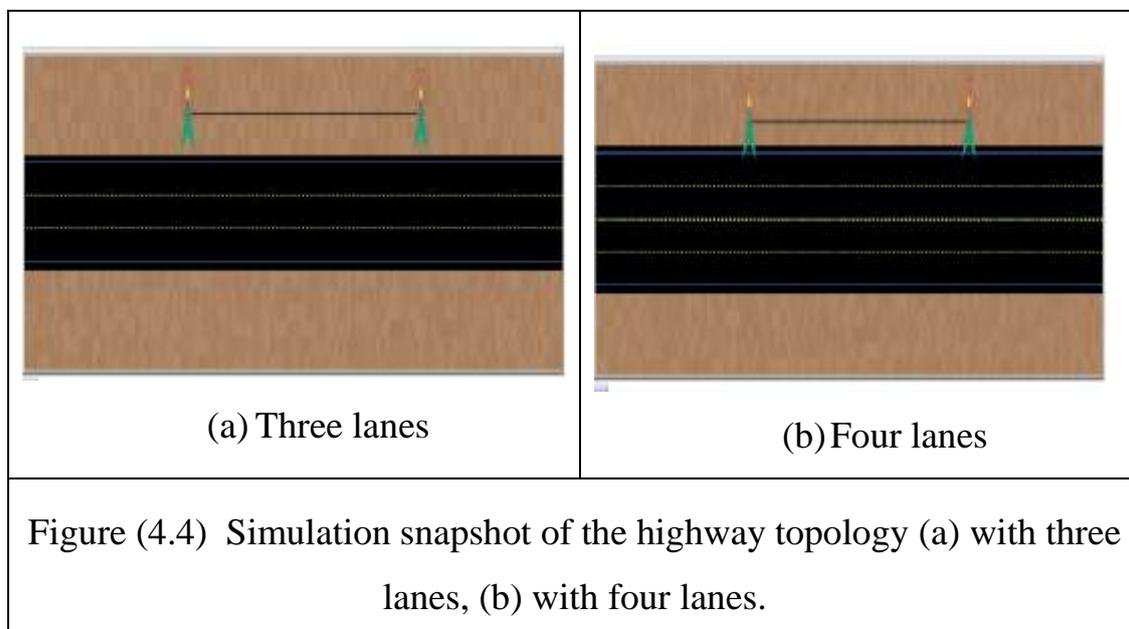
Three highway information are selected to be used in the simulation scenarios. From these three highways, the expected number of vehicles per unit time

(average or arrival rate) is calculated. Table (4.2) presents the proposed arrival rates and their associated number of vehicles based on Eq. (3.3).

Table (4.2) Levels of traffic for the proposed evaluation scenarios.

	Datasets density (No. vehicles)	Dataset Arrival-Rate	Simulation Arrival-Rate	Density (No. vehicles)
Low	881	0.98	0.058	50
Medium	1046	1.16	0.114	100
High	1334	1.48	0.168	150

A normalization process is performed in selecting these arrival rates and the number of vehicles in this dissertation road segment. Different simulation scenarios of highway environments are created one with three lanes and the other with four lanes. The variable number of lanes is created and their effect on the traffic flow on the highway is observed. Figure (4.4), (a) Show the scenario of the highway topology with three and (a) Show the scenario of the highway topology with three.



4.4 Analyzing the Car-following Mobility Models Results

The results of car-following mobility models can be analyzed in several ways. One approach is to examine the statistical distribution of vehicle velocity and acceleration, which can provide insights into the overall behavior of the traffic flow. Another approach is to compare the simulation results with real-world data to evaluate the accuracy of the model.

Figure (4.5) show the distribution behavior of real datasets (in (a) and (b) for the highD) using the (SPSS application). Where the distribution of the acceleration values is the normal distribution and the velocity is near the uniform distribution.

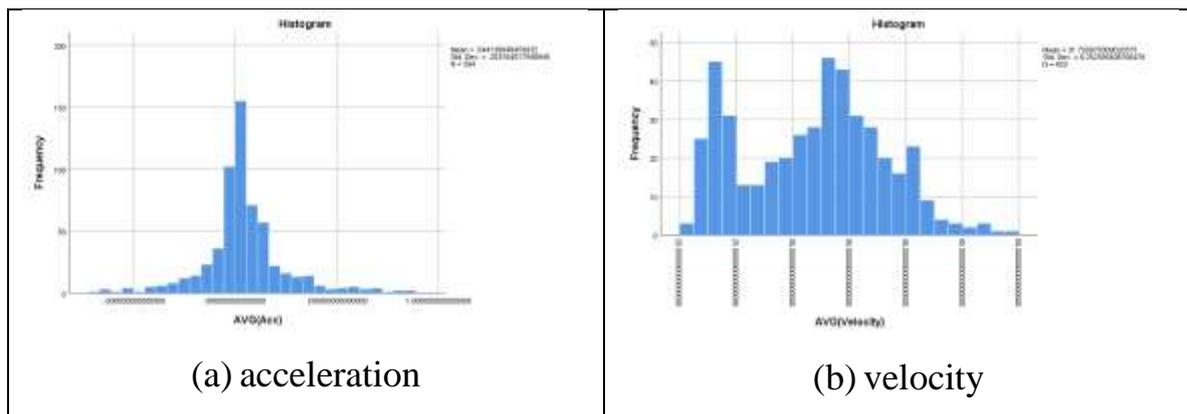


Figure (4.5) Histogram and distribution of the acceleration and velocities values for highD dataset ((a) acceleration (b) velocity).

The same performance analysis estimation process was performed on the second dataset. The velocity and acceleration behavior for each vehicle were analyzed, their averages are also estimated to be used mathematically in implementing the car-following models and can be used in generating simulation scenarios. Table (4.3) and (4.4) shows samples of the estimated results for both datasets.

Table (4.3) A sample of the estimated average velocity and acceleration for each vehicle for highD dataset.

vehicle ID	Avge(V)	Avge(Acc)
1	41.07	0.343
2	32.48	-0.167
3	36.13	0.130
4	42.76	0.026
5	43.4	-0.242
6	23.33	0.017
7	33.8	0.264
8	31.31	0.032

Table (4.4) A sample of the estimated average velocity and acceleration for each vehicle for NGSIM dataset.

vehicle ID	Avge(V)	Avge(Acc)
1	33.94	1.840
2	22.177	0.237
3	29.371	0.612
4	32.499	0.056
5	25.566	0.185
6	36.293	0.152
7	30.649	-0.056
8	33.879	0.019

HighD and NGSIM datasets are composed of two direction roads (the positive values representing the east direction and the negative values representing the west direction according to this dissertation's assumptions).

Different statistical analyses are performed on each dataset to extract useful parameters and indications. These parameters are mean, standard deviation, range, max, and min. Tables (4.5) and (4.6) show the extracted parameters for each flow direction.

Table (4.5) Sample of the extracted vehicle velocity for HighD.

Avg	Std	C.V	Min	Max	Range
41.071	0.135	0.0043	40.85	41.3	0.45
36.130	0.210	0.0067	-32.9	-32.04	0.86
23.328	0.039	0.0012	35.69	36.5	0.81
33.800	0.627	0.0202	-42.83	-42.57	0.26
22.780	0.450	0.0144	-44.26	-42.5	1.76
24.786	0.835	0.0269	23.25	23.4	0.15
35.568	1.060	0.0341	32.59	34.65	2.06

42.137	0.424	0.0136	-31.52	-31.1	0.42
35.519	0.328	0.0105	-36.62	-35.99	0.63
36.538	3.210	0.1034	22.17	23.38	1.21
33.126	0.182	0.0058	23.86	26.9	3.04
33.031	0.803	0.0258	33.04	36.69	3.65
40.113	1.105	0.0355	-39.24	-38.53	0.71
27.432	0.331	0.0106	40.85	41.3	0.45

Table (4.6) Sample of the extracted vehicle acceleration for HighD.

Avg	Std	C.V	Min	Max	Range
0.343	0.016	0.245	0.3	0.36	0.06
-0.167	0.045	0.689	-0.28	-0.08	0.2
0.130	0.018	0.275	0.08	0.21	0.13
0.026	0.090	1.378	-0.1	0.17	0.27
-0.242	0.125	1.914	-0.46	0.01	0.47
0.017	0.477	7.305	-0.05	0.05	0.1
0.264	0.404	6.187	0.14	0.37	0.23
0.032	0.069	1.056	-0.18	0.12	0.3
-0.035	0.091	1.393	-0.19	0.14	0.33
-0.112	0.196	3.002	-0.26	0.17	0.43
0.198	0.136	2.082	-0.34	0.79	1.13
-0.244	0.205	3.139	-0.73	0.24	0.97
-0.656	0.229	3.507	0.3	0.36	0.06
0.343	0.031	0.474	-0.28	-0.08	0.2

These calculations are performed as a part of the pre-processing analysis of the two datasets to indicate the stability, reliability, and validity of the collected data. The standard deviation (Std) values are to indicate the dispersion of the different measures in each frame. The coefficient of variation (C.V) is calculated to ensure the level values of the calculated Std. values and to indicate which the best value is. For example, in Table (4.6) the first row value represent the precise recorded values while the value in 6th row indicates the worst recorded values. The same process is also performed on the second dataset.

4.5 A proposed approach to Estimate the Constant Term (α)

The value of the constant term (α) in Eq. (2.2) is let to the user to suggest a certain numerical value. In this dissertation, a proposed approach is created to estimate the suitable value for the constant term (α). This approach is based on

analyzing the behavior of real datasets. After analyzing and experimenting with the GM model (Eq. 2.2), the value of the constant term (α) can be adapted to reflect the driver behavior. Driver behavior can be estimated as a random value based on the recorded vehicle's velocities and accelerations in the two datasets at different times and frames.

Another parameter in Eq. (2.2) is the $\Delta V_n^{front}(t - \Delta t)$. This parameter represents the relative velocity for the vehicle n and its front vehicle at the time $(t - \Delta t)$. Different approaches to estimate this value were used in the literature.

The value of the constant term (α) in Eq. (2.2) is suggested to be calculated in this dissertation approach by dividing the acceleration value $a_n(t)$ by $\Delta V_n^{front}(t - \Delta t)$. Collecting the acceleration and relative velocities values in all data frames for vehicles (car or truck) and feeding them to Eq. (2.2) will result in different values for (α). Table (4.7) summarized the computed values for the average (α) and frame length and their standard deviations. Figures (4.6) in (a) trucks and (b) cars show the relation between frame length and (α) value. From this figure, it is clear that the value of (α) randomly changes with the frame length. So it is important to propose a random process to expect the next value of α (which can be modeled as a driver behavior) for the next time. This approach is considered to be one of this dissertation's contributions. The average values of α are extracted after long calculations. Each vehicle has many acceleration and velocity values (one acceleration and velocity value in each frame). A relative velocity value is calculated for each vehicle between any two successive frames, from each one of them a value for α is estimated. These α values are collected for each vehicle in a dataset and their average value is considered and used for future prediction.

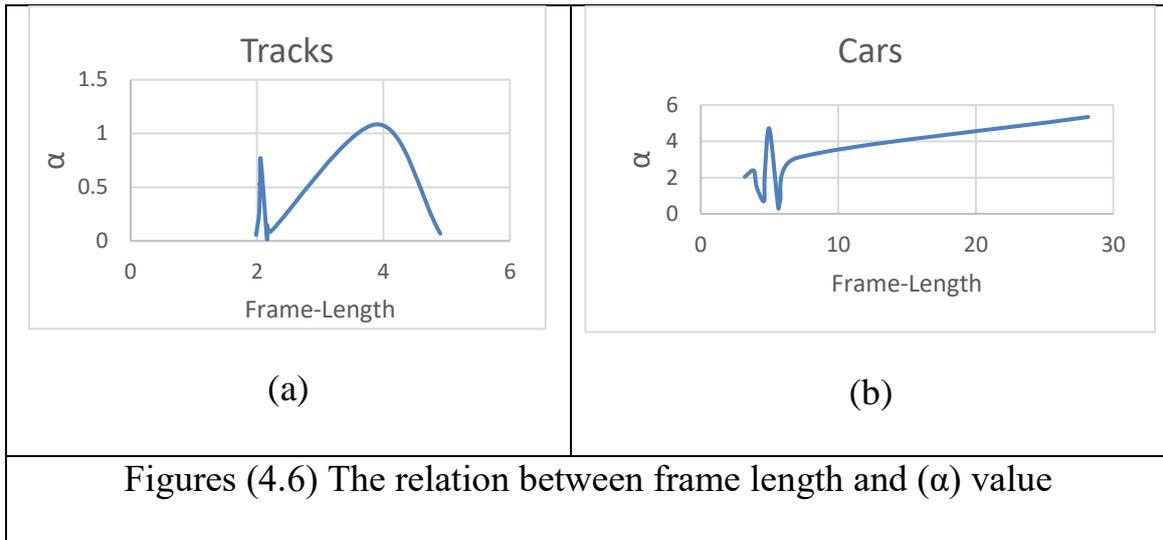


Table (4.7) sample of the computed values

Id	Type	Direction	AVG(α)	STDV(α)	C.V	Frame-length
22	Truck	1	0.14593	4.559592	0.032005	2.161871
24	Truck	1	0.025383	7.430924	0.003416	2.156699
38	Truck	1	0.087257	4.973682	0.017544	2.214988
45	Truck	1	0.758689	6.786526	0.111793	2.058219
52	Truck	1	0.056107	4.601604	0.012193	1.985683
2	Car	1	3.083409	16.3075	0.189079	6.988372
4	Car	1	0.337013	9.807303	0.034363	5.634375
5	Car	1	4.703418	19.25374	0.244286	4.980663
8	Car	1	0.697589	11.67408	0.059755	4.59949
9	Car	1	1.483741	15.6572	0.094764	4.060811
6	Truck	2	0.068328	24.09603	0.002836	4.899457
10	Truck	2	1.08536	18.78848	0.057767	3.902597
33	Truck	2	0.266978	9.040045	0.029533	2.034989
35	Truck	2	0.521388	9.287459	0.056139	2.048864
39	Truck	2	0.537246	16.69352	0.032183	2.044218
1	Car	2	5.341536	27.23345	0.196139	28.17188
3	Car	2	0.751641	18.95728	0.039649	5.778846
7	Car	2	2.064737	24.09603	0.085688	4.646907
11	Car	2	2.386629	23.69943	0.100704	3.852564
12	Car	2	2.039617	22.13256	0.092155	3.196809

Table (4.7) was calculated after conducting a set of statistical calculations to see the effect of the value of (α) on both the type of vehicles and the length of

the frames for each vehicle. Based on Table (4.7) the relationship between the frame length and the (α) was performed.

To perform a prediction process to expect the next acceleration value at time ($t + \Delta t$) based on the α and the relative velocity at time t . The values for α as average values are estimated in Table (4.7). To estimate the value of ΔV_n^{front} from the values of the dataset, three alternatives are proposed in this dissertation, and their values are compared with real dataset acceleration values to select the best closest one. These three alternatives are called (x1, x2, and x3). Their values are calculated as in developed Eqs. (3.10), (3.11), and (3.12). Tables (4.8) and (4.9) represent the calculated statistical (max, min, and mean) velocity values for moving vehicles in both directions for highD dataset.

Table (4.8) East direction

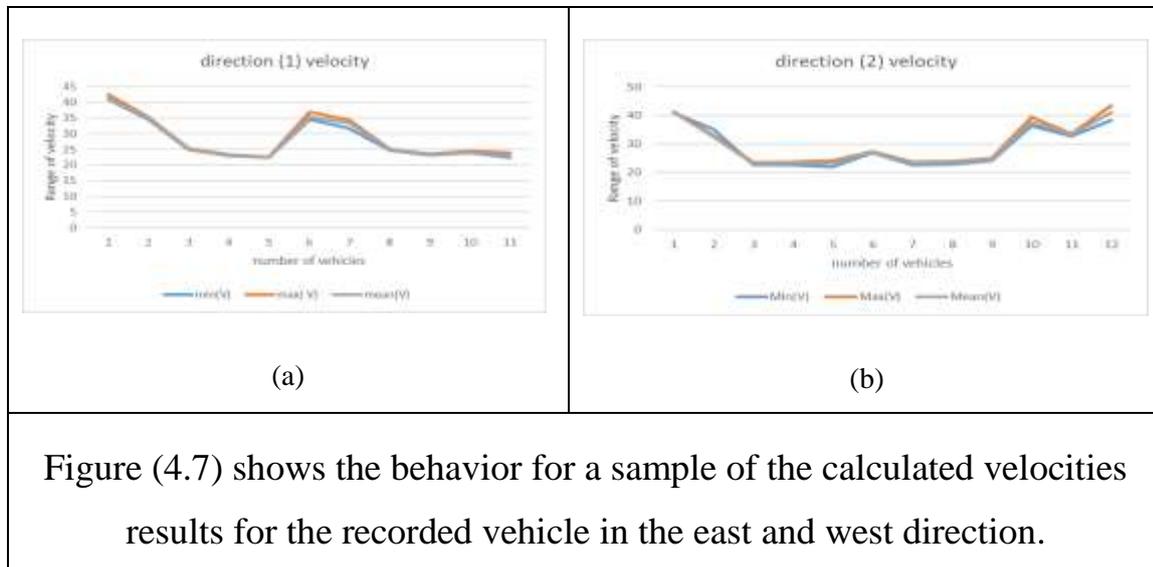
min(V)	max(V)	mean(V)
41.02	42.58	41.32
34.61	35.4	35.02
24.81	25.2	25
22.97	23.32	23.17
22.31	22.55	22.45
34.51	36.81	35.4
31.68	34.44	33.51
24.69	25.06	24.9
23.25	23.58	23.44
23.98	24.44	24.2

Table (4.9) West direction

Min(V)	Max(V)	Mean(V)
40.85	41.3	41.07
35.04	32.9	32.48
22.62	23.5	23.13
22.57	23.68	23.29
21.87	24.07	23.16
26.95	27.39	27.15
22.67	23.64	23.18
22.89	23.89	23.48
24.1	25	24.56
36.34	39.31	37.59

Figures (4.7) present a sample from direction (1) in part (a), and direction (2) in part (b). From this Figure, the behavior and the shape of the three statistical values are similar and close in values. Selecting each one can be used in estimating

the relative velocity. Due to this complexity and similarity, the three alternatives approaches are proposed.



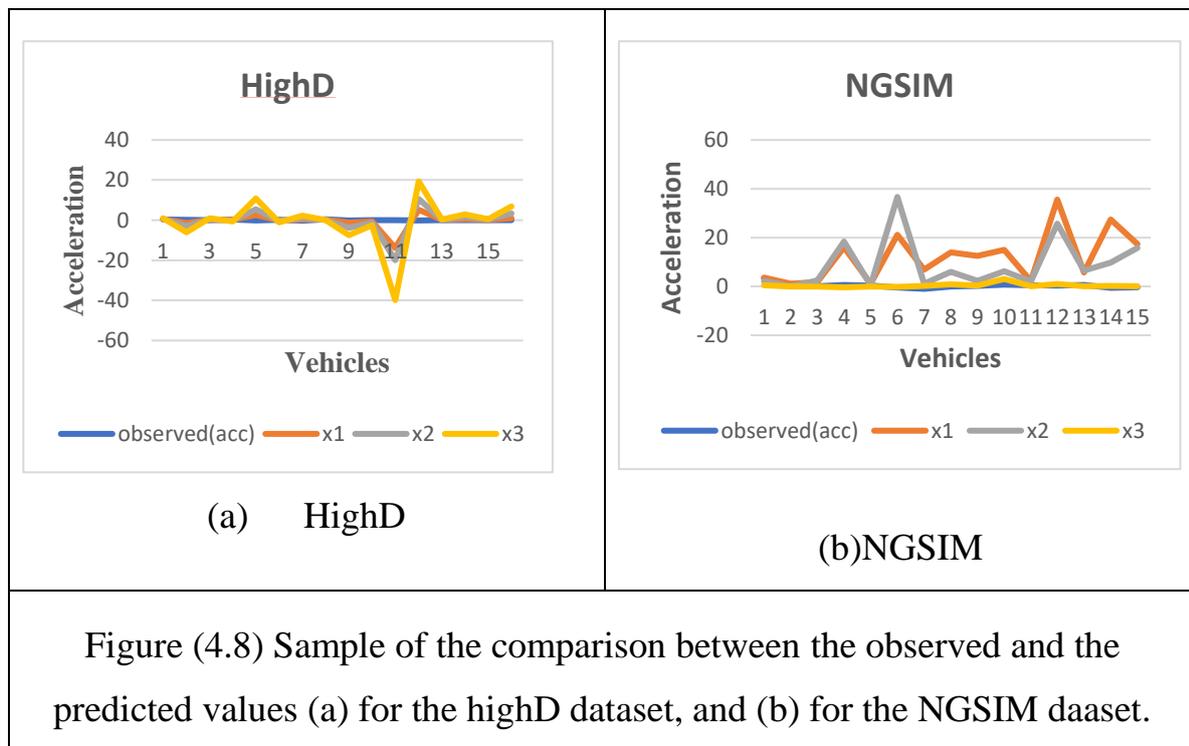
From Tables (4.8) and (4.9), the three proposed alternatives are calculated for each vehicle.

The result for the three approaches (x1, x2, and x3) that are proposed to estimate the relative velocity parameters are calculated and shown in Table (4.10)

Table (4.10) Sample of the estimated three alternatives.

X1	X2	X3
0.2288	0.2212	0.4500
0.4391	0.4209	0.8600
0.3692	0.4408	0.8100
0.1924	0.0676	0.2600
0.8987	0.8613	1.7600
0.0720	0.0780	0.1500
0.8491	1.2109	2.0600
0.2115	0.2085	0.4200
0.4311	0.1989	0.6300
0.5992	0.6108	1.2100
2.1137	0.9263	3.0400

Based on the calculated values for each alternative, the values of x_i , ($i= 1, 2,$ and 3) are multiplied by the value of α to get an acceleration value for each vehicle. The resulting acceleration values are compared with real acceleration values in datasets. The first alternative ($x1$) is considered to be used in estimating the required initial value for the relative velocity that can be used in implementing the prediction process. The comparison process is indicated in Figure (4.8).



The same processes are implemented on the second NGSIM dataset. Its results are found very close to that calculated based on highD dataset. Proposing these three alternatives and selecting the best one to be implemented in the prediction process represent the second contribution of this dissertation.

4.6 Improving the Car-Following Mobility Model Result

The traditional safety distance car-following model is studied and analyzed carefully in this dissertation to perform simulation experiments. Proposed developments are added to this model. To proceed with the datasets information, a prediction model is developed and implemented based on the fundamentals of the Markov process.

For each road (east and west), vehicles' average acceleration values in each dataset are sorted, analyzed, and arranged as an accelerated case (positive values), decelerated case (negative values), and neither acceleration nor deceleration case (zero values). These three cases are observed and counted. Table (4.11) shows the total collected results for both roads directions.

Table (4.11) Vehicles acceleration cases

Acceleration value	East dir.	West dir.
Number-of-Positive Values	313	277
Number-of-Negative Values	113	215
Number-of-Zero Values	28	103
Total	454	595

Table (4.11) is used to estimate certain fractions by dividing each file number by the total number (East or West). These fractions are applied as certain probability values. The estimated probability values are proposed as threshold values to be used for predicting the next time acceleration for each vehicle in implementing a simulation experiment. Table (4.12) shows these proposed threshold values based on table (4.12).

Table (4.12) Proposed Threshold values.

HighD	Probability P(x)	
	East	West
Increased acceleration	0.69	0.47
Decreased acceleration	0.25	0.36
Fixed acceleration	0.06	0.17

Table (4.13) Proposed Threshold values for NGSIM.

NGSIM	Probability P(x)
Increased acceleration	0.64
Decreased acceleration	0.35
Fixed acceleration	0.01

Tables (4.12) and (4.13) show that the drivers' increased acceleration in both datasets is high compared with the deceleration behavior. Driving at a fixed velocity without changing the acceleration ranges between 6% to 17% for the first dataset. To proceed with the dataset information, a prediction model is developed and implemented based on the fundamentals of the Markov model. This developed model is based on creating sequenced acceleration values after each short time period and utilizing Eq. (2.1) to create the new velocities. A next-time vehicle velocity at the time $(t + \Delta t)$ is estimated after a very short time (Δt) based on its current velocity at time t . The value of Δt is suggested to be 5 sec in this dissertation.

A simulation scenario is implemented by generating a random number for each step of the prediction to test the next behavior based on the comparison between the generated random number and the created threshold values. Certain

limits are created to generate specific categories for each case based on the generated threshold values. These categories are 0-0.64, 0.641- 0.99, 0.991-1.0 for the NGSIM dataset, 0 - 0.69, 0.691- 0.75, and 0.751- 1.0 for the East road direction and 0- 0.47, 0.471- 0.64, and 0.641- 1.0 for the West road direction for the highD dataset. These developed proposals and their extraction techniques from the real datasets are representing the 3rd contribution to this dissertation.

For the east road, if the generated random number falls in the range of (0 - 0.69), the vehicle will tend to accelerate so the value of the variable B in Eq. (3.13) will be 1. If the value of the generated random number falls between (0.691- 0.75), then the acceleration will not change so the value of the variable z will be 0. If the value of the random number is between (0.751 - 1), then the vehicle will decelerate and the value of z will be -1.

For the west road, if the generated random number falls in the range of (0 - 0.47), the vehicle will tend to accelerate so the value of the variable z will be 1. If the value of the random number falls between (0.471- 0.64), then the acceleration will not change so the value of the variable z will be 0. If the value of the random number is between (0.641- 1), then the vehicle will decelerate and the value of z will be -1.

Four steps prediction values are performed as a sample to estimate the vehicle's velocity in each time period. Eq. (3.13) is implemented to estimate the next time velocity of a vehicle based on its current velocity. Threshold categories and random numbers are utilized in these calculations. Tables (4.14) and (4.15) present the results of the experiments to estimate the vehicle's velocities on the west and east roads after certain time periods. These two tables present the next estimated velocities for the vehicles on the west and east roads. These velocities are estimated after a certain time $\Delta t = 5s$, $2 \Delta t = 10s$, $3 \Delta t = 15s$,

and $4 \Delta t = 20s$. Depicting and involving Markov models in this developed prediction process represents the 4th contribution to this dissertation.

Table (4.14) West Street Velocity Prediction

AVG(V+)	Step1(v)	Step2(v)	Step3(v)	Step4(v)
31.9861538	31.8371043	31.98615	32.17673884	32.2714952
42.7624223	42.6889942	42.75546	42.7554629	42.762428
43.3986813	43.3309864	43.45947	43.2765993	43.399177
31.3115228	31.1527279	31.33054	31.3115361	31.273475
36.4210762	36.2959959	36.43740	36.4219184	36.437446
38.8742857	38.767969	39.13248	38.8792625	38.879262
37.9635424	37.8458719	37.99361	37.9636040	37.903342
44.4743722	44.4168725	44.50938	44.4743722	44.439559
30.7895195	30.6277159	30.70130	30.7897921	30.701302
24.500645	24.309689	24.51428	24.500649	24.527917

Table (4.15) East street velocity prediction

AVG(V+)	Step1(v)	Step2(v)	Step3(v)	Step4(v)
41.071212	41.183260	41.183260	41.294093	41.184466
36.130828	36.192279	36.192279	36.192279	36.192494
23.328	23.339934	23.339934	23.351866	23.363796
33.800923	33.941294	33.941294	34.080757	34.211218
22.780818	22.699539	22.780818	22.699539	22.536696
24.786340	24.925656	24.647023	25.064600	25.064600
35.568621	35.450125	35.687118	35.330872	35.450883
42.137926	42.265748	42.264833	42.139747	42.139747
35.519103	35.488285	35.549921	35.457416	35.488336

36.538581	36.572809	36.504353	36.606967	36.572878
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Figure (4.9) present the behavior of the predicted values in Table (4.13) which slightly changes in a random manner based on the driver’s behavior. This is good evidence to show their near-reality values.

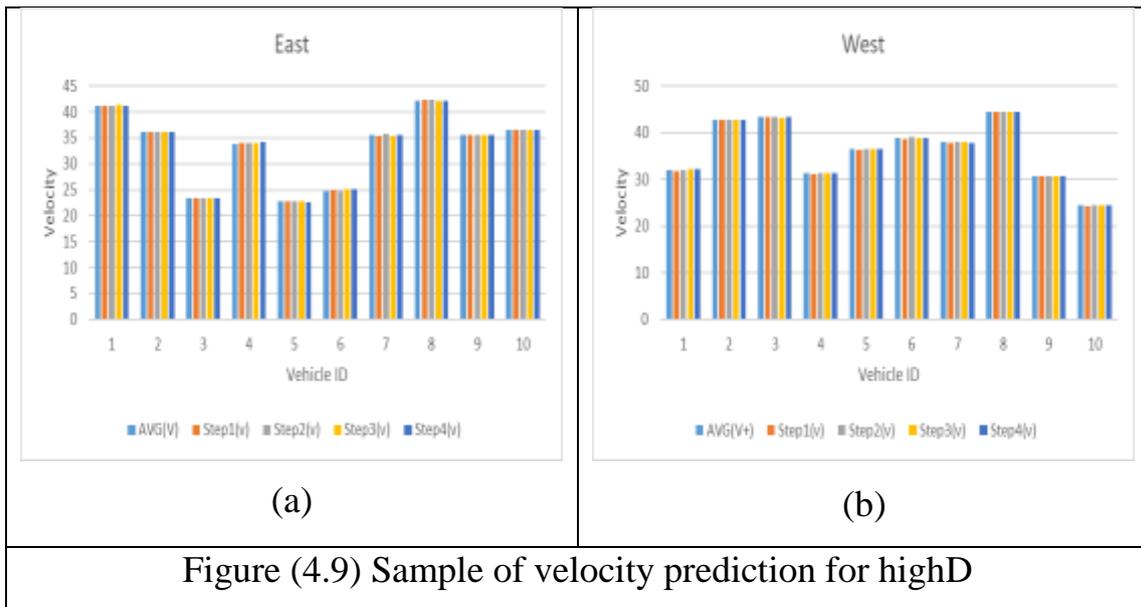


Figure (4.9) Sample of velocity prediction for highD

Observing the predicted values for each vehicle’s velocity after a certain small time period, gave a good indication of their reality and correctly reflected the real driving behavior. These values are slightly changed in a random manner. The short time measure between each two successive values coincides with the level of their value.

4.7 Proposing a Reaction Time Result

In Table (4.16) an example of the estimated reaction time is presented based on the proposed Eq. (3.4). Each value in this table represents a reactivity time for different simulation runs

Table (4.16) Estimated reaction time values

Simulation Runs	Reaction Time values
1	0.7549
2	0.4689
3	0.8174
4	0.4294
5	0.5633
6	0.5518
7	0.1695
8	0.8567

These reaction time values are generated by randomly sampling from the negative exponential distribution with a certain arrival rate. These values will represent the time it takes for a driver to respond to a certain activity (lane change or decelerate). A short reactivity time value means that the following vehicle will respond quickly to changes that happened by the lead vehicle's velocity or position.

4.8 Proposed Model to Generate the Vehicles Velocity and Acceleration Results

By incorporating the proposed model presented in Eq. (3.17) to generate the initial values of velocity and acceleration for each vehicle in each simulation scenario a car-following model that calculates vehicle velocity and acceleration into NetLogo simulation, one can generate valuable insights into traffic flow

and behavior. Table (4.17) shows the initial velocity values for some vehicles created in one of the generated simulation scenarios as an example.

Table (4.17) Initial generated velocity values sample

Car ID	Initial Velocity
(car 9)	36.676
(car 10)	36.531
(car 11)	36.730
(car 12)	74.495
(car 13)	71.256
(car 14)	71.503
(car 15)	22.392
(car 16)	20.879
(car 17)	21.386
(car 18)	43.263
(car 19)	41.403
(car 20)	41.578
(car 21)	64.977
(car 22)	59.597
(car 23)	62.0724

In a simulation scenario, variable velocity values are generated between a maximum velocity of 120km/h and a minimum velocity of 20km/h, the result would be a range of velocities that varies over time. The specific velocity at any given time would depend on the simulation's parameters and variables. For example, if the simulation is modeling a velocity traveling along a road, the car's velocity might start at 20km/h and increase over time to reach a maximum of 120km/h, and then decrease back to 20km/h. This would create a pattern of acceleration and deceleration over time. The velocity values could also be influenced by other factors in the simulation, such as traffic, road conditions, or weather.

Overall, the result of generating variable velocity values in a simulation scenario would be a range of velocity s that change over time, which can be used to model a variety of real-world situations and behaviors.

4.9 Proposing a Lane Change Model Result

Each driver has three or fewer alternatives during his/her journey on the road. Initially, the driver must take a decision to change the lane or not if a target vehicle approaches a slow-moving vehicle. After analyzing the presented study by (Alireza Talebpour, et al, 2015), they utilized the game theory approach to model the lane change on the highway and they used NGSIM dataset in implementing their model. They made a competition between change lane or not change lane strategies. In this dissertation, another developed mathematical approach is utilized. This dissertation approach is based on Binomial probability distribution and the Markov process.

A Binomial probability distribution can be used to estimate the possible probability of the driver (either yes or no). If the decision is no, which is based on the state of the neighbor lanes (left or right) if they are not empty. So the driver must reduce the vehicle's velocity by making deceleration. Else the driver will select either the left or right lane and start moving in the designated direction. These three alternatives can be modeled as a Markov process as indicated in (3.2.7).

In this stage, the mobility model and lane change model simulation have been applied to the proposed road segment. Therefore, a different number of vehicles have been created for each case as indicated in Table (4.2). This approach represents the 5th contribution to this dissertation.

In real traffic situations, there are three levels of congestion namely (low, medium, and high). To generate traffic scenarios, the number of vehicles as well as the level of congestion must be analyzed. A suggested value for the arrival

rate (the expected incoming vehicles per unit time) and the required period of time must be estimated or proposed. Based on the available datasets (highD and NGSIM), the total number of vehicles during a certain time on different highways can be calculated. Two scenarios are proposed (transient and steady state). Transient means that the road is initially empty and the vehicles arrive to enter this segment which is a special case and rarely considered by the related works. While the steady state scenario represents the general traffic case (sparse or dense number on the road).

Transient scenario:

In this scenario (transient traffic) the number of arriving vehicles is created based on certain arrival rates (to generate low, medium, and high traffic). The vehicles enter the road segment at a specific inter-arrival time. These vehicles are distributed between the road lanes (three or four in this dissertation simulation scenarios) in a random manner, each lane is observed with its counted vehicles.

Transient traffic scenario with low level and three lanes:

In a transient traffic scenario with low density, the number of vehicles on the road is relatively low compared to the capacity of the road. This means that there is a lot of space available for vehicles to maneuver, change lanes, and travel at different velocities.

In this case, the number of vehicles was 50 based on a 0.058 arrival rate. Figure (4.10) refers to the simulation results in this case. Part (a) the relation between the run time and the velocity values (min, max, and mean), and part (b) represents the relation between the simulation run time and the number of vehicles per lane which explain the change lane to reach to the final destination with less time.

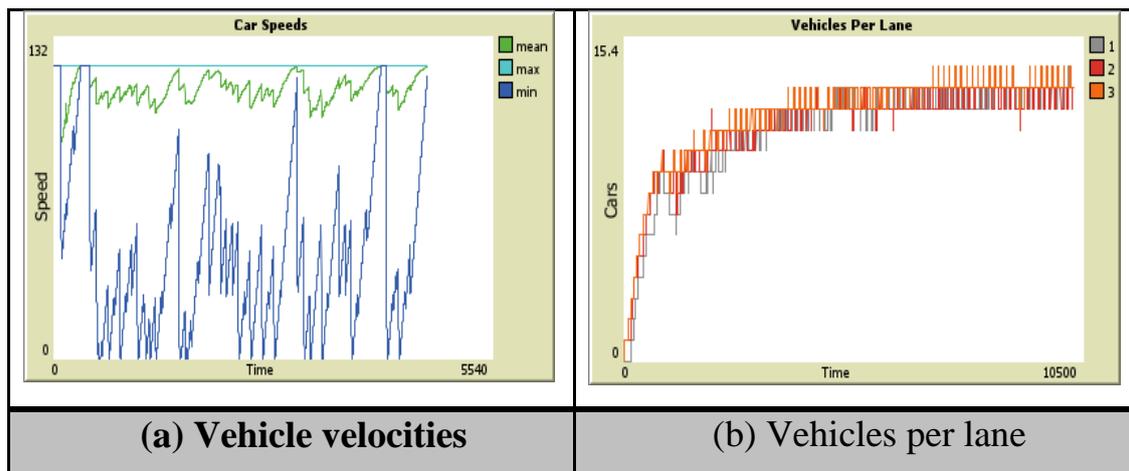


Figure (4.10) Low-level density, 50 vehicles, and three lanes.

In Figure (4.10) the process of changing lanes did not occur continuously because the level of density of vehicles on the road is low in part (a), and in part (b) with regard to the large change in speeds we see that the speed of vehicles decreases, increases, and sometimes reaches the maximum speed due to the road situation and therefore the road is not crowded and can drive at different speeds.

Transient traffic scenario with medium density level and three lanes:

In a transient traffic scenario with medium density, The road has a moderate amount of cars on it, with some empty spaces between them. Vehicles are moving at a steady pace and lane change may occur, but not too fast or too slow. Drivers are able to maintain a safe distance from one another, and there are no major bottlenecks or slowdowns.

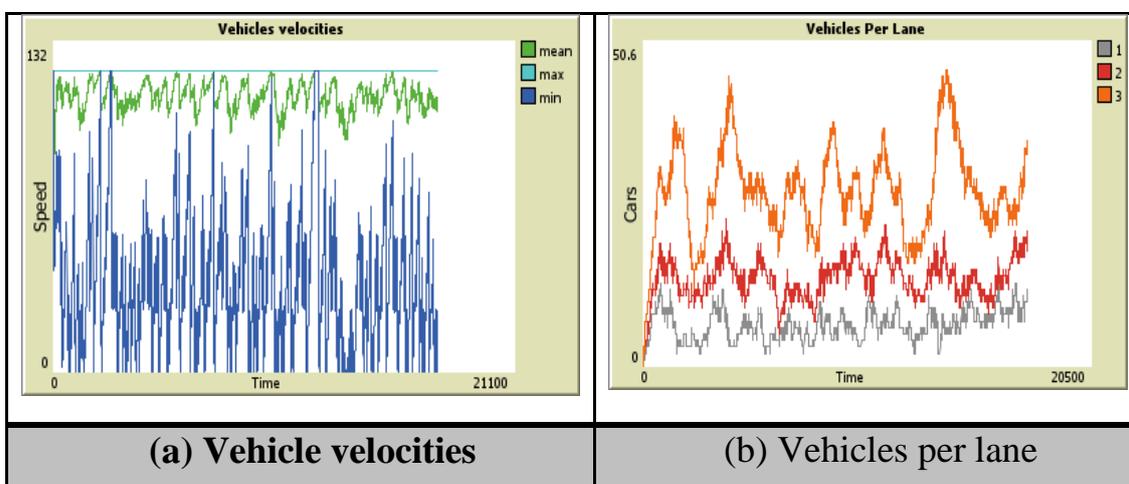


Figure 4.11 Medium-level density, 100 vehicles, and three-lanes

In this case, the number of vehicles was 100 based on a 0.114 arrival rate. Figure (4.11) refers to the simulation results in this case. Part (a) shows the relation between the run time and the velocity values (min, max, and mean), in part (b) the relation between the simulation run time and the number of vehicles per lane which explain the change lane to reach the final destination with less time.

Transient traffic scenario with high-density level and three lanes:

In a transient traffic scenario with high density, The road is heavily congested with a large number of vehicles occupying all three lanes. Cars are moving slowly and there is little space between them. Drivers may be frustrated and impatient, as they are unable to move at a faster pace.

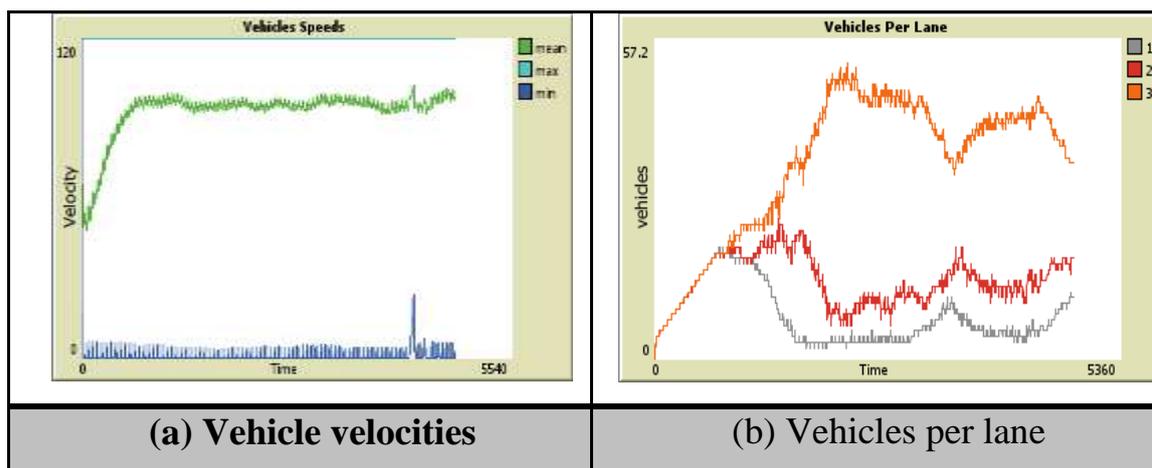


Figure (4.12) High-level density, 150 vehicles, and three lanes.

In this case, the number of vehicles was 150 based on a 0.168 arrival rate. Figure (4.12) refers to the simulation results of the stability metrics in this case. In part (a) the relation between the run time and the velocity values (min, max, and mean), in part (b) the relation between the simulation run time and the number of vehicles per lane which explain the change lane to reach to the final destination with less time.

Steady-State Scenario:

In this scenario, the created vehicles are distributed over the road segment and between lanes, and vehicles in each lane are observed and presented. The three lanes provide more options for vehicles to maneuver and change lanes, which can help to alleviate congestion and improve traffic flow. However, if drivers do not use the lanes effectively or safely, it can lead to reduced efficiency and increased risk of accidents.

Steady-state traffic scenario with low level and three lanes:

In a steady-state traffic scenario with low density, the number of vehicles on the road is relatively low compared to the capacity of the road. This means that there is a lot of space available for vehicles to maneuver, change lanes, and travel at different velocities.

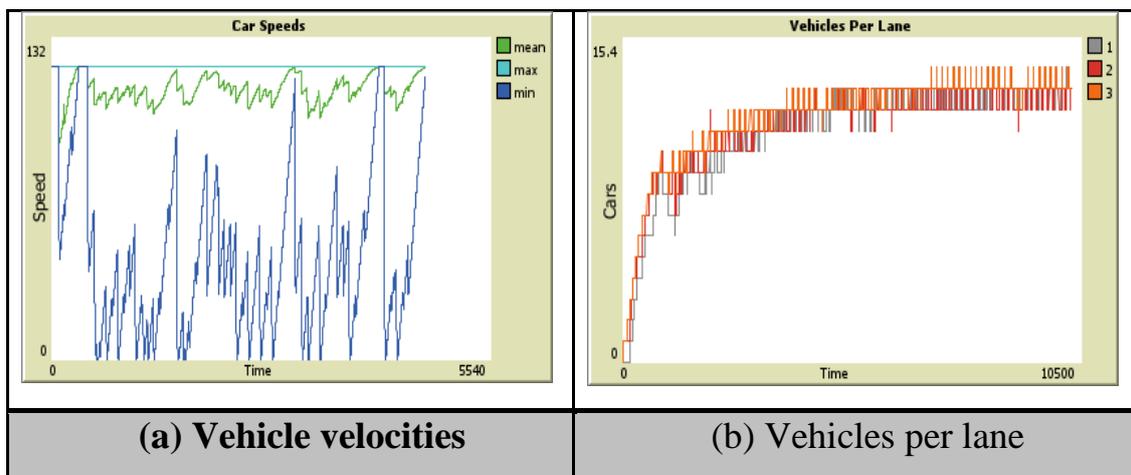


Figure (4.13) Low-level density, 50 vehicles, and three lanes

In this case, the number of vehicles was 50 based on a 0.058 arrival rate. Figure (4.13) refers to the simulation results in this case. In Figure (a) the relation between the run time and the velocity values (min, max, and mean), and in Figure (b) the relation between the simulation run time and the number of vehicles per lane which explain the change lane to reach to the final destination with less time.

Steady-state traffic scenario with medium density level and three lanes:

In a steady-state traffic scenario with medium density, The road has a moderate amount of cars on it, with some empty spaces between them. Vehicles are moving at a steady pace and lane change may occur, but not too fast or too slow. Drivers are able to maintain a safe distance from one another, and there are no major bottlenecks or slowdowns.

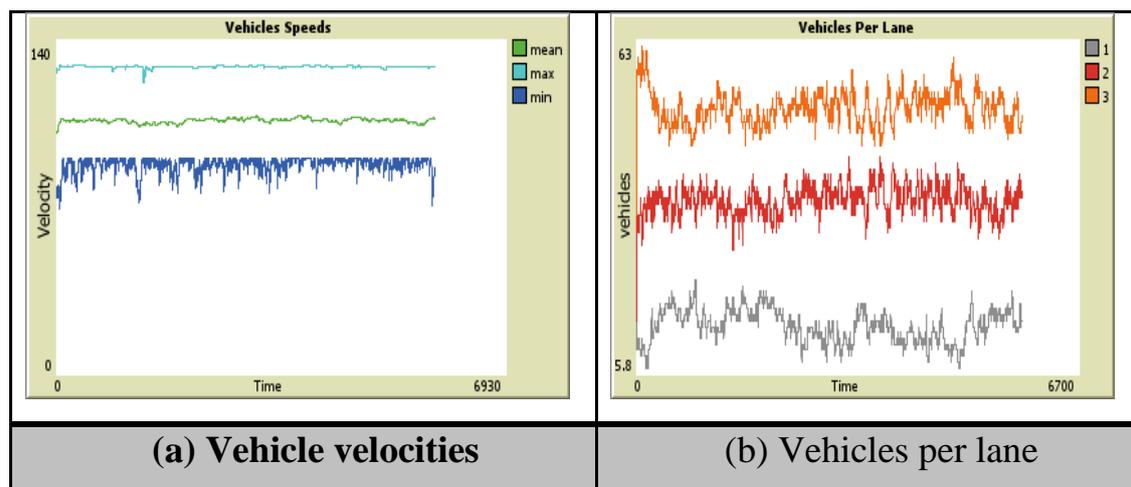


Figure 4.14 Medium-level density, 100 vehicles, and three-lanes

In this case, the number of vehicles was 100 based on a 0.114 arrival rate. Figure (4.14) refers to the simulation results of the stability metrics in this case. Part (a) shows the relation between the run time and the velocity values (min, max, and mean), and in part (b) the relation between the simulation run time and the number of vehicles per lane which explain the change lane to reach the final destination with less time.

At medium densities, traffic flow is typically stable and free-flowing, with little congestion or queue formation. This means that travel times are generally consistent and predictable. Lane-changing behavior, Drivers may still change lanes to optimize their travel times, but it is less frequent than in high-density scenarios. With less lane-changing behavior, the risk of accidents decreases in medium-density scenarios

Steady-state traffic scenario with high-density level and three lanes:

In a steady-state traffic scenario with high density, The road is heavily congested with a large number of vehicles occupying all three lanes. Cars are moving slowly and there is little space between them. Drivers may be frustrated and impatient, as they are unable to move at a faster pace.

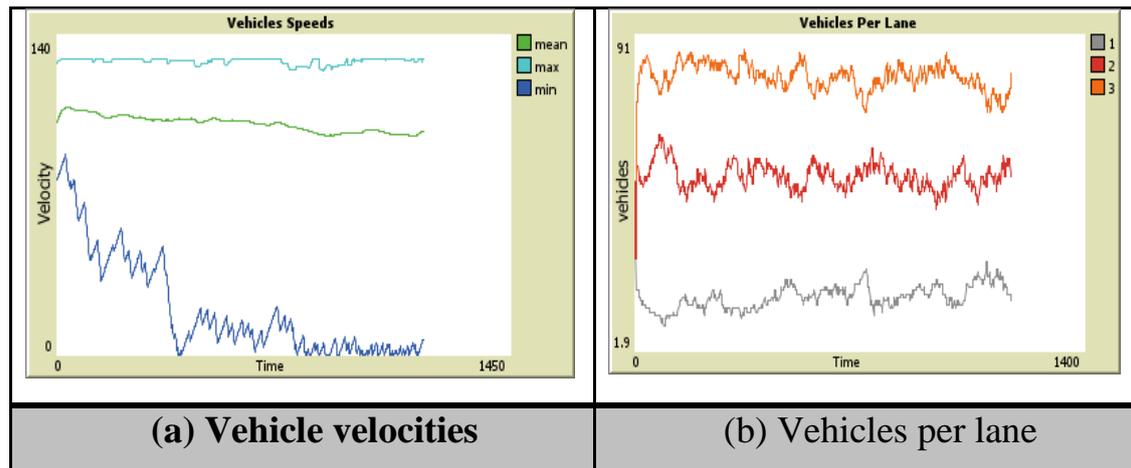


Figure (4.15) High-level density, 50 vehicles, and three lanes.

In this case, the number of vehicles was 100 based on a 0.168 arrival rate. Figure (4.15) refers to the simulation results of the stability metrics in this case. Part (a) show the relation between the run time and the velocity values (min, max, and mean), part (b) show the relation between the simulation run time and the number of vehicles per lane which explain the change lane to reach to the final destination with less time.

In the high density scenario, it can result in longer travel times, increased emissions from idling vehicles, and driver frustration. Figure (4.15 (a)) show the frequent change in the velocity and decreases most time. Drivers may change lanes frequently to find the fastest route through congestion. This can increase the risk of accidents and further reduce traffic flow efficiency.

Figure (4.16) show velocities for the two scenario, the velocity range (min, max, and mean velocity) can vary depending on several factors such as the traffic volume, the number of lanes, the speed limit, and the presence of (RSU). In

general, The minimum velocity in the steady-state traffic flow occurs during congested traffic conditions (high-level density) when there is a high volume of vehicles on the road. The maximum velocity, on the other hand, occurs during periods of low traffic volume or when there is a low number of vehicles on the road.

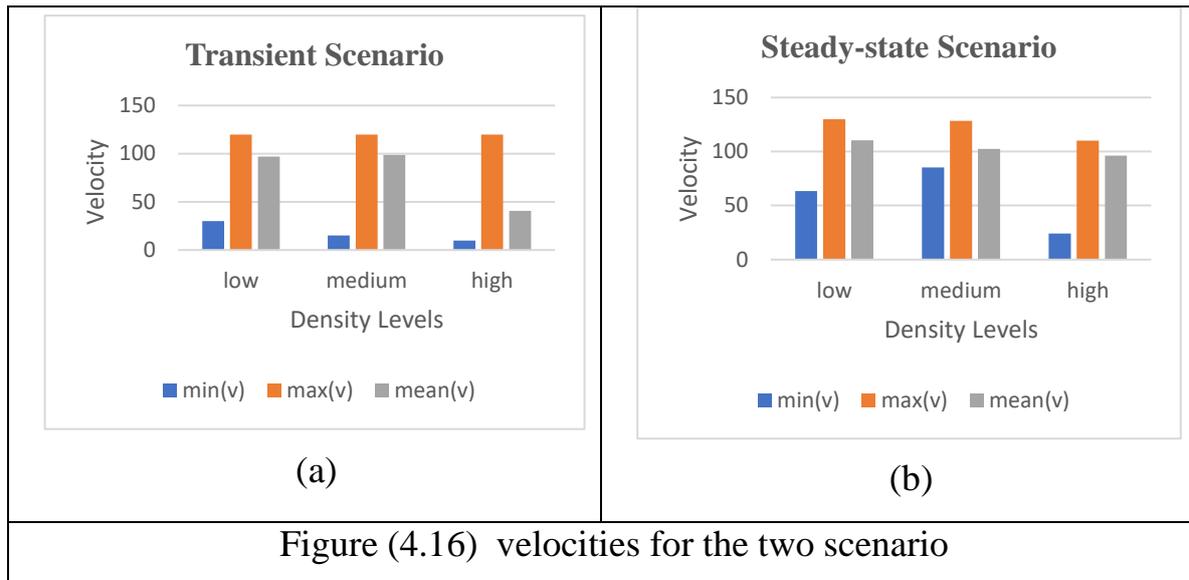


Figure (4.16) velocities for the two scenario

In a three-lane road scenario, the mean velocity is slightly higher compared to a road with fewer lanes. This is because the extra lane provides more space for vehicles to maneuver and change lanes, which can help to alleviate congestion and improve traffic flow.

4.10 Proposed Models Evaluation

Experimentally, to validate the functioning of the proposed models and the accuracy of prediction two datasets (highD and NGSIM) are used in implementing and testing these models. The result was compared with state-of-the-art models in this field. Table (4.18) present the evaluation of the developed models.

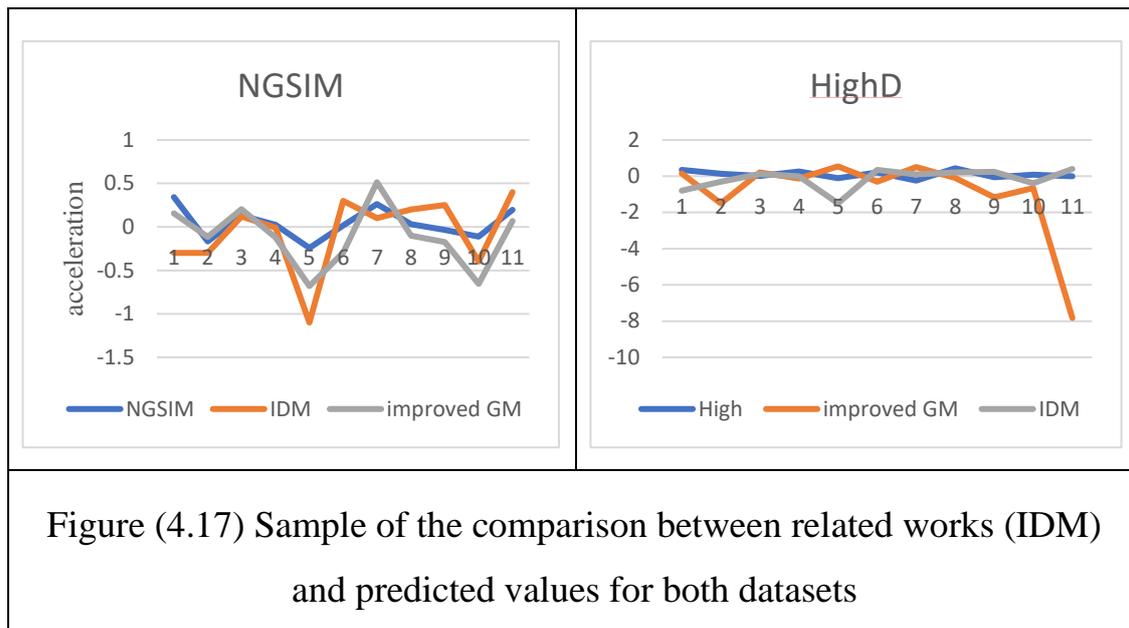
Table (4.18) Evaluation results.

RMSE	Constant Velocity	driver view prediction	Improved Safety model	Developed GM
Highd	0.511	0.482	0.0178	0.2122
NGSIM	0.535	0.531	0.2312	0.1102

The authors in the related works used constant velocity in their simulation scenarios which are not mimic the real driving situation on roads. In this dissertation simulation model, the variable vehicle's velocity was generated based on random probability behavior by incorporating real datasets.

The proposed improvements on mobility models in this dissertation demonstrate significantly lower RMSE values compared to the two related works. This dissertation's results are superior to the previous results on both used datasets. This is good evidence that the improved safety model is more accurate in capturing the behavior of vehicles and predicting their movements. In addition to that, the developed GM model achieves the lowest RMSE values among all the models tested for both datasets. Based on these results, it can be concluded that the developed GM model shows promise in accurately predicting vehicle behavior.

A second comparison is made on the developed GM motor models with (Valentina Kurtc, 2020). Figure (4.17) show the result of the developed model with the observed acceleration for both datasets and the Intelligent Driver Model (IDM).



The comparison results presented in Figure (4.17) contribute to understand the performance of the developed GM motor model in relation to observed acceleration data and a well-known car-following model like the IDM. This information can guide further improvements and refinements to the developed model and highlight its strengths and areas for enhancement in accurately capturing vehicle acceleration behavior.

4.11 Data Dissemination Results

When the performance metrics are calculated with different parameters, the throughput, delay, packet loss, and packet delivery ratio (according to Eqs. (2.10), (2.11), (2.12), and (2.13) respectively) are obtained as part of the evaluation of the proposed system. When the number of vehicles equals 50, 100, and 150 the results are as shown in Figures (4.18) and (4.19).

The results of data dissemination for the first scenario are shown in Figure (4.18).

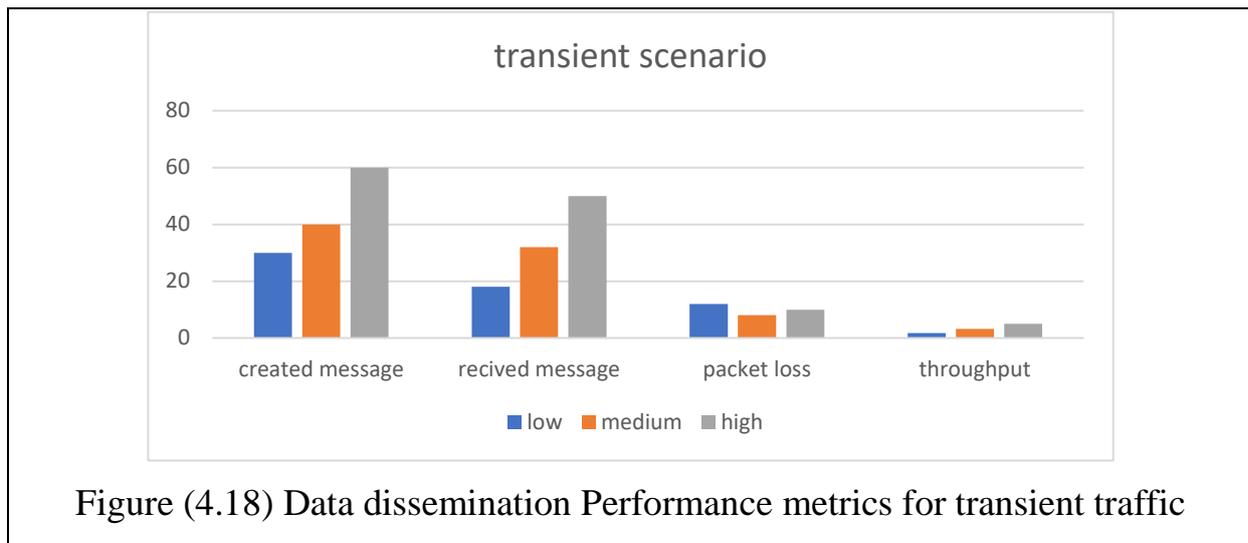


Figure (4.18) Data dissemination Performance metrics for transient traffic

The packet loss in the broadcast and unicast communication methods seem to follow the Exponential distribution. Utilizing the Exponential distribution will help in predicting the expected values and their standard deviation in a possible manner. In the Broadcast, the Packet loss was the largest when the number of vehicles was 50 and increased gradually with the number of vehicles increased. While the throughput performance metrics were opposite to packet loss. The Packet delivery ration seems to follow the Uniform distribution. Utilizing the Uniform distribution will help in predicting and easing the process of estimating the expected values in a possible manner.

Table (4.18) show the numerical results of the data dissemination performance metrics in the transient traffic scenario (packet loss, throughput, packet delivery ratio, and end-to-end delay).

Table (4.18) Data dissemination performance metrics in the transient scenario

Broadcast	Created messages	Received message	Packet loss	throughput	E-2-E delay	Packet delivery ratio
50 vehicles	30	18	12	1.8	0.0821	60%

100 vehicle	40	32	8	3.2	0.071	80%
150 vehicle	60	50	10	5	0.024	83%

On the other hand, the results of data dissemination for the second scenario are shown in Figure (4.19).

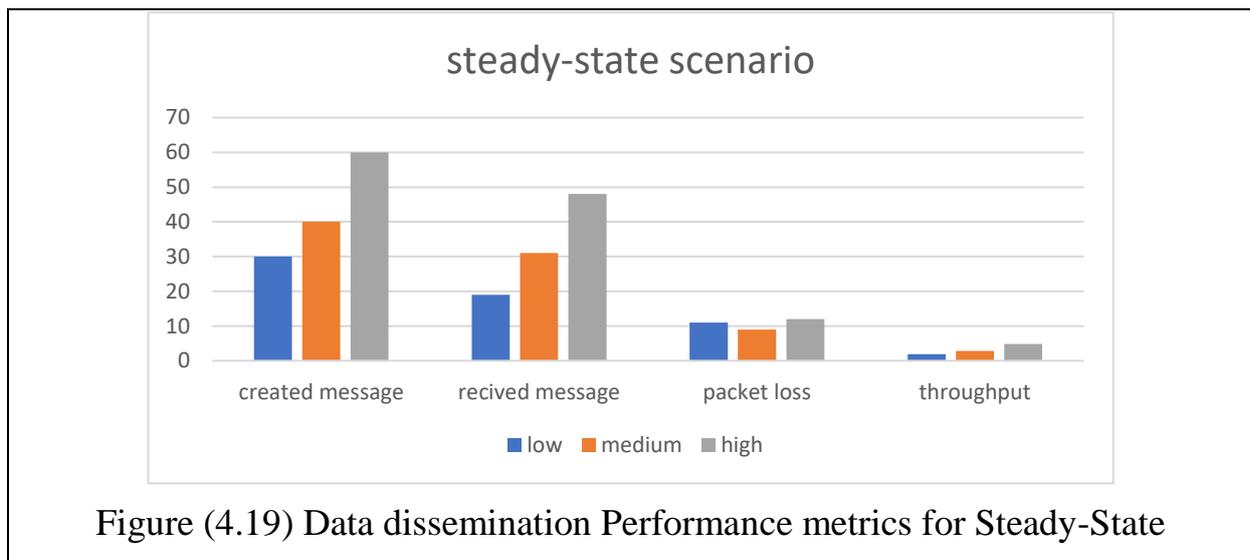


Figure (4.19) Data dissemination Performance metrics for Steady-State

The results are shown in Figure (4.19), throughput increases with the number of vehicles increasing. The packet loss seems to follow the Poisson distribution. Utilizing Poisson distribution will help in predicting the expected values and their standard deviation in a possible manner. Table (4.19) show the numerical results of the data dissemination performance metrics (packet loss, throughput, packet delivery ratio, and end-to-end delay) in the steady-state scenario.

Table (4.19) Data dissemination performance metrics in the steady state scenario.

Broadcast	Created messages	Received message	Packet loss	throughput	E-2-E delay	Packet delivery ratio
50 vehicles	30	19	11	1.8636	0.0107	61%

100 vehicle	40	31	9	2.8182	0.011	77%
150 vehicle	60	48	12	4.8	0.0098	80%

CHAPTER FIVE

CONCLUSIONS AND FUTURE

WORKS

5.1 Introduction

This chapter is to preview the conclusions and future trends of the proposed models which are inferred from the performance metrics. These conclusions are taken based on depicting real collected datasets in simulation experiments to mimic the real behavior of the vehicular networks. The results have been designed and implemented using Netlogo 6.3.0 simulation.

5.2 Conclusions

1. Research on simulating Vehicular Networks requires an in-depth focus on mobility models which can perfectly capture the movement behavior of vehicles.
2. Mobility models represent the unique reliable representation of real vehicle mobility. These models can be used in evaluating the proposed improvements in the performance of the Vehicular network behavior by simulation.
3. Developing the Mobility models and utilizing real datasets in estimating their parameters will play a vital role in Vehicular network optimization to mimic the actual behavior of road traffics.
4. In this dissertation, a proposed improvement to the safety distance model was presented by adding a new variable to capture the driver's role in the vehicle's mobility to accelerate, stay without change, or decelerate.
5. Estimating the real vehicle traffic parameters based on collected real datasets can improve the simulation results' accuracy. This approach will make the simulation results very close to real-case applications.

6. Proposing an adaptive approach to estimate the value of the constant term (α) in the GM model will add good accuracy and make this model more practical in its implementation. This proposed approach is reliable and trusted when it is based on analyzing real datasets. The findings in this dissertation model improve the previous application of this model by suggesting a certain fixed value for (α). Also, the results show a relation between the frame lengths and (α).
7. Proposing three alternatives to estimate the relative velocity in the GM model based on real datasets will cover all possible sample space. One of these three alternatives will reflect the suitable value of each environmental behavior.
8. Developing mathematical approaches to generate the velocity and acceleration of the vehicle at each time in a simulation scenario will improve the simulation results and make them close to the real values. This dissertation utilizes the collected statistics from real datasets and used them as input to feed the developed mathematical approaches.
9. Utilizing probability distribution can improve the simulation representation of the lane change problem. Utilizing the Binomial probability distribution to select the driver's decision either to change lanes or stay in the same lane improves the simulation results.
10. Using the Markov model to represent the best selection choices of the driver at each time based on its surrounding vehicles. Markov model will present the possible choices in a simulation environment based on safety distance, empty lanes, and vehicle velocity.

11. Utilizing the negative exponential distribution will contribute to simulating the driver behavior and estimating the required reaction time to respond to each sudden event.
12. Vehicles traffic behaviors have an impact on the vehicular communication and data dissemination process.

5.3 Future Works

- Implement the proposed models in this dissertation on self-driving vehicles.
- Try to build an online prediction model to give the driver (or auto vehicle) an indication of the possible lane changes.
- Study the utility of incorporating the Internet-of-Things, cellular networks, and sensor networks in vehicular networks applications.

REFERENCES

References:

Abdelgadir, Mayada, Rashid A. Saeed, and Abuagla Babiker. "Mobility Routing Model for Vehicular Ad-Hoc Networks (VANETs), Smart City Scenarios." *Vehicular Communications* 9 (July 2017): 154–61. <https://doi.org/10.1016/j.vehcom.2017.04.003>.

Ahmed, Hafiz Usman, Ying Huang, and Pan Lu. "A Review of Car-Following Models and Modeling Tools for Human and Autonomous-Ready Driving Behaviors in Micro-Simulation." *Smart Cities* 4, no. 1 (March 3, 2021): 314–35. <https://doi.org/10.3390/smartcities4010019>.

Ahmed, Hafiz Usman, Ying Huang, Pan Lu, and Raj Bridgelall. "Technology Developments and Impacts of Connected and Autonomous Vehicles: An Overview." *Smart Cities* 5, no. 1 (March 17, 2022): 382–404. <https://doi.org/10.3390/smartcities5010022>.

Akhtar, Nabeel, Sinem Coleri Ergen, and Ozgur Ozkasap. "Vehicle Mobility and Communication Channel Models for Realistic and Efficient Highway VANET Simulation." *IEEE Transactions on Vehicular Technology* 64, no. 1 (January 2015): 248–62. <https://doi.org/10.1109/tvt.2014.2319107>.

Aldegheishem, Abdulaziz, Humera Yasmeen, Hafsa Maryam, Munam Shah, Amjad Mehmood, Nabil Alrajeh, and Houbing Song. "Smart Road Traffic Accidents Reduction Strategy Based on Intelligent Transportation Systems (TARS)." *Sensors* 18, no. 7 (June 21, 2018): 1983. <https://doi.org/10.3390/s18071983>.

Ali, Yasir, Zuduo Zheng, Md. Mazharul Haque, and Meng Wang. "A Game Theory-Based Approach for Modelling Mandatory Lane-Changing

Behaviour in a Connected Environment.” *Transportation Research Part C: Emerging Technologies* 106 (September 2019): 220–42. <https://doi.org/10.1016/j.trc.2019.07.011>.

Treiber, Martin, and Arne Kesting. *Traffic Flow Dynamics*. Springer EBooks, 2013. <https://doi.org/10.1007/978-3-642-32460-4>.

Anderson, Cyrus, Ram Vasudevan, and Matthew Johnson-Roberson. “A Kinematic Model for Trajectory Prediction in General Highway Scenarios.” *IEEE Robotics and Automation Letters* 6, no. 4 (October 2021): 6757–64. <https://doi.org/10.1109/lra.2021.3094491>.

Arif, Muhammad, Guojun Wang, Md Zakirul Alam Bhuiyan, Tian Wang, and Jianer Chen. “A Survey on Security Attacks in VANETs: Communication, Applications and Challenges.” *Vehicular Communications* 19 (October 2019): 100179. <https://doi.org/10.1016/j.vehcom.2019.100179>.

Azzaoui, Nadjet, Ahmed Korichi, Bouziane Brik, and Hanane Amirat. “A Survey on Data Dissemination in Internet of Vehicles Networks.” *Journal of Location Based Services*, November 30, 2022, 1–44. <https://doi.org/10.1080/17489725.2022.2151658>.

Bakhtiari, Zohreh, Rozita Jamili Oskouei, Mona Soleymani, and Akhtar Hussain Jalbani. “Presenting an Effective Method to Detect and Track the Broken Path in VANET Using UAVs.” *Wireless Communications and Mobile Computing* 2020 (August 17, 2020): 1–12. <https://doi.org/10.1155/2020/8887285>.

Benrhaiem, Wiem, and Abdelhakim Senhaji Hafid. “Bayesian Networks Based Reliable Broadcast in Vehicular Networks.” *Vehicular*

Communications 21 (January 2020): 100181.
<https://doi.org/10.1016/j.vehcom.2019.100181>.

Brackstone, Mark, and Mike McDonald. "Car-Following: A Historical Review." *Transportation Research Part F: Traffic Psychology and Behaviour* 2, no. 4 (1999): 181.
https://www.academia.edu/23532105/Car_following_a_historical_review.

Talib, Mohammed Saad, Aslinda Hassan, Thamer Alamery, Zuraida Abal Abas, Ali Abdul-Jabbar Mohammed, Ali Jalil Ibrahim, and Nihad Ibrahim Abdullah. "A Center-Based Stable Evolving Clustering Algorithm with Grid Partitioning and Extended Mobility Features for VANETs." *IEEE Access* 8 (2020): 169908–21.
<https://doi.org/10.1109/access.2020.3020510>.

Lochert, Christian, Björn Scheuermann, Mustafa Caliskan, and Martin Mauve. "The Feasibility of Information Dissemination in Vehicular Ad-Hoc Networks," April 2, 2007.
<https://doi.org/10.1109/wons.2007.340478>.

Carraway, Robert L., and Robert Jenkins. "Introduction to Analytical Probability Distributions." *SSRN Electronic Journal*, 2017.
<https://doi.org/10.2139/ssrn.2975104>.

Chen, Kequan, Victor Knoop, Pan Liu, Zhibin Li, and Yuxuan Wang. "Modeling the Impact of Lane-Changing's Anticipation on Car-Following Behavior." *SSRN Electronic Journal*, 2022.
<https://doi.org/10.2139/ssrn.4262019>.

Cui, Qimei, Xingxing Hu, Wei Ni, Xiaofeng Tao, Ping Zhang, Tao Chen, Kwang-Cheng Chen, and Martin Haenggi. "Vehicular Mobility Patterns

and Their Applications to Internet-of-Vehicles: A Comprehensive Survey.” *Science China Information Sciences* 65, no. 11 (October 25, 2022). <https://doi.org/10.1007/s11432-021-3487-x>.

Daniel, Alfred, Anand Paul, Awais Ahmad, and Seungmin Rho. “Cooperative Intelligence of Vehicles for Intelligent Transportation Systems (ITS).” *Wireless Personal Communications* 87, no. 2 (October 6, 2015): 461–84. <https://doi.org/10.1007/s11277-015-3078-7>.

Djahel, Soufiene, Ronan Doolan, Gabriel-Miro Muntean, and John Murphy. “A Communications-Oriented Perspective on Traffic Management Systems for Smart Cities: Challenges and Innovative Approaches.” *IEEE Communications Surveys & Tutorials* 17, no. 1 (2015): 125–51. <https://doi.org/10.1109/comst.2014.2339817>.

Farooq, Danish, and Janos Juhasz. “Simulation-Based Analysis of the Effect of Significant Traffic Parameters on Lane Changing for Driving Logic ‘Cautious’ on a Freeway.” *Sustainability* 11, no. 21 (October 28, 2019): 5976. <https://doi.org/10.3390/su11215976>.

Gillani, Maryam, Hafiz Adnan Niaz, Muhammad Umar Farooq, and Ata Ullah. “Data Collection Protocols for VANETs: A Survey.” *Complex & Intelligent Systems* 8, no. 3 (January 10, 2022): 2593–2622. <https://doi.org/10.1007/s40747-021-00629-x>.

Gipps, P.G. “A Behavioural Car-Following Model for Computer Simulation.” *Transportation Research Part B: Methodological* 15, no. 2 (April 1981): 105–11. [https://doi.org/10.1016/0191-2615\(81\)90037-0](https://doi.org/10.1016/0191-2615(81)90037-0).

Haenggi, Martin. “Meta Distributions—Part 1: Definition and Examples.” *IEEE Communications Letters*, 2021, 1–1.

<https://doi.org/10.1109/lcomm.2021.3069662>.

Hamdi, Mustafa Maad, L. Audah, S. Rashid, and Sameer Alani. “VANET-Based Traffic Monitoring and Incident Detection System: A Review.” *International Journal of Electrical and Computer Engineering*, 2021. <https://www.semanticscholar.org/paper/VANET-Based-Traffic-Monitoring-and-Incident-System%3A-Hamdi-Audah/c2e3f0658dcc3c3ed0249292899a25cdfdb53bc4>.

Jia, Bingmei, Da Yang, Xiaobo Zhang, Yuezhu Wu, and Qian Guo. “Car-Following Model Considering the Lane-Changing Prevention Effect and Its Stability Analysis.” *The European Physical Journal B* 93, no. 8 (August 2020). <https://doi.org/10.1140/epjb/e2020-10028-3>.

Kesting, Arne, Martin Treiber, and Dirk Helbing. “General Lane-Changing Model MOBIL for Car-Following Models.” *Transportation Research Record: Journal of the Transportation Research Board* 1999, no. 1 (January 2007): 86–94. <https://doi.org/10.3141/1999-10>.

Kurtc, Valentina. “Studying Car-Following Dynamics on the Basis of the HighD Dataset.” *Transportation Research Record: Journal of the Transportation Research Board* 2674, no. 8 (June 23, 2020): 813–22. <https://doi.org/10.1177/0361198120925063>.

Maad Hamdi, Mustafa, Lukman Audah, Sami Abduljabbar Rashid, Alaa Hamid Mohammed, Sameer Alani, and Ahmed Shamil Mustafa. “A Review of Applications, Characteristics and Challenges in Vehicular Ad Hoc Networks (VANETs).” *2020 International Congress on Human-Computer Interaction, Optimization and Robotic Applications (HORA)*, June 2020. <https://doi.org/10.1109/hora49412.2020.9152928>.

Mastrogiacomo, Elisa, and Emanuela Rosazza Gianin. “Time-Consistency of Risk Measures: How Strong Is Such a Property?” *Decisions in Economics and Finance* 42, no. 1 (February 7, 2019): 287–317. <https://doi.org/10.1007/s10203-019-00233-2>.

Rehman, Osama, Rehan Qureshi, Mohamed Ould-Khaoua, and Moazzam Fareed Niazi. “Analysis of Mobility Speed Impact on End-To-End Communication Performance in VANETs.” *Vehicular Communications* 26 (December 2020): 100278. <https://doi.org/10.1016/j.vehcom.2020.100278>.

S, Pradeep Kumar T. “Real-Time Traffic Simulation of Vehicular Ad Hoc Networks.” *Modelling and Simulation of Fast-Moving Ad-Hoc Networks (FANETs and VANETs)*, 2023, 109–23. <https://research.vit.ac.in/publication/real-time-traffic-simulation-of-vehicular-ad-hoc-networks>.

Shen, Qiangru, Yujie Ni, Hui Cao, Wangping Qian, and Gen Li. “How Do Vehicles Make Decisions during Implementation Period of Discretionary Lane Change? A Data-Driven Research.” Edited by Zhenzhou Yuan. *Journal of Advanced Transportation* 2023 (February 14, 2023): 1–15. <https://doi.org/10.1155/2023/2586372>.

Shinde, Swapnil Sadashiv, and Daniele Tarchi. “Towards a Novel Air–Ground Intelligent Platform for Vehicular Networks: Technologies, Scenarios, and Challenges.” *Smart Cities* 4, no. 4 (December 9, 2021): 1469–95. <https://doi.org/10.3390/smartcities4040078>.

Singh, Er. “Overview of Challenges in VANET.” Accessed March 24, 2023. <http://ijirse.com/wp-content/upload/2016/02/142ijirse.pdf>.

Srisurin, Punyaanek, and Alexandra Kondyli. “Integrating Car Following and Lane Changing in a Mixed Traffic Model of Connected Automated Vehicles and Conventional Vehicles.” [trid.trb.org](https://trid.trb.org/view/1759634), 2021. <https://trid.trb.org/view/1759634>.

Sutariya, Dharmendra, and S. N. Pradhan. “Data Dissemination Techniques in Vehicular Ad Hoc Network.” *International Journal of Computer Applications* 8, no. 10 (October 10, 2010): 35–39. <https://doi.org/10.5120/1240-1725>.

Talebpour, Alireza, Hani S. Mahmassani, and Samer H. Hamdar. “Modeling Lane-Changing Behavior in a Connected Environment: A Game Theory Approach.” *Transportation Research Procedia* 7 (2015): 420–40. <https://doi.org/10.1016/j.trpro.2015.06.022>.

Treiber, Martin, Ansgar Hennecke, and Dirk Helbing. “Congested Traffic States in Empirical Observations and Microscopic Simulations.” *Physical Review E* 62, no. 2 (August 1, 2000): 1805–24. <https://doi.org/10.1103/physreve.62.1805>.

Treiber, Martin, Ansgar Hennecke, and Dirk Helbing. “Congested Traffic States in Empirical Observations and Microscopic Simulations.” *Physical Review E* 62, no. 2 (August 1, 2000): 1805–24. <https://doi.org/10.1103/physreve.62.1805>.

Ur Rehman, Sabih, M Khan, Tanveer Zia, and Lihong Zheng. “Vehicular Ad-Hoc Networks (VANETs) -an Overview and Challenges.” *Journal of Wireless Networking and Communications* 2013, no. 3 (January 2013): 29–38. <https://doi.org/10.5923/j.jwnc.20130303.02>.

Wahid, Ishtiaq, Sadaf Tanvir, Masood Ahmad, Fasee Ullah, Ahmed S.

AlGhamdi, Murad Khan, and Sultan S. Alshamrani. "Vehicular Ad Hoc Networks Routing Strategies for Intelligent Transportation System." *Electronics* 11, no. 15 (January 1, 2022): 2298. <https://doi.org/10.3390/electronics11152298>.

WEI, Da, Yan-Xi WANG, Jian WANG, Yan-Heng LIU, and Wei-Wen DENG. "A Survey on Mobility Models of Vehicular Ad Hoc Networks." *Chinese Journal of Computers* 36, no. 4 (March 13, 2014): 677–700. <https://doi.org/10.3724/sp.j.1016.2013.00677>.

Zhang, Hong, and Li Wei. "Topology Characteristic Analysis of Vehicular Ad Hoc Network Based on Time-Varying Complex Network." *AIP Advances* 11, no. 11 (November 1, 2021): 115011. <https://doi.org/10.1063/5.0067357>.

Zhang, Kekun, Dayi Qu, Hui Song, Tao Wang, and Shouchen Dai. "Analysis of Lane-Changing Decision-Making Behavior and Molecular Interaction Potential Modeling for Connected and Automated Vehicles." *Sustainability* 14, no. 17 (September 5, 2022): 11049. <https://doi.org/10.3390/su141711049>.

Zhang, Kekun, Dayi Qu, Hui Song, Tao Wang, and Shouchen Dai. "Analysis of Lane-Changing Decision-Making Behavior and Molecular Interaction Potential Modeling for Connected and Automated Vehicles." *Sustainability* 14, no. 17 (September 5, 2022): 11049. <https://doi.org/10.3390/su141711049>.

Zong, Fang, Meng Wang, Ming Tang, Xiyang Li, and Meng Zeng. "An Improved Intelligent Driver Model Considering the Information of Multiple Front and Rear Vehicles." *IEEE Access* 9 (2021): 66241–52.

<https://doi.org/10.1109/access.2021.3072058>.

Hasson, Saad Talib, and Abbas E. Abbas. A Clustering Approach to Model the Data Dissemination in VANETs, 2021. <https://doi.org/10.1109/bicits51482.2021.9509890>.

Yeferny, Taoufik, and Sofian Hamad. “Vehicular Ad-Hoc Networks: Architecture, Applications and Challenges.” arXiv.org, January 12, 2021. <https://doi.org/10.48550/arXiv.2101.04539>.

الخلاصة

أهم ميزة لشبكات المركبات هي حركة تنقلها السريعة. تجعل هذه الميزة نموذج التنقل أهم عامل يجب اختياره بحكمة عند تنفيذ أي سيناريو محاكاة. أصبح تطوير مناهج النمذجة لمحاكاة أنماط التنقل في شبكات المركبات ذا أهمية متزايدة في السنوات الأخيرة. يجب أن تعكس نماذج التنقل بدقة الحركة الحقيقية للمركبات على الطرق. تأخذ هذه النماذج في الاعتبار عوامل مختلفة مثل السرعة والتسارع والتباطؤ وتغيير الحرارة والتفاعلات بين المركبات. تم أخذ نموذجين للتنقل في السيارة في الاعتبار في هذه الرسالة (Safety Distance and General Motor models). في هذه الأطروحة، تم إنشاء دراسة متعمقة لتحليل هذه النماذج وإيجاد مطلب لتحسينها وكذلك تطوير طرق لتقدير متغيراتها بناءً على مجموعة بيانات حقيقية. تم استخدام مجموعتي بيانات حقيقتين. يتم استخدام إحصائيات مجموعات البيانات في تقدير متغيرات النموذج هذه وكذلك في إنشاء إعدادات المحاكاة. تم استخدام من التوزيعات الاحتمالية المختلفة أيضاً في توليد حركة المركبات ومعلومات المرور لتناسب تطبيقات الحالات الحقيقية بالاعتماد على البيانات الحقيقية. ستؤدي إضافة متغير معين إلى نموذج Safety Distance إلى جعله أكثر دقة ومناسباً للتنبؤ بالسرعات والتعجيل بعد فترة من الزمن. هذه القيم المتغيرة المضافة مقترحة ومشار إليها (0 ، 1 ، -1). أيضاً ، تم تطوير نهج رياضي لتقدير المصطلح الثابت (α) في نموذج General Motor بناءً على تحليل مجموعات البيانات التي تم جمعها. في نموذج General Motor تعتبر السرعة النسبية (ΔV) هي العامل الرئيسي الذي يجب تقديره بشكل صحيح. تم إنشاء وتنفيذ ثلاثة مناهج مقترحة في هذه الرسالة لتقدير القيمة المناسبة للسرعة النسبية. تستند هذه القيم الثلاث إلى (أقل، أعلى، و معدل) السرعة التي تم جمعها بعد تحليل مجموعات البيانات. سيتم تحديد إحدى هذه القيم الثلاث عند تنفيذ حساب النماذج بناءً على سلوك بيانات السيارة والشارع. تم اقتراح نموذج رياضي متطور لتغيير المسار بطريقة رياضية باستخدام أساسيات التوزيع ذي الحدين ونظرية نماذج ماركوف. تمت محاكاة جميع هذه النماذج المقترحة وملاحظة نتائجها. تظهر المقارنة مع الأعمال ذات الصلة تفوق النماذج المطورة على الأعمال ذات الصلة. يتم تنفيذ نتائج المحاكاة لإظهار تأثير حركة مرور المركبات على نشر البيانات وتقييم أداء الشبكة أيضاً. تم تسجيل النتائج المقبولة في سيناريوهات محاكاة مختلفة مما يعكس موثوقية الأساليب المقترحة.



جمهورية العراق
وزارة التعليم العالي والبحث
العلمي
جامعة بابل

كلية تكنولوجيا المعلومات

طريقة نمذجة مطورة لمحاكاة انماط الحركة في شبكات المركبات

أطروحة

مقدمة إلى مجلس كلية تكنولوجيا المعلومات في جامعة بابل كجزء من متطلبات الحصول
على درجة الدكتوراه فلسفة في تكنولوجيا المعلومات – قسم الشبكات

مقدمة من قبل

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