The Relationship between Traffic Safety and Macroscopic Fundamental Diagram (MFD)

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The Relationship between Traffic Safety and Macroscopic Fundamental Diagram (MFD)

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The Macroscopic Fundamental Diagram (MFD) is a common tool of choice for evaluating and controlling urban traffic networks. The MFD captures the relationship between traffic parameters that reflect on the network behaviour, including the average network density, speed and flow. Considerable research has been conducted in recent years on the urban MFD and its use for area-wide network monitoring and control purposes to improve a network's operational efficiency. An important consideration in network traffic performance is its safety performance. However, there is an apparent lack of understanding on how the MFD is connected with road safety. This thesis explores the relationship between MFD and safety performance on urban network, through proposing a novel theoretical model, referred to as a "Macroscopic Safety Diagram" (MSD). The MSD relates the probability of crash occurrence in the network with its current state (i.e., average density). The safety of urban networks is vital given the characteristic nature of urban traffic that is dynamically evolving. In this thesis, a theoretical model is presented to show that MSDs exist for networks that have a well-defined network MFD. Furthermore, a proof is provided to show that the density associated with maximum crash propensity is larger than the density associated with maximum network performance. This finding suggests that congested states are not only inefficient in urban networks, but they might also be more unsafe. These theoretical results are validated using a surrogate safety assessment model in a microsimulation for 2 networks: 1) 10 x 10 grid network and 2) city of Bellevue/Redmond, Washington, USA network. Additionally, field empirical data from a small arterial network in Riyadh, the capital and largest city of the Kingdom of Saudi Arabia is adopted to validate the results. The existence of such MSDs can be used to evaluate safety performance at the network level. It can also be used to develop more comprehensive network-wide control policies that can ensure both safe and efficient network operations.

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"All Praise be to the Almighty God for all of the gifts that he has bestowed upon me"

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Dedication

"This thesis is dedicated to my late father whom I learnt a lot from during his lifetime, my mother and siblings who are always there for me, my wife, whom I wish to thank immensely for her support and patience during my PhD and finally my lovely daughters Fatima and Dana."

Abstract

The Macroscopic Fundamental Diagram (MFD) is a common tool of choice for evaluating and controlling urban traffic networks. The MFD captures the relationship between traffic parameters that reflect on the network behaviour, including the average network density, speed and flow. Considerable research has been conducted in recent years on the urban MFD and its use for area-wide network monitoring and control purposes to improve a network's operational efficiency. An important consideration in network traffic performance is its safety performance. However, there is an apparent lack of understanding on how the MFD is connected with road safety. This thesis explores the relationship between MFD and safety performance on urban network, through proposing a novel theoretical model, referred to as a "Macroscopic Safety Diagram" (MSD). The MSD relates the probability of crash occurrence in the network with its current state (i.e., average density). The safety of urban networks is vital given the characteristic nature of urban traffic that is dynamically evolving. In this thesis, a theoretical model is presented to show that MSDs exist for networks that have a well-defined network MFD. Furthermore, a proof is provided to show that the density associated with maximum crash propensity is larger than the density associated with maximum network performance. This finding suggests that congested states are not only inefficient in urban networks, but they might also be more unsafe. These theoretical results are validated using a surrogate safety assessment model in a microsimulation for 2 networks: 1) 10 x 10 grid network and 2) city of

Bellevue/Redmond, Washington, USA network. Additionally, field empirical data from a small arterial network in Riyadh, the capital and largest city of the Kingdom of Saudi Arabia is adopted to validate the results. The existence of such MSDs can be used to evaluate safety performance at the network level. It can also be used to develop more comprehensive network-wide control policies that can ensure both safe and efficient network operations.

List of Relevant Publications and Conference

- Alsalhi, R. & Dixit, V. (2015) The Relationship Between Traffic Safety and Macroscopic Fundamental Diagram (MFD). *Proceedings of the 37th Australasian Transport Research Forum*, Sydney, New South Wales, Australia.

- Alsalhi, R. & Dixit, V. (2016) The Relationship between Surrogate Safety and Macroscopic Fundamental Diagram. *Proceedings of the 95th Transportation Research Board Annual Meeting, January 2016, Washington D.C., USA.*

- *Alsalhi, R. & Dixit, V. (2017*) Macroscopic Fundamental Diagram and safety in Urban Network. *Accepted at the International Engineering Conference & Exhibition.* Riyadh, Saudi Arabia, 04-07 DEC.

Paper under Review in peer-reviewed journal

- Alsalhi, R., Dixit, V. & Gayah, V.V. On the existence of network Macroscopic Safety Diagrams: Theory, simulation and empirical evidence. *In review with Transportation Research Part B: Methodological*

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Chapter 1: Introduction

1.1 Background

Movement of people and goods requires a good support of infrastructure such as road and communication networks. With time, the size of these transport networks has grown to accommodate the rapid rise in population. In particular, there has been a rapid growth in urban areas both for developing and developed countries over the past five decades. The increase in road traffic movements is attributed to the increase in population, economic and business activates. According to the WHO (2015), the number of registered motorised vehicles has increased by 16% over the past three years. The report also states that a record of 67 million new passenger cars was observed on world's roads in 2014 (WHO, 2015).

Despite all the benefits of increased traffic movements for the society, there are significant issues that arise such as environmental pollution, traffic congestion, and loss of life and injuries resulting from road accidents. The overall costs of road accidents on individuals, property and society are well documented in the literature including the severe results like deaths. As a result, road safety theory has become a high priority for traffic engineers and it has been gaining great attention from researchers worldwide. Research on traffic accidents mostly focuses at mitigating or avoiding the associated risks, and on lowering the impacts resulting from road accidents. This includes research conducted on the reasoning behind the occurrence of accidents along with factors contributing towards road safety. The aim of the existing body of knowledge in road accidents is to design and operate the traffic system meeting the best road safety standards.

1.2 Research Motivation

According to Mathers (2008), there will be 28% increase of deaths between 2004 and 2030. This will be significant as a result of an increase in road accident-aligned deaths. It is projected that there will be an increase of 1.1 million of deaths caused by road accidents from 2004 to 2030. National Highway Traffic Safety Administration (NHTSA) stated that there were more than 5.5 million motor vehicle crashes as reported by the police. Out of these cases, 1.5 million (28%) crashes resulted in injuries, 30,797 (fewer than 1%) resulted into deaths and 3.4 million (73%) entailed property damage only (NHTSA, 2009). There was a fatality rate per 100 million Vehicle Miles Travelled (VMT) of 1.03, with a 3.6% increase of fatality rate per 100 million VMT (NHTSA, 2013).

Furthermore, according to a report released by WHO (2013), the total number of road fatalities remains at 1.24 million per year worldwide, even though it has been decreasing set against a 16% increase in motorisation and 4% increase in global population (WHO, 2015). They suggested that the effort over the last three years on road safety have contributed to save lives. Yet they conclude that there is still an urgent need of many effective measures, which need to be implemented in a lot of the countries worldwide to strengthen road safety legislation.

The Macroscopic Fundamental Diagram (MFD) represents a very essential tool that can be used in the evaluation of the performance of traffic within an urban network at macroscopic level. It is also a vital tool to monitor, manage and control the traffic flows in road networks. The MFD captures the correlation between traffic characteristics which encompass the average system density, speed and flow (Godfrey, 1969; Herman and Prigogine, 1979). The description of macroscopic traffic flow was initially explored in the 1960s and 1970s. Most recently, the dynamics of urban congestion have been explored, including the relationship between macroscopic traffic variables (Geroliminis and Sun, 2011b; Geroliminis and Boyacı, 2012; Geroliminis and Daganzo, 2008; Daganzo, 2007; Gayah et al., 2014), and demonstrating the existence of an MFD. The MFD is an extremely powerful tool especially for monitoring and controlling road networks to improve efficiency (He et al., 2014; Mahmassani et al., 2013; Zheng and Geroliminis, 2013; Knoop and Hoogendoorn, 2013; Doig et al., 2013). However, there is no or lack of understanding on how the MFD is connected with safety measures. Some work has been done in order to relate safety to another macroscopic traffic flow model called the two-fluid model (Dixit et al., 2011; Dixit, 2013). In fact, Herman and Prigogine (1979) showed that the two-fluid model is actually related to an urban MFD.

Although considerable research has been conducted on the urban MFD and its use for area-wide network monitoring and control purposes, but there is no clear indication of how the dynamics of the MFD is related to accident rates and frequencies. Despite the existence of a wide range of research studies that have been conducted with the aim of relating crash rates and occurrences to traffic flow parameters, but mixed evidence of the effect of traffic parameters was concluded.

With regards to the accident and traffic flow relationship, Belmont and Forbes (1953) found a positive linear relation between the accident rate (number of accidents per year per million vehicle-kilometres) and the hourly flow of two lanes road. On the other hand , Gwynn (1967) found a U-shaped relationship. Ceder (1982) analysed the accidents and hourly flow relationship under various flow conditions; in addition, the author concluded that, under a free-flow condition, the accident rate and hourly flow follows a U-shaped curve, while traffic flow and accidents increase abruptly under a congestion condition. Martin (2002) examined the relationship between traffic flow and accidents on a French motorway and found that in light traffic, accident rates are highest as compared to rates in heavy traffic. Lord et al. (2005) investigated the flow–accidents relationship for rural and urban freeway segments and determined that it was positive.

Additionally, the effect of speed on road accidents has gained much attention from many studies. Baruya (1998) found that a negative relationship exists between the average speed and the accident rates. Taylor et al. (2000) found an inverse relationship between the average speed and frequency of accidents on European rural roads. Aarts and Van Schagen (2006) showed that increased speeds are associated with crash rates. On the other hand, Quddus (2013) showed that the accident rate is not affected by the average speed. Taylor et al. (2002) concluded that the accident frequency increases with increases in the average speed on rural roads in England. The accident rate and speed were found to be positively related with a power function (Elvik et al., 2004; Nilsson, 2004).

The relationship between accidents and traffic density and the Volume/Capacity (V/C) ratio has received less attention in the literature as compared to other traffic flow parameters. Rural highway accident rates should theoretically rise with increases in travel density (Brodsky and Hakkert, 1983). Zhou and Sisiopiku (1997) investigated the V/C ratio and hourly accident rates for an interstate highway in the US and found a U-shaped pattern; as the V/C increased, the accidents involved in fatalities and injuries decreased. The relation between single and multi-vehicle crash rates and traffic density (volume/capacity) on highways was investigated by (Ivan et al., 2000). For single-vehicle crash rates, they found a gradual exponential relationship with traffic density, but for multi-vehicle crashes, the relationship was insignificant. Lord et al. (2005) studied the effect of density and V/C on road accidents on a freeway segment, and they found that the number of accidents had an overall inverse relationship with density and the V/C ratio.

The above research efforts clearly indicate the importance of adopting the MFD as an extremely powerful tool for monitoring and controlling road networks to improve efficiency. However, no effort has been made to clearly examine how accidents are related to the dynamics of the MFD and other Macroscopic Traffic Quantities. Thus, there is a lack of literature on theoretical aspects that examine the potential of using the MFD as a safety tool in traffic control.

In order to cover the existing gaps in the literature, this thesis explores the relationship between Macroscopic Traffic Quantities, such as average network density, average network flow and average speed with safety. This has been achieved through the assessment of influence areas making use of conflict analysis technique at the first stage. The results obtained from this analysis are identified via the observation of the simulated traffic patterns. A test is then performed using Surrogate Safety Assessment Model (SSAM) conflict analysis software. Two simulation networks have been used in the analysis of this thesis and validated at second stage of the research with the highly accurate field data that was gathered. Additionally, this thesis proposes a novel mathematical model, referred to as a "Macroscopic Safety Diagram" (MSD). This is used to estimate traffic safety at the network-wide level, which is examined in line with the network fundamental diagram. It is expected that the model and results of this thesis will provide a clearer understanding of the relationships between safety and macroscopic traffic characteristics. This is will lead to the development of dynamic control measures, which will improve safety. Such relationships will also help policy makers to conduct cost benefit analysis as well as evaluate different policies.

1.3 Research Aims, Objectives and Contribution

The main aim of this research is to propose a base and novel method to estimate traffic safety in large-scale networks for safety analysis and decision-making. In order to achieve the overall goal, we propose the following important sub objectives:

- To comprehend the relationship between macroscopic traffic characteristics and accident occurrence on freeways and arterials,
- To develop a novel mathematical model to estimate the probability of crashes at the network-wide level,
- To explore the relationship between the shape of the MFD and accident from the simulation model,
- To understand the relationship between the shape of the MFD and road accident from field data that was gathered,
- To compare the simulation data findings with field data findings in order to validate outcomes and demonstrate the applicability of models to estimate traffic safety levels.

In terms of theoretical contributions, this thesis aims to develop innovative models to assess traffic safety dynamically. This will help traffic engineers and planners to evaluate road safety while developing efficient traffic plans.

To achieve the aims and objectives of this thesis, following two simulation networks are utilised:

1. 10 by 10 grid network, and
2. City of Bellevue/Redmond, Washington, USA.

In addition, real-world arterial road data is collected from Al Urubah and Abu Bakr Al Siddiq Roads in Riyadh, the capital and largest city of the Kingdom of Saudi Arabia (KSA).

1.4 Research Plan Frameworks

The research-planning framework of this thesis is presented in Figure 1.1. First of all, we review the literature to provide information on three key aspects:

1. The relationships that currently exist between traffic flow characteristics and road accidents,
2. The MFD and its existing uses and underlying relationships,
3. The conflict analysis techniques and its use in accident prediction.

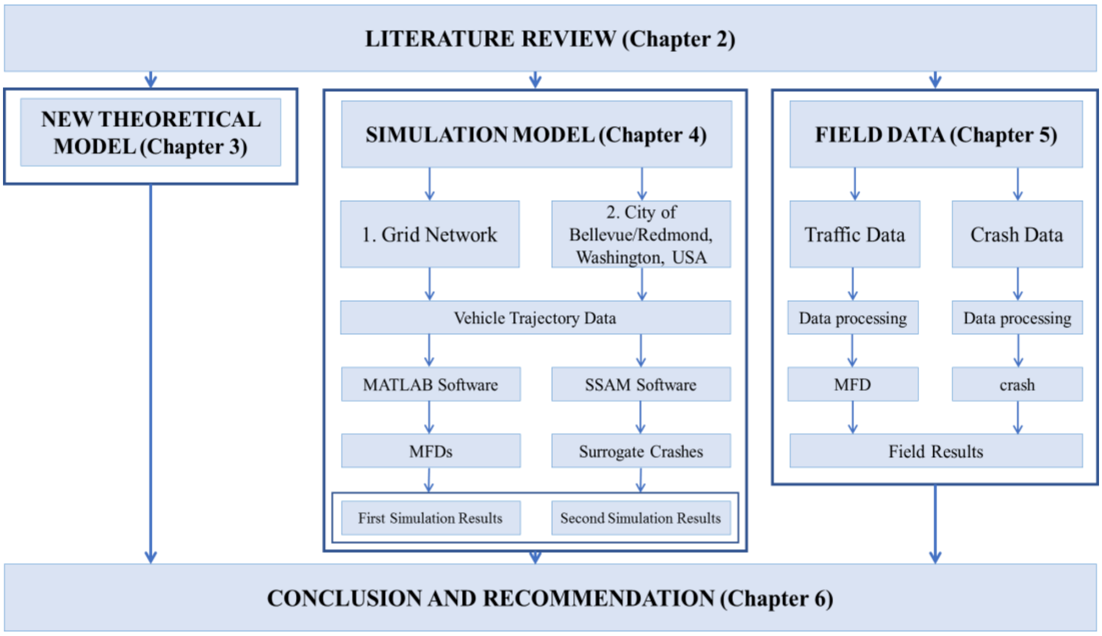


Figure 1.1: Research Plan Framework

1.5 Thesis Outline

This thesis is divided into six chapters. This section provides an overview of each subsequent chapter.

Chapter 2: This chapter is divided into three sub parts and each part describes the previous research in the relevant field. The first part is the relationships that exist between traffic flow characteristics and road accidents, the second part is related to the MFD, and third part summarises the conflict analysis techniques. The major goal of this chapter is to portray the value of the proposed research in relation to previous research studies and identify the gap for the proposed research.

Chapter 3: The aim of this chapter is to present and describe the development of the new proposed model, which is referred to as a "Macroscopic Safety Diagram" (MSD). The model assumptions and the type of data required are also explained in this chapter.

Chapter 4: The aim of this chapter is to present and describe the data used in simulations and then analyse the results of the experiments. This chapter contains two simulation networks 1) grid network and 2) city of Bellevue/Redmond, Washington, USA network. In addition, the relationship between traffic safety and MFD as well as to validate the existence of MSD model has been explored.

Chapter 5: This chapter describes the datasets related to field data analysis. The study area is Al Urubah and Abu Bakr Al Siddiq roads in in Riyadh, the capital and largest city of the Kingdom of Saudi Arabia (KSA). This is supported by the analysis of the data and comparisons between the characteristics of traffic flow (weekdays and weekends) and the crash data. Finally, associated plots are explained and the main findings are presented.

Chapter 6: A brief summary of the key findings from previous Chapters 3, 4 and 5 is given in this chapter. Furthermore, thesis conclusion along with its contribution to knowledge is explained. Finally, the limitations of the proposed research are highlighted followed by the recommendations for planners, engineers, policy maker and further research direction.

Chapter 2: Literature Review

This chapter provides an overview of current literature and findings related to the thesis "*The Relationship between Traffic Safety and Macroscopic Fundamental Diagram (MFD)".* This literature review is divided into the three sections. A comprehensive literature review and research on the effect of traffic characteristics on road accidents are summarised in Section 2.2. Section 2.3 provides a brief introduction on traffic models. Also, MFD Simple principles are given followed by moving from a historical overview to more recent remarkable expansions. In addition, discoveries in macroscopic relationships between network traffic state variables and its characteristics and applications are given. Section 2.4 reviews the most frequently used Surrogate safety measures, which are traffic conflicts.

2.1 Impact of Traffic Characteristics on Road Safety

In this section, the previous studies on the effect of traffic flow, density and speed on road accidents are discussed. There have been a range of studies that have been conducted with the aim of identifying the connection between the road accidents on one hand and the traffic characteristics on the other hand. For example, Ceder and Livneh (1982), Martin (2002), Dixit et al. (2011), Dixit (2013) conducted majority of these studies that have accounted and analysed both the characteristics of the traffic flow and crash frequencies for specified periods, ranging from several hours to a set of years. The studies have shown that indeed there exists a link between the rate of accidents and traffic variables. Accidents tend to take place when the traffic is on the move. In the light of this, it is natural to investigate the attributions of traffic in order to achieve a clear understanding of their impact on road accidents (Martin, 2002). Mostly, the characteristics of traffic can be classified as speed, flow and density. These attributes usually affect road safety (Martin, 2002).

2.1.1 Flow

Concerning the relationship between accidents and traffic flows, there were numerous researches that have been conducted during the last few decades. The early studies, which tried to understand this relation, were in the 1950's, 1960's, and 1970's such as Belmont and Forbes (1953), Gwynn (1967), Ceder and Livneh (1978), Ceder (1982), Turner and Thomas (1986). The hourly accident rates, which are defined as "number of accidents per year per million motor-vehicle kilometres" and hourly traffic flow were the common measures used. Belmont and Forbes (1953) developed a theory linking accident occurrence and traffic volume, they found that for the 2-lane road sections, the accident rate was found to increase linearly with an increase in hourly traffic volumes. Later, Gwynn (1967) found that for 4-lane road sections, a U-shaped relationship exists between accident rates and traffic flow. Ceder and Livneh (1978) explored the relationships between Average Daily Traffic (ADT) and accident (density and rate) for inter-urban road sections. They applied power function and found that as the ADT increased, the total accident density increased.

Ceder and Livneh (1982) had one additional step, and that was to examine the relationship between accident rate and traffic flow by using hourly traffic flow instead of Average Daily Traffic (ADT) in terms of applying the power function model. The authors examined multi-vehicle and single-vehicle accidents separately. They found that the relationship between hourly traffic flow and accident rate are different based on the difference of accident types. For instance, the hourly traffic flow was found to have an inverse relationship with accident rates in all single-vehicles while some mixed results were found in multi-vehicle accidents. Ceder (1982) investigated the relationship between hourly traffic flow (under different flow conditions) and the accident rate. The author found that for the congestion condition especially, the multi-vehicle accident rate was found to have sharp increase with hourly traffic flow, while for both single and multi-vehicle accidents a U-shaped relationship was fond for free flow conditions.

Turner and Thomas (1986) conducted a study on the motorway to examine the relationship between accidents and traffic volumes in which the model for both dual 2-lane and dual 3-lane were proposed. The authors found a negative liner relationship between severe accidents and traffic flow. Martin (2002) investigated the relationship between accident rates and traffic volume based on the observation of French inter-urban motorways, which are over 2000-km long, and a study period of 2-years. They found at the low traffic volume (under 400 vehicles per hour) that the accident rates reach the maximum and the number of accidents on weekends are higher than on weekdays. For night-time and day-time accidents, there is no significant difference observed. Also, for a given level of traffic volume, no difference in accidents severity was observed by period in the week or number of lanes. Low hourly traffic and night-time accidents were much worse, when the accident severity was considered. The authors concluded that low traffic volume was a safety problem in terms of severity and frequency of accidents. On the other hand, Vitaliano and Held (1991) used accidents data for rural and urban roads in New York State (USA) and they concluded that no significant relationship was detected between accident rates and traffic flow. These studies suggested that the relationship between number of accidents and traffic volume was negative.

Positive relationships between number of accidents and traffic volume have been found in many studies. The study undertaken by Dickerson et al. (2000) investigated the accident and traffic flow relationship for different geographical areas and road types. They found that when the traffic flow was low, the accident externalities are almost zero, while the accident externalities highly increased at high traffic flow. Lord et al. (2005) investigated the accident and traffic flow relationship by applying predictive model for urban-freeway and rural segments. They found a positive relationship. Caliendo et al. (2007) used a data for 4-lane median-divided motorway in Italy. The authors found a positive relationship between number of accidents and traffic flow (Annual Average Daily Traffic (AADT)). Chang (2005) investigated the number of accidents for the National Freeway in Taiwan with respect to daily traffic flow for 1997-1998 and found that the frequency of accident increased with an increase in traffic flow per-lane.

Hiselius (2004) used rural roads in Sweden to study the effect of different types of traffic flows (homogenous and inhomogeneous vehicles) on accident frequency. Different accident rates were associated with different traffic flow types. Golob et al. (2004) determined a strong relationship between accidents and traffic flow condition. The author's main objective was to monitor the real-time level of safety of traffic flow. Golob and Recker (2003) used data for a freeway in Southern-California to examine the relation between traffic flow conditions and accidents where the traffic flow was measured 30-s prior to each accident occurrence; the study found that accident severity had negative relation on traffic flow.

The effects of traffic flow on road accidents have been clearly investigated in this literature review. However, a few researches attempted to study the effect of Volume to Capacity (V/C) ratio on accident occurrences.

Shefer (1994) proposed the hypothesis suggesting that the relationship between the total accidents and V/C ratio follows a bell-shaped curve. Subsequently, Shefer and Rietveld (1997) completed the investigation between accidents frequency and congestion similar to the early approach of Shefer (1994); they argued that the total number of severe accident decreased on congested traffic due to the lower speed related to congestion. Zhou and Sisiopiku (1997) examined the hourly-accident rates and hourly-traffic volume/capacity relationship. A 26-km segment of inter-state (I-94) in the Detroit area was examined. The authors calculated the V/C ratio from average hourly-traffic volume counts collected in 1993-1994 and the accident rates were obtained by distributing hourly accidents number in the same period. They found that the correlation between accident rates and V/C values followed U-shaped and the accident rates were high in congestion but the severity of accidents was comparatively less.

Noland and Quddus (2005) studied Inner and Outer London to examine the congestion effects on traffic safety. They found that in urban areas, the effects of congestion on accident severity were minor. Kononov et al. (2008) investigated the relationship between accident rate and traffic congestion by using urban freeways data in Colorado, California, and Texas. The study used the Annual Average Daily Traffic (AADT) as a measure of congestion. The author found that fatal and injury accidents increased with an increase in traffic congestion. Wang et al. (2009) explored the traffic congestion and frequency of accidents. They used M-25 London orbital motorway to conduct the study and the motorway was divided into 70-segments. The difference between the free flow travel time and the actual travel time were used to calculate congestion index. The congestion index was used to reflect the congestion level. The authors found that the accident frequency was not affected by traffic congestion. Quddus et al. (2009) used the same data as Wang et al. (2009) and applied a different model to investigate the effect of traffic congestion on the severity of the accidents. They found that the level of congestion had no impact on the severity of road accidents. A recent study by Wang et al. (2013) also investigated the traffic congestion and accidents relationship and found that increased traffic congestion was correlated with an increase in severely injured and fatal accidents. Also, they found that traffic congestion had slight impact on less injured accidents.

The studies reveal that there is usually a statistical interrelationship between the traffic flow which are time varying on the accident outcomes. Finally, it can be concluded that the aggregate level of accidents often increases as the flow of traffic increases.

2.1.2 Density

In the literature, there has been significantly little research on the relationship between traffic density and accidents, and this may be because of the fact that the type of data required is not always available. Brodsky and Hakkert (1983) stated that theoretically rural highway accident rates tend to increase with increase of travel density.

Ivan et al. (2000) investigated the relationship between single-vehicle and multi-vehicle highway crash rates with respect to traffic density. The Poisson regression model was used to analyse the data. The authors found that for a single-vehicle accident, there is a negative exponential relationship with traffic density (Volume/Capacity), while for multi-vehicle accidents, the relationship was found insignificant. Lord et al. (2005) investigated the effect of volume, density and V/C ratio on the accidents frequency on rural and urban motorway in Montreal, Quebec. They found that accident rates exhibit an overall U-shaped relationship with density and V/C ratio. U-shaped relationship exists in single-vehicle accidents while multi-vehicle accidents have linear positive relationship.

The authors concluded that the accidents should be modelled separately depending on whether it is a single or multi-vehicle accident. In addition, the accident predictive models should rely on traffic volume, density as well as V/C ratio to obtain better explanation instead of used just traffic flow. Later, Kononov et al. (2012) investigated the relationship between speed, flow-density and accident rates on freeway in Colorado, USA. The authors found that the accident rate remained constant when flow-density increased, until a certain critical value of threshold (combination of density and speed) was reached. After passing this threshold, the accident rate increased rapidly. They stated that this rise in accident rates may be caused by an increase in the number of flow without significant reduction in speed, and this actually leads to reduce the headway and it is impossible for the drivers to avoid the accident. Studies have established that the relationship between density and safety (accidents) is sort of mixed. This clearly indicates that there is limited existing research in the area and that further investigations are required.

2.1.3 Speed

The effect of speed on road accidents has gained much attention from many studies. Researchers have adequately investigated the effect of average speed, speed variance and speed limit on road accidents in the past.

Many researchers suggested that the increase in speed resulted in an increase in the number of accidents and accident rates (Elvik et al., 2004; Nilsson, 2004; Taylor et al., 2002; Aarts and Van Schagen, 2006). Taylor et al. (2002) used the rural roads data for 174 road segments in England and applied a cross-sectional analysis on these data. The authors found a positive relationship between average speed and accidents frequency. Nilsson (2004) comprehensively investigated the effect of change in speed on safety. The researcher incorporated the use of before-and-after studies conducted in Sweden using the Power Model. The researchers established that changes in the rate of accidents could rightly be associated with changes in speed. It was also found that there was a positive relationship between speed change and accidents. While this is the case, the researcher clarified that the magnitude often depends on the forms of accidents, whether it is injury related or fatal. In another study, Elvik et al. (2004) conducted an extensive analysis on exploring the speed and accidents relationship and they applied before-and-after studies. The authors also used the power model and the study found that a causal relationship between the changes in speed and the rate of crashes exists. As such, the rate of crashes goes down if the speed decreases and vice versa. Aarts and Van Schagen (2006) concluded that the accident rate and speed relationship are positive with a power function/ exponential.

On the other hand, some other studies suggested a negative relationship between average speed and road accidents. Baruya (1998) used a cross-sectional analysis to investigate the relationship between average speed and frequency of accidents and found that frequency of accidents is negatively associated with average speed. Taylor et al. (2000) found an inverse relationship between mean speed and frequency of accidents on European rural roads where fewer accidents occurred when average speed was increased. This result was based on data from England, Netherlands and Sweden.

It was also proposed in some studies that the speed variance affect the accident rates rather than the speed itself (Solomon, 1964; Warren, 1982; Lave, 1985). Solomon (1964) found that the relationship between speed and accident rates followed U-shaped and the average speed had lower effect on accident rates while higher accidents rates were associated with higher speed variance. Warren (1982) stated that the greater the variation in speed on a given road, the higher the possibility of an accidents occurring. Lave (1985) found that the speed variance affects the accident frequency rather than the speed itself and the fatality rate is not related to average speed, while there is a strong relationship with speed variance. Garber and Gadirau (1988) showed that the accidents rates increases with an increase in speed variance rather than average speed. Recently, Quddus (2013) investigated the relationship between accident rates and average speed and speed variations, and found that the accident rates are not affected by the mean speed when other factors such as road geometry and traffic volume are controlled. However, accident rates are found to have a positive correlation with speed variation. On the other hand, Kockelman and Ma (2010) investigated the speed, speed variation and crash occurrence relationship for Southern freeways in California. They found that there was no evidence that accident occurrence is affected by speed and speed variance.

Many researchers examined the effect of speed limit on road accidents as well. Brown et al. (1991) investigated the effect of increasing the speed limit in Alabama, USA and found that despite the severity of accident were not affected, a considerable increase in accident frequency (18.88%) was observed. Rock

(1995) studied the effect of change in speed limit from 55 to 65 mph in 1977 on certain roads in Illinois, USA and found that the increase in speed-limit was associated with an increase in accident rates and fatalities. Johansson (1996) investigated the effect of speed limit reduction on the number of accidents; the data was collected in several Swedish counties from 1982 to 1991. The author found that the reduction in speed limit was related with reduction in the number of accidents involving minor injuries and vehicle damage. Shefer and Rietveld (1997) stated that the lower speed caused by congestion would leading to lesser fatal accidents. Aljanahi et al. (1999) examined the speed and accidents relationship and found that the number of accidents would be reduced with lower speed limits, also the relationship between rate of accidents and speed variation were found to be strong. Ossiander and Cummings (2002) examined the effect of changing the speed limit in Washington-State USA and found that a high fatality rate was associated with an increased speed limit. Vernon et al. (2004) examined the effect of increasing speed limits in Utah, USA on accident rates from 1992-1999, and found that the increase in speed limit had no major effect. Wong et al. (2005) used a data for Hong Kong for period 1999-2002 to study the effect of change the speed limit on number of accidents; the authors found that the number of accidents increased after the speed limit was increased. A recent study De Pauw et al. (2014) investigated the relationship between speed-limit and road safety. A total of 61 road sections were included with a total length of 116-km and they applied before and after analysis to find the effect of changing the speed limit on accidents. The authors found that speed-limit restrictions seemed to have a positive effect on road safety, especially on accident fatalities.

From this literature, studies evidenced that speed often has mixed impacts on safety. However, other studies have reported dissimilar findings, stating that speed tends to reduce safety or speed increases safety. Even some researchers argued that speed might not pose as a safety issue, however variation in speed could do. These differences imply that there is a need for more research in order to clarify on the correlation between speed and safety.

2.2 Macroscopic Fundamental Diagram

2.2.1 Traffic Flow Modelling

There are three different traffic flow models, microscopic, mesoscopic and macroscopic models, which are classified based on level of traffic details. These models are briefly discussed in the following sections.

2.2.1.1 Microscopic Traffic Models

A microscopic model records the detail of individual vehicle movements and parameters, such as accelerations, deceleration, speeds, space headways, time headways and the driving behaviour such as car following, lane changing, etc. This model needs very accurate input data details.

2.2.1.2 Mesoscopic Traffic Models

A mesoscopic model is a mixture between macroscopic and microscopic models. Mesoscopic model describes the individual vehicles activities and interactions at an aggregated level.

2.2.1.3 Macroscopic Traffic Models

A macroscopic model is an aggregation of the interaction activities performance from the microscopic models at higher level. The network traffic flow characteristics such as average flow, density and speed are gathered, and macroscopic models represent mutual relations among traffic flow characteristics. These models are used to evaluate the large-scale network performance.

2.2.2 Traffic Principle

A Fundamental Diagram (FD) describes the traffic flow at a particular location. Three related variables, average speed, average flow and average density, characterise the road link's traffic. These three variables exhibit relationships in cases of stationary conditions by the traffic fundamental relationship where the speed equals flow divided by density. This shows a kind of independence among these three variables. Hence there exists a behavioural relationship, called traffic fundamental diagram, between two of the remaining independent variables from the above formula. This relationship enables evaluation and modelling of traffic.

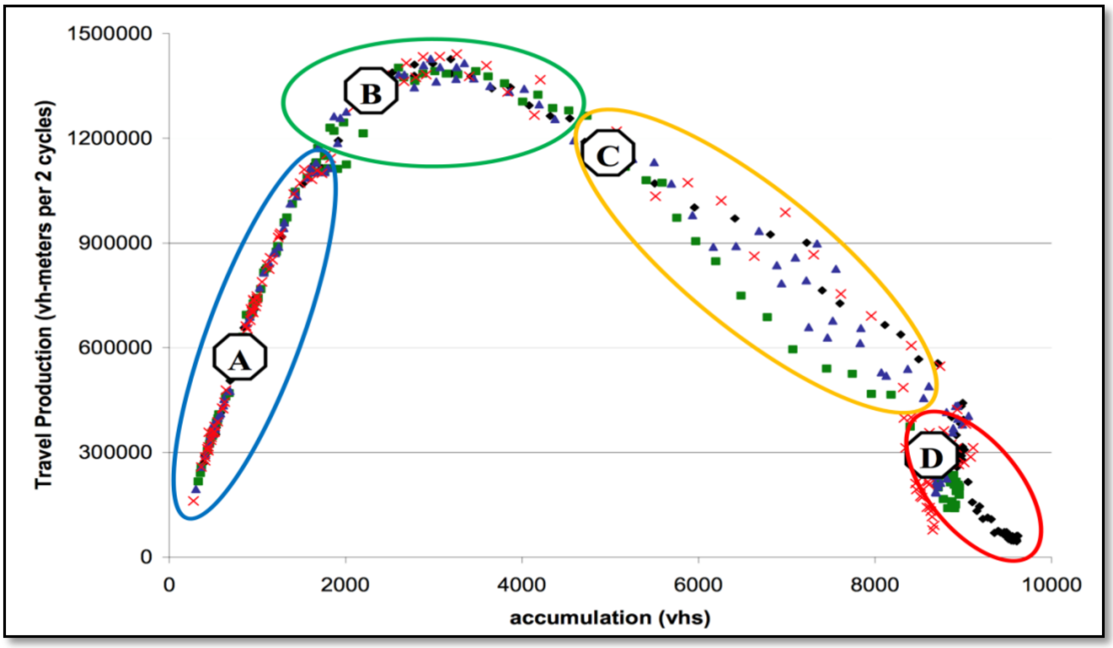


Figure 2.1: MFD from San Francisco City Data

Source: Geroliminis and Daganzo (2007)

A Macroscopic Fundamental Diagram (MFD) is related to the average network flow and average network density. Different traffic regimes are clearly illustrated in Figure 2.1. When the network is in free flow condition (in blue); a linear relationship exists between average flow and average density. The Majority of the links in the network are homogenous until a certain threshold is reached. Once the number of vehicles increases, the threshold region is reached. This region represents the optimal regime (in green) at which the maximum traffic flow occurs. The scatter appears because of the fact that the traffic load in the network is less homogenous. Further increase in the numbers of vehicles in the network results in a congestion regime (in orange) and the distance travelled becomes much lower than the optimal state. Further congestion results in total grid-lock condition (in red).

2.2.3 Historical Background on Macroscopic Traffic Flow

Over the past few decades, considerable attention has been given to the evaluation of wide network performance. Traffic characteristics have been observed in many experiments. Formulae have been proposed to describe the macroscopic traffic variables relationships.

The early works on traffic flow theory was introduced in the 1940s by Greenshields et al. (1935), where the photographic method was used to observe the traffic stream for one direction on two lane single road to measure flow, speed and density. From the observations, the FD was proposed and it was revealed that the speed and density had a declining relationship (Figure 2.2) and the flow had a parabolic relationship with speed (Figure 2.3).

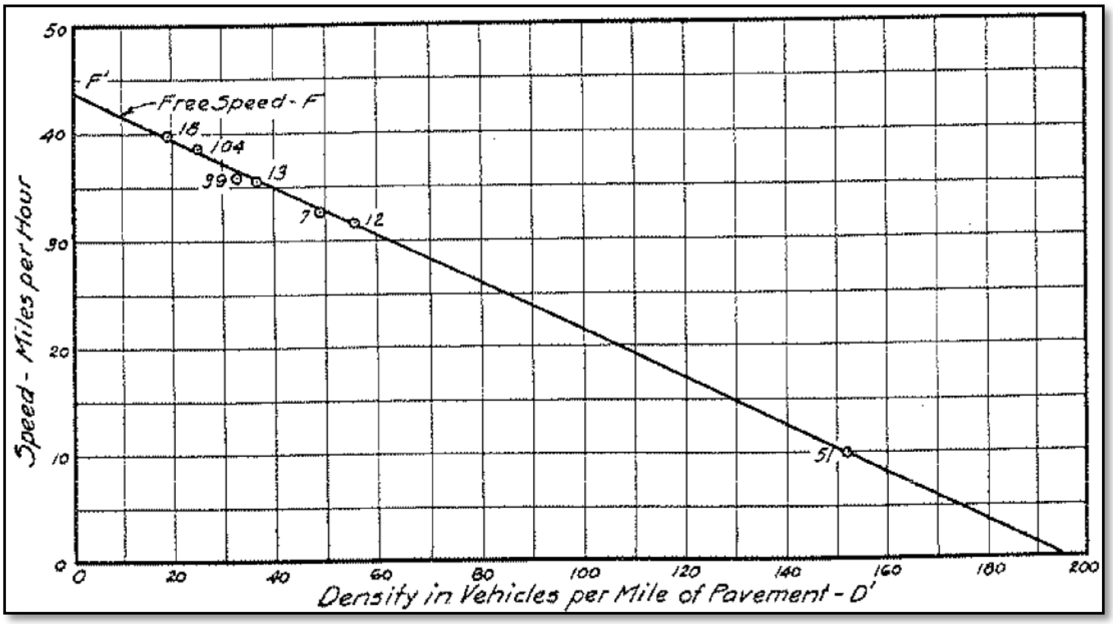


Figure 2.2: Speed and Density Relationship

Source: Greenshields et al. (1935)

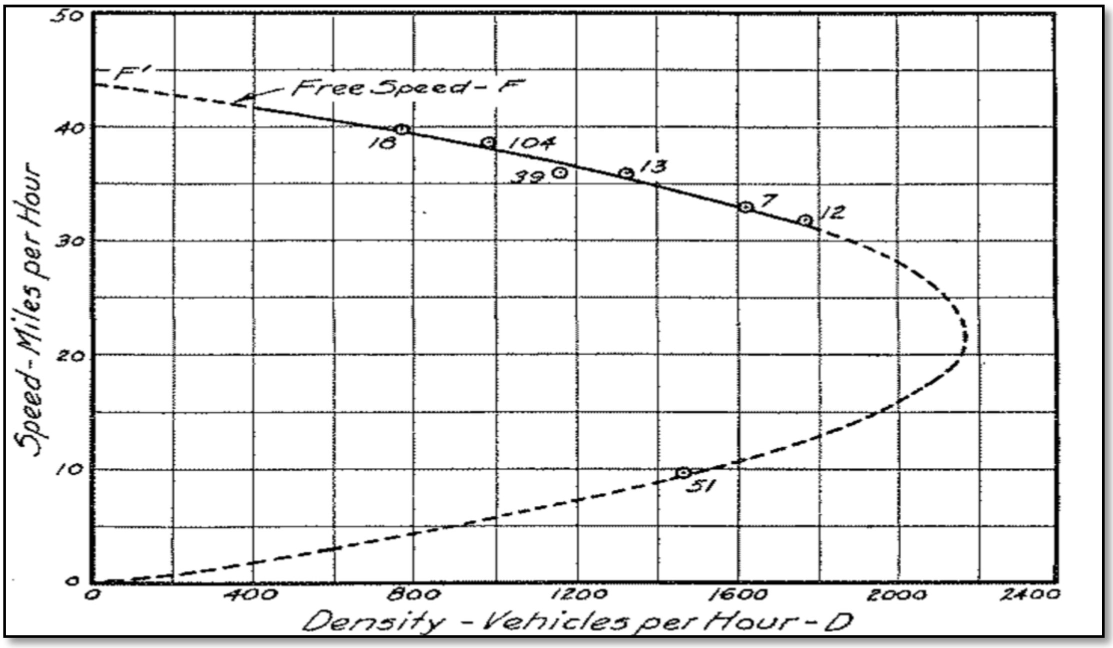


Figure 2.3: Speed and Traffic Volume Relationship

Source: Greenshields et al. (1935)

Godfrey (1969) was the first to propose a unimodal relationship between average flow and average density and between average speed and average flow in macroscopic level. The models were developed using the moving observer method and taking aerial photos for the road network in a town centre. Thomson (1967) studied macroscopic traffic variables in central London, and collected data for a fourteen-year period and found that the average network speed decreased linearly with the increase in average weighted traffic flow. Smeed (1967) proposed a function, which related the number of vehicles that could be travelled in the central area on the city with the area of the city (capacity of the road). Wardrop (1968) conducted a study for traffic in central London and found an increase in the number of junction per mile decrease with the average speed for any level of traffic flow. Zahavi (1972) found an inverse monotonic relationship between average speed and average flow based on filed date for various cities in the United States and the United Kingdom.

Herman and Prigogine (1979) developed a two-fluid model of traffic flow from the kinetic theory. In this model, the vehicles were divided into two components; first section was stopped vehicles, which did not include parking vehicles, and the second was moving vehicles. The two-fluid model indicated that the average vehicles speed in the network was related to the fraction of stopped vehicles in network. Further investigation on the two-fluid theory were done by (Herman and Ardekani, 1984). They found that the fraction of stopped vehicles can be formulated by the average density of network. Mahmassani et al. (1984) conducted simulation experiments to verify the network relationship between flow, speed and density by using two-fluid model. The models were succeeded in demonstrating the network fundamental relationships, but they faced some restrictions when the traffic flow conditions such as Origin-Destination (OD) patterns were extremely changed.

2.2.4 Macroscopic Fundamental Diagram Development

Daganzo (2007) confirmed the existence of the reproducible relationship between macroscopic traffic variables (network flow, density and speed) in a large urban area. These relationships, which were considered as urban dynamic traffic models, were found in the field data (Geroliminis and Daganzo, 2008) and simulation data (Geroliminis and Daganzo, 2007).

Daganzo (2007) first introduced the macroscopic dynamic model with the idea of a reproducible macroscopic variables relationship on an urban network. This model aimed to monitor and control city network without the need to the full knowledge of origin-destination data that were sometimes very hard to achieve. The model related the exit-flow rate (the rate vehicles that have completed their journey) and total number of vehicles in the network (vehicular accumulation). The study argued that the proposed model was valid only if the network was homogeneously congested.

The value of MFD in urban network analysis was sufficiently explored by Geroliminis and Daganzo (2008) in which a field experiment in Yokohama was used to investigate evidence on MFD. Yokohama, is the second largest city in Japan, and with a population of 3.6 million, the study only engaged a triangular region of 10 square kilometres at the centre of the city. Data collections for the study were from two different sources; first data was from 500 fixed detectors for vehicles counts and occupancy measurements data. The second data were from 140 taxis which were installed with GPS. As seen in Figure 2.4, the average weight flow and the average weight density with road lengths established a clear macroscopic relationship between flow and density of traffic. The result suggested that in certain networks, it was possible to relate the average flow and the average density independently to the traffic demand.

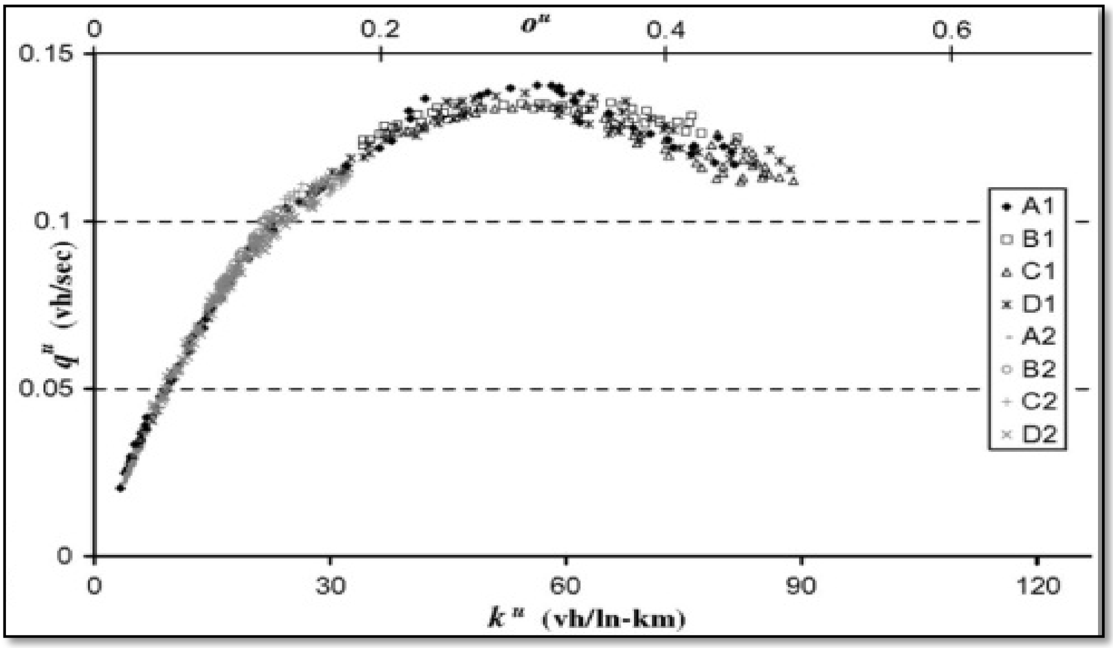


Figure 2.4: MFD from Yokohama City Centre Data

Source: Geroliminis and Daganzo (2008)

In Geroliminis and Daganzo (2007), a simulation study carried out during rush hour in San Francisco downtown, which was also used to validate the MFD existence in large urban networks. They showed that the unimodal, low scatter reproducible curve were presented by aggregated flow and density of the network. A liner relationship between exit flow and network accumulation was found.

These findings encouraged the researchers to further explore and investigate the properties of MFD. Hence researchers conducted many empirical studies and developed associated theories for it. A considerable amount of experiments and studies attempted to understand the hysteresis phenomenon by examining the impact of heterogeneity of roadway segments and variability of vehicle densities on the MFD (Buisson and Ladier, 2009; Mazloumian et al., 2010;

Gayah and Daganzo, 2011; Geroliminis and Sun, 2011a; Geroliminis and Sun, 2011b; Cassidy et al., 2011). A few other studies had considered investigating the effect of traffic signal and distancing between the loop detectors on the shapes of the MFD (Helbing, 2009; Wu et al., 2011; Boyacı and Geroliminis, 2011; Zhang et al., 2013). Several studies revealed vital benefits of using the MFD for network traffic monitoring and management as well as network control strategies (Ji and Geroliminis, 2012; Aboudolas and Geroliminis, 2013; Gayah and Dixit, 2013; Haddad et al., 2013).

Daganzo and Geroliminis (2008) described the VT from Daganzo (2005a), Daganzo (2005b), and proposed analytical formulae to mathematically predict the MFD shape. With these formulae, the highest flow on the network could be calculated. However, the network must meet the regularity conditions including the lengths of the links, control strategies, slow-varying demand and a symmetric network structure. Buisson and Ladier (2009) studied the shape of the MFD and they formed the first study comments on MFD's development by examining the inhomogeneity of network. They examined the impact of the traffic signal and loop detectors distribution in surface network on the MFD. The detectors data were used for three different weekdays in city of Toulouse, France. The network involved in their study contained different types of freeways and urban roads. The resulting MFD's were highly scattered and they concluded that the shape of the MFD's was strongly affected by heterogeneity.

Ji et al. (2010) used a traffic simulation model (VISSIM) to investigate the shape of the MFD for a part of Amsterdam network. The network was of mixed or hybrid nature which consisted of urban roads and freeways. Also, they examined the factors that influence the shape of MFD such as type of the roads, traffic demand, ramp metering, onset and offset of congestion. They found that the shape of the MFD is not only the property of the network itself, but also of the applied traffic control measures. Moreover, they found that the rapid change in traffic demand strongly affects the shape of the MFD. They concluded that uneven onset and offset congestion could be a reason for hysteresis loops in the MFD. Mazloumian et al. (2010) Simulated lattice network to investigate the effect of inhomogeneity spatial distribution of densities on the shape of MFD. They showed that a robust relationship exists between observed network flows and the standard deviation of vehicle densities across the network. In addition, the highest observed flows were obtained when the spatial variability of vehicle densities were lower. Finally, they found that the network flow for a given density decreased with time. This could mean that the spatial variability of the network densities increases continuously over time.

Gayah and Daganzo (2011) used the simulation in two-bin system model to explore the hysteresis loop phenomenon. Three types of hysteresis loops were introduced based on the loop direction. They showed that the hysteresis loops were expected even when both the demand and structure of network were symmetrical. One important factor in this phenomenon was the loading and recovering process in the network. This was showed for clockwise hysteresis, the instability during the recovery phase, where congestion resolved slower in congested area and this was the cause of spatiotemporal heterogeneity. This heterogeneity had led to an increase in the flow during the loading phase and reduced the flow during recovery phase. Daganzo et al. (2011) used simulation experiments to examine and explain the heterogeneity phenomena. They found that the key factor that caused a drop network performance was turning at intersections. Also, the study showed that in real-life the drivers tend to choose their routs more adaptively, which leads to an increase in the critical density and the network is less likely to go into a gridlock situation.

Cassidy et al. (2011) analysed vehicle trajectories for two freeway stretches. Based on real-world data, they suggested that the MFD was observed in case all the lanes and links in the network were either in uncongested or congested regime. They found that it is in fact necessary to filter the data to meet the single-regime traffic condition in order to obtain freeway MFDs. They concluded that by applying policies, which equally spread the congestion over a freeway network, could be valuable in maximizing the flow rate.

Geroliminis and Sun (2011b) explored the properties of well-defined MFD by using loop data from Yokohama downtown in Japan. They also investigated the causes of scattering in the MFD. They found that variations of link densities had robust impact on network performance. This means that a well-defined MFD with the highest network flow and lower-scatter should exist when the spatial variability of vehicle densities is small. In other words, the network flow will be lower when the variability of vehicle densities is high. Geroliminis and Sun (2011a) investigated the existent of well-defined macroscopic relationship on freeway network by using field data from Minnesota’s freeways. The results demonstrated the MFD with hysteresis phenomena and consequently two associated causes were explained. The first cause is because of the fact that there exist different spatial and temporal distributions of congestion for the same degree of density. The second cause is synchronised occurrence of transitions during the offset of congestion in which the capacity drops.

Knoop et al. (2011) studied different routing strategies by using simulation grid network. They found that the light information such as standard deviation of vehicle densities could be utilised as an indicator for the network performance. Also it was concluded that as the spatial fluctuation of density increases the performance of network decreases. Saberi and Mahmassani (2012) studied the properties of well-defined MFD in a freeway network and explored the hysteresis phenomena. The data was collected form loop detector in Portland metropolitan area. The study found that the hysteresis loop occurred because of the fact that there was high variation in the vehicle densities during congestion recovery period. Leclercq and Geroliminis (2013) examined the effect of different routing strategies on the shape of the MFD. The study found that the shapes of MFD were affected by the variation of link densities.

Helbing (2009) provided a model to predict the fundamental relationships for an urban network. The study found that the average network flows were not only dependent on the network density, but also relied on the signal-operation schemes, distribution of density and other factors as well. Wu et al. (2011) studied the effect of signal operation on arterial fundamental diagram by using major arterial in the Twin-Cities area. They found that the capacity of the arterials was strongly affected by signal coordination, green to cycle length ratio and turning movements at intersections. Also, they showed that the stability of AFD was affected by the queue over the detector during red time. Boyacı and Geroliminis (2011) used the VT to investigate the effects of different link length, signal cycles and signal offsets and determined their effect on the MFD. They concluded that the decent signal timing planning could maximise the network performance and/or increase the density range of the capacity. Zhang et al. (2013) studied the effect of different types of signal systems on MFDs of arterial road network. They showed that changing in the signal system will result in changing the shape of MFD. It was also found that the spatial heterogeneity of both flow and density deliver significant indicators of network performance. A conclusion was drawn that the higher capacity and improved performance could be reached by adaptively homogenising the density of the network.

Ji and Geroliminis (2012) proposed partitioning algorithm for heterogeneously congested networks. Firstly, the study's main objective was to reduce the variance of link densities to increase the flow in the network. Secondly, spatial compactness of each cluster should be utilised for perimeter control. Aboudolas and Geroliminis (2013) proposed a methodology for perimeter and boundary control strategies by using feedback in n-reservoirs system. Haddad et al. (2013) developed optimal control for a large scale mixed transportation network containing a freeway and an urban network. They stated that the approach of the paper can be used to implement effective control strategies for large-mixed traffic networks. Gayah and Dixit (2013) presented a method that used travel speed information collected from circulating probe vehicles with

MFD to satisfactorily estimate the average vehicle density of the network in real-time.

Dixit and Geroliminis (2015) used more than 20,000 probe vehicles from China to examine the relationship between Two-Fluid Model and the Macroscopic Fundamental Diagram. An exploration of how different monitoring techniques can affect the estimation parameters was studied. The study showed the existence of a fundamental diagram both theoretically and empirically. Also, it was found that the network MFD and Two-Fluid can be reliably estimated with 30% probe vehicles in the network.

2.3 Traffic Conflict Technique

Traffic crashes are known as a direct measure of traffic safety. Consequently, the development of reliable and accurate crash prediction models are very important for decision-makers, traffic engineers and planners in order to give a strong vision about current and future facilities of safety.

The approach of traditional crash prediction models is based on statistical methods. This requires significant efforts in collecting and analysing vehicle crash historical data to measure the safety of traffic facilities. In some cases, these methods are not applicable due to the limitation of the data sources for the traffic facility. Traditionally, traffic safety studies are based on field observation and manual count, which results in consumption of time, higher labour cost and sometimes inaccuracy due to different observers having different perspectives.

Surrogate safety measures are events other than real crash frequency or an event that can be linked with crash rates. These events occur more frequently than actual crashes, therefore, it should be capable of evaluating the safety of any traffic facilities without waiting for a huge number of crashes to actually occur. There are a several numbers of surrogate safety measures that have been proposed in the literature and the most prevalent one in literature is traffic conflicts technique (Gettman and Head, 2003).

The first study on traffic conflicts technique was conducted in 1950s and 1960s (Moseley and McFarland, 1954; Perkins and Harris, 1967). In Amundsen and Hyden (1977), a conflict refers to a situation that is observable when two or more road users approaching each other in space and time to an extent that increases the chances of a collision; the collision occurs in the event that their movements remain constant. The traffic conflicts were collected based on field observations.

A laboratory owned by Detroit General Motors was the initial site for the development of the traffic conflict technique methods in the late 1960's with an objective of the identification of safety problems (Perkins and Harris, 1967). This method relied on observer judgments and utilised time-lapse filming. However, it proved to be a time consuming and costly technique. They correlated the types of accidents to conflict patterns. Spicer (1973) conducted a study on the safety of six intersections and came with the conclusion of a relationship between reported injury accidents and serious conflicts. Miglez et al. (1985) came up with a methodology with the objective of predicting traffic accidents arising with observable conflicts. There was also the development of statistical procedures with an objective of determining conflict rate values that can be treated as “abnormally" high. The study concluded that traffic conflicts had the capability of producing approximations of almost accurate average rates of accident and hence outstanding accident surrogates.

Sayed (2000) carried out a research study with an objective of estimating the safety of interactions that are un-signalised making use of traffic safety technique. Conflicts with time-to-collision (such as the critical traffic event in simulating driver behaviour) were studied using a computer simulation model. The use of data that was realised from 30 conflict surveys established severity standards and traffic conflict frequency for un-signalised intersections. These standards have the capability of allowing the relative comparison of the conflict risk at different intersections.

Gettman et al. (2008) carried out a study on a safety assessment method making use of an analysis technique for traffic conflicts. This was applicable to simulation models of intersections, roundabouts, and interchanges. They came up with a software application to the purpose of automating the analysis of traffic conflicts. They also carried out validation testing with an objective of gauging the assessment method’s efficiently. There has also been the development of a number of applications to be used in the assessment of highway safety. There are such surrogate conflict measures such as gap time, deceleration rate, encroachment time, proportion of stopping, time-to-collision, and post-encroachment time alongside speed differential.

It is generally agreed that higher traffic conflicts rates have the capability of indicating lower safety levels for a certain facility considering that misunderstanding or lack of communication are the primary sources of conflicts within a network. This applies to the various categories of road users (Risser, 1985; Archer, 2000).

In recent years, as result of computer technology, simulation software have been utilised for the study of traffic facilities. Due to substantial input variables, simulation software's can provide traffic environment close to real life. The traffic data and traffic conflicts are automatically collected for each moment of running time. Recently, Surrogate Safety Assessment Model (SSAM) has been developed to analyse and evaluate traffic conflicts from simulated traffic (Gettman et al., 2008).

2.3.1 SSAM Conflict Analysis Tool

The SSAM software is owned by FHWA. As stated by Pu and Joshi (2008), SSAM's operation is subjected to data processing which gives a description of the trajectories of vehicles driving via a traffic facility alongside conflict identification. The input data of vehicle trajectory for SSAM is generated by traffic simulation software in a trajectory file format. This software has the principal objective of calculating safety surrogate measures corresponding to all vehicle-to-vehicle interactions. The software also has the objective of determining whether or not the various interactions meet the criteria of official conflicts. Figure 2.5 is an illustration of the workflow for utilising SSAM.

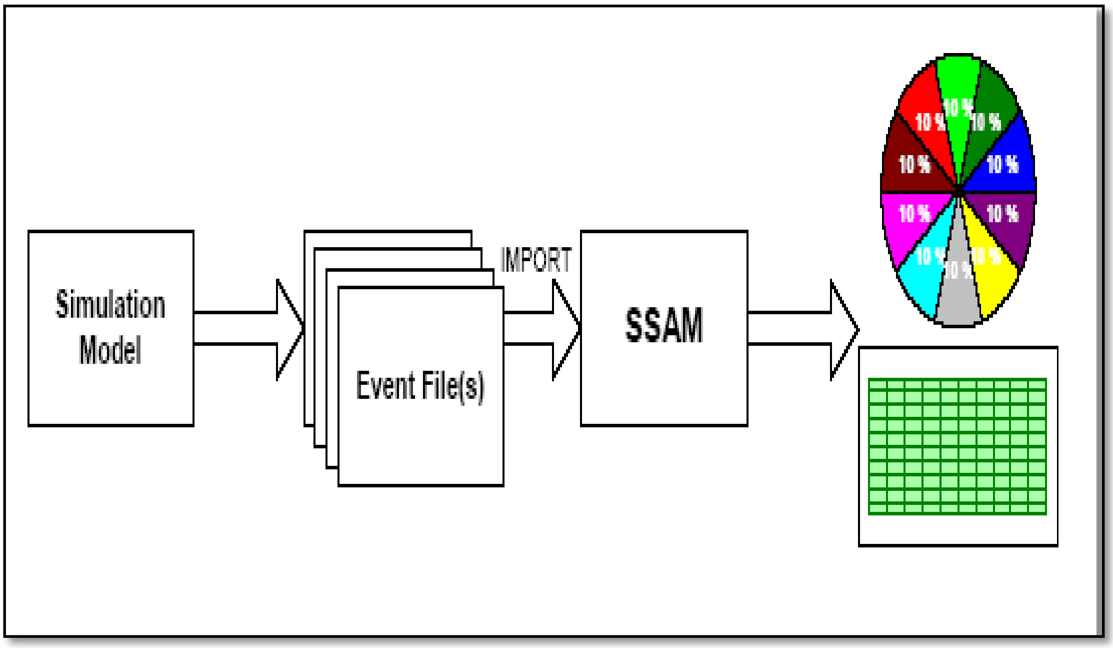


Figure 2.5: SSAM Operational Concept Event-File Based Information Flow Diagram (An Illustration)

SSAM software is characterised by two threshold values for surrogate safety measures with the objective of delineating which vehicle-to-vehicle interactions that qualify as conflicts. Post-Encroachment Time (PET) and Time-to Collision (TTC) are the two thresholds. SSAM has the capability of automatic filtering out conflicts, which do not meet the thresholds.

TTC is the time remaining until two vehicles collide if they continue at their current speed and on the same path (Hayward, 1972). PET, which is defined as time laps from the moment that the encroaching vehicle leaves the conflict point to the moment that the other vehicle arrives at the prospective point of collision (Hydén, 1987). TTC is also used as indicator of conflicts severity. The conflict severity is classified into four levels according to TTC values (1.5, 1, 0.5 and 0), where 1.5 represents low risk. As the TTC value decreases, the situation becomes more dangerous.

Absolute value of the Conflict Angle is made use of classifying the event type. Ideally, the classification of a conflict as classified on conditions that the angle of conflict is, rear-end if ||Conflict Angle|| < 30°, crossing if ||Conflict Angle|| > 85°, lane change if 30° _ || conflict angle || _ 85° and Unclassified: if the angle of conflict unknown value. Figure 2.6 illustrates the conflict angle. Experimentation was used in the determination of threshold angles (30° and 85°).

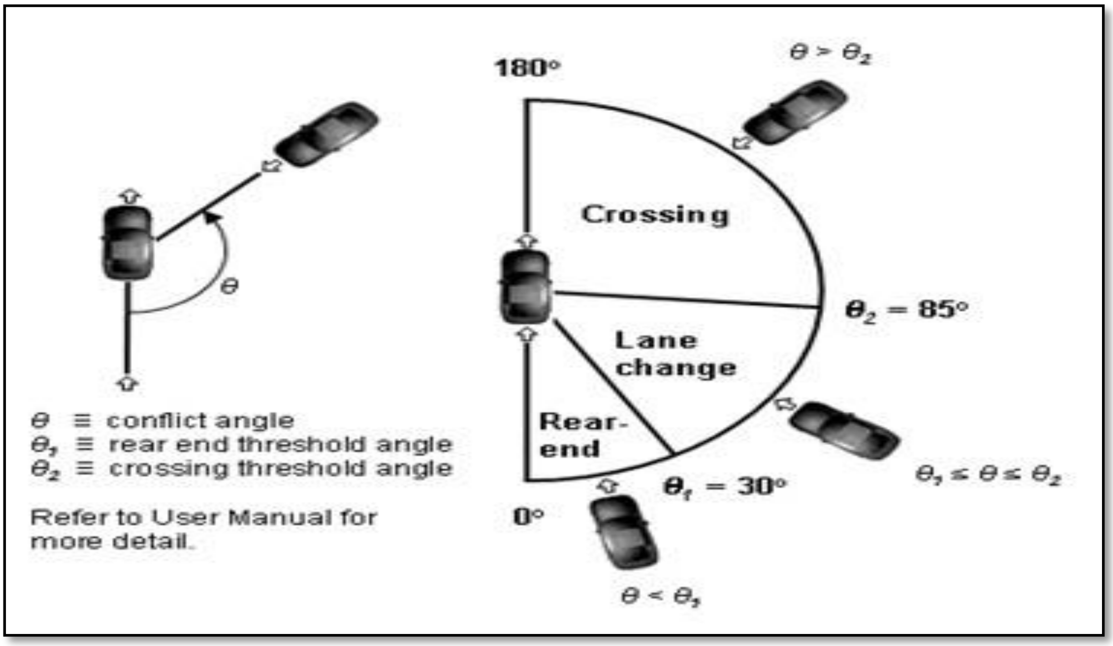


Figure 2.6: Illustration of Conflict Angle Diagram (SSAM Software)

2.3.2 Simulation Modelling

2.3.2.1 Choice of a Simulation Tool

There has been an increasing need for simulation modelling with the objective of enhancing the understanding of traffic behaviour in a time when the transportation systems have become more complex. A couple of past researchers carried out studies on diversity of simulation tools and their ability to model different traffic and geometric configurations, alongside roadway type.

Gettman and Head (2003) carried out a study with the objective of evaluating the different simulation models' capabilities for the production of intersection safety. Multi-purpose micro simulation software includes: CORSIM, SIMTRAFFIC, HUTSIM, PARAMICS, AIMSUN, VISSIM, TEXAS, INTEGRATION, and WATSIM. Notably, AIMSUN, VISSIM, PARAMICS, and TEXAS give out the appropriate TRJ files as per SSAM requirements.

VISSIM is seemingly a full-featured microscopic simulation model. VISSIM is capable of obtaining detailed state variable information on all vehicles on time scales with a higher accuracy. In addition, there are interfaces of VISSIM with other external software such as MATLAB. VISSIM supports an enormous deal of modelling features, which are required in order to obtain surrogate measures at a reasonable accuracy level. As a result of the accompanying competitive advantages, and the ability to analyse networks of all sizes, VISSIM is the platform of choice in the performance of traffic simulation modelling.

VISSIM has become a traffic simulation-modelling tool of choices as a result of its compatibility with SSAM. Other reason why it became a tool of choice is that it is inclusive of its versatility with respect to the analysis of large-scale networks alongside its capability of providing users with the potential to model any type of geometric configuration. Furthermore, it generates different data files that are required by other software and analysis. Considering the above factors, PTV VISSIM (version-8) has been selected as the simulation program.

This program has been used to create and model the different networks, which will be discussed in Chapter 4.

2.4 Summary

In this chapter, a comprehensive literature review have been presented regarding the MFD. As supported from previous studies, it is observed that the MFD model plays a significant role in evaluating and controlling different traffic characteristics in an urban network, which can be obtained from traffic simulations or real-world data. Also, the effect of different networks characteristics such as variability of vehicle densities, heterogeneity of roadway segments, distancing between the loop detectors, traffic signals and control strategies on the shape of MFDs have been widely investigated. Despite the efforts so far, there is a limited set of knowledge when it comes to understanding the relationship between the dynamics of the MFD and safety.

It is concluded from the given literature in this chapter that the traffic flow parameters exhibit mixed effects on road safety. Furthermore, the relationship between safety and speed limit is well documented in the literature, with speed being identified as an essential factor that affects crash occurrences and severity. Other studies concluded that the speed variation affects the road accidents more than speed itself. Few studies found a significant relationship between traffic density and the volume to capacity ratio and accident rates while other studies have found that traffic flow is a statistically significant predictor of accident rates. Some studies imply nonlinear relationship while other suggests an existence of linear correlation.

As mentioned earlier, the relationship between road safety and MFD is not mature and hence not fully understood yet. This research focuses on exploring and analysing the correlation of traffic safety and MFD, and other macroscopic traffic characteristics using highly precise accidents and traffic flow data. This thesis proposes a base and novel method to estimate traffic safety in large scale network with respect to macroscopic dynamic approach as described in coming chapters.

Chapter 3: Macroscopic Safety Diagram (MSD)

3.1 Introduction

Most recently, Macroscopic Fundamental Diagram (MFD), as discussed in Chapter 2, has been particularly targeted in the area of area-wide network performance. It is widely accepted that MFD is a very essential tool that can be used in the evaluation of the performance of traffic in urban network at a macroscopic scale. It can also be used as a vital tool to manage the traffic (Daganzo, 2007; Geroliminis and Daganzo, 2007; Geroliminis and Daganzo, 2008; Ji and Geroliminis, 2012; Gayah and Dixit, 2013).

The traffic engineers and planners desire to develop an efficient traffic plan for the urban network to enhance mobility and improve safety. One way of achieving this is by reducing the number of crashes. At the same time, reducing congestion and keeping the traffic flow on optimal state based on MFD are important considerations. It is however not clear so far that how the safety is related to the MFD (i.e. traffic performance) that is formed in large-scale networks.

Despite the existence of numerous studies on the characteristics and applications of the MFD, there still exist no prior studies related to dynamics of traffic particularly associated with traffic safety. In this chapter, we aim to incorporate MFD along with road safety. A novel mathematical model is presented to relate the probability of crashes for operational performance (i.e., current traffic state) in traffic facilities. This unconventional new model is referred to as the **"Macroscopic Safety Diagram" (MSD)**, which can be used to evaluate the traffic safety particularly at the network level.

The organisation of this chapter is as follows. In Section 3.2, the MSD model development is presented in which the conceptions and formulations are highlighted. Section 3.3 summarises the chapter.

3.2 Macroscopic Safety Diagram Model Developments

In order to effectively identify and analyse the nature of the correlation between MFD and crash potential on traffic networks, the probability of crash model was developed. The model proposed in this chapter can be used to evaluate the traffic safety at the macroscopic scale by using network traffic variables.

The safety model concept is based on the space-time area available for a manoeuver, within which it can safely move without colliding into another vehicle. The spatial component of the manoeuvre is proportional to a vehicle's spacing (s), while the temporal component is proportional to the vehicle's headway (h). One would expect that the larger the area, the lower the likelihood of the crash, and vice-versa. Since the former implies vehicles experience greater separation spatially, temporarily or both. Thus, the risk of a vehicle being involved in a crash can be expressed as being inversely proportional to spacing and headway as follows:

$$P(crash) = \gamma.\left(\frac{1}{s}\right)^{\alpha}.\left(\frac{1}{h}\right)^{\beta} \tag{3.1}$$

$$Q = 1/h \tag{3.2}$$

$$k = 1/s \tag{3.3}$$

Thus, by substituting Eq. (3.2) and Eq. (3.3) into Eq. (3.1)

$$P(crash) = \gamma.(k)^{\alpha}.(Q(k))^{\beta} \tag{3.4}$$

Where

$P(crash)$ = probability of crash over the analysis time frame.

$(h\ x\ s)$ = space-time area,

(h) = average vehicles headway (inverse of flow),

(s) = average vehicles spacing (inverse of density),

$(Q(k))$ = average traffic volume on the network,

(k) = average traffic density on the network,

(γ) = network characteristics constant coefficient, and

(α) & (β) = coefficients capture the risk induced by differences in manoeuvrability in space and time respectively.

Note that Eq. (3.4) provides a direct relationship between the network probability of crash and both the overall traffic state (density) and the network flow, which we now refer to as the network Macroscopic Safety Diagram (MSD).

Theorem 1: For any set of positive α and β and unimodal MFD, the critical density associated with the largest probability of crash from (3.4) is greater than the critical density associated with maximum network flow.

The fundamental relation between the three macroscopic variables: flow ($Q(k)$), density (k) and mean speed ($v(k)$) is presented in Eq. (3.5).

$$Q(k) = k.v(k) \tag{3.5}$$

Proof: The critical density associated with maximum network flow (k_c is obtained as follows:

$$Q(k) = kv(k) \tag{3.6}$$

$$Q'(k) = v(k) + kv'(k) = 0 \tag{3.7}$$

$$k_c = \left|\frac{v(k)}{v'(k)}\right| \tag{3.8}$$

The critical density associated with maximum collision risk (k_{max}) is obtained as follows:

$$P(crash(k)) = \gamma k^{\alpha} Q^{\beta}(k) \tag{3.9}$$

$$P(crash(k)) = \gamma k^{\alpha+\beta} v^{\beta}(k) \tag{3.10}$$

$$P'(crash(k)) = \gamma(\alpha+\beta)k^{\alpha+\beta-1}v^{\beta}(k) + \gamma\beta k^{\alpha+\beta}v^{\beta-1}(k)v'(k) = 0 \tag{3.11}$$

$$k_{max} = \left(\frac{\alpha+\beta}{\beta}\right)\left|\frac{v(k)}{v'(k)}\right| \tag{3.12}$$

Comparing (3.8) and (3.12), it follows that $k_{max} > k_c$ as long as $\alpha, \beta > 0$.

Theorem 1 is reveals that crash probability is highest (and thus, safety performance is worst) when the network operates within a congested state. Thus, the theoretical MSD suggests that congested traffic states should not only be avoided because they are inefficient (i.e., offer lower network flows or trip completion rates than the maximum possible) but they are also more unsafe than capacity states. Both network efficiency and safety performance can be improved implementing control to avoid congested traffic states.

Also, it can be shown that:

(A) From Triangular Fundamental Diagram, where

$$v(k) = \begin{cases} v_f, & k < k_c \\ \omega = \dfrac{(Q-0)}{(k-k_j)}, & k \geq k_c \end{cases} \tag{3.13}$$

With v_f = free speed, k = density and k_j = jam density.

The function $Q(k)$ can be written as:

$$Q(k) = \begin{cases} v_f.k\,, & k < k_c \\ -\omega.k + \omega.k_j, & k \geq k_c \end{cases} \tag{3.14}$$

Eq. (3.13) states that if the density is less than the capacity density, the speed will be free flow speed. On the other hand, if the density is greater than or equal to the capacity density, then the speed will be backward moving in congestion. The next step involves taking the derivative of Eq. (3.14), i.e. the flow, in order to substitute later in Eq. (3.18).

$$\frac{dQ}{dk} = Q'(k) = \begin{cases} v_f\,, & k < k_c \\ -\omega, & k \geq k_c \end{cases} \tag{3.15}$$

In terms of finding the critical value, k_{max} at which the maximum point on the probability of crash curve exists, the derivative of Eq. (3.4) is taken into account to find the critical value:

$$P'(crash) = 0 = \alpha.k^{\alpha-1}.Q(k)^{\beta}.\gamma + k^{\alpha}.\beta.Q(k)^{\beta-1}.Q'(k).\gamma \tag{3.16}$$

After factoring, this becomes:

$$P'(crash) = 0 = \gamma.k^{\alpha-1}.Q(k)^{\beta-1}.(\alpha.Q(k) + \beta.K.Q'(k)) \tag{3.17}$$

Because k cannot be equal to zero, Eq. (3.17) can be rearranged to give:

$$P'(crash) = 0 = \alpha.Q(k) + \beta.K.Q'(k) \tag{3.18}$$

By substituting Eq. (3.14) and Eq. (3.15) into Eq. (3.18), we get:

$$P'(crash) = 0 = \alpha.\left(-\omega.k + \omega.k_j\right) + \beta.k.(-\omega) \tag{3.19}$$

Simplifying Eq. (3.19) to remove fraction terms yields Eq. (3.20):

$$0 = -\omega.k.\alpha + \omega.k_j.\alpha - \omega.k.\beta \tag{3.20}$$

As a result, based on Eq. (3.20), the critical value of density at which the largest crash probability is obtained using Eq. (3.21):

$$k_{max} = k = k_j.\left(\frac{\alpha}{\alpha + \beta}\right) \tag{3.21}$$

We found that k_{max} > k_c as long as α, β >0

(B) Using the Fundamental Diagram of Greenshields, we obtain the following relation:

$$v(k) = v_f\left(1 - \frac{k}{k_j}\right) \qquad (3.21)$$

The function $Q(k)$ follows:

$$Q = k.v \Rightarrow Q(k) = \left(k.v_f - \frac{k^2.v_f}{k_j}\right) \tag{3.22}$$

Again, by taking the derivative of Eq. (3.22) in order to substitute in Eq. (3.18).

$$Q'(k) = \left(v_f - \frac{2k.v_f}{k_j}\right) \tag{3.23}$$

By substituting Eq. (3.22) and Eq. (3.23) into Eq. (3.18), Eq. (3.24) is produced:

$$P'(crash) = 0 = \alpha.v_f.k.\left(1 - \frac{k}{k_j}\right) + \beta.v_f.k.\left(1 - \frac{2k}{k_j}\right) \tag{3.24}$$

After factoring, this becomes:

$$0 = \alpha.\left(k_j - k\right) + \beta\left(k_j - 2k\right) \tag{3.25}$$

As a result, based on Eq. (3.25), the critical value at which the maximum point on the curve exists is obtained using Eq. (3.26):

$$k_{max} = k = k_j.\left(\frac{(\alpha+\beta)}{(\alpha+2\beta)}\right) \tag{3.26}$$

The critical value (k_{max}) from Greenshields model is greater than k_c as long as α, β >0

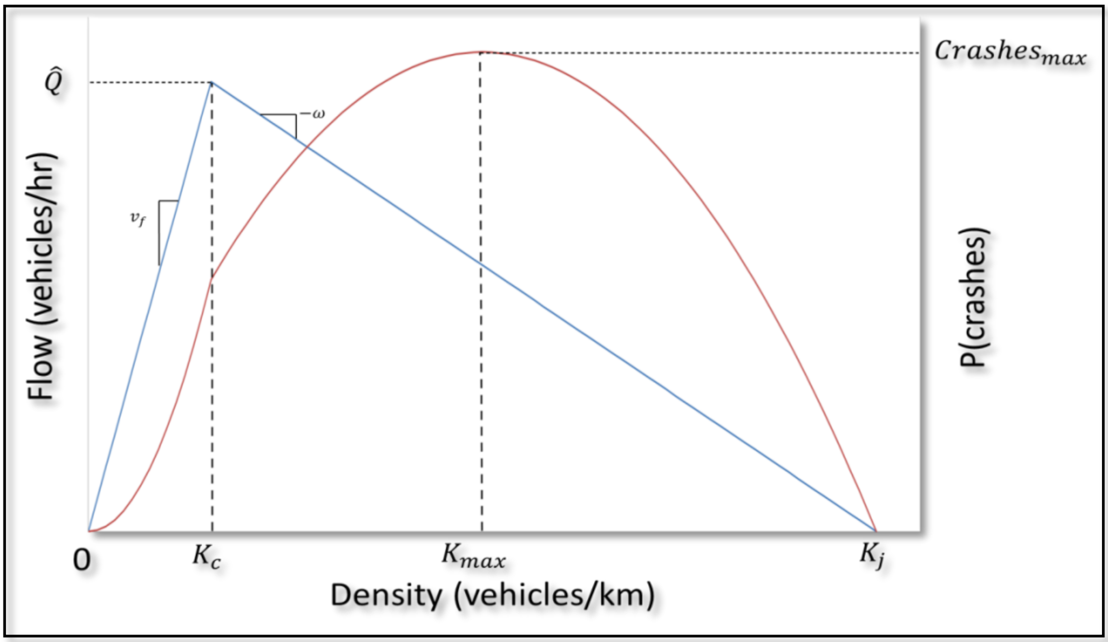
The nature of the data used for generating the MFD for the network is based on very small time intervals, where the data observation normally ranges start from 5 min to 15 min time intervals. Therefore, zero crash is observed during the majority of these periods. It is very important to calculate the crash probability ($P(crash)$) for the whole study area over the analysis time frame. This is also very essential for the model as it can be applied for both simulation data and field data. This proposed calculation is made such that the measures that are adopted are dependent on the certain value of traffic parameters for the whole study area. It means that for each traffic parameter, the probability of crashes is calculated as the total number of crashes observed for all time intervals divided by the total traffic observed that fall in the specific traffic parameter interval, as represented in Equation (3.27). For example, if there are five crashes that occur during traffic density between (5-6 veh/km) and there are 100 traffic observations during the same density interval, the probability of crash will be 0.05.

$$P(crash\ (*)) = \frac{\sum Crashes\ (*)}{\sum traffic\ observations\ (*)} \qquad (3.27)$$

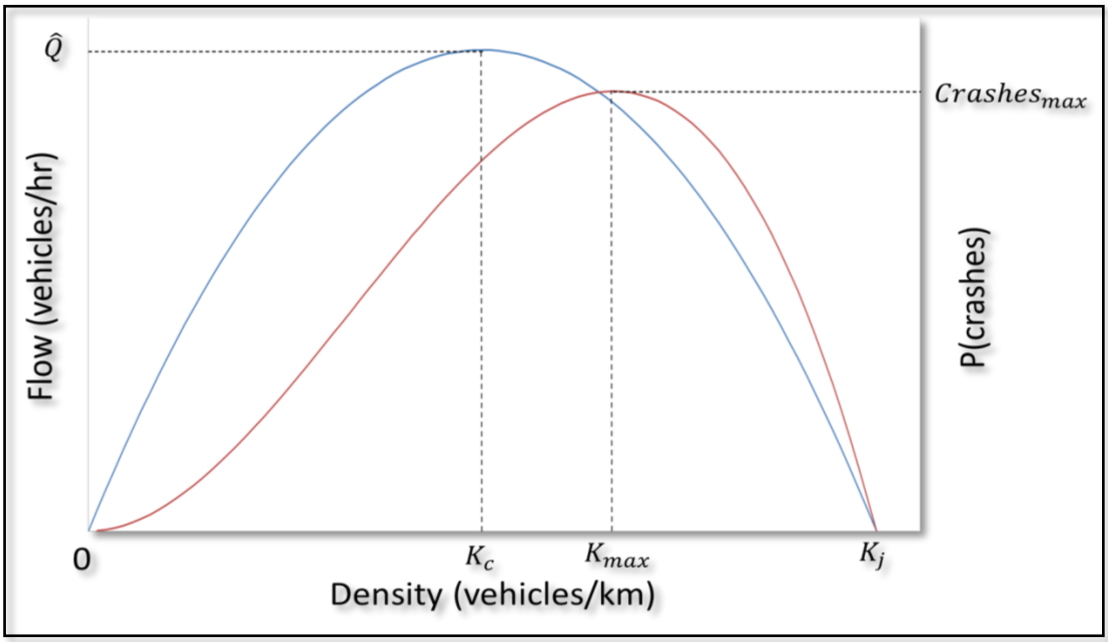
Where $P(crash\ (*))$ is probability of crashes and (*) is average speed, average density and average flow.

Based on the mathematical model as in Eq. (3.4), the coefficients γ, α and β are estimated by using non-linear regression of the independent variables. It is very important to know that α and β values take on a positive value for the networks that have three traffic states (full MFD).

Figures 3.1a and 3.1b illustrate how the hypothetical MSD is formed along with triangle and Greenshields fundamental diagrams respectively.



(a) Triangle FD with Probability of Crashes



(b) Greenshields FD with Probability of Crashes

Figure 3.1: Hypothetical Road Probability of Crashes and Flow vs. Density

Figure 3.1a is obtained by plotting Eq. (3.14) for flow and Eq. (3.4) for crashes, while Figure 3.1b is obtained by plotting Eq. (3.22) for flow and Eq. (3.4) for crashes. It is clear from the visual inspection of Figure 3.1 (a and b) that both plots follow the same trend, where the maximum likelihood of crashes occurrence exists after the traffic optimal state at traffic density (K_c). From the MSD described in Figure 3.1 (a and b) the following was observed:

1. During the free-flow condition of the network, only few vehicles are traveling and interacting, at the same time the (space-time) headways are relatively larger, therefore, few crashes occur,

2. Then, as the once the number of vehicles increases (i.e. traffic density and (space-time) headways decrease), the frequency of crashes also increases.

Therefore, by knowing that the traffic density has an inverse relationship with traffic speed, it is expected that at higher average network speeds, the number of crashes is lowest.

The frequencies of crashes continue to increase after passing the optimal traffic state at K_c. Once the traffic density exceeds a certain point (K_{max}) at which the network gets to a congested state, the probability of crashes rapidly decreases again. The K_{max} value is always greater than the K_c value. Major reasons for these decreases in crashes, as observed in the above illustrative figures, are due to the effect of network congestion and due to minor movement in the network. It is also good to note that whenever the average network speed is lower, usually at heavily congested regimes, the number of crashes is low.

The trend of probabilities of crash follows a right skewed bell-shaped curve, where the tip of the curve is found to occur for relatively high network densities (congestion regimes). From this hypothesis, it is hence proposed that, the lowest values of crashes that occur are represented by two extremes; the first one occurs if there are only a few vehicles that exist in the network (far left in Figure 3.1 (a and b)), the second one occurs if the network is heavily congested and only minor movement is observed (far right in Figure 3.1 (a and b)). Furthermore, it is observed that the highest values of crashes do not occur at the highest value of the network flow (saturation regime), but occur at congestion regime. It is important to point out that the full MSD curve exists in congested networks; otherwise a liner-relationship will appear between the crash probability and network density.

3.3 Conclusion

A novel mathematical model, Macroscopic Safety Diagram" (MSD), is proposed in this chapter, which aims to evaluate the traffic safety at network level. We believe that the proposed model represents an innovative alternative to assist researchers in understanding how the traffic parameters affect road safety at the larger network level. The main target of the model is to enable transport planners and decision makers to improve the traffic safety performance and improve the traffic performance simultaneously for the network. Its applications can also be further extended, by developing algorithms that can improve traffic conditions and traffic safety for urban network. The next chapter will present the validation of the proposed MSD model using simulation data.

Chapter 4: Simulation Data Analysis

4.1 Introduction

The previous chapter presented the theoretical background to develop a novel mathematical model referred to as a "Macroscopic Safety Diagram" (MSD), aimed to evaluate the safety performance for large-scale networks. This chapter is more practical in the sense that two simulation experiments were conducted on traffic networks in order to explore and examine the relationship between network performance (MFD) and road safety. Also, we examined the existence of the MSD model in simulated urban networks. This thesis has utilised a VISSIM microsimulation model to evaluate the operational performance of traffic facilities in conjunction with the Surrogate Safety Assessment Model (SSAM) to evaluate the safety performance for the traffic facilities using the vehicles trajectory files generated by VISSIM. From these two software, analysis of the relationship between traffic flow variables describing the MFD and road safety can be conducted.

This chapter is organised into five sections. The Section 4.2 describes the procedural framework that has been followed to conduct each experiment. Section 4.3 provides the configuration of the first experiment that has been used, which is a 10 by 10 grid network with results and discussion of the analysis. Section 4.4 represents the second simulation network experiment that has been conducted on the city of Bellevue/Redmond, Washington, USA along with the results and discussions. Finally, Section 4.5 provides the summary of the findings and conclusions of this chapter.

4.2 Procedural Framework

In order to conduct the simulation experiments in this thesis, a framework is introduced in this section, which is composed of six main components, which must be followed. Figure 4.1 illustrates the overall experiments procedure framework.

- Network creation in microscopic traffic simulation model (VISSIM)
- Run the simulation to evaluate the network and collect the vehicle trajectories files
- Traffic performances are measured by importing the vehicle trajectories files to (MATLAB) software and generating the MFDs
- Safety performances are measured by importing the vehicle trajectories files to (SSAM) software and determining the surrogate crashes
- Processing the data that has been collected from MATLAB and SSAM software by applying the filtration and combining them
- Analyse results to find the correlation between MFD and road safety

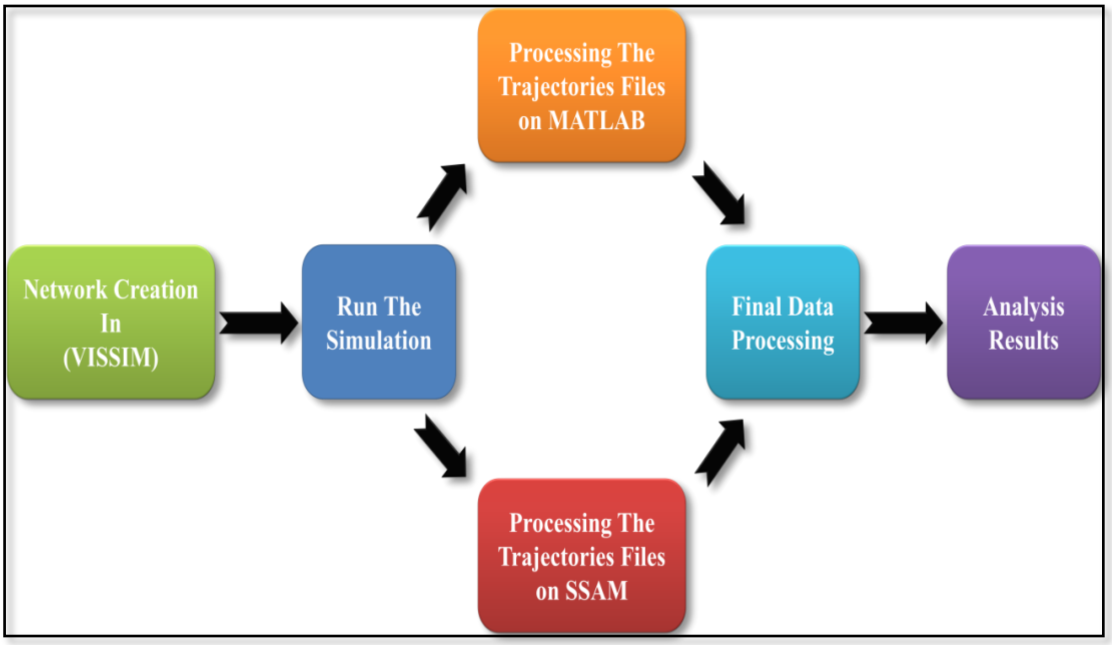


Figure 4.1: Experiments Procedure Framework

4.3 Experiment I: Grid Network

In this section, we explore the correlation between MFD and traffic safety by using a simulated urban grid network. Also, we try to prove the existence of a new traffic safety model mentioned in the previous chapter called "MSD".

4.3.1 Network Creation and Data Description

This section performs an experiment on a large-scale simulated grid network. The structuring and evaluation of the network are completed by using VISSIM simulation software. The grid network size is quite large as it represents a typical large-scale urban network. This network is newly generated for the purpose of this thesis and, therefore, no information is available about this network, including its configuration layout, signal setting, origin-destination matrix and route choice; all of these have to be created from scratch.

The network in this thesis is a 10 x 10 typical road grid network with a hundred fixed-time signalised intersections with uniform settings. Each intersection has identical four-phase signal timing plans. The cycle length of 92-seconds, with 19 seconds of green, 2 seconds yellow time and 2 seconds lost time (all red), at each signal phase, and also with no offset time applied between adjacent traffic signals. All movements' types such as left-turns, right-turn and through passes are allowed for all drivers at all intersections; U-turns are however not permitted. The priority rules were set and the conflict areas were determined at all intersections. In addition, all vehicles have to stop and all types of movements are not allowed when the signal is red. The total area of the network is around $30.25 km^2$. There are 220 links in this network; all links are designed with same length (500 metres), free-flow speed and capacity. All the streets are two-way direction and only a single lane is provided for each direction of the network. The network layout is shown in Figure 4.2. The traffic volumes are dynamically assigned to generate different traffic states such as free-flow, capacity and congested traffic conditions. A total of 121 origins and 121 destinations (O-D) exist in the network that is spatially uniformly distributed at the middle blocks locations of each internal link as well as at the boundaries of network (i.e. entry/exit points of all links). The trip generation is spatially uniform where the same number of trips is generated by each origin, and similarly, each destination attracts almost the same number of trips. In this network, for the route choice, all the vehicles randomly choose the path between each pair of O-D.

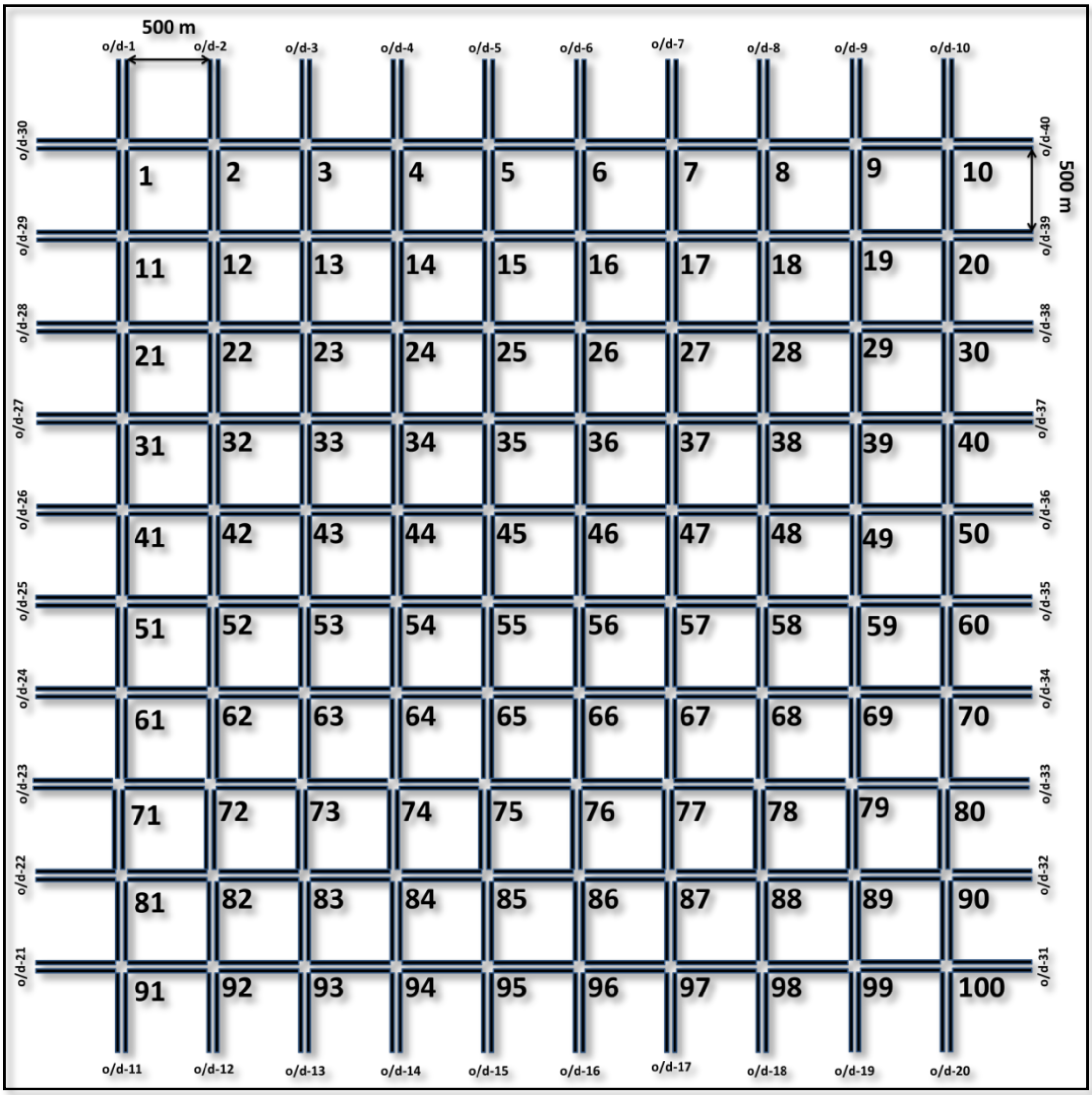


Figure 4.2: Grid Network Layout

4.3.2 Simulation Runs Output Data File Generation

Within each simulation run, all the vehicles are loaded on the network to enable all vehicles to reach their destinations over the simulation period of the experiment, i.e., 2 hours. The detailed information for each vehicle per second in the network is collected during the simulations. This information includes the vehicle ID number, total distance travelled, simulation time in the network, as well as link and lane ID number. These details are gathered and recorded by

VISSIM into vehicles trajectory text files at the specified time interval. These files are processed later (i.e., after the end of simulation experiment) with MATLAB and SSAM software in order to generate the MFDs and surrogate crashes respectively for the whole network. The experiment is conducted with fifteen different random seeds to remove small demand fluctuations and make the trips stochastically variable. In case the network is empty (i.e., all vehicles have reached their destinations in the network and the total simulation time has finished) or in case the entire network is in gridlock (i.e., the network is heavily congested and the vehicles movements are very minor), the simulation is ended and vehicles trajectory files are exported for further analysis.

4.3.3 Obtaining the Network Traffic Performances

This section describes the approach to estimate MFD for all the study areas. Once the vehicles trajectory text files are obtained from the VISSIM as a result of simulation experiments, the trajectory files are imported into MATLAB software. The text files are then converted to suitable MATLAB vector format. The vehicles trajectory data are aggregated based on five-minute time intervals, with the purpose to calculate the network traffic performances. In order to generate the MFDs for the network, the average flow, density and speed for five-minute intervals were computed for whole network. The MFDs are generated in this thesis by using a generalised function of average network flow, density and speed (Edie, 1963) which is based on vehicle trajectory and produces the most accurate MFD. The formulae adopted are shown in Equations (4.1), (4.2) and (4.3).

$$Q = \left(\frac{\sum d_i}{L.T}\right) \tag{4.1}$$

$$k = \left(\frac{\sum t_i}{L.T}\right) \tag{4.2}$$

$$v = \left(\frac{\sum d_i}{\sum t_i}\right) \tag{4.3}$$

In the above equations, Q denotes the average network flow, k is the average network density, v is the average network speed, $\sum d_i$ is the total distance travelled by all vehicles during the aggregation interval, $\sum t_i$ is the total time spent by all vehicles in the network, T is the time period of evaluation (5 min) and L is the total network length (110 km). The MATLAB code used for estimating the MFD for the whole network is provided in Appendix A.1 of this thesis.

4.3.4 Obtaining the Safety Performances

The SSAM software is used here to process the vehicle trajectories that are contained in the trajectories files to determine surrogate crashes on the traffic facilities. The imported vehicle trajectory data file for SSAM is generated by VISSIM. The surrogate crashes are determined by conflict analysis (vehicle-to-vehicle interactions) based on surrogate measures for safety. After the analysis is conducted on SSAM, a new file is generated which includes significant details on all the recognised conflicts, which were occurred during the whole simulation time. Time to collision (TTC) is a commonly used measure that has been applied to evaluate the level of safety in different traffic conditions (Gettman et al., 2008). TTC is adopted as the Surrogate Safety Measure in this thesis. We determine surrogate crashes by evaluating different thresholds of TTC, namely TTC=0, TTC≤0.5, TTC≤1 and TTC<=1.5. All the Surrogate Safety Measure not taking place in the specified range of TTC threshold has been filtered out. Events of Conflict can be classified normally into many different types such as lane-change, crossing and rear-end; they can also be unclassified based on the trajectories and relative position of each of the vehicles involved in a conflict. For this network and because of the design specifications, only rear-end surrogate crashes are included and all other classifications are excluded from the data. Finally, the individual surrogate crashes are aggregated over 5-minute intervals, so as to compare them with the MFD of the network.

4.3.5 Final Data Processing

With the completion of two previous steps, the processing of the two analysed data files (traffic and crash data) obtained from MATLAB and SSAM respectively commenced. First of all, for traffic data, a unique reference number was created for each traffic observation. After that the surrogate crashes were filtered to remove any inconsistent observations. All surrogate crashes recorded for two vehicles from different links were removed along with duplicated surrogate crashes from the data files. A unique reference number was created for all crashes that have been aggregated over the 5-minute interval in order to match them with the relevant traffic data. Based on the timestamp and by using both reference numbers of surrogate crashes and traffic data, the two datasets were linked together and all the files were combined into one file in order to commence exploring and analysing the relationship between macroscopic traffic variables and road safety. A comparison was then made between the 5-minute interval aggregated surrogate crashes and the MFD.

4.3.6 Analysis Results

The analysis results for the data that have been collected from the first simulation experiment were divided into two sections:

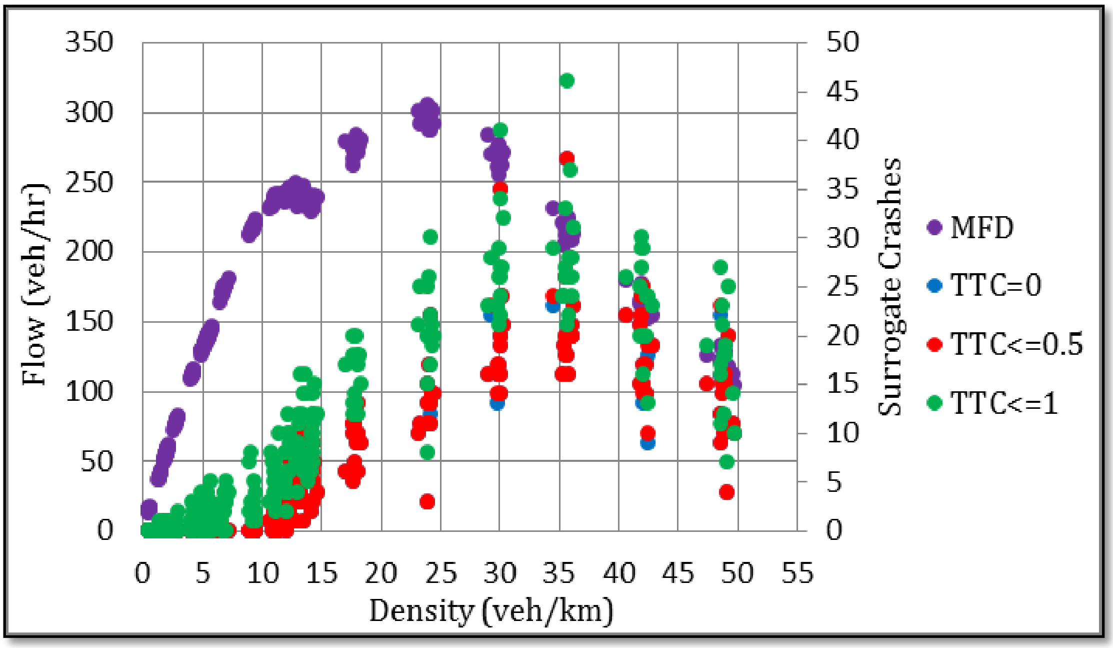
- The first section investigates the correlation between macroscopic traffic variables and surrogate crashes
- The second section examines the relationships between the probability of crashes and macroscopic traffic behaviour

4.3.6.1 Relationship of Surrogate Crashes with Traffic Flow Variables

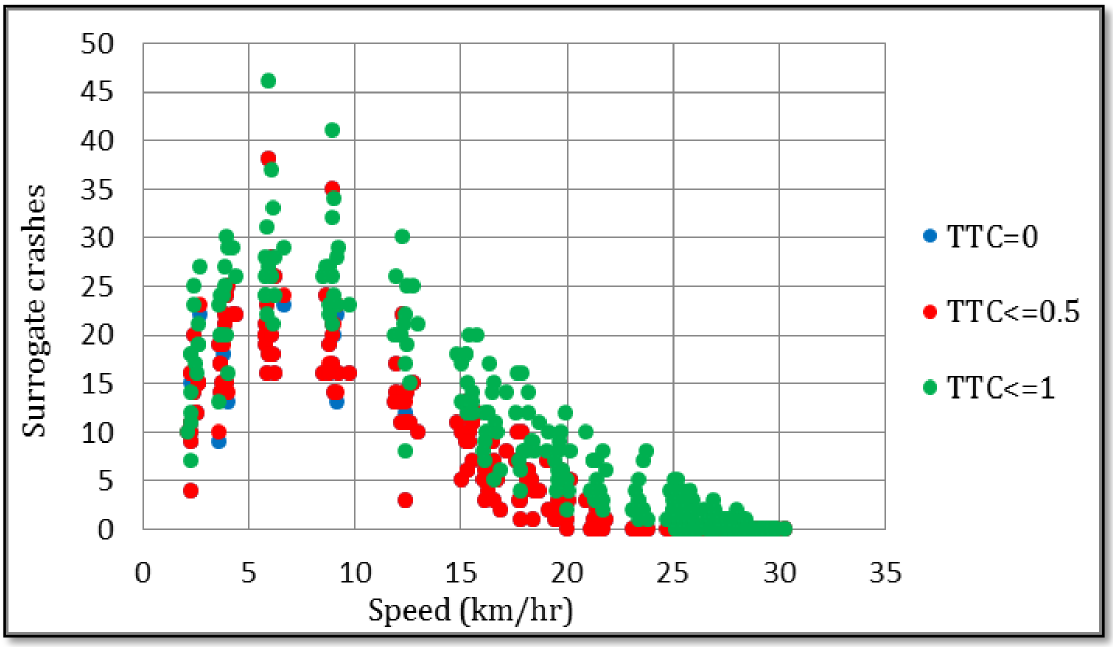
Figure 4.3 shows the relationship of surrogate crashes with the traffic flow variables were analysed. The pictures represent the values observed over the 15 simulation iterations. It can be clearly observed that the trend in the relationship between using TTC thresholds of 0, 0.5 and 1 are almost the same. As expected, the number of conflicts observed increases with the TTC threshold selected; i.e., higher thresholds provide more conflicts. Threshold TTC of 1.5 is very radically different from the others; therefore, it will be excluded from the analysis and will be presented separately in Appendix B.1.

Figure 4.3a shows the relationship between average network flow and density in (purple colour) and shows a well-defined MFD with no scatter in the free flow branch and relatively low scatter near capacity and congestion. The highest flow observed occurs at a critical density of about 24 veh/km. The surrogate crashes with different TTC thresholds (shown in blue, red and green) are found to be low at lower density and then they start to increase as the average network density increases. Afterwards, they start decreasing in the congestion regime. Remarkably, for all TTC thresholds chosen, the peak observed surrogate crashes occur at a critical density that is greater than the density that is associated with maximum network flow. This result is in complete agreement with the MSD model, which reveals that the crashes are following a parabolic-shaped curve when assessed against traffic density.

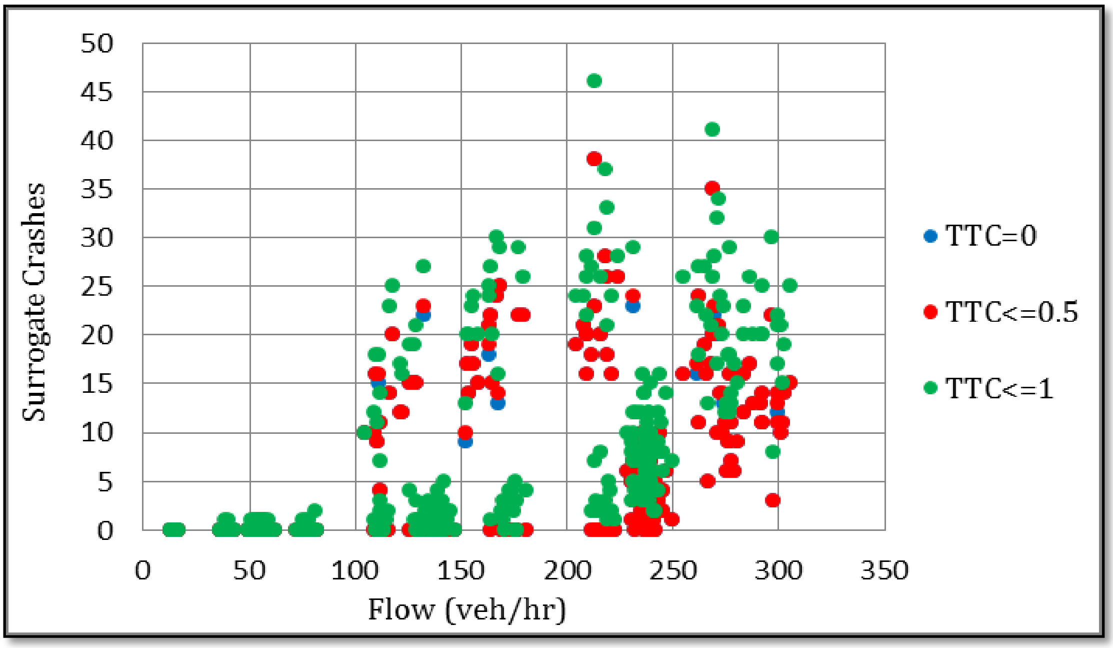
A negative correlation exists between average network speed and surrogate crashes, as shown in Figure 4.3b. However, this correlation becomes positive when the network becomes in a heavily congested condition. It is important to note that the higher average speed is associated with the lowest surrogate crashes. This is also consistent with the theory developed in this thesis. On the other hand, surrogate crashes have almost U-shaped relationship with average flow, as presented in Figure 4.3c. This figure can be explained as follows: the surrogate crashes increase with increasing traffic volume until the certain point of congestion is reached, which represents the maximum surrogate crashes value. After this point, the surrogate crashes starts to drop again due to minor movement in the network. This figure suggests that for the same value of traffic volume there are two values of surrogate crashes: one value in free flow condition and the other one in congestion condition.



(a) Flow and Surrogate Crashes vs. Density



(b) Surrogate Crashes vs. Speed



(c) Surrogate Crashes vs. Flow

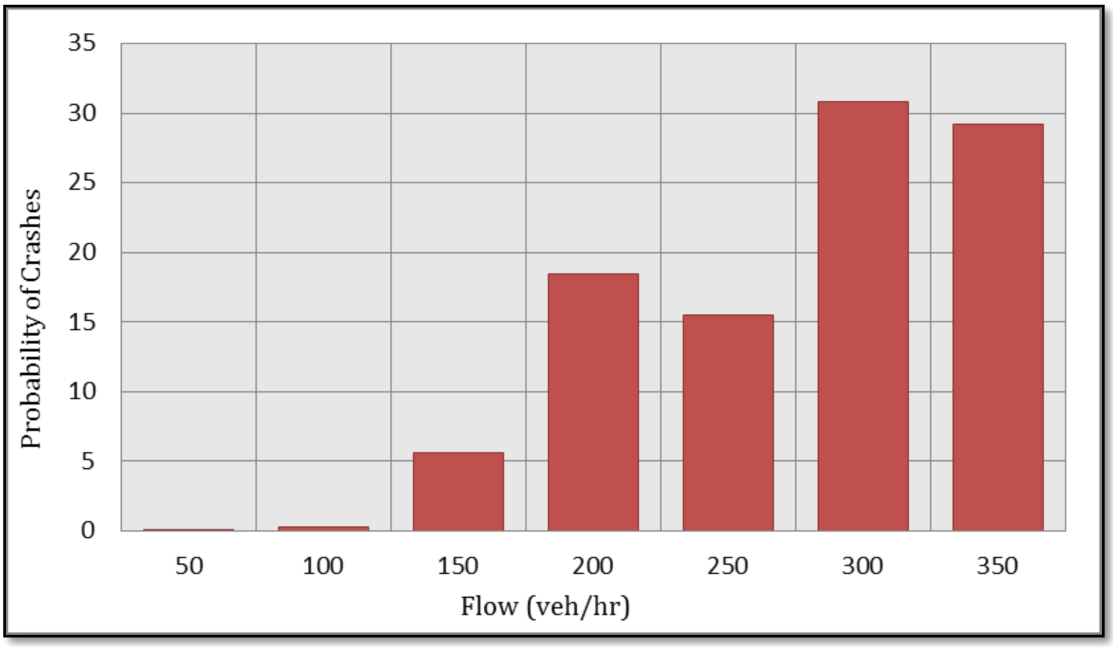
Figure 4.3: Surrogate Crashes vs. Traffic Flow Variables with Different TTC Thresholds

4.3.6.2 Relationship of Probability of Crashes with Traffic Flow Variables

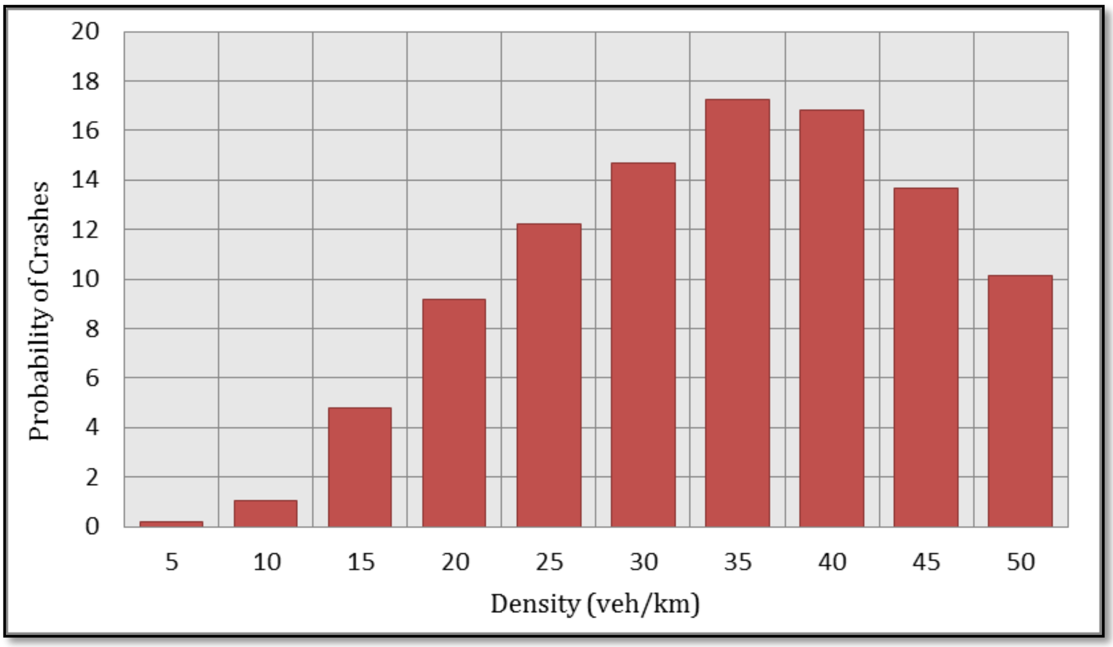
The probabilities of crashes are calculated for the whole study area, which is essential for examining the existence of an MSD model in simulation experiments. Additionally, it is very important to compare the simulation results with field data results.

The probability of crashes is calculated for each value of traffic parameter, as the ratio of the total number of crashes observed for all 5-minute intervals to the total traffic observed that fall in specific traffic parameter category as described in Chapter 3, Equation (3.27). Based on the visual inspection of Figure

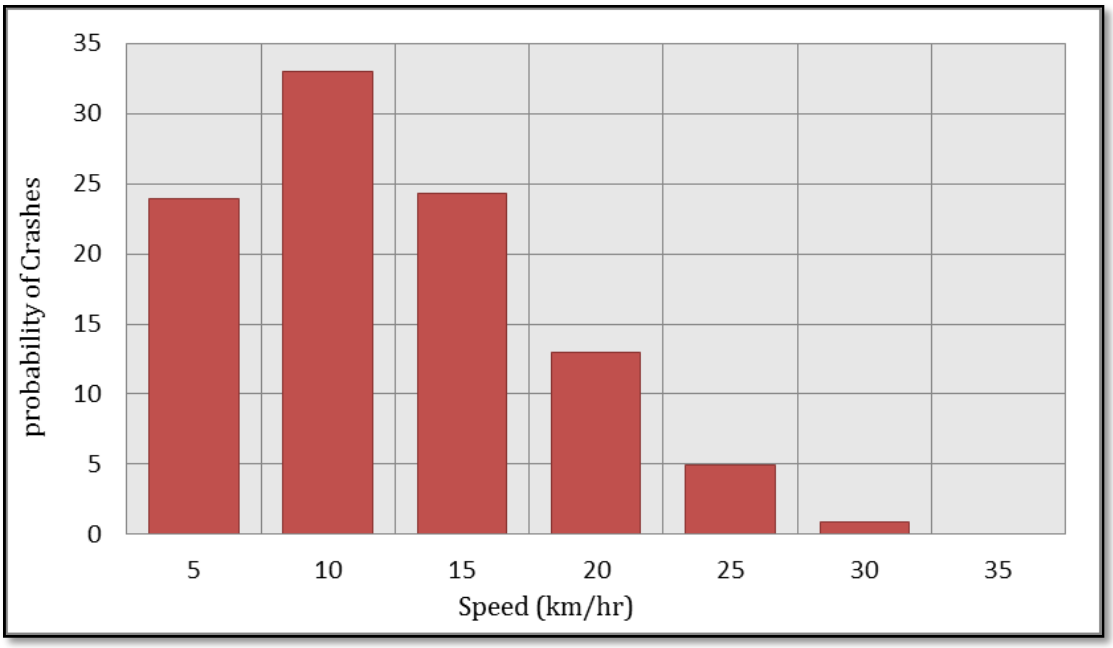
4.3 in the previous section, threshold of TTC<=1 was considered reasonable, and is chosen for the rest of the analyses. The rest of the analyses with different TTC values are presented in Appendix B.2.



(a) Probability of Crashes vs. Flow



(b) Probability of Crashes vs. Density



(c) Probability of Crashes vs. Speed

Figure 4.4: Relationship Probabilities of Crashes and the Traffic Parameters for TTC<=1

Figure 4.4 represents the relationship between probability of crashes and the traffic parameters. It is clear from Figure 4.4a that the probability of crashes has a positive relationship on traffic flow, where the higher values of probability of crashes were associated with higher average traffic flow. However, this relation contains some fluctuation. The probabilities of crashes uniformly increase with the increase in average network density, and once the network gets to a congested state, it decreases again, as can be seen in Figure (4.4b). In particular, this relationship is found to be smoothly defined. At lower average network density, the probabilities of crashes is lowest; it then starts to increase with the increase in density, passing through the optimal condition of the network at traffic density of around 24 veh/km. When the network becomes congested, the probabilities of crashes start to decrease at a certain point around the traffic density of 35 veh/km. This result has strengthened our confidence in MSD hypothesis that probabilities of crashes follow a parabolic-shaped curve with traffic density. The most notable observation to emerge from this figure is that the maximum value of the curve is found in higher network densities. Figure 4.4c presents the negative relationship between the probability of crashes and the average network speed. It is worth mentioning that the result suggests that at free flow condition (i.e., at higher average speed), probability of crashes is very low and that also powerfully supports our hypotheses presented in this thesis.

The relationships are further examined by conducting a statistical analysis on the observations. For simulation data, since numbers of the observations for each traffic density interval are the same and only observed surrogate crashes data is available in the simulation environment, the crash probability in Eq. (3.4) is replaced with the number of surrogate crashes observed for each TTC threshold. Non-linear regression is used to estimate the model parameters for each of the four TTC thresholds considered. The parameter estimates, associated standard errors, and goodness-of-fit statistics (R^2 and sum of squared errors) are provided in Table 4.1. The number of observations included in the regression model is 360 in each case (24 observed densities in each of the 15 simulation iterations).

Table 4.1: Parameter Estimates for Theoretical Model Applied To Simulated Data for Various TTC Thresholds

	$TTC = 0$		$TTC \leq 0.5$		$TTC \leq 1.0$		$TTC \leq 1.5$	
	est.	std. error	est.	std. error	est.	std. error	est.	std. error
α	1.97532	0.089081	1.987415	0.886227	1.314498	0.044663	0.402045	0.005612
β	1.538389	0.086227	1.545900	0.085452	1.249237	0.058487	1.349833	0.012966
$\gamma_{conflicts}$	4.41E-06	3.24E-06	4.09E-06	2.98E-06	2.90E-04	1.24E-04	9.56E-02	6.82E-03
R^2	0.9188		0.9208		0.9417		0.9968	
Sum of sq. errors	2171.905		2148.098		3056.739		141548.3	

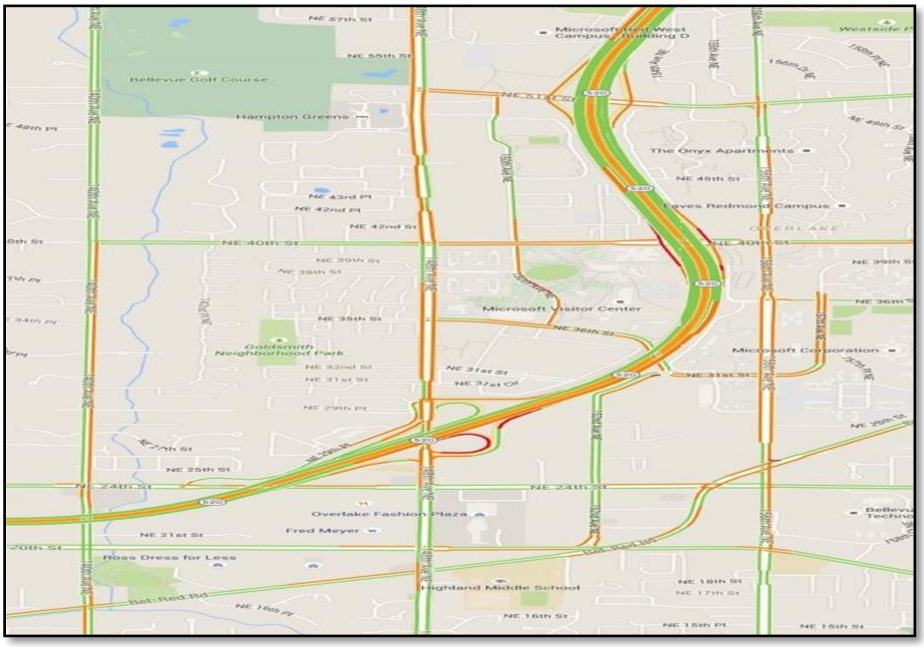
From the results above, it clearly shows a good fit of the proposed models based on the R^2 values exceeding 0.90 in all cases. It is important to note that the parameter estimates for α, β and γ values are all positive. The parameter estimates for both α and β are statistically significant in all models, which suggest a statistically significant relationship between operational parameters (network density and flow) and safety performance.

4.4 Experiment II: Bellevue/Redmond, Washington, USA Network

This section utilises the simulation data that were provided by David Evans & associates for the city of Bellevue/Redmond, Washington, USA. In this experiment, we attempt to explore the relationship between MFD and traffic safety as well as to validate and support the initial results from the grid network Experiment I.

4.4.1 Network Creation and Data Description

The network includes a two-mile by one-mile network of congested arterial streets and a saturated freeway. The microsimulation model for Bellevue includes 37 fixed time signalised intersections, one all-way stop controlled intersection, several stop-controlled driveways throughout the model, three closely spaced interchanges, six ramp meters and two collector-distributor roads. Fifty two origins and destinations for the city that are distributed on the boundaries and the traffic volumes are dynamically assigned. This model is set up to provide routes travel-times, delay from the intersection, Level of Service (LoS) of intersection and approach, length of queue, vehicle miles travelled, and volume output. Only the arterial urban streets are used for the purpose of the analysing of the urban network (see, e.g., Figure 4.5a and 4.5b).



(a) Study Site Bellevue/Redmond, Washington, USA

(b) Modelled Network Area in VISSIM

Figure 4.5: Overview of (a) Study Site Bellevue/Redmond, Washington, USA, and (b) Modelled Network Area in VISSIM

4.4.2 Generating Output Data Files Using Simulation Runs

After the loading of all vehicles in the network, the vehicles are allowed to reach their destinations over the running time of the simulation experiment, which is set to around three-hours. The detailed information for each vehicle in network is collected on per second basis during the simulation period. This information includes the vehicle ID number, simulation time in network, total distance travelled, link number as well as lane number in the network. At the fixed time interval, these details are gathered and recorded into a trajectory text file by VISSIM. These trajectory files are utilised and processed later (after the simulation ends) by MATLAB and SSAM software in order to generate the MFDs and Surrogate crashes respectively for the network. The experiment is conducted with five different random seeds. The simulation is terminated in two cases; firstly, if the network is empty (i.e., all vehicles have reached their destinations in the network and the total simulation time have elapsed) or in the second case, if the entire network reaches a gridlock state (i.e., the network is heavily congested and the vehicle movement is very minor). At the end of simulation, the trajectory files are carefully imported for further investigations.

4.4.3 Vehicles Trajectories Data Processing Using MATLAB

In this section, we describe how the MFD for the whole study domain is generated. After the vehicles trajectory text files were obtained from VISSIM, the files were imported into MATLAB, and data were prepared for further processing like compatibility and appropriate formats and a soft code was developed. Since the analysis was specifically conducted for the urban network, all the data that was collected from the freeways were excluded from the data recorded. As a result, only the arterial urban streets data were used. In order to calculate the network traffic performances and generate the MFD for the network, the vehicle trajectory, flow, density and speed data were aggregated for five-minute time interval. The MFDs were generated using generalised function of network flow, density and speed (Edie, 1963). Formulae (4.1), (4.2) and (4.3) have been presented above in section 4.3.3. The MATLAB code used to generate the MFD for the urban network are annexed in Appendix A.2

4.4.4 Vehicles Trajectories Data Files Processing Using SSAM

At the first stage, we input the vehicle trajectories files that were generated by VISSIM into SSAM software to analyse the conflict (vehicle-to-vehicle interaction) based on surrogate measures for safety. A new file was generated by SSAM after SSAM analysed the trajectory files. The generated file included huge details about all the identified conflicts that had occurred during the whole simulation period. TTC was applied as the surrogate safety measure to evaluate the level of safety in traffic conditions. We determined surrogate crashes by evaluating different threshold of TTC, namely: TTC=0, TTC≤0.5, TTC≤1 and TTC<=1.5. All the Surrogate Safety Measure not taking place in the specified range of TTC thresholds were filtered out. Only rear-end and lane-change surrogate crashes were included in this analysis and all crossing surrogate crashes are excluded. This was due to the network specifications. Finally, the individual Surrogate Crashes were aggregated over 5-minute intervals, so that we can start comparing them with the MFD of the network.

4.4.5 Final Data Processing

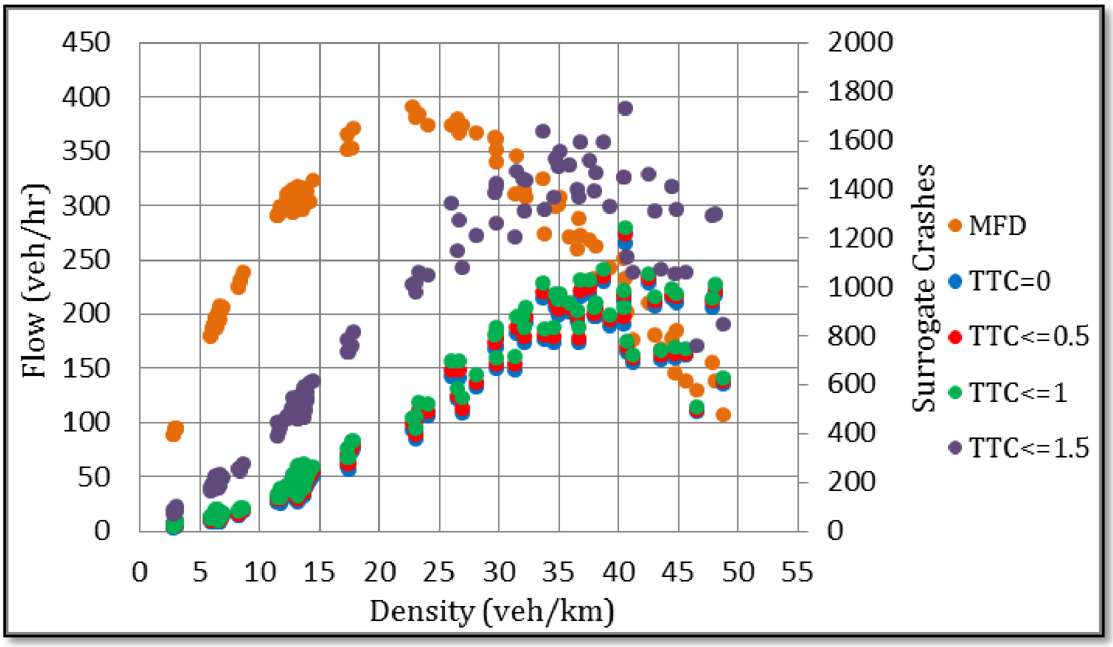
At the conclusion of previous steps, we filtered the traffic data, i.e., all the traffic data records that have occurred on interchanges, on ramp and off ramp, were excluded from this data. This is due to the differences in terms of road designs as compared to road segments. Then a unique reference number was generated for each traffic observation in the traffic data files. Then, the surrogate crashes were filtered in order to remove inconsistent observations. All the surrogate crashes observed that have occurred on interchanges, on ramp and off ramp, were excluded from this crash data. All surrogate crashes recorded for two vehicles from different links were removed as well as the duplicated surrogate crashes. A unique reference number was created for all crashes that have been aggregated over a 5-minute interval in order to match them with the corresponding traffic data. The traffic and surrogate crashes data files were linked together and were combined into one file that is based on both reference numbers of surrogate crashes and traffic data as well as timestamp. Once this was achieved, the exploration and analysis of the relationship between macroscopic traffic variables and road safety commenced.

4.4.6 Analysis Results

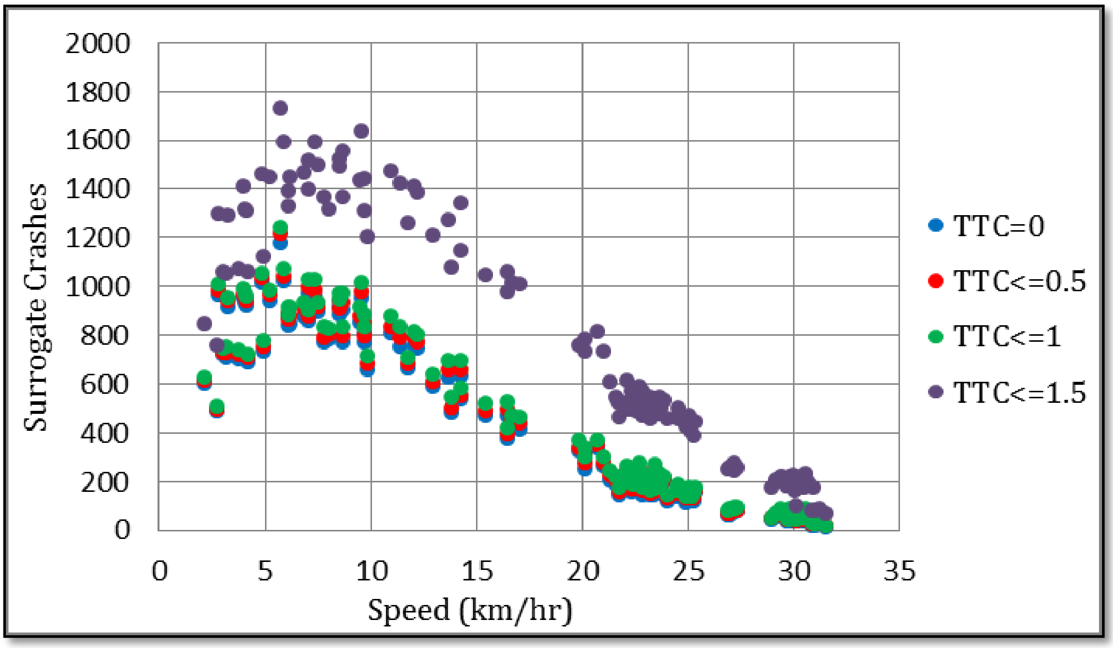
As in Experiment I, the analysis results for the data that have been collected were also divided into two sections. The first section investigates the correlation between macroscopic traffic variables and surrogate crashes. The second section examines the relationships between the probability of crashes and traffic flow variables.

4.4.6.1 Relationship of Surrogate Crashes with Traffic Flow Variables

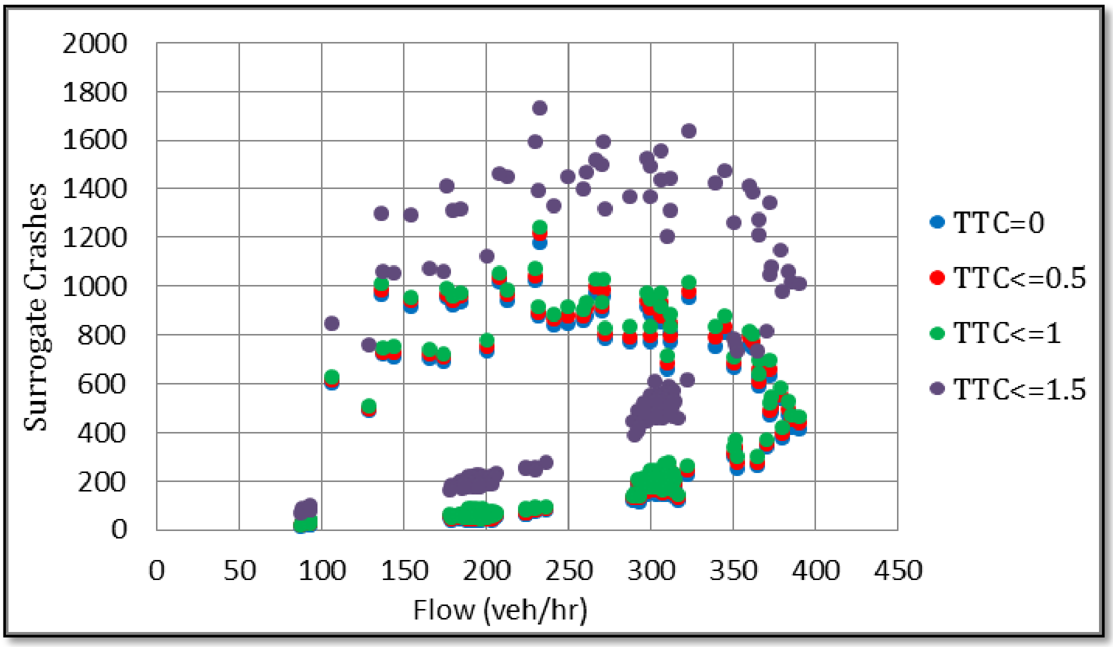
The relationship of surrogate crashes with the traffic flow variables is given in Figure 4.6. Figure 4.6a presents the relationship between the average flow and density for the network (in orange), and shows a well-defined MFD. As is observed in Figure 4.6a, the number of surrogate crashes increases as the density in the network increases and then decreases again in the congestion regime. This is consistent with our assumption that crashes are following a parabolic-shape when assessed against network density. However, there is little scattering in the congested regime, i.e., higher network density. Furthermore, as expected, the number of surrogate crashes has a negative relationship with average speed (Figure 4.6b), where the higher speeds are associated with lower surrogate crashes. This trend supports well the previous findings in the first simulated Experiment I. Also, a similar scattering of data is observed at low speeds in the congested regime. The surrogate crashes have a U-shaped relationship with traffic flow (Figure 4.6c), which has been found in earlier experiments as well. The U-shaped curve suggests that for the same traffic flow value, there is more surrogate crashes expected than in the case of free-flow conditions.



(a) Flow and Surrogate Crashes vs. Density



(b) Surrogate Crashes vs. Speed



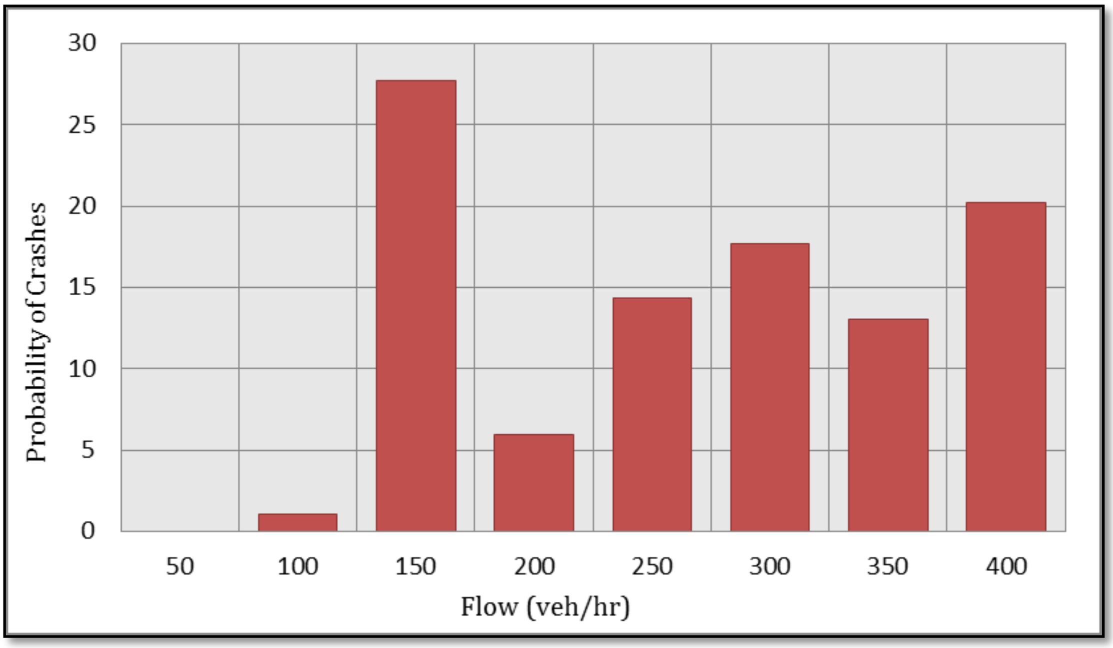
(c) Surrogate Crashes vs. Flow

Figure 4.6: Surrogate Crashes vs. Traffic Flow Variables with Different TTC Thresholds

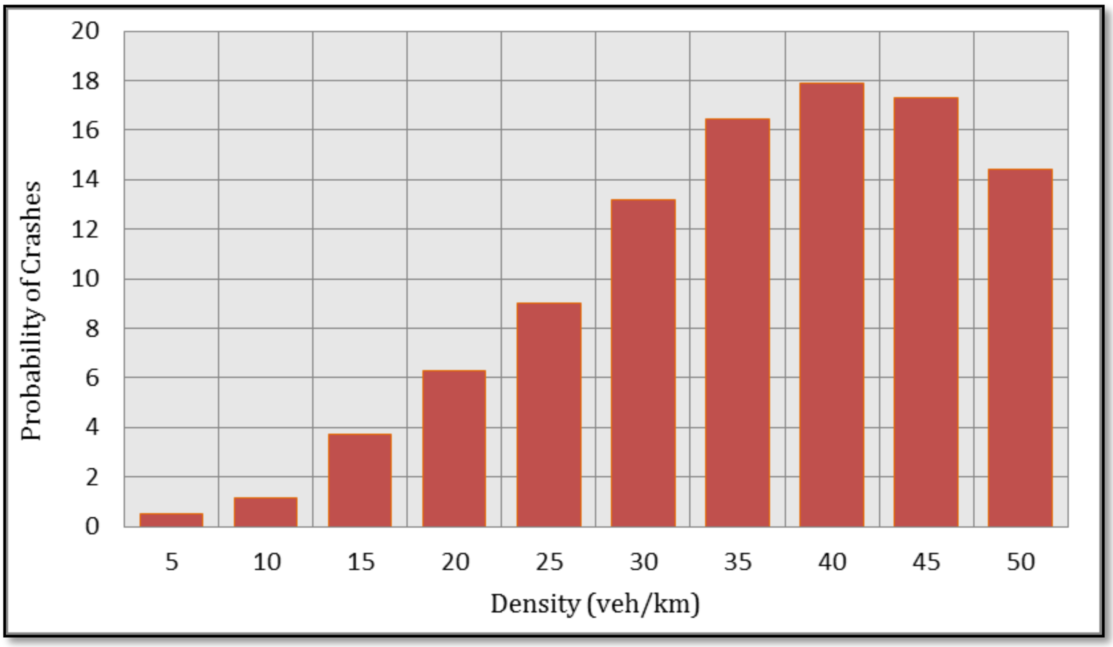
The analysis results for the relationship between the probability of crashes and the MFD for the whole network are provided in the next section. This will be used to confirm the existence of an MSD model on the second simulated experiment. It can be clearly seen that the trend in the relationship between using a threshold TTC of 1.5 is radically different from TTC thresholds of 0, 0.5 and 1. Based on visual inspection of Figure 4.6, threshold of 1 second was considered reasonable, and used for the rest of the analysis in next section. The rest of the analyses with different TTC values are presented in Appendix C.1.

4.4.6.2 Relationship of Probability of Crashes with Traffic Flow Variables

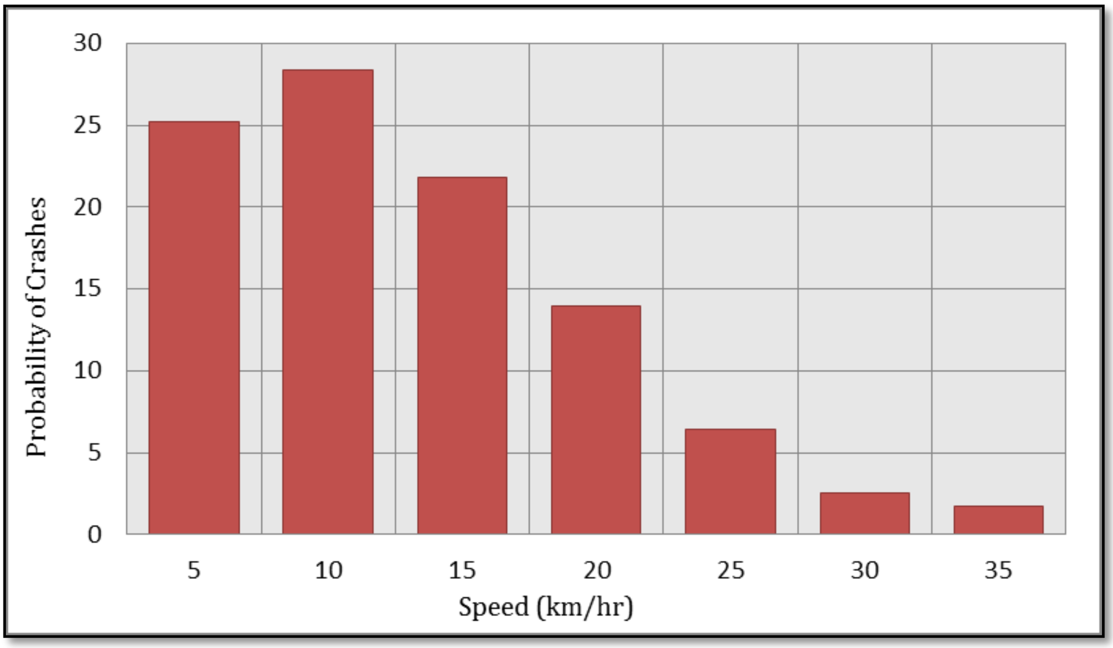
Similar to the gird network Experiment I, the probability of crashes is calculated for the entire network. This analysis is very important to prove the existence of MSD in the simulated urban network and to validate the findings from the previous experiment conducted.



(a) Probability of Crashes vs. Flow



(b) Probability of Crashes vs. Density



(c) Probability of Crashes vs. Speed

Figure 4.7: Relationship between Probabilities of Crashes and the Traffic Parameters for TTC<=1

It can be observed from Figure 4.7a that the probability of crashes is found to have a fluctuating relationship with traffic volume and there is no significant correlation. This fluctuation is also observed in the grid network results. The probability of crashes is found to increase uniformly with network density (Figure 4.7b). In the congestion state and after the optimal state, the probability of crashes starts decreasing at traffic density of around 40 veh/km. This concurs well with MSD curve and also confirms our earlier findings from the grid network simulated experiment. The results suggest that the free flow regime (i.e., lower number of vehicles in network) displays the lowest value probability of crashes, while the maximum crashes probability exists at the congestion regime. A negative relationship has been found to exist between average speed and probability of crashes as presented in Figure 4.7c, where the higher speeds at free flow condition are associated with lower crashes occurrence. These results are in line with the results found in a previous experiment, which support the hypothesis of this thesis.

For Bellevue/Redmond simulation data, non-linear regression is used to estimate the model parameters (α, β and γ) for each of the four TTC thresholds considered based on the mathematical model provided in Equation (3.4) in Chapter 3. The parameter estimates, associated standard errors, and goodness-of-fit statistics (R^2 and sum of squared errors) are provided in Table 4.2. The number of observations included in the regression model is 180 in each case (36 observed densities in each of the 5 simulation iterations).

Table 4.2: Parameter Estimates for Theoretical Model Applied To Simulated Data for Various TTC Thresholds

	$TTC = 0$		$TTC \leq 0.5$		$TTC \leq 1.0$		$TTC \leq 1.5$	
	est.	std. error	est.	std. error	est.	std. error	est.	std. error
α	1.722005	0.0421908	1.673628	.0401275	1.616013	0.0374377	1.086103	.0169709
β	0.7431864	0.0397208	0.7329814	0.0389232	0.731355	0.0377686	.7129754	.0254272
$\gamma_{conflicts}$	0.0271691	0.0091645	0.0351903	0.011457	0.0451786	0.0140005	0.523237	.0919927
R^2	0.9847		0.9850		0.9855		0.9924	
Sum of sq. errors	499846.258		522902.026		543150.156		791863.256	

In all cases, the proposed theoretical model shows an extremely good fit to the observed simulation data, as reflected by the R^2 values exceeding 0.95 in all cases. As expected, the parameter estimates for α, β and γ are all positive. The parameter estimates for both α and β are statistically significant in all models, which suggests statistically significant relationship between operational parameters (network density and flow) and safety performance

4.5 Summary and Conclusions

This chapter of the thesis has investigated the correlation between the MFD and traffic safety by employing two simulation experiments 1) 10 by 10 grid network and 2) city of Bellevue/Redmond, Washington, USA. In fact, this is the first attempt to explore the relationships between MFD and road safety, where a new approach and model in terms of crash analysis is presented.

The surrogate crashes and probability of crashes are studied along with the network fundamental diagram. The findings of this chapter clearly indicate that the MSD curve relationship exists in both simulation networks. The results are found consistent with model assumptions as discussed in Chapter 3. The surrogate crashes results suggest that 1) crashes tend to follow parabolic–shaped curve with traffic density; and 2) crashes tend to decrease with an increase in the traffic speed. The probability of crashes results support the hypothesis that 1) probability of crashes follows a parabolic-shaped curve with average network densities (MSD); 2) free flow regimes for the network exhibit a lower value of probability of crashes as compared with saturated and congested regimes; and 3) the maximum value of the MSD curve is associated with the congested state, after the optimal traffic state takes place in the network.

The simulation results also confirm that at free flow condition of the network (i.e., few vehicles travelling and high travel speeds) only a few interactions between the vehicles occur in the network, therefore, a few crashes are observed. As the number of vehicles increases in the network, the number of crashes also increases until the network becomes congested. At this point, the crashes reduce due to little or no movement in the network. It is important to note that these results validate our hypothesis that was presented in Chapter 3.

Finally, the simulation results revealed that MSD is a promising alternative model to evaluate the safety performance on urban networks. This approach can be used to improve the traffic and safety performance at the same time. This chapter's results are based on two simulation experiments, which require additional investigations using real-world data as well. The next chapter presents the corresponding results based on real-world field data.

Chapter 5: Field Data Analysis

5.1 Introduction

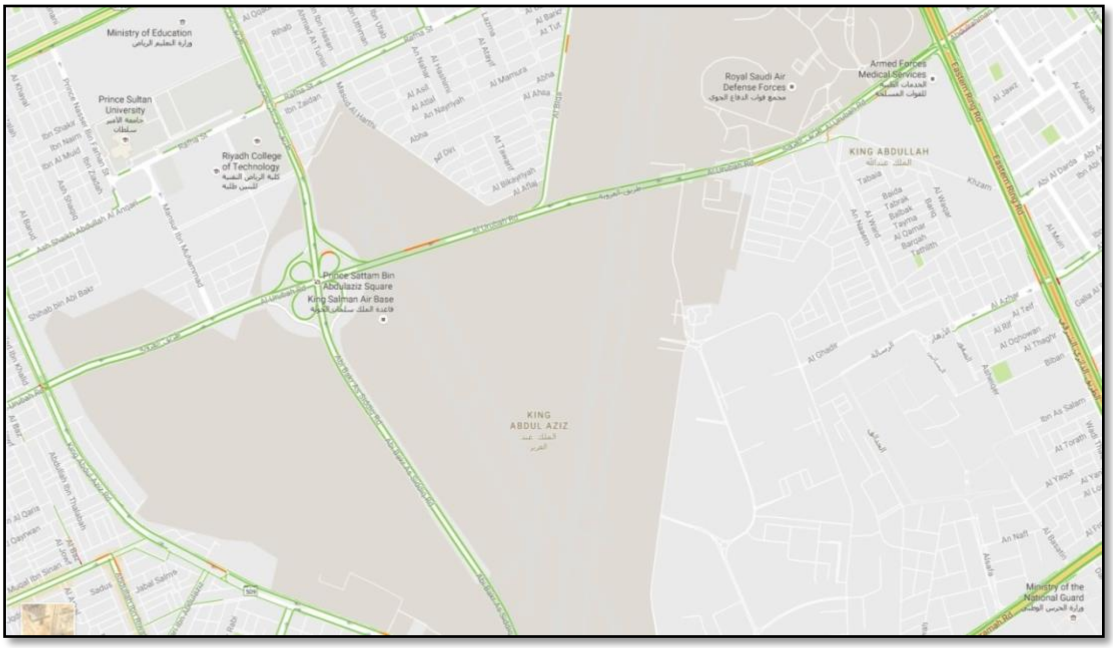
The primary objective of this chapter is to explore and examine the results related to the relationship between MFD and road crashes. Relevant empirical data to validate the models developed in this thesis have been collected from major arterial roads in Riyadh city, the capital of the Kingdom of Saudi Arabia (KSA). Also, testing the existence of the MSD on urban network will also be included, which states that the traffic crashes follow parabolic-shape with average network densities.

The site, traffic and crash data details used in this chapter are presented in the coming sections. A brief description of the data processing is presented in section 5.5. This is followed by exploratory analysis, which is a comparison of general trends of crashes and average traffic flow parameter between weekdays and weekends.

Based on the initial findings from the exploratory analyses, the MFDs are generated and the correlation analysis between MFD and road crashes for weekdays and weekends are further studied and investigated separately. The results with respect to weekdays and weekends are presented in Section 5.7.1 and Section 5.7.2 respectively. Section 5.8 presents the summary and conclusion of this chapter.

5.2 Site and Data Description

In this thesis, the empirical data have been collected for the year 2015 to investigate the relationship between MFD and traffic crashes. The roads chosen are the Al Urubah and Abu Bakr Al Siddiq arterial road connected by an interchange in the centre of Riyadh, the capital and largest city of Kingdom of Saudi Arabia (KSA). The main reasons for choosing these roads are mainly due to the fact that they had very similar characteristics. Secondly, these roads are equipped with very advanced traffic management systems to monitor and control traffic flow. Thirdly, the data obtained from the field are very accurate, which enable us to study the connotation between macroscopic traffic quantities and crashes and establish a reasonable relationship. Al Urubah Road has a total length of about 13 km, starting from the Eastern Ring Road eastbound and ending at King Fahad Road from the west. Only 6 km were included in this research because only that portion of the road contains a Closed-Circuit Television (CCTV) system to monitor traffic and crashes. The total number of lanes in each direction is 3 lanes with a width of 3.6 m for each lane. In addition, there is a 2.8 m width of emergency lane. A 3.5 m Central Island is also present in the middle. The road of Abu Bakr Al Siddiq has a total length is about 5 km, beginning from King Abdullah Road on the north side and extending up until King Abdul Aziz Road on the south side. Each direction of the road has similar dimensional characteristics as described for Al Urubah Road. Figure (5.1a) illustrates the roads map and Figure (5.1b) illustrates the beginning and the ending of study area.



(a) The Roads Map of Study Area

(b) The Road Beginning and the Ending in Study Area

Figure 5.1: Map of Study Area in Riyadh City, Kingdom of Saudi Arabia

The roads involved in this research are equipped with CCTV system for traffic counting and monitoring and along the roads there are 260 fixed cameras and 34 coaxial cameras. Also, the roads are equipped with 161 functional variable message signs such as (Variable Speed Limit), 22 instructional variable message signs as well as 120 signboards controlling the paths distributed along the road. These traffic management systems work consistently to achieve the maximum traffic capacity and safety level. Figure 5.2 shows a sample of the road's equipment.

Figure 5.2: A Sample of the Road's Equipment

5.3 Traffic Data

Traffic data were extracted from the Central Control Room (CCR) of Saudi Arabia's Arriyadh Development Authority (ADA) database, which operates on a 24/7 basis., covering various major arterials in the city of Arriyadh. The main purposes of the CCR are traffic control and monitoring, facility inspection, maintenance and repairs, give instruction to the drivers automatically in case of traffic congestion, crashes or planned activities. Figure 5.3 shows the configuration inside a typical CCR.

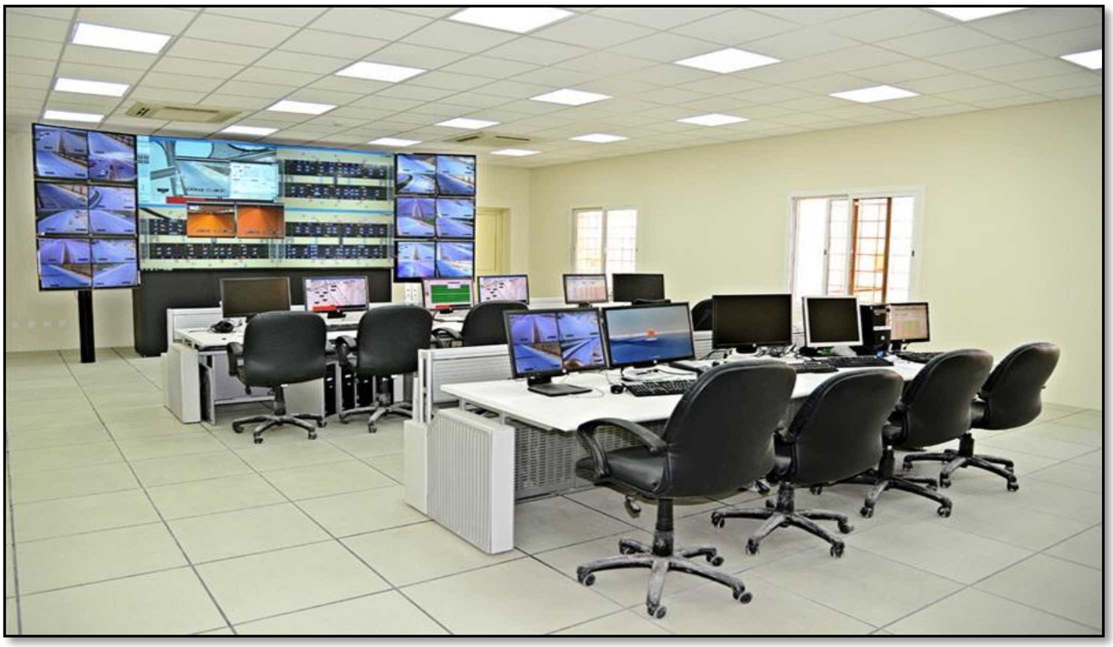


Figure 5.3: A Central Control Room in Riyadh

The CCR system generates hourly reports containing traffic flow conditions during the whole day. The resulting data is gathered from each single detector. This data is comprised of the date, time, camera source ID, average travel speed and average traffic flow (counting the number of vehicles passing through a camera sensor point). The traffic data were measured at a 15 min interval over a 24-hour basis. Within the dataset, there are approximately 9,110,400 traffic observations during the year 2015 from all detectors. Such intervals may be reducing the chance to capture short-term variations in the traffic conditions. The issue, however, was that collecting data over an even shorter aggregation interval is not possible due to some technical difficulties. Table 5.1 displays an example of a data report generated by the CCR system.

Table 5.1: Sample of Time Series of Speed and Counting (flow) from Different CAM for 31st January 2015

Start time	Source	Speed (km/h)	Vehicle count
2015-01-31 00:00:00	CAM_AB_NS_01	78.14	401
2015-01-31 00:00:00	CAM_AB_NS_02	85.52	453
2015-01-31 00:00:00	CAM_AB_NS_03	76.66	457
2015-01-31 00:00:00	CAM_AB_NS_04	80.01	431
2015-01-31 00:00:00	CAM_AB_NS_05	76.97	461
2015-01-31 00:00:00	CAM_AB_NS_06	85.51	426
2015-01-31 00:00:00	CAM_AB_NS_07	53.73	491
2015-01-31 00:00:00	CAM_AB_NS_08	74.97	586
2015-01-31 00:00:00	CAM_AB_NS_09	85.6	417
2015-01-31 00:00:00	CAM_AB_NS_10	76.49	374
2015-01-31 00:00:00	CAM_AB_NS_11	82.27	433
2015-01-31 00:00:00	CAM_AB_NS_12	82.7	394
2015-01-31 00:00:00	CAM_AB_NS_13	88.49	415
2015-01-31 00:00:00	CAM_AB_NS_14	82.11	427
2015-01-31 00:00:00	CAM_AB_NS_15	86.62	390
2015-01-31 00:00:00	CAM_AB_NS_16	88.36	417
2015-01-31 00:00:00	CAM_AB_NS_17	86.73	423
2015-01-31 00:00:00	CAM_AB_NS_18	84.06	437
2015-01-31 00:00:00	CAM_AB_NS_19	82.53	442
2015-01-31 00:00:00	CAM_AB_NS_20	77.29	431
2015-01-31 00:00:00	CAM_AB_NS_21	73.64	416
2015-01-31 00:00:00	CAM_AB_NS_22	70.99	400
2015-01-31 00:00:00	CAM_AB_NS_23	67.6	416

5.4 Crash Data

Detailed information regarding the crashes that occurred on Al-Urubah and Abu Bakr Al-Siddiq roads were collected from ADA's database. In this thesis, a period of 1 year was considered for the analysis. Data collected within the single year period include all crashes that occurred during 2015. The crash reports provided by ADA contained high detailed information immediately after the occurrence of each crash. The information of the crash includes crash date, accurate crash time of the day, camera source ID, direction of travel, location of crash by zones and precise location of crash by distance from predefined reference points. This data consisted of both serious (fatal or injury crashes) and non-serious (property damage-only) crashes. While the latter might be less critical for safety applications, they are still vital as they can disrupt operations along the arterial network. In order to use these crash data in the research analyses, a unique crash reference number was created for each crash to match the time and location of the crashes with the relevant traffic data. Hence it became possible to integrate the crash data files with the traffic data files easily based on these unique reference numbers. Table 5.2 shows a sample of crash reports.

Table 5.2: A Sample of Crash Reports for Study Roads

Weekly Accident Report

DATE	TIME	CAMERA	TYPE	ZONE	GROUPZONE	DISTANCE
2/1/2015	7:44:55 AM	CAM_AB_NS_25	S	ZONE 6	ABU BAKER NS ZONE 2	2+679
2/1/2015	8:44:54 AM	CAM_T2_EW_02	S	ZONE 6	ORUBA EW ZONE 3	4+090
2/1/2015	9:30:27 AM	CAM_OR_EW_45	S	ZONE 10	ORUBA EW ZONE 1	0+600
2/1/2015	3:26:25 PM	CAM_OR_EW_47	S	ZONE 11	ORUBA EW ZONE 1	0+400
2/1/2015	6:03:00 PM	CAM_AB_NS_27	S	ZONE 7	ABU BAKER NS ZONE 2	2+879
2/2/2015	9:20:19 AM	CAM_OR_EW_23	S	ZONE 6	ORUBA EW ZONE 2	3+200
2/2/2015	5:10:02 PM	PTZ_AB_NS_05	S	ZONE 9	ABU BAKER NS ZONE 3	4+170
2/2/2015	8:12:22 PM	CAM_OR_WE_49	S	ZONE 11	ORUBA WE ZONE 3	5+927
2/2/2015	10:11:03 PM	CAM_OR_EW_08	S	ZONE 2	ORUBA EW ZONE 3	5+230
2/2/2015	9:26:33 AM	CAM_T1_EW_10	S	ZONE 7	ORUBA EW ZONE 2	2+700
2/2/2015	10:21:34 AM	CAM_OR_EW_25	S	ZONE 6	ORUBA EW ZONE 2	3+000
2/2/2015	8:08:47 AM	CAM_T1_EW_09	S	ZONE 7	ORUBA EW ZONE 2	2+700
2/3/2015	2:56:36 PM	CAM_T2_WE_05	B	ZONE 7	ORUBA WE ZONE 3	3+400
2/4/2015	6:53:35 PM	PTZ_AB_NS_05	S	ZONE 9	ABU BAKER NS ZONE 3	4+170
2/5/2015	9:42:20 PM	CAM_OR_EW_49	S	ZONE 11	ORUBA EW ZONE 1	0+200
2/5/2015	8:39:46 AM	CAM_OR_EW_25	S	ZONE 6	ORUBA EW ZONE 2	3+000
2/5/2015	8:21:16 AM	CAM_OR_EW_01	S	ZONE 1	ORUBA EW ZONE 3	5+927
2/5/2015	12:48:07 AM	CAM_OR_WE_24	B	ZONE 6	ORUBA WE ZONE 2	2+900

5.5 Data Processing

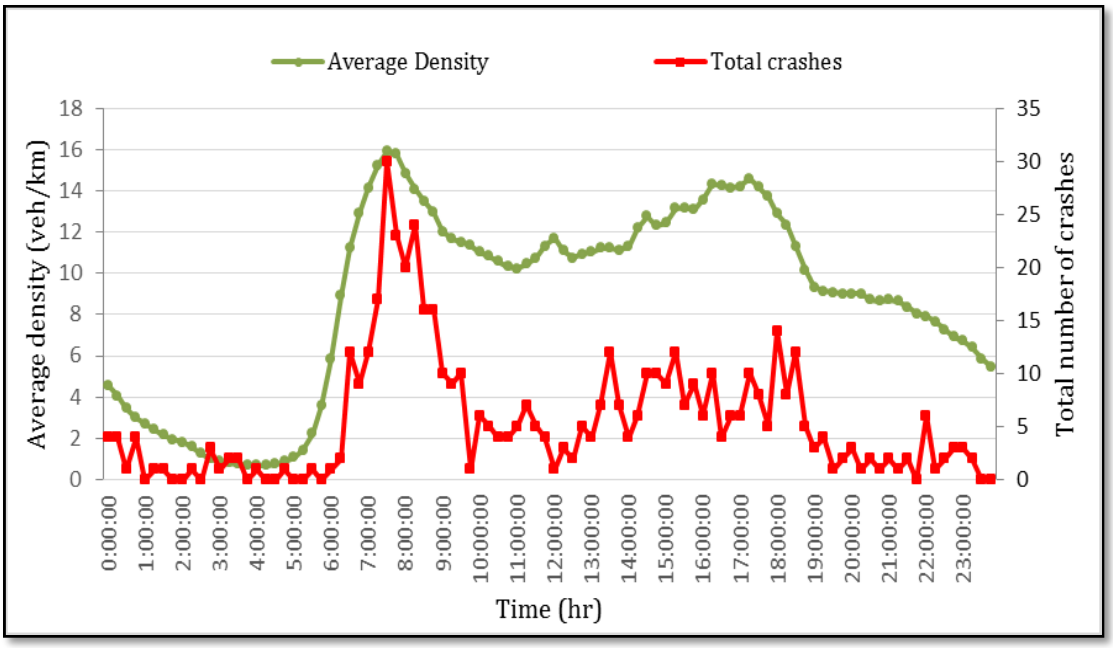
The first step involved the processing of the traffic data was described previously in Section 5.3. This is a rigorous procedure since large sets of traffic data need to be analysed. The traffic data were filtered before the start of the analyses; all the data records that were occurred on Cloverleaf interchange, on ramp and off ramp, were excluded from this research. This was due to the differences in terms of road design compared to road segments; hence obtaining the traffic flow measures at these road sections was made difficult. Also, these ramp locations have reduced speeds and did not reflect mainline traffic conditions. Moreover, all abnormal or erroneous on traffic data records such as the error resulting from the source of the data itself had to be screened. For example, any instance such that the data reported traffic flow as being greater than zero while the speed is set at zero or if the traffic flow is set to zero along with speed greater than zero have been filtered out this data. After that the average density was estimated by using flow and speed data at each of the monitored sections using the fundamental traffic relationship. A unique reference number was created for each traffic observation after the data was filtered. In order to generate MFDs for the network, the flow, speed and density were aggregated for every 15 min interval to obtain average values across the arterial network, after that the whole files were combined together into one single file. The number of traffic intervals during the year was supposed to be 365 x 24 x 4 = 35040 periods, but after filtering, the total of traffic periods dropped down to 34037 average flow, density and speed observations for entire arterial network. This represented 97.13% of the total possible observations for the year 2015. At the second step, the crash data as described in Section 5.4 was processed. The first stage of the second step contained 728 crashes recorded during 2015. This crash database was again filtered to remove an inconsistent observation. All the crashes that were located at cloverleaf interchange, on-ramp and off-ramp were removed from database. This also included all the crashes that were recorded without corresponding traffic data were also removed. The total number of crashes that were included in this analysis after filtering was 605 crashes, which represented 83% of the total crashes observed available. The majority of the crashes that were removed occurred at the ramp locations.

By knowing the time and place of each crash and by using the unique reference numbers for both crashes and traffic data, it was now possible to integrate the data with the corresponding traffic flow conditions and start exploring the relationships between them.

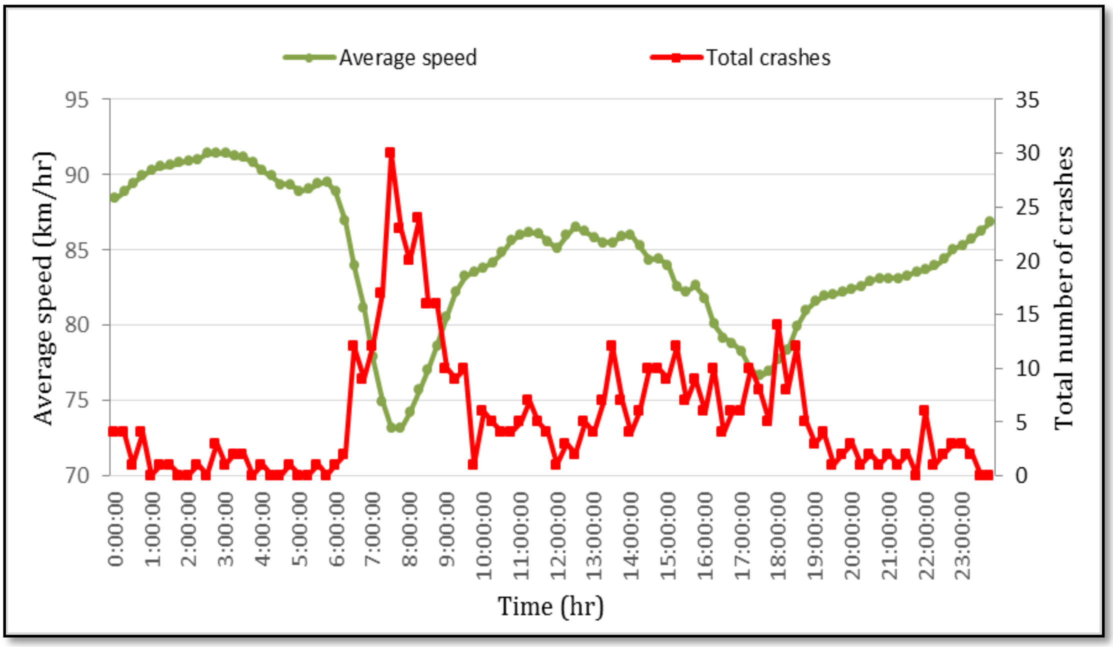
5.6 Exploratory Analysis

As mentioned earlier, two databases (traffic and crash), were combined together for deeper analysis, and it was decided to investigate and analyse the data further in different ways before turning to look at the correlation between the MFD and road crashes. This allowed us to examine all opportunities which may support our basic hypothesis. The traffic data have been analysed and tested based on the different periods in the day to obtain more insight into the causes and effects of the change of traffic parameters on crash occurrence. It is important to note that the time effects were considered in this study by looking at crash occurrence and traffic observations on a day basis. Whether the day observed was a weekday (working day) or a weekend had to also be determined. This is because the purposes of trips differ depending on the day of the week. The trips made on a weekday are typically for work, school and commercial commutes. Alternatively, trips made on weekends are typically for social and recreation purposes, such as vacations and visiting friends.

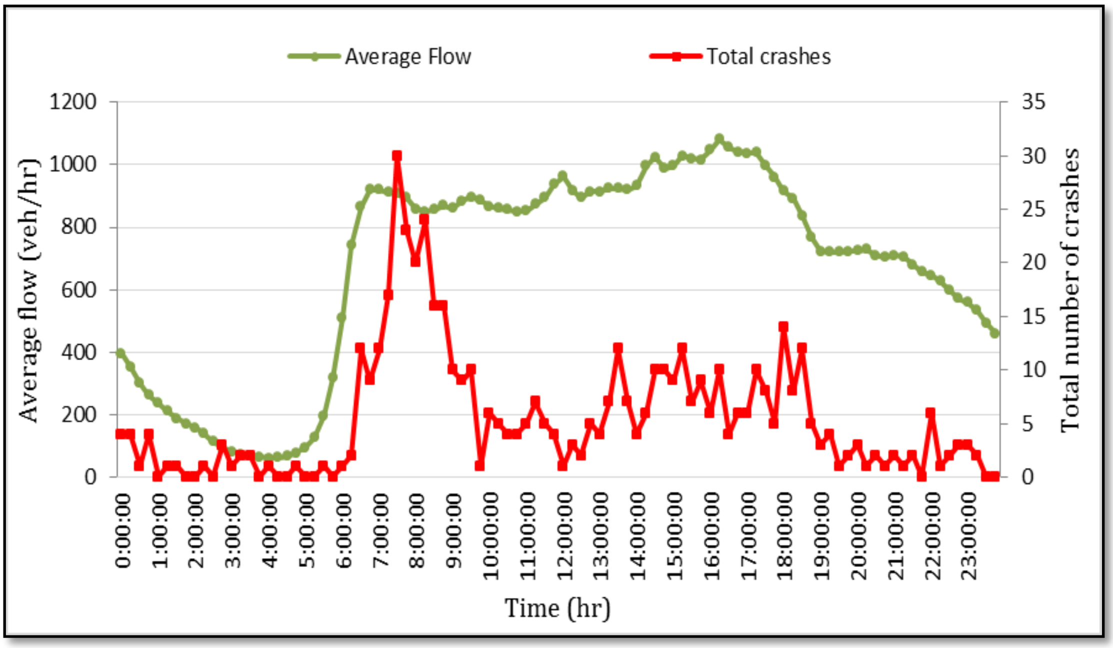
Therefore, the traffic data and crash data were aggregated according to whether the record occurred on weekdays or weekends (Friday, Saturday in Saudi Arabia). A time series of the average network density, speed and flow and the total number of crashes for each 15 min interval in the day are plotted and presented in the following plots (Fig. 5.4). These analyses illustrate how the levels of traffic characteristics are impacted due to change the trips that happen during the entire of day and to explore the general features and trends of crashes based on the chosen research topic. The values on the figures were calculated by taking the 15 min average traffic densities, speeds and volumes for one year and the total number of crashes that occurred in the corresponding time period.



(a) Average Density and Crashes Time Series



(b) Average Speed and Crashes Time Series



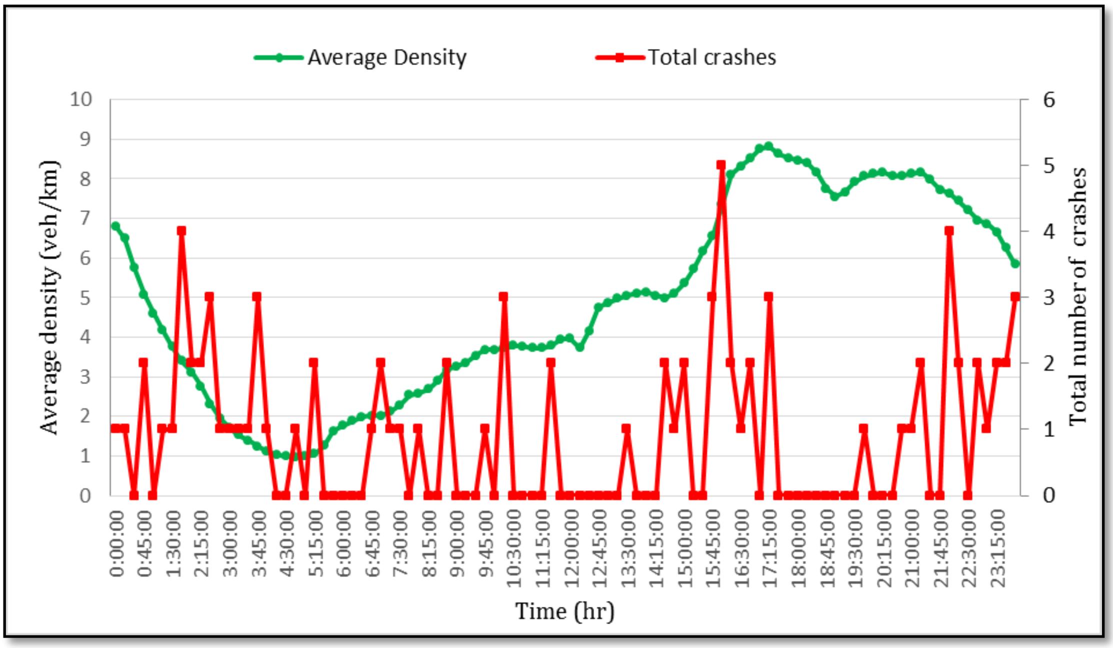
(c) Average Flow and Crashes Time Series

Figure 5.4: Time Series of Average Traffic Network Quantities Along With the Total Number of Crashes during the Study over a Day (Weekday)

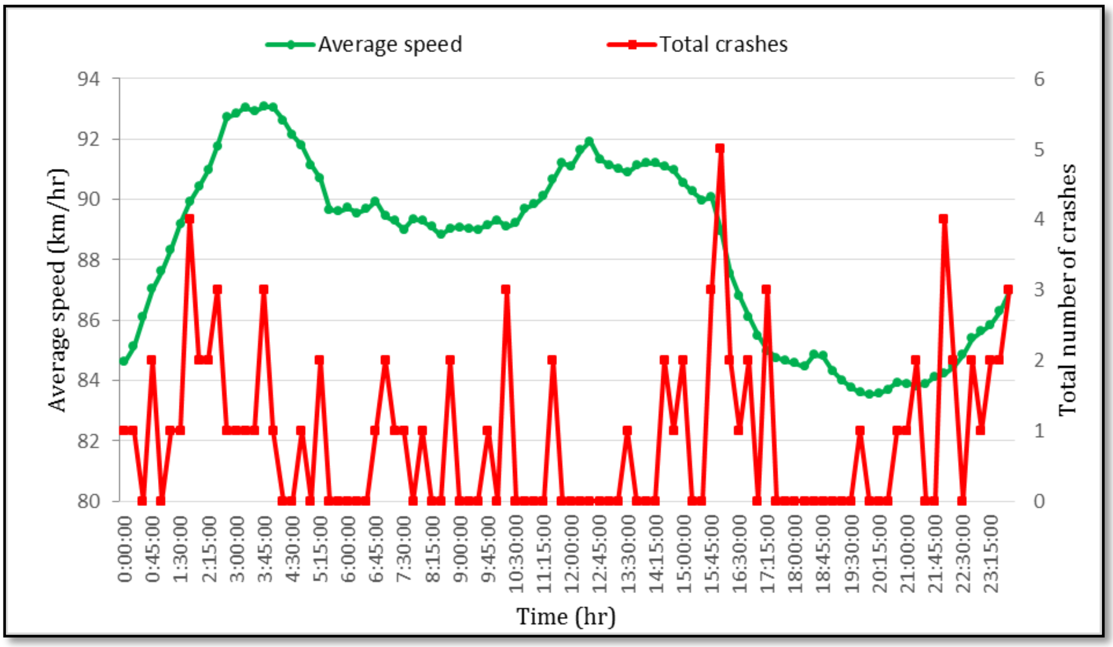
The average traffic network parameters for the weekdays and total number of crashes profiles over the time of the day from the Riyadh city for the year 2015 are presented in Figure 5.4 (a, b and c). Figure 5.4a shows the average traffic density along with the total car crashes time series chart. At the beginning of the day, the total number of crashes is low and suddenly increases with an increase in traffic density between (6:00-8:00 A.M.), the hours of peak morning traffic. Crash frequency subsides with the tail of the morning rush period (from about 8AM to 10 AM) and remains fairly consistent until the PM peak period. When traffic density increases during the evening peak hours between (3:00-7:00 P.M.), the total number of crashes also increases during the same time period. The correlation between the total number of crashes and density is not as strong during the PM peak period; however, this PM peak is characterized by a much less sharp increase in density over time. After that, traffic density decreases and the number of crashes are reduced, indicating there is a positive and very strong correlation between the number of crashes and average traffic density. With regards to the total number of crashes, the results suggest that the increased average traffic density is associated with the increased total number of crash occurrences. Also, the results suggest that, the morning peak period is associated with the highest total number of crashes per hour, while during evening peak traffic, the total number of crashes is less than that during morning peak traffic. This phenomenon occurs because people are not in as much of a hurry as in the morning. It is conceivable that the number of road crashes continue to increase with the increase of traffic density (Brodsky and Hakkert, 1983; Kononov et al., 2012). It is interesting to note from Figure 5.4b that the total number of crashes has an almost negative relationship with the average network speed, where the minimum average traffic speed is associated with the maximum total number of crashes at 7:30 A.M. It is also interesting to note that the average traffic speed in Figure 5.4b displays an inverse pattern relative to the average traffic density in Figure 5.4a, which indicates that high speed occurs when the traffic density is low, and vice versa. This seems reasonable since when a network exhibits a well-defined, concave network MFD. From Figure 5.4c, at the early hour of the day (1:00-5:00 A.M.), the traffic volume is very low, therefore, relatively a few crashes are recorded. The total number of crashes is high during the morning peak time. The average traffic volumes continue to increase after the morning peak time until evening peak time, while the total number of crashes suddenly drops after morning peak hours and is only slightly affected by the change of average traffic volume. This Figure 5.4c does not show a strong correlation between traffic volume and crashes during the day, where a high number of crashes does not occur when traffic volume is high during PM peak period.

Correlation coefficients were computed for each of these traffic operational measures and the total number of crashes. The correlation values were 0.694536, -0.75053 and 0.552162 for average network density, speed and flow, respectively. Overall, these results are consistent with Figure 5.4.

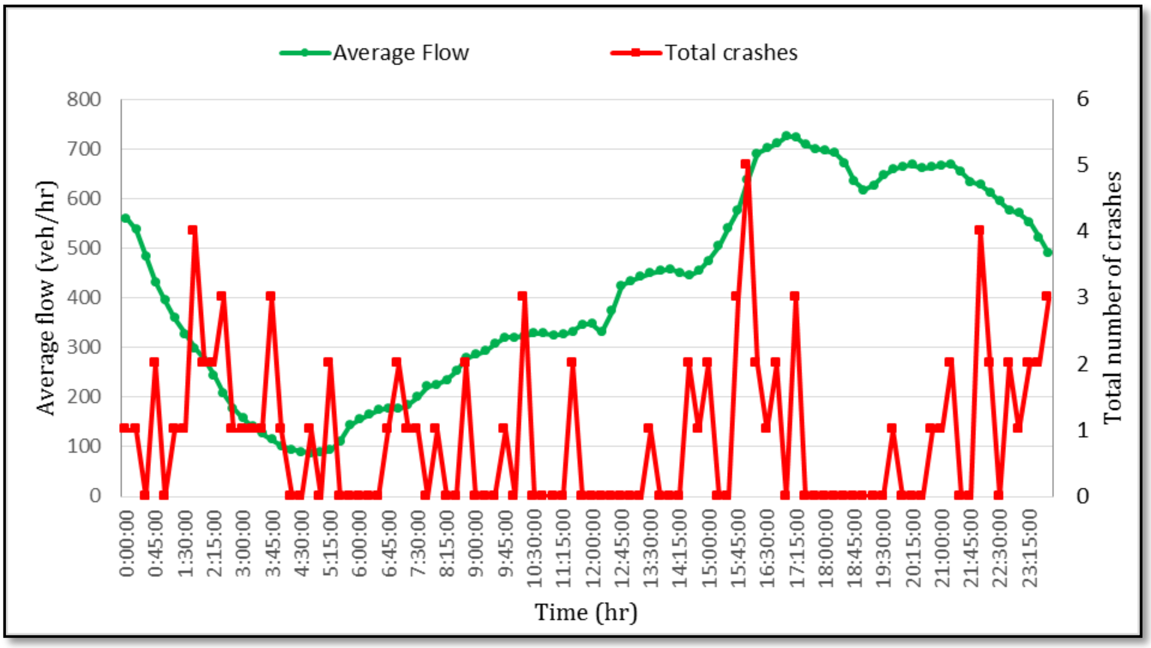
Results from Figures 5.4 visibly confirm further an increase in the number of crashes during morning peak periods in which the network densities at these peak hours are the highest and the average speed at the same corresponding time is lowest according to the data on the Al Urubah and Abu Bakr Al Siddiq roads. Overall, these results are consistent with our MSD hypothesis that less road crashes are associated with a less congested network (free flow condition), meanwhile, the A.M. peak period in general is one of the most congested ones throughout regular weekdays.



(a) Average Density and Crashes Time Series



(b) Average Speed and Crashes Time Series



(c) Average Flow and Crashes Time Series

Figure 5.5: Time Series of Average Traffic Network Quantities Along With the Total Number of Crashes during the Study over a Day (Weekends)

The time series of the weekend's traffic data as well as crash data differ dramatically from the weekday data for the city of Riyadh, as shown in Figure 5.5 (a, b and c). The average traffic density and the average traffic volume, both have the same trend in the time series, Figure 5.5a and 5.5c respectively. As can be noticed, there is only one peak traffic period during the evening time. This higher level of traffic flow during evening and night-time may be because of the higher activities that usually characterise weekend nights. The total number of crashes fluctuates all the time and higher values occur during the evening time. There is mixed evidence for the correlation between the total number of crashes with average traffic density and average traffic volume. This is possibly due to the number of traffic observations and the number of crashes occurring during weekends being relatively small. Therefore the trend of crashes and the effect of traffic parameters on crashes are not clear. Figure 5.5b shows the average traffic speed profile, where the higher speed occurs after midnight and early in the morning. This obviously may be due to the time that the drivers return to their home. The correlation between average traffic speed and the total number of crashes do not have any clear indicators.

Correlation coefficients were computed for each of these traffic operational measures and the total number of crashes. The correlation values were 0.04137, 0.02913 and 0.04686 for average network density, speed and flow, respectively. Overall, these results are consistent with Figure 5.5 and show very low correlation.

From the previous Figures 5.4, 5.5, it can be inferred that the traffic flow patterns varies between weekdays and weekends on the study area. The average traffic speed is almost higher on weekends as compared to weekdays while the average traffic volume and average traffic density are higher on weekdays relative to weekends. It is also clear that peak periods differ between weekends and weekdays. There are two peak periods on working days while one peak period on weekends. Additionally, the crashes that occur during weekdays are higher than those happening on weekends. The weekdays and weekends display very different crash behaviours along with the time over the day, which is definitely influenced by the traffic flow parameters. Therefore, the next part will provide the analysis of the data separately for weekdays and weekends.

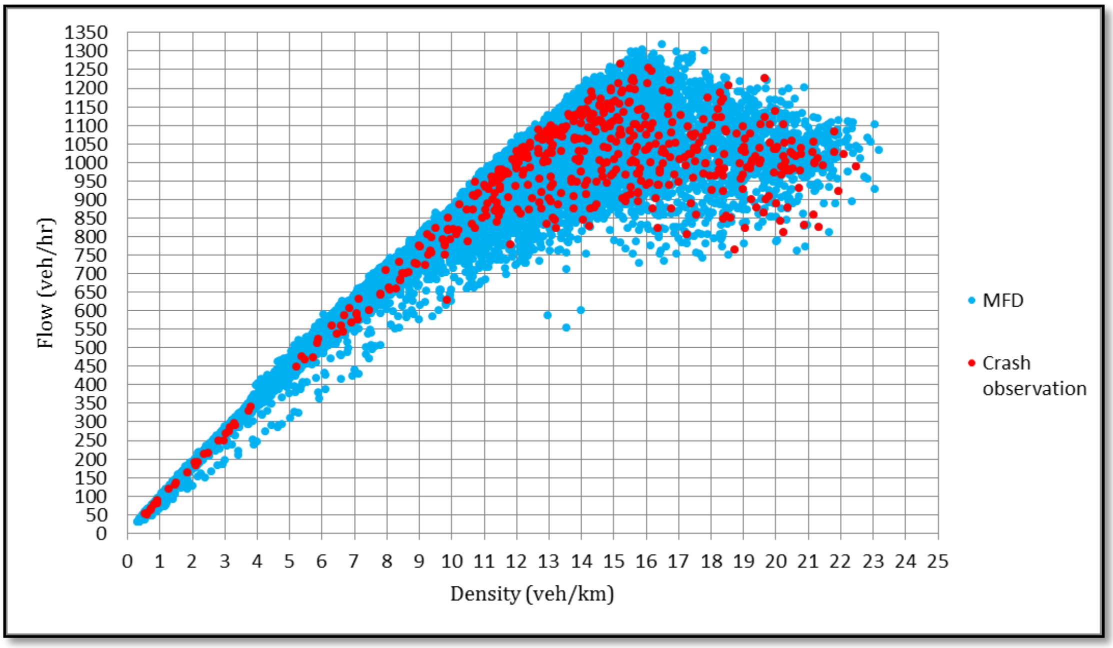
5.7 Analysis and Results

5.7.1 Analysis and Results for Weekdays

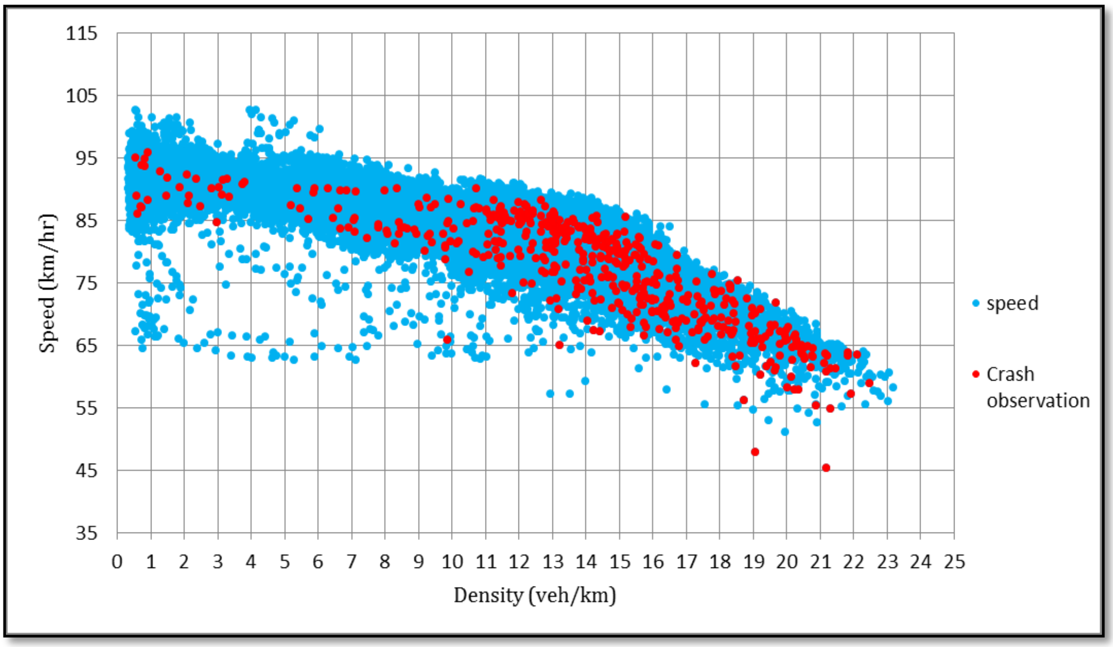
In this section, the results collected for weekday traffic behaviour and crashes are analysed. Various relationships are examined, including the relationship occurring between crashes and macroscopic traffic flow variables and relationships between the probability of crashes and macroscopic traffic flow behaviour.

5.7.1.1 Relationship of Crashes with Macroscopic Traffic Flow Variables

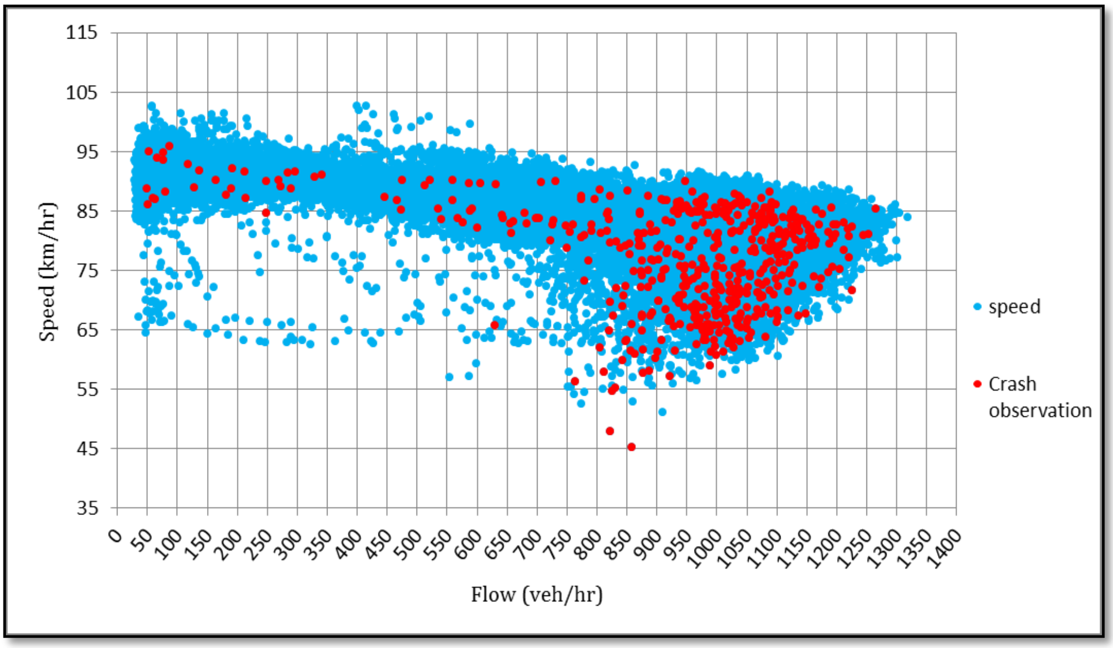
A deep analysis has been conducted on the data to find the most relevant factor affecting road crashes during weekdays. In total, 86% of crashes occur on weekdays. To generate the MFD for the whole study areas, the traffic data were aggregated for 15 min intervals and then the flow, speed and density are averaged. An overview of average traffic characteristics of the network during weekdays is presented in Figure 5.6 (a, b and c).



(a) Flow and Crashes Observed vs. Density



(b) Speed and Crashes Observed vs. Density



(c) Speed and Crashes Observed vs. Flow

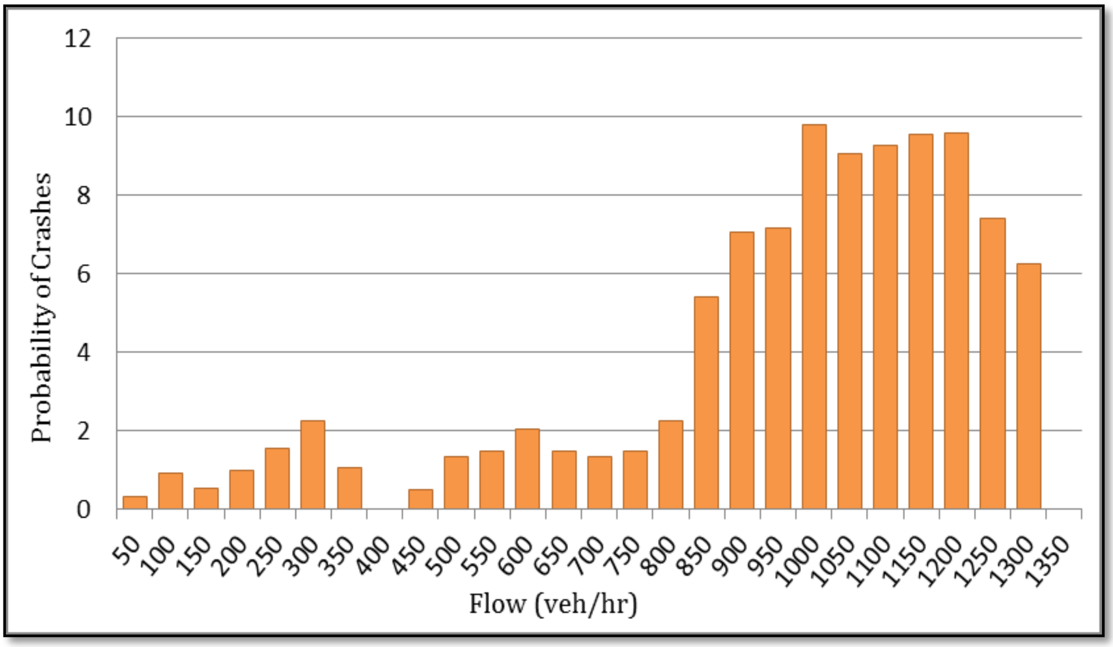
Figure 5.6: Network Characteristics with Crash Observation for Weekdays

Figure 5.6a shows the macroscopic flow–density relationship for the arterial network (i.e. the observed network MFD) with crash observations highlighted in red. Each red point in the plot represents where the crash occurred with respect to the MFD of study area. This figure clearly shows the existence of a well-defined MFD and the peak flow observed for densities in the range of about 14 to 16 veh/km. The Figure shows a Large amounts scatters because traffic conditions are not homogeneous across the arterial network. Furthermore, the presence of queues on the ramps that connect the two arterial segments could influence traffic operations and contribute to this scatter. Figure 5.6a also reveals that a full range of traffic conditions are not observed: the observed maximum density is only about 23 veh/km and thus does not include highly congested or gridlocked states. Only free-flow, saturation and the beginning of congestion regimes are represented in the graph. The data proves that only few crashes occur at free flow condition (on the left side), while the crashes happen to be clustered on saturation and congestion regimes (on the middle and right side), which have higher number of vehicles, is the system. The average network speed–density relationship along with crash observations is shown in Figure 5.6b, where the average network speed is smoothly reduced with an increase in network density. This figure again confirms our hypotheses and findings reported in the simulation results. The occurrences of crashes in free flow conditions (higher average speed) are clearly lower than the saturated and congested conditions (lower average speed). Figure 5.6c represents the average network speed–flow relationship along with crash observations, which also shows three network traffic states. As we identified above, the crashes are clustered at saturation and congestion regimes, while a few crashes occur at the free flow regime.

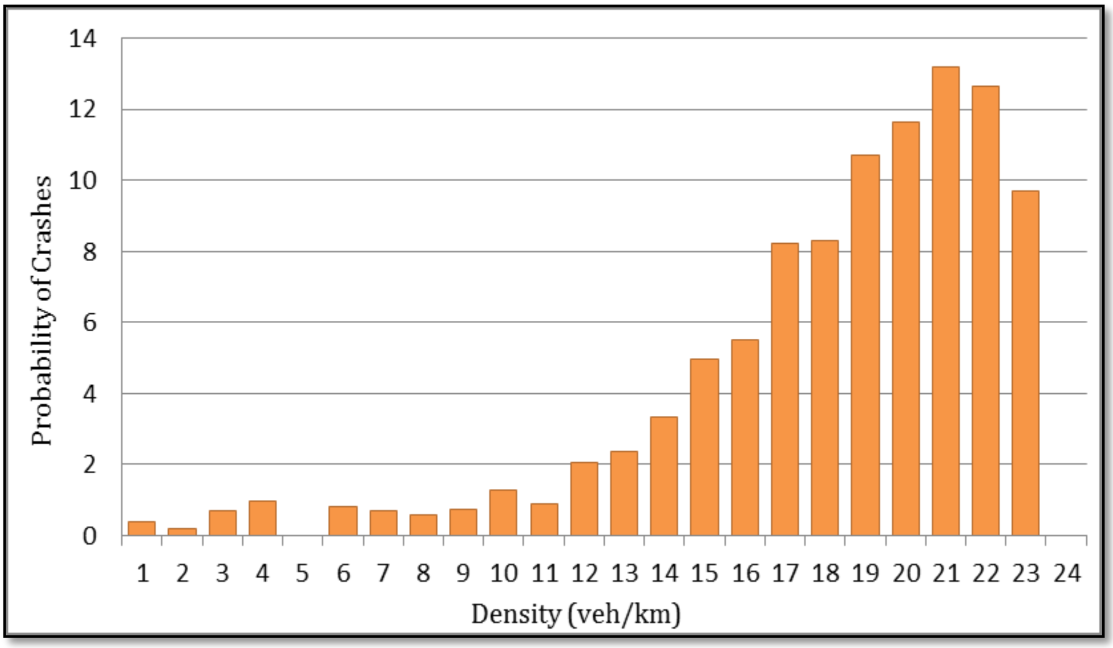
It is clear from a visual inspection of these three figures, i.e., Figure 5.6 (a, b and c) that most of the crashes are clustered in the saturated and congested states, while few crashes are associated with free-flow conditions according to the data from the city of Riyadh. This phenomenon can be described as follows: when the traffic is in a free-flow condition, only a few vehicles are traveling and interacting in the network, therefore, few crashes occur. Then, once the number of vehicles increases, the frequency of crashes also increases. Also, it is good to note that this network, which have been presented here as a case study is not heavily congested, it means that the impact of network congestion state on crash occurrence may not clearly be identified as free flow and as saturated states due to the small number of data observed in the congestion state.

5.7.1.2 Relationship of Probability of Crashes with Traffic Flow Variables

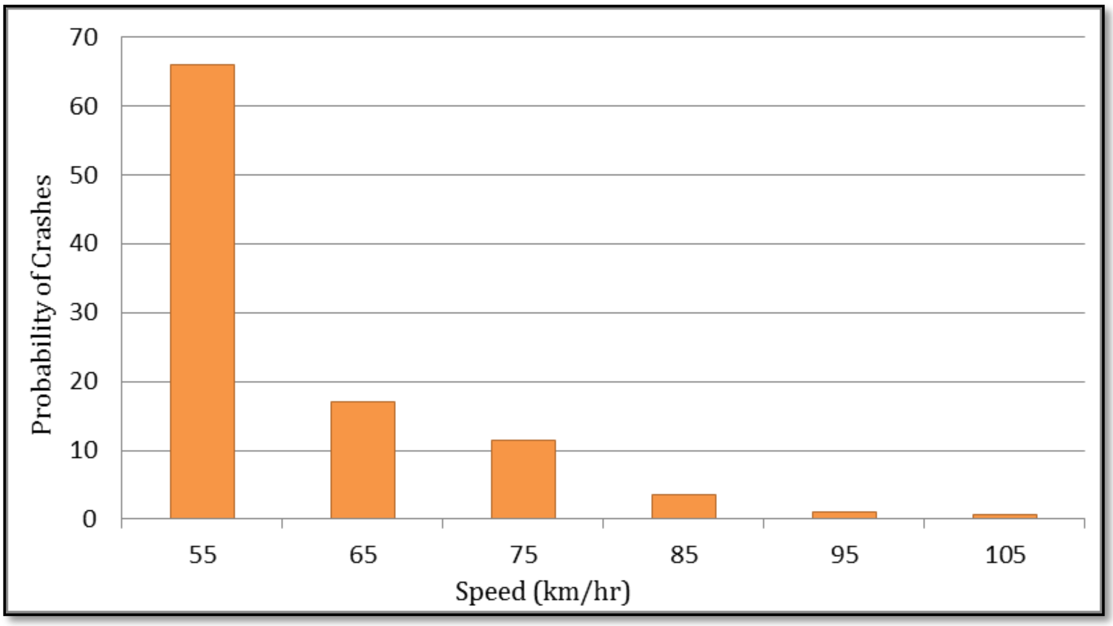
In this section, the probability of crashes for the whole network is presented and analysed to confirm whether or not the MSD relationship exists, and if so, whether a correlation between MFD and MSD is consistent with our hypothesis. The calculation formulae for the probability of crashes have been introduced in Chapter 3, Eq. (3.27). It is calculated as the total number of crashes observed relative to the total traffic observed.



(a) Probability of Crashes vs. Flow



(b) Probability of Crashes vs. Density



(c) Probability of Crashes vs. Speed

Figure 5.7: Relationship Probabilities of Crashes with Traffic Parameters

In Figure 5.7, the probability of crashes is plotted against average traffic parameters. From Figure 5.7a, we can note that approximately more than 81%

of crashes happen in traffic flows between (800-1200 veh/hr), which almost represents saturation and beginning of congestion states. Interestingly, as expected, for lower values of average traffic volume (free flow condition), the probabilities of crashes were found to be low, while the higher values of probabilities of crashes were associated with higher average traffic volumes (above 800 veh/hr).

The probability of crashes is very low for low network average densities (Figure 5.7b). It then starts to increase gradually with the increase in traffic densities. The average number of crashes continues to increase after passing the optimal traffic state at traffic density; this occurs around 16 veh/km mark. Once the traffic density exceeds a certain point, (21 veh/km at congested state), the probability of crashes drops down. This figure also shows a clear trend and this relationship represents the true network MSD that relates the crash risk with traffic network performance. The simulation results of the previous chapter also validated. The trend of probabilities of crashes follows a right skewed bell-shaped curve, where the tip of the curve is found for relatively high network densities and this network MSD relationship reveals that the largest probability of crashes occurs within a density range of 20-21 veh/km. The probability of crashes decreases with an increase in the average network speed as can be seen in Figure 5.7c. There is also strong evidence suggesting that crashes rarely happen at high average speed (free-flow regime). It is important to note that crashes are better represented through the graph of Figure. 5.7b due to the smooth relationship defined between the probability of crashes and average network density.

In order to further examine the relationships, a statistical analysis is also conducted on the observations. Similar to the simulation results, the non-linear regression is used to estimate the model parameters for empirical data. Table 5.3 provides the parameter estimates of the theoretical model proposed in Eq. (3.4) using the data presented in Figure 5.7. As shown, the parameter estimates are positive and in line with expectations. These results validate the theoretical and simulation trends that suggest safety performance peaks at a density greater than the critical density associated with maximum network flow (i.e., when the network operates within a congested state).

Table 5.3: Parameter estimates for theoretical model applied to empirical data

	est.	**std. error**
$\boldsymbol{\alpha}$	3.212821	.2306801
$\boldsymbol{\beta}$	2.723276	.3644055
$\boldsymbol{\gamma}$	4.96E-12	1.50e-11
$\boldsymbol{R^2}$	0.9895	
Sum of sq. errors	8.2250258	

5.7.1.3 The Correlation between Traffic Variables Based on Vehicle Crash Time

The relationships among the traffic flow variables 15 min before a crash, at the time of a crash and 15 minutes after the crash have been studied. Table 5.4 shows that the R^2 values form a good fit linear relation. In Table 5.4, the shaded boxes represent strong correlations between traffic parameters before the crash and at the time of the crash, while these correlations disappear at the time of the crash and 15 minutes after the crash. These results highlight that before a crash occurs, we can predict that a crash will happen based on the level of correlation for a given traffic parameter at time intervals around the crash.

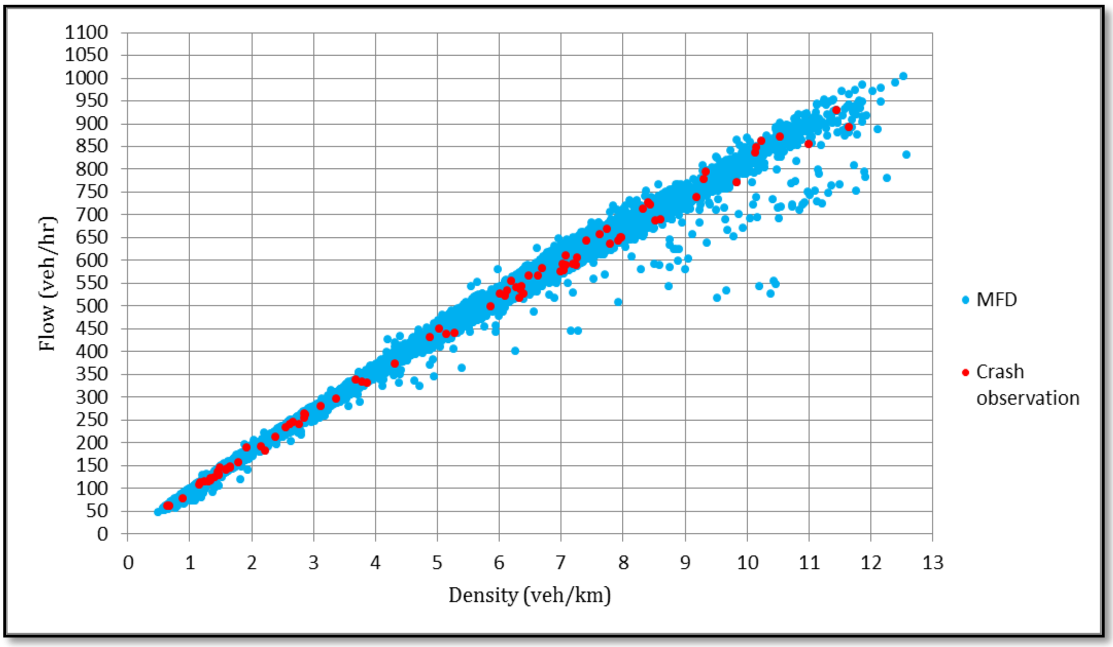
Table 5.4: The Correlation between Traffic Variables at Crashes Time and 15 min before and After Crashes

Weekdays	**Average traffic flow**			**Average traffic density**			**Average traffic speed**		
	Before	At crash	After	Before	At crash	After	Before	At crash	After
Before	1	0.5567	0.0727	1	0.5131	0.0988	1	0.4632	0.1228
At crash	0.5567	1	0.0125	0.5131	1	0.0152	0.4632	1	0.0179
After	0.0727	0.0125	1	0.0988	0.0152	1	0.1228	0.0179	1

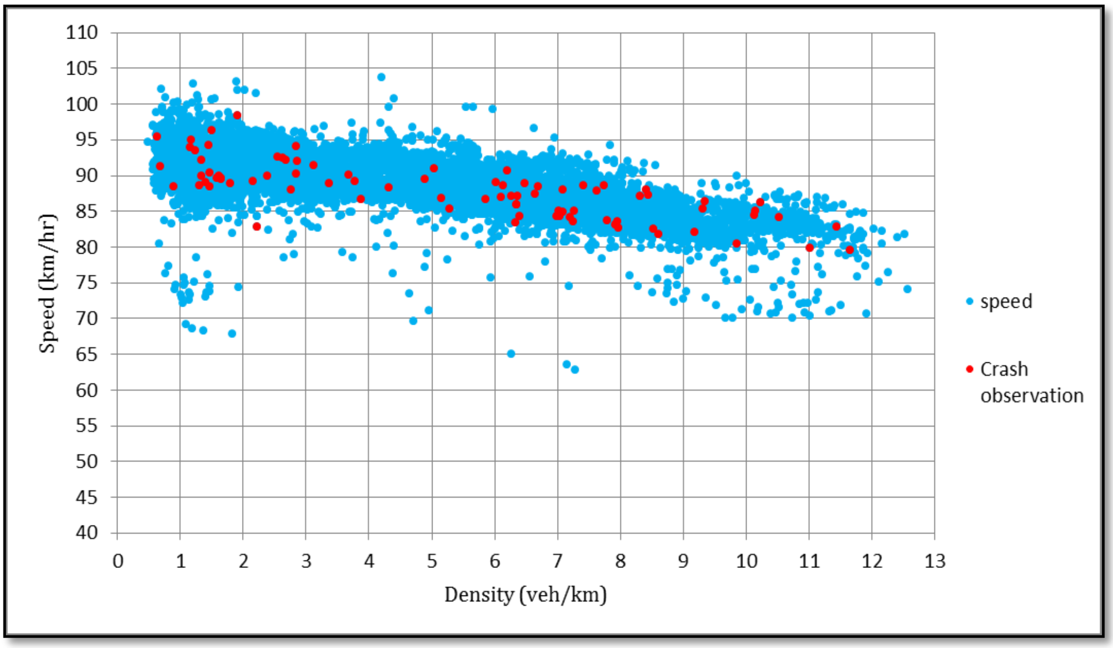
5.7.2 Analysis and Results for Weekends

5.7.2.1 Relationship of Crashes with Macroscopic Traffic Flow Variables

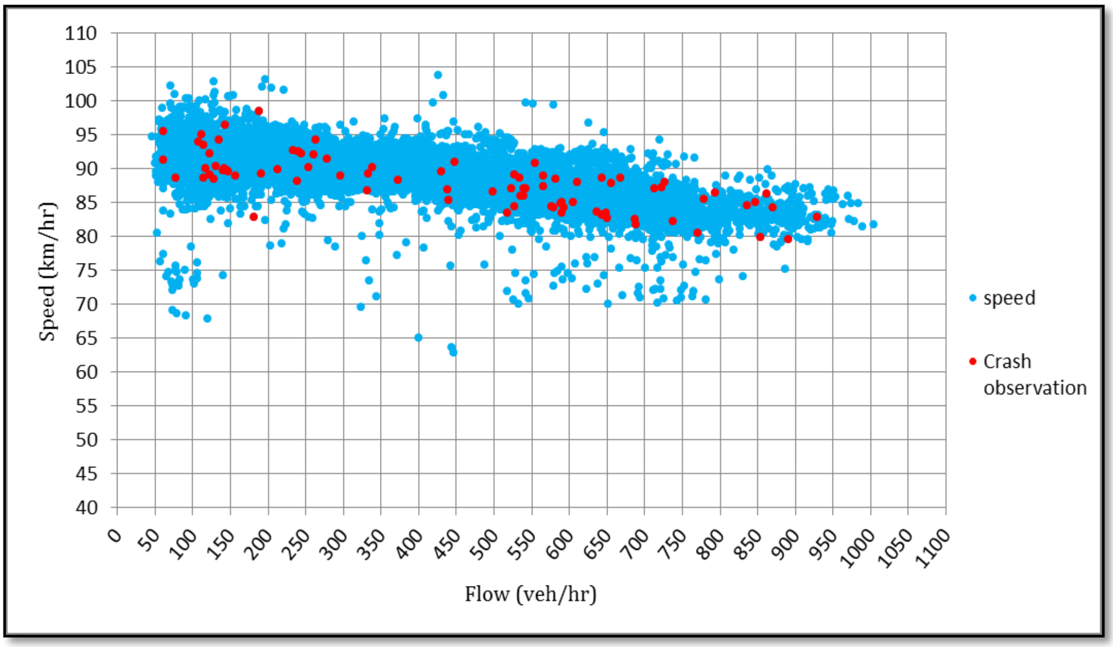
In this section, the MFD for weekends are generated for the whole study area. The correlation between network traffic variables and crashes are shown in Figure 5.8.



(a) Flow and Crashes Observed vs. Density



(b) Speed and Crashes Observed vs. Density



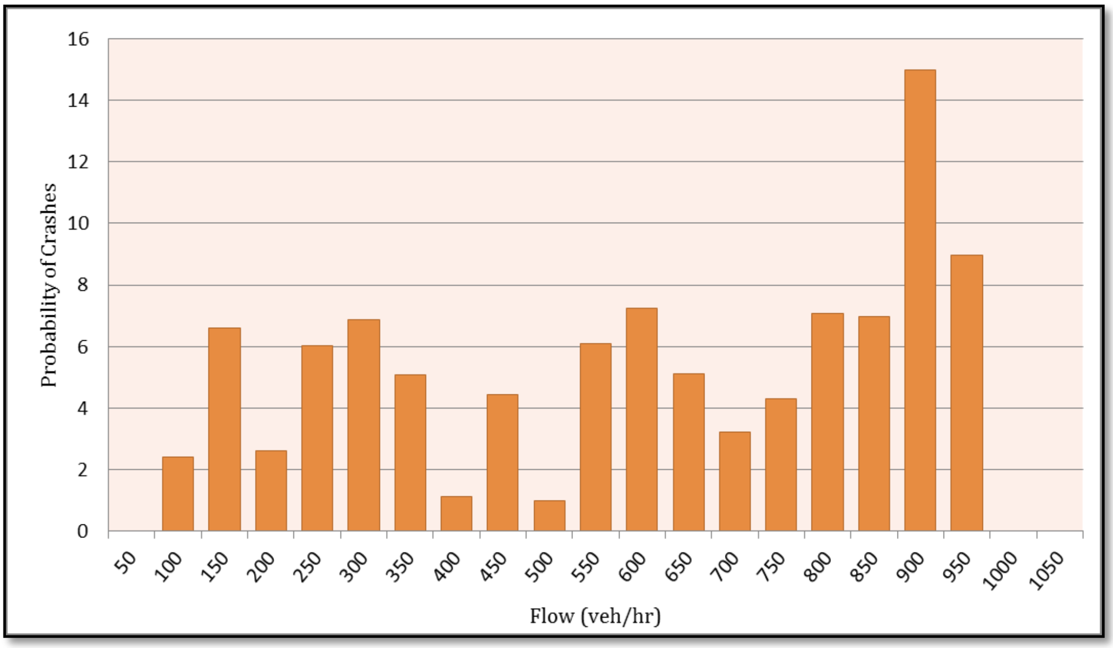
(c) Speed and Crashes Observed vs. Flow

Figure 5.8: Network Characteristics with Crash Observation for Weekends

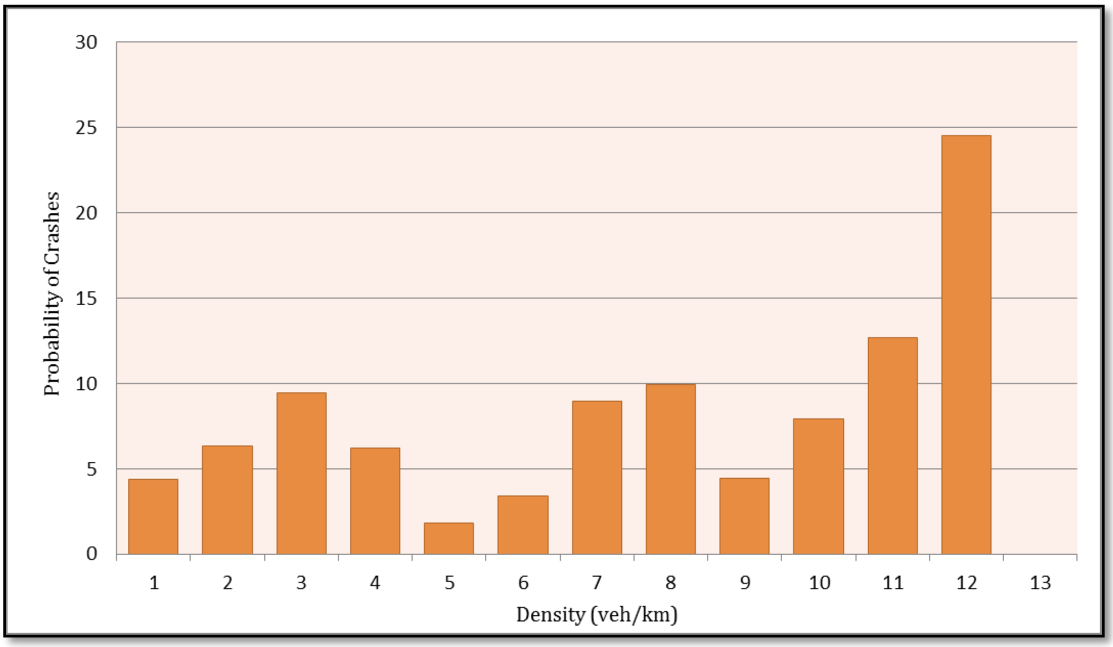
Given the results of Figure 5.8, it is clear that there is a significant difference between weekdays and weekends in network performance where the congestion level on weekends is much lower than that on weekdays. The weekend's traffic flow data have different characteristics than the weekday's data, and only 14% of all car crashes recorded in study area occur on weekends. The MFDs of the network for the weekends show that the network is always in a free-flow condition and at the beginning of saturation regime throughout the whole year as presented in Figure 5.8. Figures 5.8a, 5.8b and 5.8c represent the flow–density, speed–density and speed–flow relationships, respectively for the network during the weekends, with crash observation in highlighted red. It can be seen in these figures that the crashes are almost evenly distributed along the network traffic performance, as the results do not show any clear cluster.

5.7.2.2 Relationship of Probability of Crashes with Traffic Flow Variables

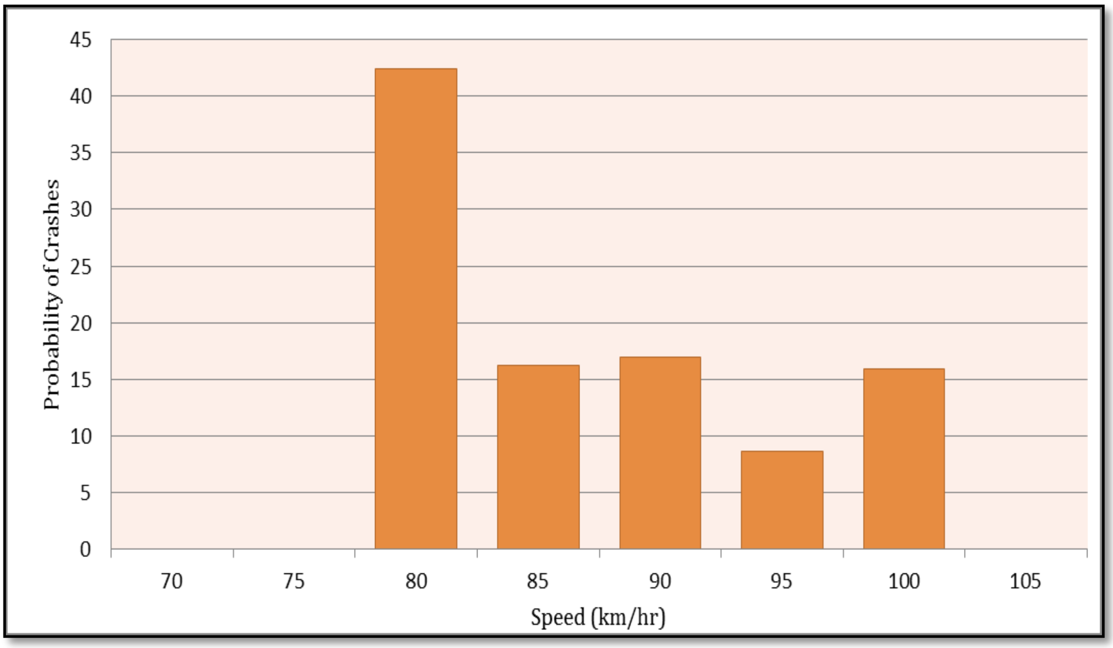
In this section, we will attempt to find if the probability of crashes occurrence for weekends follows the MSD curve with respect to average traffic density or not, in comparison with weekday analysis.



(a) Probability of Crashes vs. Flow



(b) Probability of Crashes vs. Density



(c) Probability of Crashes vs. Speed

Figure 5.9: Relationship Probabilities of Crashes with Traffic Parameters

Figure 5.9 shows the probability of crashes against traffic flow variables during the weekends. The probability of crashes fluctuates with network traffic volume and network traffic density and it is good to note that the higher value of probability of crashes occurs at higher average network volumes and density, as seen in Figures 5.9a and 5.9b respectively. These results indicate that the vehicle crashes tend to increase with the increase of number of vehicles in the network. As shown in Figure 5.9c, 70% of crashes occur at an average network speed between (80-90 km/h), which is not the highest average speed of the network. The possible explanation for these results is the network performance is always on free flow condition, therefore, the full MSD curve does not exist for weekends. Overall, the results do not seem to indicate a clear relationship.

5.7.2.3 The Correlation between Traffic Variables Based on Vehicle Crash Time

For weekdays, Table 5.5 is drawn to examine the correlations between the traffic flow variables, at the 15 min interval around the crash occurrence. The results show R^2 values from a liner regression. It is noted that unlike the results as in Table 5.4, the values of Table 5.5 cannot be used to predict the occurrence of traffic crashes based on the correlations of the traffic variables due to the lack of a definitive relationship.

Table 5.5: The Correlation between Traffic Variables at Crashes Time and 15 min before and After Crashes

Weekends	**Average traffic flow**			**Average traffic density**			**Average traffic speed**		
	Before	At crash	After	Before	At crash	After	Before	At crash	After
Before	1	0.5456	0.543	1	0.5456	0.5268	1	0.5617	0.5386
At crash	0.5456	1	0.5739	0.5456	1	0.5673	0.5617	1	0.5628
After	0.543	0.5739	1	0.5268	0.5673	1	0.5386	0.5628	1

5.8 Summary and Conclusions

This chapter of the thesis has presented the investigations from the field data to be employed in the MFD analysis. A close examination of the relationship between MFD and road safety on urban roads was therefore conducted by utilising high-resolution traffic and crash data. In particular, the field data based on the Al Urubah and Abu Bakr Al Siddiq roads in the centre of Riyadh, the capital and largest city of the Kingdom of Saudi Arabia (KSA), were analysed. This is the first time that such an approach has been attempted. The novelty of the proposed approach lies in terms of crash analysis.

Initially, we conducted an exploratory analysis in trends to investigate how the number of crashes varies with the change of traffic parameters level over the time of the day. The results were found to be consistent with our previous assumptions, which are summarised as:

- Crashes tend to increase with an increase in the traffic density,
- Crashes tend to decrease with an increase in the traffic speed.

The crashes and probability of crashes were linked with MFDs of the network to explore the correlation between them. The findings from weekday data confirm our hypotheses, which are summarised as:

- probability of crashes follows parabolic shaped with average network densities (network MSD),
- At free flow condition of the network, the probability of crashes are low as compared with saturated and congestion condition,
- The tip of the MSD curves is found to be in congestion state after the optimal traffic state of MFD.

Finally, the analysis of the results revealed the existence of an MSD relationship on urban networks. The major conclusion of this chapter is that the combination of MFD and MSD model can be utilised to improve the network safety and traffic performance simultaneously. It is interesting to know that the MSD gives a full parabolic shape in heavily congested networks.

Chapter 6: Conclusions and Recommendations

This chapter summarise the main findings of the research work along with some practical limitations followed by the future research directions. Furthermore, the recommendations for planners, engineers, and policy maker are presented.

6.1 Concluding Remarks

In this thesis, the correlation between the MFD and road safety of urban streets has been explored through the proposition of a novel MSD model and framework. This is achieved by a rigorous investigation of the existence of a relationship between common traffic parameters and safety of the underlying network. The major contribution of the proposed work is the formulation of an innovative MSD model that estimates and evaluates road safety performance at the network level. The model is validated and the findings of the research work are justified with two simulation experiments. It is further validated and assessed through empirical data collected from real case studies. It is believed that the proposed MSD is very effective; which will help traffic engineers and planners to evaluate road safety while developing efficient traffic plans.

Chapter-wise contributions of the thesis are summarised as follows:

In **Chapter 1,** the background and motivation of the proposed research work were presented. In particular, the need for integrating road safety measures with the common MFD, which was relied on in traffic management and control, was elaborated. Also, some potential factors influencing the road safety were briefly discussed.

Chapter 2 provided an up to date literature review in the relevant field. This chapter was divided into three sub sections. The first section included a comprehensive literature review on 'the effect of traffic characteristics on road accidents'. A summary of the state-of-the-art literature that incorporates safety measures in traffic planning is also presented. The second section was related to 'the general concept of MFD'. The major principles of MFD were first presented followed by an overview of relevant literature. This encompassed both a historical overview of common literature studies along with some of the more recent advances, which were thoroughly expanded on. The third section summarised 'the conflict analysis techniques' and presented an overview of the most frequently used Surrogate Safety Measures in the literature. The major goal of this chapter was to portray the value of the proposed research in relation to previous studies, which enabled us to identify the gap for the proposed research.

Chapter 3 described the development of an unconventional new proposed model to evaluate the traffic safety at large-scale networks. The concept was dubbed "Macroscopic Safety Diagram" (MSD), in relation to the original Macroscopic Fundamental Diagram (MFD). The concept of the MSD is based on the space-time area available for a manoeuver on a links of the network, which is essentially the product of time and space headways. The model suggested that the probability of crashes follows a parabolic-shaped curve when assessed against average density of the network, where the head of the curve was found to occur at a congested regime (higher density).

Chapter 4 demonstrated the first step to explore the relationship between traffic safety and MFD. In addition, the existence of an MSD model, as described in Chapter 3, in an urban setting was achieved through simulation of realistic networks. In particular, the results of two main simulations were reported in this chapter. The first experiment was a 10 x 10 grid network, where the analysis of the results revealed the existence of the MSD model in the network level and that the maximum value of the curve existed in a congested condition. Also, it was observed that at the free flow condition (higher average speeds), the probability of crashes was lowest. The second experiment was conducted on a network that resembled the city of Bellevue/Redmond, Washington, USA network. This network was comprised of arterial streets and a freeway. Only the arterial urban streets were used for the purpose of the analysis of the urban network. The results of exploring the correlation between MFD and road crashes were found to have similar findings as reported for the grid network experiment. Furthermore, the resulting graphs confirm the existence of the MSD relationship in the examined network.

Chapter 5 examined the datasets related to field data analysis. The study area was chosen as Al Urubah and Abu Bakr Al Siddiq roads, which are considered to be major arterial roads in Riyadh, the capital and largest city of the Kingdom of Saudi Arabia (KSA). The main objective of this chapter was to examine the relationship between MFD and road safety on urban roads and also to validate the existence of MSD on real-world data. The initial step was an exploratory analysis, where the trends of crashes and traffic parameters were investigated based on weekdays and weekend travel trends. We found that for the weekday results, the crashes tend to increase with an increase in traffic density. Also, the crashes tend to decrease with an increase in the traffic speed. These results were found to be consistent with our previous findings, while the weekend results did not show strong correlation. An explanation for this is that the results of the limited weekend observation data are a very few and the network not being congested during the weekends. Overall, the analysis of the results revealed the existence of an MSD curve on real-world urban networks. At free flow condition of the network (higher average speeds), the probability of crashes were low when compared with saturated and congestion condition. The maximum value on the MSD curve was found to be in congestion state, occurring at a later stage as compared to the optimal traffic state of MFD.

In conclusion, the comparison of simulation results with real-world data results were in a very close agreement and the MSD curve followed the same trend. The two simulation experiments and the field data in this thesis confirmed the validity of the MSD hypothesis, which states that the probability crashes have parabolic-shaped relationship with average network densities. This relationship is what was referred to as the MSD in this thesis. The results of this thesis revealed that the MSD is a power tool for evaluating the traffic safety dynamically for large scale urban networks. Based on integrating the MFD and MSD, the quality of traffic safety and traffic flow can be enhanced by better understanding the relationship between them.

Obviously, this research work has some practical limitations. First of all, the field crash data that have been used in this thesis were not classified based on accident severity. The MSD curve may vary based on different severity levels of crashes in real-world data. Secondly, the empirical findings are somewhat limited by the lack of available traffic data in highly congested or gridlocked traffic states. Further work is needed to examine that empirical MSD relationships also hold in these highly congested situations. This is especially important since these highly congested network states are typically characterized by inhomogeneous congestion patterns that could further influence expected safety performance. The relationship between safety performance and congestion inhomogeneity should also be further studied, especially since network MFDs have been shown to be sensitive to congestion distributions within the network. Fortunately, most networks do not operate within these highly congested states for long, as evidenced by the lack of empirical MFDs with very large average densities. Thirdly, the field traffic data that had been studied in this thesis were based on 15-minute time intervals (which were relatively big). This was due to the fact that traffic data with a lower time interval were not available. Therefore, the impacts of the interval in data recording on the results of the MSD relationship were thus not examined. At last but not the least, this thesis has managed successfully to fulfil the gap of studying the relationship between MFD and traffic safety.

6.2 Further Research Directions and Recommendations

Since this thesis has revealed the first investigation of a novel approach that links the MFD with road safety, a number of avenues exist where further research can be undertaken. We propose the following future directions to enhance the proposed research work:

- The Effect of Changing Different Network Characteristics: The effect of changing different network characteristics on macroscopic safety diagram needs to be conducted. For instance, traffic signal operation and offset time between adjacent traffic signals, number of lanes, heterogeneous link capacities and density variation in the network, are some examples of relevant parameters that can be further investigated. These impacts may lead to a change in the MFD of the network, i.e., the optimal state may go upward or downward based on the alteration. As a result, the MSD curve may differ respectively.
- The Effect of Network Size: It is important to concentrate on the effect of network size on MSD. This also encompasses the effect of network partitioning techniques and how the MFDs of sub-networks are associated with the MSD.
- The Effect of Different Traffic Management Strategies: Further experimental investigations are required to estimate the effect of different traffic management strategies. For example, congestion pricing, routing strategies, network boundary control and speed limits can be studied in the context of the MSD. The effects of these different traffic

management strategies can be examined by evaluating the network safety performances before and after their application.

- More Real-World Traffic and Accident Data: The preliminary results presented in this thesis are encouraging and more real-world traffic and accident data for urban and freeway networks with different observation time intervals as well as with different crash severity levels, such as fatalities, severe accidents, low severe accidents and property damages, could contribute to strengthen the presented hypothesis and make it more generalised.
- Strategic Policies: Finally, since the maximum number of crashes was found to take place in congested conditions, some policy implications are proposed that are aimed to optimise the traffic flow and improve the traffic safety for urban network at the same time; which includes applying congestion pricing strategies, sub-network control and route choice strategies. These strategies are widely used to reduce the network congestion; therefore, further investigation is vital to examine the efficiency of these proposed policies in improving network road safety.

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Appendix A

A.1 MATLAB Code for Estimate the MFD for Grid Network

```
%% Import data from text file.

%    D:\Gridnetwork10_001.fzp

%% Initialize variables.

filename = 'D:\Gridnetwork10_001.fzp';

delimiter = ' ';

endRow = inf;

%% Format string for each line of text:

%   column: double (%f)

formatSpec = '%f%f%f%f%f%f%[^\n\r]';

%% Open the text file.

fileID = fopen(filename,'r');

%% Read columns of data according to format string.

dataArray = textscan(fileID, formatSpec, endRow, 'Delimiter', delimiter, 'MultipleDelimsAsOne',
true, 'ReturnOnError', false);

%% Close the text file.

fclose(fileID);

%% Create output variable

Gridnetwork10001 = [dataArray{1:end-1}];

%% Clear temporary variables

clearvars filename delimiter endRow formatSpec fileID dataArray ans;

R=Gridnetwork10001;

%% MFD calculation

% t     : Simulation Time [s]

% DistX : Total Distance Traveled in the Network [m]

% VehNr : Number of the Vehicle
```

```
% Link  : Number of the Active Link
% Data must be similar to below:
%  t;    DistX;     VehNr;  Link;
% Indexing
% First ; Data must be sorted based on time.
[y,I]=sort(R(:,1));
Data_sort=R(I,:);
Data_sort(:,4:5)=[];
ALL=[];
Data_all=Data_sort;
for j=300:300:7200
bb=find(Data_all(:,1)<=j);
V=size(bb);
Data_T=Data_all(1:size(bb),:);
ALL_M=[];
for k=min(Data_T(:,3)):max(Data_T(:,3))
    M=[0 0;
       0 0];
    DD_M=[];
      n=find(Data_T(:,3)==k);
M=   Data_T(n,:) ;
DD_M=M;
      if DD_M~=0;
    ALL_DD=[min(DD_M(:,1)) min(DD_M(:,2)) max(DD_M(:,1)) max(DD_M(:,2))
(max(DD_M(:,1))-min(DD_M(:,1))) (max(DD_M(:,2))-min(DD_M(:,2))) k j ];
  ALL_M=[ALL_M; ALL_DD ];
      end
   end
  ALL =[ALL ; ALL_M];
  Data_all=Data_all(size(bb)+1:end,:);
```

```
end
```

A.2 MATLAB Code for Estimate the MFD for the City Of Bellevue/Redmond, Washington, USA

```
%% Import data from text file.
%    D:\ DynAssign_Redmond.US.fzp
%% Initialize variables.
filename = 'D:\ DynAssign_Redmond.US.fzp';
delimiter = ' ';
endRow = inf;
%% Format string for each line of text:
%   column: double (%f)
formatSpec = '%f%f%f%f%f%[^\n\r]';
%% Open the text file.
fileID = fopen(filename,'r');
%% Read columns of data according to format string.
dataArray = textscan(fileID, formatSpec, endRow, 'Delimiter', delimiter, 'MultipleDelimsAsOne',
true, 'ReturnOnError', false);
%% Close the text file.
fclose(fileID);
%% Create output variable
Redmond = [dataArray{1:end-1}];
%% Clear temporary variables
clearvars filename delimiter endRow formatSpec fileID dataArray ans;
k= Redmond;
%% split the network in two type (freeway and arterial)
m=ismember (k(:,4),FLN); % FLN= freeway link number (:,4)= link number colum
bb=[k m];      % to insert m after i405dat
FREE=find(bb(:,5)==1);  % which row number (:,5)=1 to know all Freeway road line
```

```
ART=find(bb(:,5)==0); % which row number (:,5)=1 to know all arterial road line
FREEWAY=bb(FREE,:); % freeway row with all colume
ARTERIALROAD=bb(ART,:); % arterial row with all colume
ARTERIALROAD(:,4:5)=[];
R= ARTERIALROAD;
%% MFD calculation
% t     : Simulation Time [s]
% DistX : Total Distance Traveled in the Network [m]
% VehNr : Number of the Vehicle
% Link  : Number of the Active Link
% Data must be similar to below:
%  t;    DistX;     VehNr;  Link;
% Indexing
% First ; Data must be sorted based on time.
[y,I]=sort(R(:,1));
Data_sort=R(I,:);
Data_sort(:,4:5)=[];
ALL=[];
Data_all=Data_sort;
for j=300:300:10800
bb=find(Data_all(:,1)<=j);%
V=size(bb);
Data_T=Data_all(1:size(bb),:);
ALL_M=[];
for k=min(Data_T(:,3)):max(Data_T(:,3))
    M=[0 0;
       0 0];
    DD_M=[];
      n=find( Data_T(:,3)==k);
```

```
M=   Data_T(n,:) ;

DD_M=M;

       if DD_M~=0;

     ALL_DD=[min(DD_M(:,1)) min(DD_M(:,2)) max(DD_M(:,1)) max(DD_M(:,2))
(max(DD_M(:,1))-min(DD_M(:,1))) (max(DD_M(:,2))-min(DD_M(:,2))) k j ];

   ALL_M=[ALL_M; ALL_DD ];

       end

    end

  ALL =[ALL ; ALL_M];

  Data_all=Data_all(size(bb)+1:end,:);

end
```

A.3 MATLAB Code For Aggregate The Accident Based On Road Network Type And TTC Thresholds For Five Min Interval.

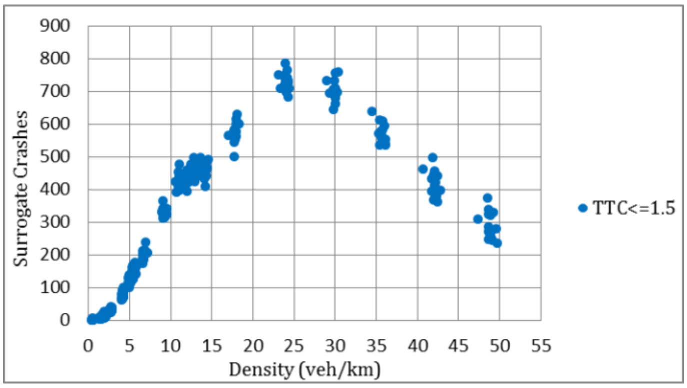
```
%% To creating Accident groups based on type of the network road.

% split the accidents into two groups based on network type (freeway and arterial)

L= accidents;

m=ismember (L(:,[4,5]),FLN);

% FLN= freeway link number, (:,4)= first link number column, (:,5)= second link number column

bb=[L m];

bb(:,8)=bb(:,6)|bb(:,7); % art==0

bb(:,9)=bb(:,6)&bb(:,7); % free=1

FREE=find(bb(:,9)==1);  %Make all Freeway road = 1

ART=find(bb(:,8)==0); %Make all arterial road = 0

FREEWAY=bb(FREE,:);

ARTERIALROAD=bb(ART,:);

FREEWAYACC=FREEWAY(:,[1:5]);

ARTERIALACC=ARTERIALROAD(:,[1:5]);
```

```
ARTERIALACC(:,4:5)=[];
%% Number of accident for each type of networks (Indexing)
%sorting data first based on time
[y,I]=sort(ARTERIALACC(:,1));
Data_sort=ARTERIALACC(I,:);
Data_all=Data_sort;
z=300;TTC_all=[];PET_all=[];
for j=300:300:10800
bb=find(j-300<Data_all(:,1)&Data_all(:,1)<=j);%
Data_T=Data_all(bb,:);
    n1=find(Data_T(:,2)==0);             NoTTC0=size(n1,1);
    n2=find(Data_T(:,2)<=0.5);            NoTTC05=size(n2,1);
    n3=find(Data_T(:,2)<=1);             NoTTC1=size(n3,1);
    n4=find(Data_T(:,2)<=1.5);            NoTTC15=size(n4,1);
    TTC=[j NoTTC0 NoTTC05 NoTTC1 NoTTC15];
     TTC_all=[TTC_all;TTC];
    m1=find(Data_T(:,3)==0);             NoPET0=size(m1,1);
    m2=find(Data_T(:,3)<=1);             NoPET1=size(m2,1);
    m3=find(Data_T(:,3)<=2);             NoPET2=size(m3,1);
    m4=find(Data_T(:,3)<=3);             NoPET3=size(m4,1);
    m5=find(Data_T(:,3)<=4);             NoPET4=size(m5,1);
    m6=find(Data_T(:,3)<=5);             NoPET5=size(m6,1);
    PET=[j NoPET0  NoPET1 NoPET2 NoPET3 NoPET4  NoPET5];
    PET_all=[PET_all;PET];
end
ACCFINAL=[TTC_all PET_all];
```

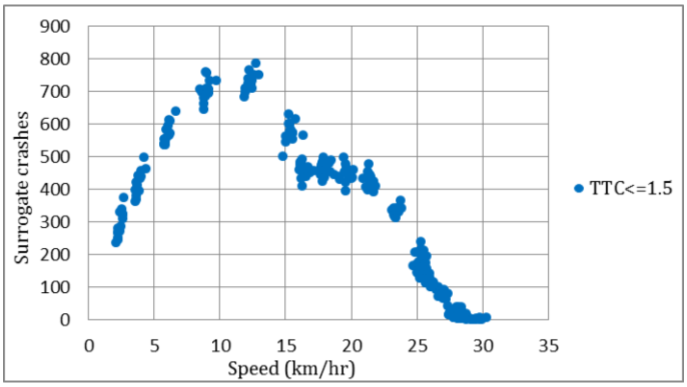
Appendix B

Experiment I: Grid Network Results

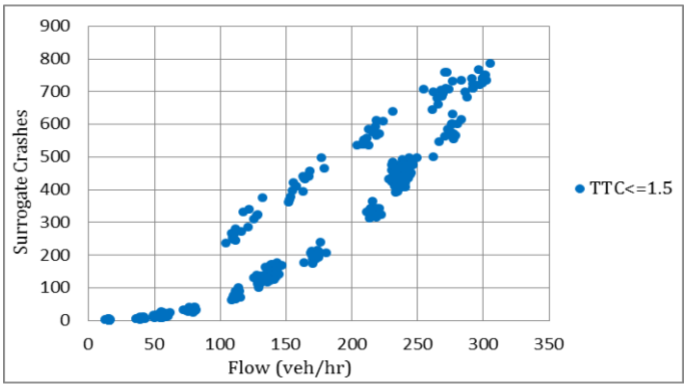
B.1 Relationship of Surrogate Crashes with Traffic Flow Variables



(a) Surrogate Crashes vs. Density



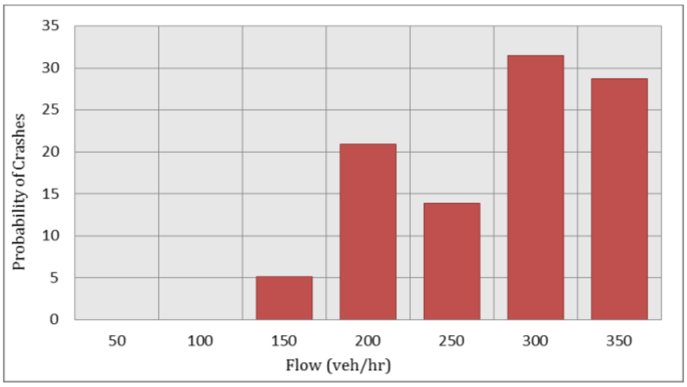
(b) Surrogate Crashes vs. Speed



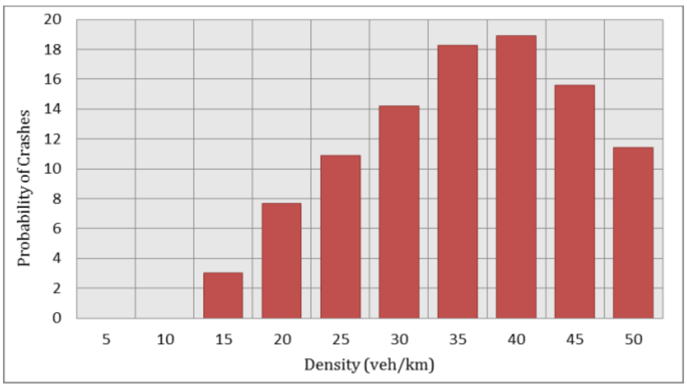
(c) Surrogate Crashes vs. Flow

Figure B.1.1: Surrogate Crashes vs. Traffic Flow Variables with 1.5 TTC Thresholds

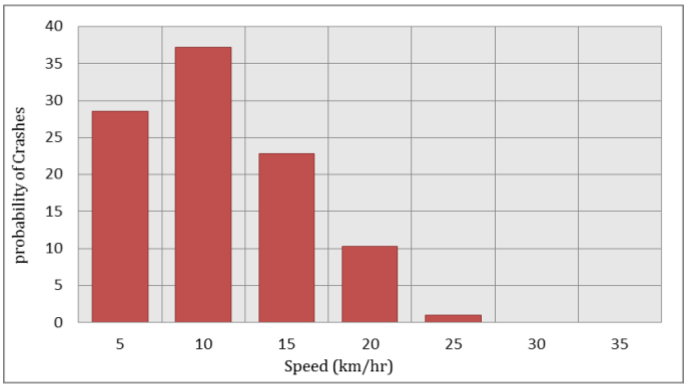
B.2 Relationship of Probability of Crashes with Traffic Flow Variables



(a) Probability of Crashes vs. Flow

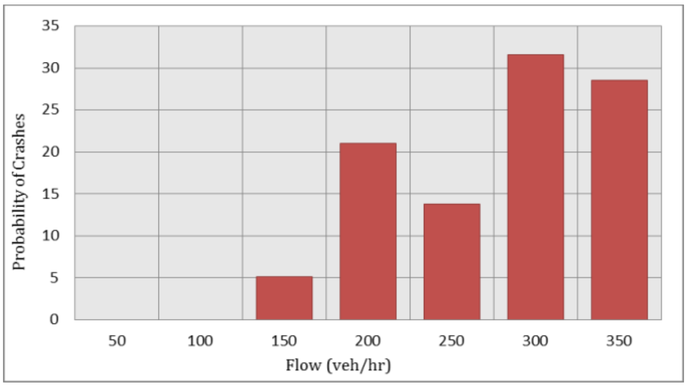


(b) Probability of Crashes vs. Density

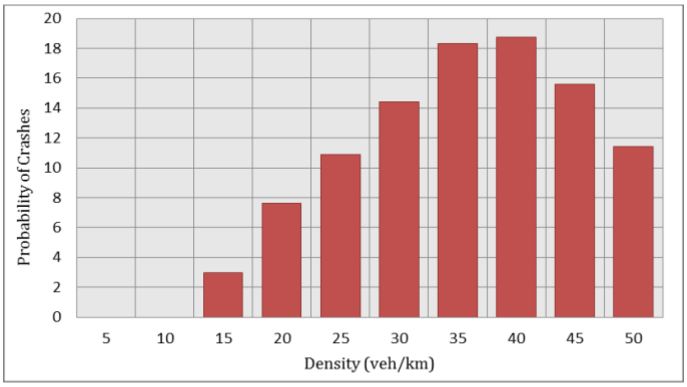


(c) Probability of Crashes vs. Speed

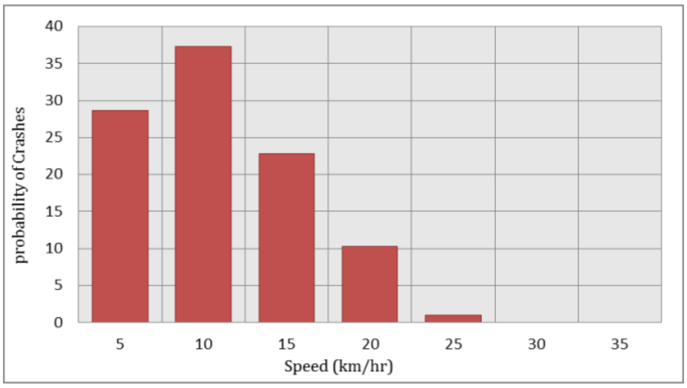
Figure B.2.1 Relationship Probabilities of Crashes and the Traffic Parameters for TTC=0



(a) Probability of Crashes vs. Flow

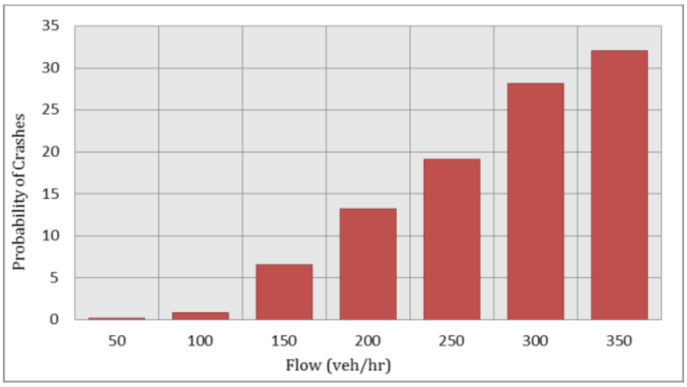


(b) Probability of Crashes vs. Density

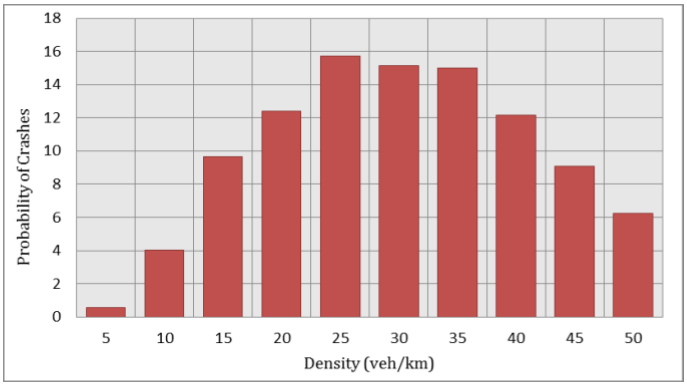


(c) Probability of Crashes vs. Speed

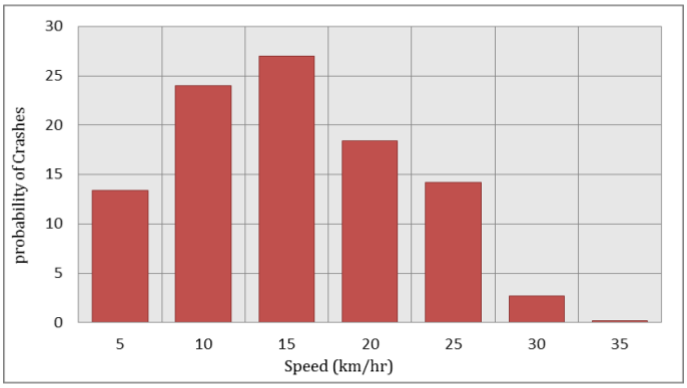
Figure B.2.1 Relationship Probabilities of Crashes and the Traffic Parameters for TTC<=0.5



(a) Probability of Crashes vs. Flow



(b) Probability of Crashes vs. Density



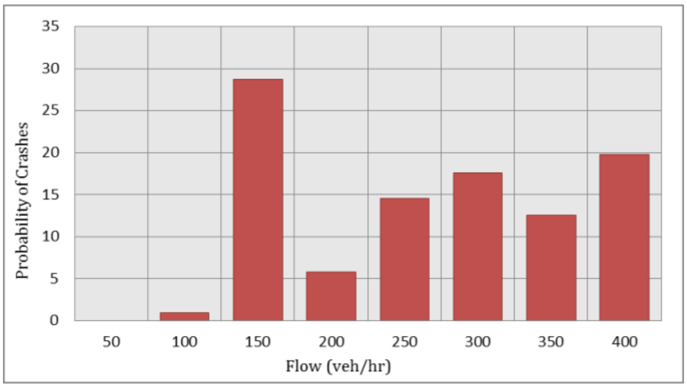
(c) Probability of Crashes vs. Speed

Figure B.2.1 Relationship Probabilities of Crashes and the Traffic Parameters for TTC<=1.5

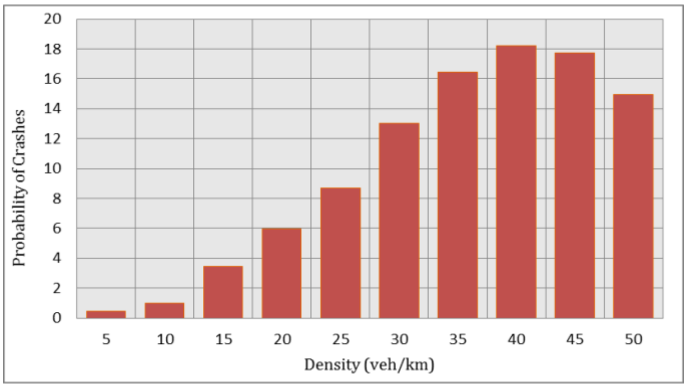
Appendix C

Experiment II: Bellevue/Redmond, Washington, USA Network Results

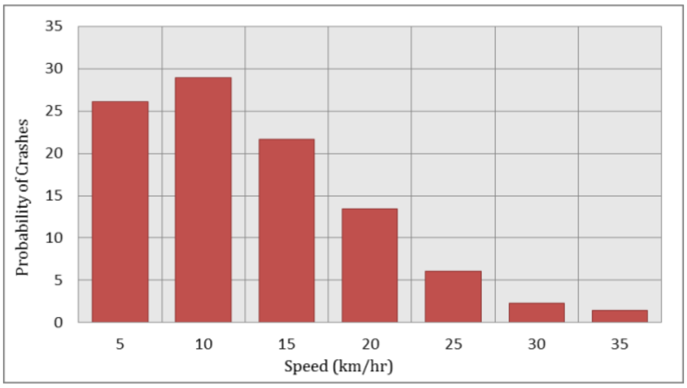
C.1 Relationship of Probability of Crashes with Traffic Flow Variables



(a) Probability of Crashes vs. Flow

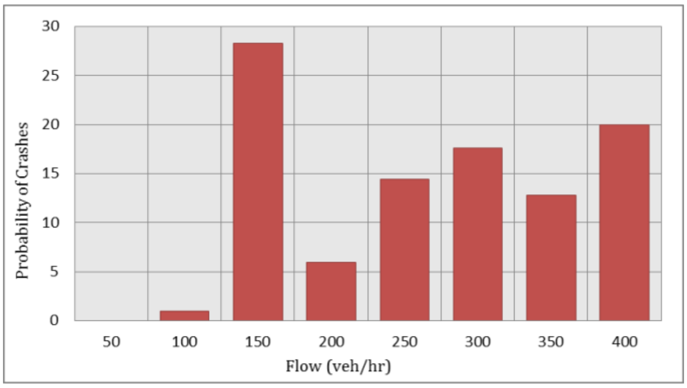


(b) Probability of Crashes vs. Density

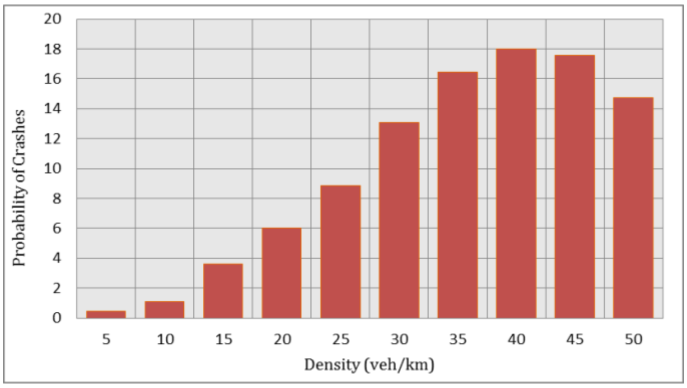


(c) Probability of Crashes vs. Speed

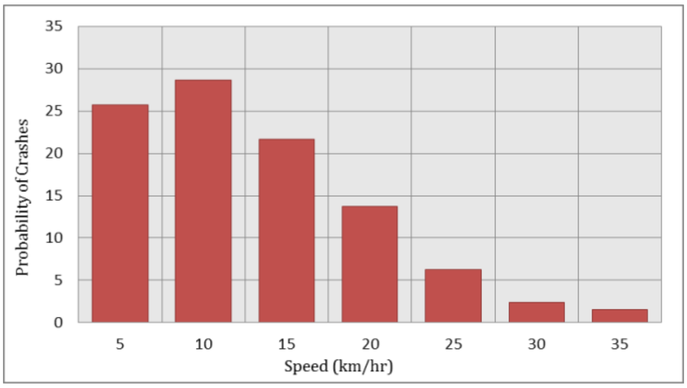
Figure C.1.1: Relationship Probabilities of Crashes and the Traffic Parameters for TTC=0



(a) Probability of Crashes vs. Flow

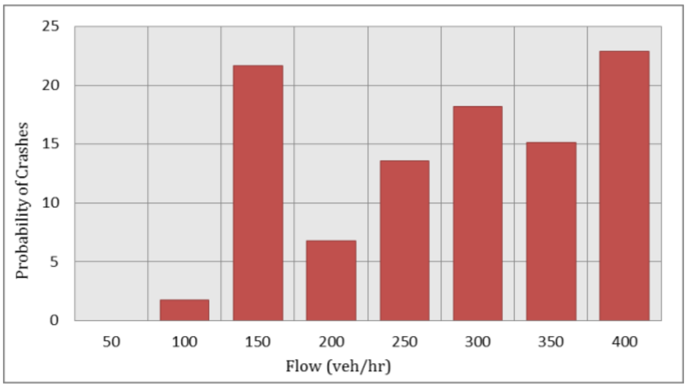


(b) Probability of Crashes vs. Density

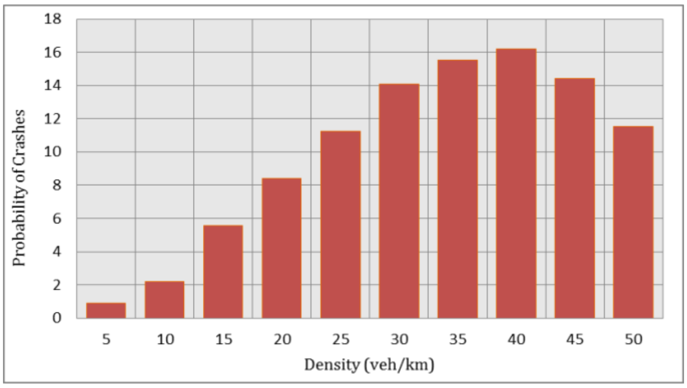


(c) Probability of Crashes vs. Speed

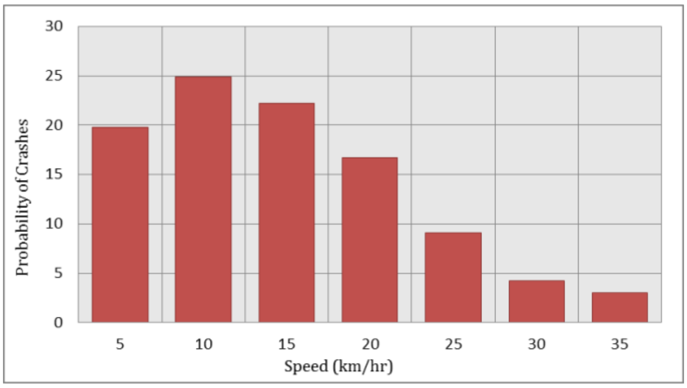
Figure C.1.2: Relationship Probabilities of Crashes and the Traffic Parameters for TTC<=0.5



(a) Probability of Crashes vs. Flow



(b) Probability of Crashes vs. Density



(c) Probability of Crashes vs. Speed

Figure C.1.3: Relationship Probabilities of Crashes and the Traffic Parameters for TTC<=1.5