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Impact Assessment Through Microscopic Simulation:

A Sustainable Approach to Improving Traffic Congestion

Dissertation submitted in partial fulfilment of the requirements for the degree of Master of Science in Engineering (MSc (Eng)) in Civil Engineering

by

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DEDICATION

I want to dedicate this thesis to my entire family for their non-exhausted moral and financial support. I appreciate their positive and robust contribution to my education up to this level.

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ABSTRACT

This study assesses the changes in travel time patterns on the N2 highway in Cape Town, South Africa. A microsimulation model is developed to analyse average travel times and speeds along the specified route between 2005 and 2023. Historical data is incorporated into the PTV Vissim software, and peak-hour traffic congestion and patterns are investigated. This thesis focuses on the influence of travel time on urban mobility and transport planning. The results reveal the need for innovative solutions to enhance traffic flows along the N2 highway corridor.

The introduction provides an overview and sets the context of the study, stipulating the research objectives, scope, and relevance of the research. The methodology details the data collection procedure, model simulation layout, and the approach to assessing travel time patterns. The results section presents a detailed analysis of the PTV Vissim simulation, addressing traffic flow behaviour, peak flow congestion, and the efficiency of the road infrastructure. Research findings are summarised, focusing on areas that require improvements and the advantages of the proposed solutions.

The study emphasises the need for innovative and sustainable traffic management strategies. Recommendations detail the requirement to implement enhanced traffic control systems, infrastructure upgrades, and interventions to improve urban mobility and reduce traffic congestion. Ramp metering is investigated as a sustainable approach intervention and the results are discussed. The model predicts that ramp metering techniques could improve highway flows reducing average delays by at least 8%. The model also predicts that congestion charging could improve traffic flows by at least 7%. The conclusion highlights the significance of addressing travel time to create a sustainable and effective transportation network in Cape Town. Future research proposals are suggested, emphasising the necessity for continuous traffic monitoring and adaptive systems to cope with changing traffic patterns.

Furthermore, the study underscores the importance of stakeholder engagement in developing and implementing traffic management solutions. Collaborative efforts between government agencies, urban planners, and the community are essential for the success of the proposed interventions.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

AIMSUN	Advanced Interactive Simulator for Urban and Non-Urban Networks
CAV	Connected and Autonomous Vehicles
CBD	Central Business District
CCT	City of Cape Town
CF	Car-following
CITP	Comprehensive Integrated Transport Plan
CORSIM	Corridor Simulation
COTO	Committee of Transport Officials
CTM	Cell Transmission Model
DYNASMART	Dynamic Network Assignment-Simulation Model for Advanced Road Telematics
FHWA	Federal Highway Administration
FRESIM	Freeway Simulation
GEH	Geoffrey E. Havers Statistic
HOT	High-Occupancy Toll
IRT	Integrated Rapid Transit
ITMS	Intelligent Traffic Management System
ITS	Intelligent Transportation Systems
KPI	Key Performance Indicator
LC	Lane Changing
LOS	Level of Service
LOV	Low Occupancy Vehicle
LWR	Lighthill-Whitham-Richards
m/s^2	Meters per Seconds Squared
MBT	Minibus Taxi
MITSIMLab	Microscopic Traffic Simulation Laboratory

NHTS	National Household Travel Survey
O-D	Origin-Destination
ODOT	Oregon Department of Transportation
PTV VISSIM	Planning Transport Verkehr-Verkehr In Städten-SIMulationsmodell
SANRAL	South African National Roads Agency Limited
SPI	Speed Performance Index
SUMO	Simulation of Urban Mobility
TDACT	Transport and Urban Development Authority Cape Town
TDM	Travel Demand Management
TTI	Travel Time Index
vph	Vehicles per Hour

1. INTRODUCTION

This chapter aims to explore the background and overview of traffic congestion, as well as to define the problem statement and objectives of the study.

1.1 Overview of Traffic Congestion

Traffic congestion is hated universally. Downs (2004) stated this and argued that, despite all efforts to alleviate it, it continues to worsen. Metropolitan cities across the world experience traffic congestion. People's inclination to interact with each other causes them to want to move and occupy the same spaces. Movement, such as commuting to school and work, propels economic activities. The author highlighted that traffic congestion is not the problem, the road network having limited space to accommodate every user causes mobility drawbacks.

Traffic congestion is a condition that arises from an imbalance of supply and demand on road networks, due to increased usage, resulting in reduced speeds, longer travel times, and more vehicles idling in queues. This phenomenon is a pervasive issue that significantly impacts the economic, environmental, and social aspects of urban life (Downs, 2004).

Grant-Muller (2005) mentioned that several indicators have been established to quantify traffic congestion. However, a few parameters are used to regularly monitor the transport network, and more performance indicators are required to quantify congestion (Grant Muller & Laird, 2006).

1.1.1 Global Context

Das & Keetse (2015) and Bhattacharjee & Goetz (2012) mentioned that various cities globally experience traffic congestion, which results in unwanted negative impacts. Rao & Rao (2012) conducted a systematic review that assessed the practices that countries such as Japan, South Korea and the United States of America use to monitor congestion. These countries have organised programs within the traffic and transport departments that identify congestion using performance measures, such as freeway average speed, Level of Service (LOS), vehicle miles and hours of travel, person miles of travel etc.

The United Nations (2019) published a report that mentioned that more people reside in urban areas than in rural areas worldwide, with 55% of the world's population living in urban settlements in 2018. It is predicted that by 2050, 68% of the global population will reside in urban areas. This shows that the current transport infrastructure and services are under strain, raising the demand for improved accessibility and mobility. The United Nations (2004) highlighted that there has been a fast growth of vehicle owners in developing countries. This is due to credit accessibility, low vehicle prices and the abundance of used cars. Individual mobility combined with urbanisation has escalated traffic congestion. Various sources (Lu & Elefteriadou, 2013; Falcocchio & Levinson, 2015; Heaslip et al., 2011; Fields, 2014) identified the main causes of traffic congestion, namely incidents or accidents, weather conditions, road geometry, insufficient highway capacity and variability of demand in a single day. These causes can assist in categorizing strategies to alleviate congestion by having demand-oriented and supply-oriented solutions.

Figure 1.1: Congested Road

Source: Downs, 2004

Muneera & Karuppanagounder (2018) highlighted that traffic congestion affects the economic and social aspects of road users. Air and noise pollution affect the health and safety of motorists. Time is wasted resulting in the inability to predict travel time. The frequent braking and acceleration of vehicles lead to wear and tear of tyres because of congestion. The costs arising from traffic congestion are divided into external and internal parameters. External costs are a result of using the road network, such as road crashes, and pollution. Internal costs are produced by road users through non-productive activities on the road (Thomson & Bull, 2002).

Important studies (Osman et al., 2019; Mondschein & Taylor 2017; Thomas et al., 2018; Jin and Raferty, 2017) have focused on the effects of traffic congestion on economic growth, such as employment and household income (Moyano et al., 2021). Mondschein & Taylor (2017) highlighted that income-levels influence trip generation and that trip-generating rates are low for households with low income.

Measuring traffic congestion on a global scale is fundamental. Moyano et al. (2021) pointed out that TomTom provides comprehensive traffic and road network information. This Big Data web engine contains datasets by scholars for the analysis and assessment of socio-economic factors concerning mobility. **Table 1.1** shows the traffic index ranking for the most congested cities in the world and Africa. Metrics, such as lost time, average travel time, congestion level, and average speed are used for this ranking system.

Table 1.1: Traffic Index Ranking for the most congested countries in the world and Africa

Rank	City	Average travel time per 10 km (mm: ss)	Change from 2022 (mm: ss)	Congestion level (%)	Time lost per year at rush hours (hr)	Average speed in rush hour (km/h)
World Rank						
1	Dublin, Ireland	29:30	01:00	66	158	16
2	Mexico City, Mexico	26:30	00:50	63	152	18
3	Bengaluru, India	28:10	01:00	63	132	18
4	Bangkok, Thailand	21:40	01:00	62	108	23
5	Lima, Peru	28:30	01:20	61	157	17
Africa Rank						
1	Cairo, Egypt	20:20	01:00	00:40	72	26
2	Pretoria, South Africa	16:00	No change	00:28	49	32
3	Cape Town, South Africa	15:50	00:20	00:32	49	33
4	Bloemfontein, South Africa	14:50	00:10	00:20	41	34
5	Durban, South Africa	14:50	No change	00:29	44	35

Source: TomTom, 2024

The top three congested cities in the world are Dublin, Mexico City, and Bengaluru with congestion levels of 66%, 63% and 63%, respectively. The top three congested cities in Africa are Cairo, Pretoria, and Cape Town. The data shown in the table indicates that South Africa has the most congested cities in Africa.

1.1.2 South African Context

Various South African cities experience traffic congestion, especially in Central Business Districts (CBD) and large cities go through this problem periodically during the day (Das &

Keetse, 2016). Vanderschuren (2006) conducted a case study for South Africa and stated that transport shapes the society and economy of a nation. Muller (2005) mentioned that the discovery of the country by European mariners was the birth of the transportation system. Transportation routes were created to ease the trading of goods and to provide Europeans with supplies from South Africa. Cape Town was founded as the border for economic activities between the East and West. The intricate road network originated in Cape Town and was developed inland through the rough topography.

The Worldbank (2024) provided the trend of the economic state of South Africa as shown in **Figure 1.2**. There was a declining trend from the 1970s to the 1990s. The performance of the economy during the apartheid regime was low because of the unequal distribution of growth on a micro level which did not change nationally (Lundahl & Petersson, 2009). South Africa's economy has been growing at a slow and erratic pace for much of the period following the 2007–2009 global financial crisis. Over the five years preceding the outbreak of the COVID-19 pandemic, real GDP growth rate averaged 0.84 percent per annum, which is lower than the population growth rate.

South Africa's economic performance has been sluggish over the last decade. This poor performance has been attributed to several factors, including its structural constraints that favoured extractive industries and financialisation instead of innovation-driven industrialisation (Mohamed, 2019). Without comprehensive reforms and a strategic reorientation, the economy is unlikely to break out of its low growth inertia and reach a sustainable growth path. Whereas the contribution of innovation to industrial competitiveness is generally accepted as a stylised fact in the neo-Schumpeterian tradition, quantifying this contribution remains a daunting challenge, owing to the methodological complexities. (Habiyaremye et al, 2022).

However, South Africa's slow economic growth has had a direct influence on public infrastructure spending, particularly in urban transit networks. Limited government spending on road network extensions and advanced traffic management systems has contributed to increased congestion, particularly in major cities like Cape Town. The backlog in meeting basic infrastructure needs, such as housing, public transportation, and road maintenance, has increased urban traffic congestion. To minimise congestion, innovation-driven economic initiatives could include the integration of smart transport technologies and sustainable traffic management systems (Infrastructure South Africa, 2022).

The slow growth of South Africa's economy can be linked to the government's emphasis on addressing historical backlogs in housing, education, and healthcare, which, although vital, has hampered investment in critical infrastructure and technological innovation. This underinvestment in transport infrastructure, in particular, has resulted in worsening road conditions and out-of-date traffic control systems, adding to urban congestion (Gordhan, 2020)

In the context of neo-Schumpeterian economics, technological innovation plays a critical role in improving productivity and addressing urban challenges such as traffic congestion. Implementing innovative traffic management solutions, such as adaptive signal control systems, ramp metering, and congestion charging, can enhance mobility in South African cities, thereby contributing to economic growth through reduced travel times, improved logistics, and increased access to economic opportunities (Geels,2005).

Nowak (2005) stated that the Total Factor Productivity (TFP) contributed to half of the economic growth, because trade restrictions were removed, and South Africa was interacting with international markets. Post 2004, the economy gradually declined with the global financial crisis and COVID-19 causing massive spikes in the trend in 2008/2009 and 2021 respectively (Steytler & Powell, 2010; Erero & Makananisa, 2021; Burger & Calitz, 2021).

National Household Travel Survey (NHTS) (2003) stated that pollution and choking congestion exist commonly in South Africa and traffic volumes are increasing by 7% annually. There is a growing trend of users using private cars to commute to work and that has increased by 15% from 1997 to 2003.Despite slow economic growth, traffic volumes and private car usage increased between 1997 and 2003, which can be attributed to several interrelated factors. During this time, urbanisation and population growth drove up demand for mobility. The lack of a stable and large public transit network encouraged private car use as a more convenient and dependable option.

Furthermore, societal trends towards car ownership as a status symbol, combined with greater access to vehicle financing, made cars more affordable to a larger segment of the population. This trend was especially prevalent among middle-income households looking to improve their quality of life. Finally, urban sprawl and bad urban planning frequently forced people to rely on private vehicles for transportation, which contributed to the observed increase in traffic volumes (International Transport Forum, 2003; Fourie & Burger, 2009).

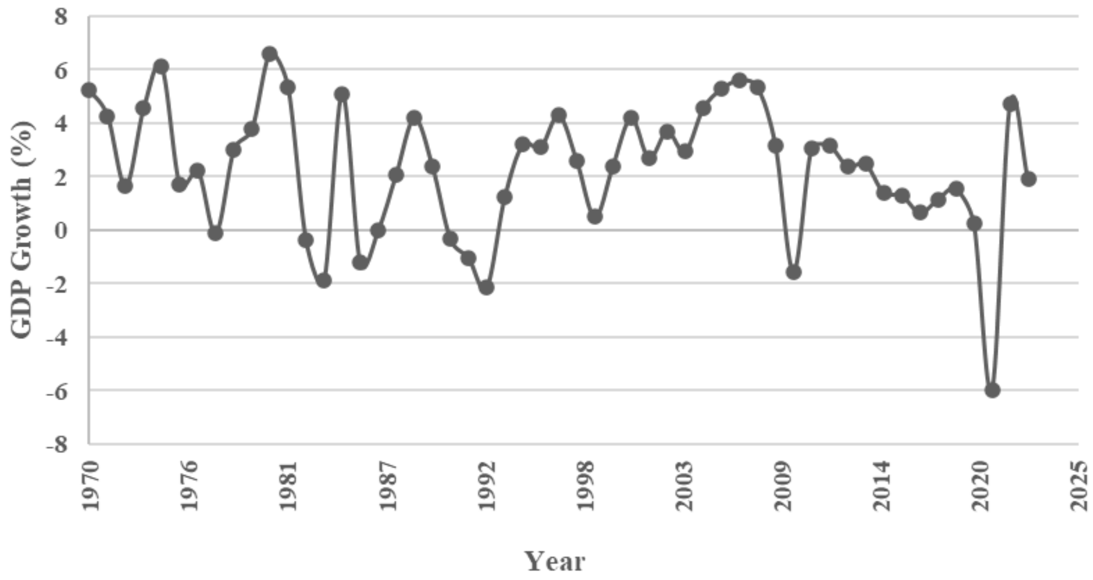


Figure 1.2: GDP per Capita Growth for South Africa

Source: World Bank, 2024

Behrens (2002) studied mobility patterns with income groups and found that high-income road users use private vehicles, middle-income households mostly walk and use private cars and low-income road users walk or use public transport. Vanderschuren & Lane-Visser (2024) assessed the changes in the transport mode distributions after a decade from 2003 based on gender. The study revealed that there was a decline in the use of Bus Rapid Transit (BRT) in 2013 and 2020 for both males and females, as shown in **Figure 1.3**. There was an increase in the number of people who walk. The use of trains has declined significantly, however, the use of Minibus Taxis (MBT) remained stable. The percentage of passengers declined while the number of drivers increased. The authors highlighted that modal choice is based on cost, safety and personal security factors. The decline in BRT usage in 2013 can be attributed to several factors. Despite being an affordable public transportation option, operational inefficiencies such as inconsistent service schedules, overcrowding, and limited route coverage may have reduced its appeal. Furthermore, competition from the flexible and widely available minibus taxi system likely diverted passengers away from BRT. Public perceptions of safety, comfort, and reliability may also have played a role.

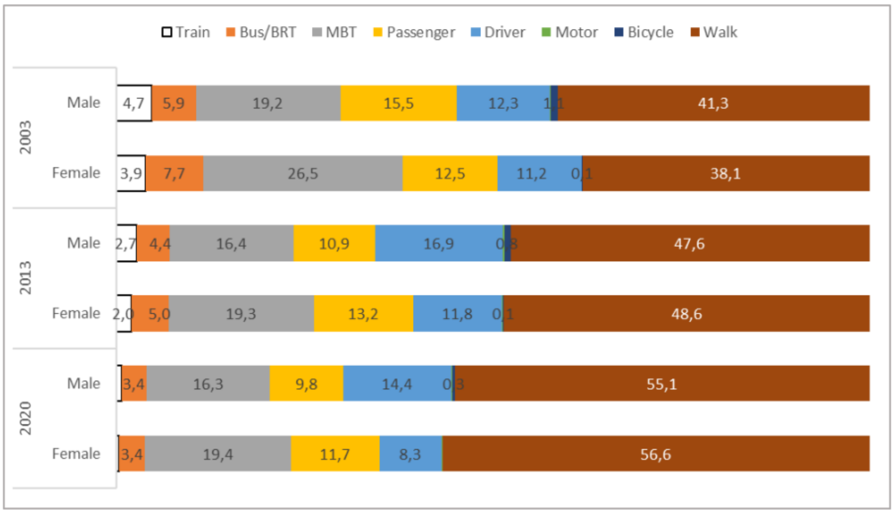


Figure 1.3: Transport mode distribution based on gender (%)

Source: South African Household Travel Survey Raw Data 2003, 2013 and 2020

Road crashes are also caused by traffic congestion. Vanderschuren (2006) found that South Africa has the highest casualties on the road. In comparison to the Netherlands, the casualties in South Africa are ten-fold. **Figure 1.4** shows South African cities have the most casualties in the world. Fatal accidents are caused by jaywalking, alcohol abuse, speeding and vehicles which are not roadworthy (Ojungu-Omara, 2006).

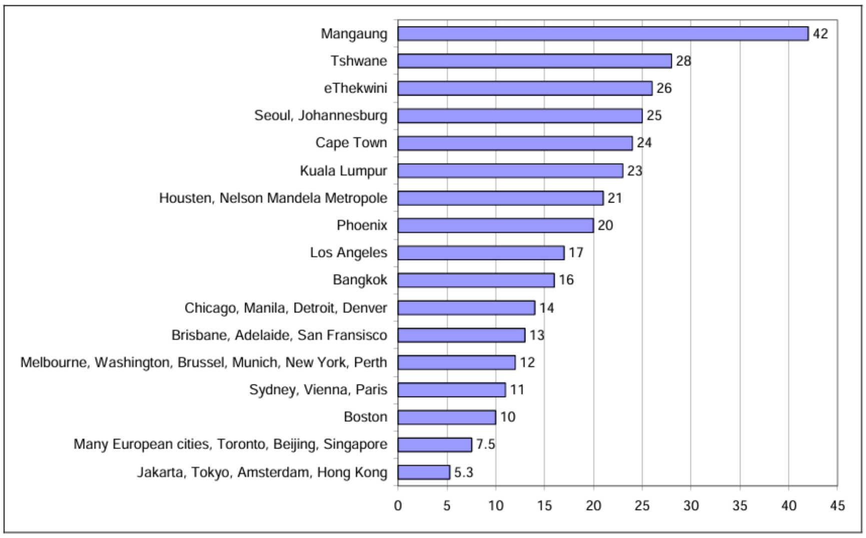


Figure 1.4: Road accident casualties for cities around the world (/100 000 inh)[6]

Sources: CMC, 2000; Pladsen, 2002; Newman and Kenworthy, 1999

Vanderschuren (2006) mentioned that a huge percentage of road users in South Africa rely on public transport. Rail infrastructure exists; however, the cost of maintenance is high. Bus services that work on timetables exist and unscheduled mini-bus taxi services provide transport in urban areas and long distances. The author stated that there have been strategies put in place to encourage the use of public transport such as the Gautrain Rapid Rail. Van Der Merwe et al. (2001) stated that the objective of the Gautrain project was to improve the economy in Gauteng through job creation and to reduce traffic congestion. More initiatives still need to be developed to encourage the use of public transport in South Africa.

1.2 Importance of Sustainable Traffic Management

Mobility is important for people in every country as it drives economic and social activities, and people can move safely and freely. To solve transport demand problems, upgrading existing infrastructure does cater, to some extent, for transportation demand growth. Therefore, traffic management is a strategy that can mitigate traffic-related issues and promote sustainable development. Traffic management aims to balance transport supply and demand to yield positive impacts (Boltze & Tuan, 2016). Vanderschuren (2006) highlighted that Intelligent Transport System (ITS) applications effectively manage traffic and reduce transport-related problems. The author mentioned that SANRAL has been exploring integrating ITS into their strategies for reducing congestion and improving road safety.

The benefits of applying ITS are safety, mobility, efficiency, productivity, energy and environment and customer satisfaction (Mitretek Systems, 2001). ERTICO is a European ITS organisation that subdivided ITS into three categories, namely Intelligent Traffic Management Systems (ITMS), Intelligent Passenger Information Systems, and Intelligent Public Transport Systems (Vanderschuren, 2006). ITMS assesses traffic flow information through measuring and analysis of various traffic metrics. These systems are highway and traffic flow management systems, traffic signal control, incident management systems, intelligent speed management, electronic licensing, and electronic toll and traffic enforcement systems. **Table 1.2** provides the ITS measures based on the objectives.

Table 1.2: ITS measures concerning objectives

	Intelligent Traffic Management Systems	Intelligent Passenger Information Systems	Intelligent Public Transport Systems
Safety	• Variable speed limits • Lane management • Incident management • Warning systems • CCTV cameras • Automatic vehicle identification • Intelligent Speed Adaptation • Weight in motion	• Navigation systems • Parking guidance • Cruise control • Warning systems • Intelligent Speed Adaptation • Black-box systems • Automated vehicle identification • Docking systems • Distance warning	• Fleet management • Navigation systems • Electronic ticketing • CCTV cameras • High-speed ground transportation • Automatic vehicle identification • Intelligent Speed Adaptation • Distance warning
Mobility and Efficiency	• Variable speed limits • Lane management • Incident management • Warning systems • CCTV cameras • Ramp metering • Traffic control • Electronic toll collection • Real-time information • Parking guidance	• Navigation systems • Parking guidance • Cruise control • Warning systems	• Public transport priority • Fleet management • Navigation systems • Electronic ticketing • System integration • High-speed ground transportation • Real-time Information
Customer satisfaction	• CCTV cameras • Lane management • Warning systems • Electronic toll collection • Real-time information • Parking guidance	• Navigation systems • Parking guidance • Real-time information • Electronic toll collection • Docking systems • Warning systems	• Real-time information • System integration • Electronic ticketing • CCTV cameras

Source: Vanderschuren, 2006

1.3 Rationale for Microscopic Simulation

Microscopic traffic simulation is used to predict and solve traffic-related problems, such as crashes and congestion. Microscopic simulation models are created, and each particle represents a car, making it easy to differentiate individual vehicles and analyse the behaviour of vehicles. The input data inserted into the model must be reliable so that realistic results can be produced by the simulation (Abe et al., 2023). Microscopic traffic simulations, which offer detailed analysis of individual vehicle movements, have emerged as a vital tool in sustainable traffic management.

The rationale for microscopic simulation is to model the behaviour and interactions of individual units, such as vehicles, drivers, and pedestrians in complex systems that cannot be easily analysed by analytical methods. Microscopic simulation can capture the heterogeneity, stochasticity, and dynamics of these units and their effects on the system performance and outcomes (Barceló & Casas, 2005). For example, traffic congestion microscopic simulation can model how different types of vehicles, drivers, and road conditions affect traffic flow, speed, and safety (Krogscheepers & Kacir, 2001). Microscopic simulation can also evaluate the impact of different policies or interventions on the system, such as traffic control, road design, or public transportation. This simulation type can provide detailed and realistic insights that may inform decision-making and improve the sustainability of the system (Abe et al., 2023).

1.4 Objectives of the Study

The primary objective of this study is to assess the level of traffic congestion in one of the capital cities of South Africa, Cape Town. The impact of traffic behaviour on road users is investigated. The aim is to use travel time, average delay and, average speed as congestion metrics to evaluate traffic patterns on the N2 national road, a major highway corridor in the City of Cape Town. An understanding of traffic behaviour on major roads and insights from the study can be used to propose strategies to reduce congestion and improve traffic flow and safety.

1.4.1 Main Objective

The main objective of this thesis is to use a microscopic simulation tool to measure one of the traffic congestion metrics, travel time and evaluate its effectiveness as a sustainable approach to improving traffic flows. This research aims to analyse traffic flows using a microscopic traffic simulation software PTV Vissim. The approach involves modelling the road network, calibrating the model using the existing data collected in 2005, and analysing the simulation model using the data collected in 2023. The research also involves measuring travel times on the same corridor during one of the busiest days.

1.4.2 Specific Objectives

The specific objectives of this thesis are:

1. To review the literature on traffic congestion and the use of microscopic simulation in traffic management.
2. To collect travel time data and identify changes between 2005 and 2023.
3. To develop a PTV Vissim model for the N2 highway in Cape Town (From the airport on-ramp to the Main Road off-ramp).

4. To calibrate and validate the model using the 2005 and 2023 data (measured traffic volumes and travel times).
5. To run the simulation using the 2023 collected data.
6. To compare the traffic flows from 2005 to 2023, to ascertain the changes and produce an intervention to improve traffic flows.
7. To calculate Measures of Effectiveness related to traffic congestion and present the findings.

1.5 Research Scope and Limitations

The geographical scope is the N2 National Route Highway in Cape Town from the airport to the Main Road, where the traffic management strategies are implemented and evaluated. The period in which data was collected in the study area was limited to one weekday between 06:00 to 10:00. The Committee of Transport Officials (2017) stated that traffic count surveys that are conducted short-term are done on 'normal days' which are weekdays not influenced by school or public holidays. Hence, undertaking a traffic count on a weekday reduces variability in the results. Extensive data collection was not feasible, due to financial constraints. Rahman et al. (2022) conducted a study that summarised congestion metrics from various sources. The metrics are Travel Time Index (TTI), vehicle density, travel time, traffic speed, Speed Performance Index (SPI), delay time, vehicle miles travelled, excess Carbon Dioxide (CO_2) due to congestion, travel time, modal shift, annual excess fuel consumption, volume-to-capacity ratio, length of congested road, hourly average congestion length, total social cost, and total average per capita travel time. These metrics were estimated by applying different study methods in the study area. This study made use of travel time, average delay and, average speed only to measure traffic congestion in PTV Vissim. No study in the literature focused on these parameters and modelled the study area of the N2 highway corridor in Cape Town using PTV Vissim.

1.6 Overview of the study

This report consists of six chapters which are described as follows:

Chapter Two is a literature review on traffic congestion and lists the causes and effects of the phenomenon. Congestion in a global and South African context was discussed to assess general patterns and trends. Sustainable traffic management, the contribution of microsimulation in traffic studies and ramp metering are studied and research gaps were identified.

Chapter Three provides the methodology in which data was collected from SANRAL dual loops and the measurement of travel time from the field. Key Performance Indicators relevant to the study were specified.

Chapter Four focuses on the development, calibration and validation of the base model. Calibration and validation criteria were used to create an accurate model.

Chapter Five provides a detailed analysis of simulated travel times, average delay, and speed. A comparison of measured and simulated travel time is conducted to assess traffic trends. A ramp metering and congestion charging interventions are introduced in the model and analysed. Changes in traffic behaviour are noted and compared to the base model.

Chapter Six discusses the results and highlights the impact of adding interventions in the study area. It also provides the conclusion and recommendations of the study.

2. LITERATURE REVIEW

2.1 Background

This chapter presents the literature review on traffic congestion. It also reviews the causes and effects of traffic congestion, which are imbalances between transport demand and infrastructure supply, leading to increased travel times, fuel consumption, and negative environmental impacts. Furthermore, the chapter reviews sustainable approaches to traffic congestion, microscopic simulation in traffic studies, comparative analysis with similar studies, previous studies, and identifies the research gap.

2.2 Traffic Congestion: Causes and Effects

In many urban areas across the world, traffic congestion is a widespread problem that negatively affects people's quality of life, society, the environment, and the economy (Muneera & Karuppanagounder, 2018). The primary factors contributing to traffic congestion are the growing number of cars on the road, insufficient capacity of the roads, inadequate public transportation, and inefficient use of time and space on the roads (Vanderschuren, 2008). Talukdar (2013) stated that causes of traffic congestion can be grouped into three categories namely traffic demand, road infrastructure and events that influence traffic.

Traffic influencing events are work zones on the road, debris on the road, traffic crashes, vehicle breakdowns and incidents, and unfavourable weather conditions. **Figure 2.1** shows how weather conditions, such as rain and floods can impede traffic flow and lead to congestion. Adverse weather conditions such as snow, fog, smoke, and bright sunlight reduce visibility and driver perception. Traffic demand includes changes in traffic flow in normal traffic and special events. Road infrastructure features, such as poor traffic control devices, geometric design and road bottlenecks cause traffic congestion. The mismatch between the supply and demand of road space, particularly during peak hours when most people travel to and from work or educational institutions, causes infrastructure-related congestion.

Figure 2.1: Traffic congestion due to bad weather conditions

Source: ADB, 2018

In addition, the lack of other transportation options like walking, bicycling, or public transportation, the overcrowding of the roads and reliance on private vehicles also cause this (Vanderschuren, 2007). **Figure 2.2** shows the influence of poor road infrastructure on traffic.

Figure 2.2: Poor Road infrastructure

Source: Nienaber & Booysen, 2015

Traffic congestion has numerous detrimental effects. According to Meneera & Karuppanagounder (2018), traffic congestion raises the price of goods and transport while wasting time, and fuel, which lowers economic productivity and competitiveness. In addition to increasing greenhouse gas and air pollution emissions, traffic congestion harms public health and the environment by producing noise and stress (United Nations, 2021). People's social and psychological well-being is also impacted by traffic congestion, as it lowers social cohesion and equity, access to opportunities and services, and quality of life (Vanderschuren, 2008).

While there are several potential ways to lessen or avoid traffic congestion, none of them are simple or inexpensive (Thomas, 2013). There are various approaches to alleviate this problem, such as land use management, Transport Demand Management (TDM) and supply management (Ceylan & Bell, 2004; Meyer, 2003). Applying land-use management measures takes long for land-use patterns and, subsequesntly, human behaviour to change. Transportation Demand Management (TDM) encourages road users to use other alternatives such as routes, modes, and time to reduce the demand for infrastructure. Measures such as congestion pricing, alternative work schedules, park and ride etc. are implemented in TDM strategies (Taylor, 2002).

2.3 Sustainable Approaches to Traffic Management

Sustainable traffic management strategies seek to improve the effectiveness, safety, and accessibility of the transport network, while minimising the detrimental effects of traffic congestion, pollution, and crashes on the environment, the economy, and people's quality of life. Transport infrastructure upgrades alone cannot handle traffic-induced problems, therefore, traffic management is an effective approach to addressing these issues and simultaneously achieving sustainable development (Boltze & Tuan, 2016).

Boltze (2013) set a framework that defined the main goals for achieving sustainable traffic systems similar to Mitretek Systems (2001). Boltze & Tuan (2016) stated that these goals are achieved by implementing three strategies shown in **Figure 2.3**. Avoiding traffic helps reduce traffic in a specific area. Shifting traffic involves changing the mode, destination, route and road users travel time. Traffic control strategies assist with regulating vehicle movement to enhance efficiency. Transport demand can be controlled by shifting departure times to reduce peak-hour congestion. Encouraging road users to use bikes, walk and public transport. Vanderschuren & Lane (2011) suggested the same strategies to address congestion challenges and shifting to green transport systems enhances the economy through job creation, and also reduces poverty, emissions and traffic congestion. The A-S-I (Avoid-Shift-Improve) approach, developed in Germany in the early 1990s and officially recognised in 1994, structures policy measures to mitigate the environmental impact of transport and enhance urban quality of life. Embraced by international NGOs and development organisations, it offers a more holistic and demand-focused alternative to the predict-provide-manage approach for creating sustainable transport systems (Bongardt et al., 2019).

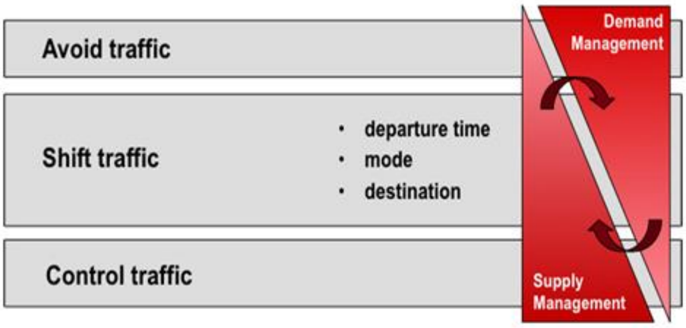


Figure 2.3 : Traffic management strategies

Source: Boltze & Tuan, 2016

Modal choice can be implemented by making lower preference modes such as buses and trains more attractive. Boltze & Tuan (2016) highlighted that the Denmark government applied a policy that combined bus and train services to allow passengers to pay for a single ticket and allow children to travel for free. The authors affirmed that modal choice depends on the location and that intermodal travel should be accommodated, such as Bike and Ride and Park and Ride.

Mobility pricing instruments, such as applying variable and demand-actuated prices to public transport services and road pricing can assist with controlling traffic. Airlines use the same concept to shift passengers to travel during off-peak periods. There would be a distribution of departure time and traffic, which in turn reduces congestion (Boltze & Tuan, 2016). The Organisation for Economic Co-operation and Development (OECD) (2002) underscored that Singapore initiated an Area Licence Scheme (ALS), which reduced traffic during peak periods in Central Business Districts (CBD) by making use of an electronic road pricing system. Congestion was reduced because vehicles avoided accessing the CBD during peak periods.

Traffic demand fluctuates over time and space; however, the capacity of transport systems remains constant. Therefore, transport systems must be operated in a manner that manages dynamic traffic demands (Ben-Akiva, 2015). This strategy can reduce the need for private vehicles and the number of people crammed onto the roadways, which will lessen traffic, pollution, and crashes. The social and economic advantages of public transport, such as its mobility, accessibility to opportunities and services, social cohesion, and equity, can also be emphasised by using this strategy (Beirão & Cabral, 2007; Steenkamp & van As, 2016; Taylor & Miller, 2001; Farber et al, 2011).

The acceptance, regulation, integration, and coordination of traffic management strategies has difficulties. Coordinating various public transport operators and modes can be challenging and complex, necessitating a clear and consistent vision and strategy. It can be difficult and contradictory to integrate public transport with other elements of urban planning and development, such as land use, housing, and the environment (Moyo et al., 2022; Kanyama, 2023). Hence, this calls for an all-encompassing and collaborative approach. Public transport regulations, particularly those regarding new and developing technologies, can be ambiguous and contentious, necessitating a balance between safety and innovation. The degree of acceptance of public transportation among users and stakeholders can vary and be influenced by factors such as comfort, convenience, quality, and perception.

Therefore, traffic management is a complicated issue with many facets that necessitate an all-encompassing strategy for sustainability. Traffic management can be made more effective, safe, and sustainable, and the advantages of a more resilient and liveable urban environment can be realised by enhancing the road infrastructure and public transportation, managing and controlling traffic flow and demand, and altering the drivers' and commuters' attitudes and behaviours (Afrin & Yodo, 2020).

2.3.1 Ramp metering

Ramp metering works in real-time, whereby the on-ramp sensors gather traffic data which is utilised to dynamically modify signal timing for ramp metering. The system has adaptive signal control which modifies the speed at which cars are permitted to enter the highway in response to current traffic conditions, improving merging and reducing congestion.

Pearson et al. (2001) defined ramp metering as a method of controlling traffic on on-ramps to reduce congestion on the highway. The system was first used in the 1960s in cities in the United States of America. Khan et al. (2016) stated that traffic data for ramp metering is collected using loop data (collected on the road to be joined), to adjust real-time traffic conditions. Studies have shown that implementing a ramp meter improves overall traffic conditions by reducing travel time, vehicle emissions, and fuel consumption and enhances traffic management, freeway capacity and safety (Ghamdi, 2019; Wattleworth & Berry,1999; Ríos-Torres & García-Ródenas, 2017; Williams & Gan, 2016).

Mizuta et al. (2014) underscored that without the presence of ramp meters, drivers on the ramp would be looking for a gap to occupy on the main road, which would cause vehicles to slow down or stop. **Figure 2.4** shows that a ramp meter would allow vehicles to enter the freeway in a trickle or drip manner, with minimum interruption and speed reduction on the freeway. Adding a ramp meter decreases the peak hour lane occupancy leading to a fast recovery of the freeway to operate below the critical occupancy threshold.

Mizuta et al. (2014) mentioned that four approaches are used by road agencies to control traffic. These are single or multi-lane metering, single or dual-release metering, freeway-to-freeway connection and bypass lanes. Single or multi-lane metering permits one vehicle to pass in a signal cycle in each lane. Single or dual-release metering allows one vehicle to pass per green time. Two vehicles are allowed to pass per cycle for dual release, hence, a longer green time is allocated for this system. Freeway-to–freeway connections are not commonly metered, because they pose high safety risks, such as collisions, due to the high travelling speed of vehicles. Bypass lanes are used for specific vehicles to travel along the ramp. This study makes use of single-release metering.

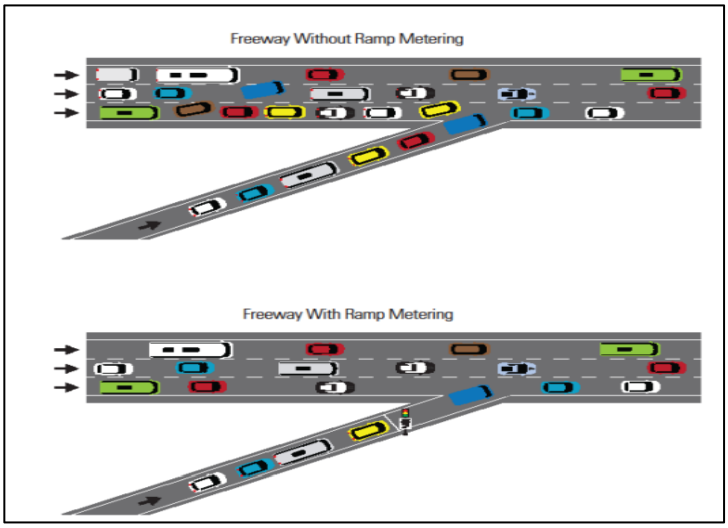


Figure 2.4: Comparison of a road with and without ramp metering

Source: Mizuta et al., 2014

In South Africa, Intelligent Transport Systems (ITS) provided ramp meter data that showed that average speed decreased by 44% to 45% and travel time by 27% to 32% (Mkhizi & Thomas, 2005). Vanderschuren (2006) conducted an ITS study that involved assessing the influence of adding ramp metering to two major highways, Ben Schoeman Highway (BSH) and the N2 highway in Cape Town. Comparisons between the base case and ramp metering scenario were made. **Figure 2.5** shows travel time results before and after implementing ramp metering. The results showed that after the introduction of ramp metering, the throughput on the N2 highway reduced, while the throughput increased for BSH. The travel times for BSH were almost similar for the Tshwane to Johannesburg and Midrand to Johannesburg route. Other attributes, such as traffic volume, and vehicle speed were assessed and showed that applied ramp metering to BSH improves traffic flow. There was a better utilisation of the road capacity. The application of ramp metering on the N2 produced unfavourable results, a decrease in throughput indicated that vehicles would have difficulties entering the highway which reduced vehicle speed and headway and posed a safety risk. This shows that the success of implementing ramp metering depends on the current traffic conditions of the road and its infrastructure.

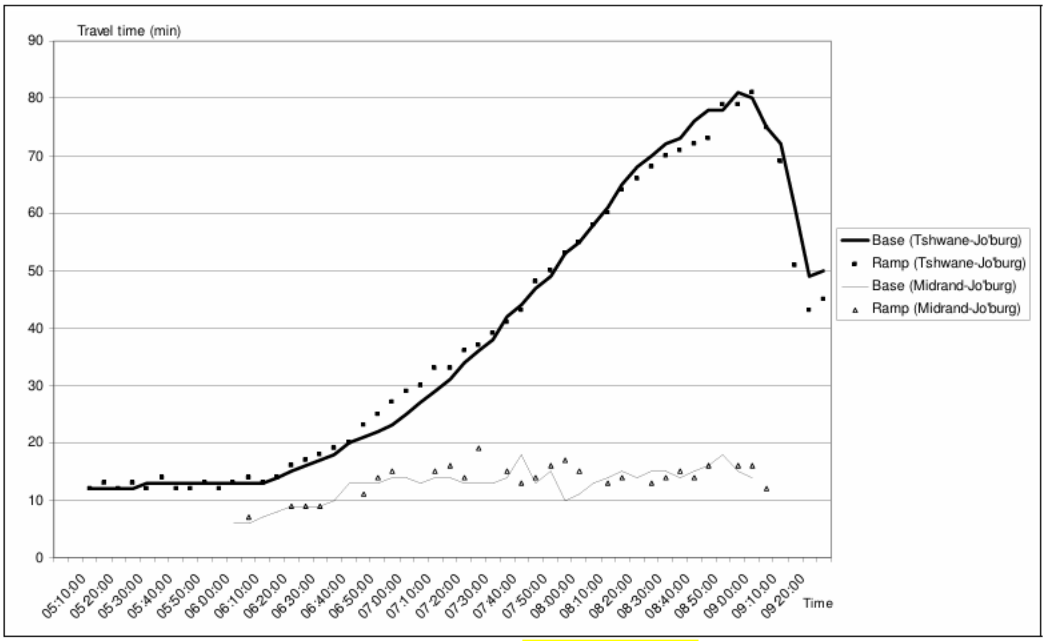


Figure 2.5: Travel time results for ramp metering scenarios for BSH and N2 highway

Source: Vanderschuren, 2006

The use of new ramp metering models, such as local ramp metering, coordinated ramp metering, or adaptive ramp metering, and the use of new lane management models, such as lane closure, lane reversal (counterflow), or lane allocation, were among the opportunities and challenges of microscopic simulation models for ramp metering and lane management that Ntousakis et al. (2016) identified. They used the AIMSUN microscopic traffic simulation model to create an optimal motorway traffic flow control model, which they then implemented on an Athens, Greece, motorway network. They measured the effects of the strategies on traffic performance, efficiency, and sustainability.

They also implemented and compared various ramp metering and lane management strategies, such as fixed-time, reactive, or predictive. They discovered that the best model for controlling traffic flow on motorways could also simulate user behaviour, and optimise lane management, and ramp metering strategies by applying various optimisation techniques. Additionally, they discovered that, while the ideal motorway traffic flow control model was more realistic, flexible, and detailed, than the macroscopic and mesoscopic models, it was less suitable for medium-scale and medium-term traffic analysis and required more data and computational resources.

The use of novel route choice models, such as dynamic route choice, stochastic route choice, or learning route choice, and the use of novel route guidance models, such as pre-trip route guidance, route guidance, or cooperative route guidance, were identified by Ben-Akiva et al. (2004) as opportunities and challenges of using microscopic simulation models for route choice and route guidance.

A variety of route choice and guidance scenarios, including fixed routes, real-time information, and optimal guidance, were simulated and evaluated, and their effects on traffic performance, efficiency, and sustainability were assessed. Ben-Akiva et al. (2004) discovered that the dynamic traffic assignment and simulation model could simulate and compare various route guidance and choice scenarios using various simulation techniques, as well as the traffic flow and route choice behaviour of urban users. Additionally, they discovered that, although the dynamic traffic assignment and simulation model was less suitable for large-scale and long-term traffic analysis, and required more data and computational resources, it was more flexible, realistic, and detailed than the macroscopic and mesoscopic models.

According to Vanderschuren (2006), ramp metering is a successful traffic control technique that manages the speed at which cars enter the highway using on-ramp signals. This system has several important advantages:

- *Managed Merging*: Vehicles entering the highway are limited in speed by ramp metering signals, avoiding sudden surges that could impede traffic flow and create congestion further down the line.

- *Smoother Traffic Flow*: Ramp metering helps maintain a more constant traffic flow on the highway by controlling the merging process, which lessens the stop-and-go situations that frequently cause congestion.
- *Traffic Congestion Reduction*: Ramp metering helps prevent bottleneck formation and lowers overall traffic congestion by regulating the number of vehicles entering the highway at any time.
- *Enhanced Throughput*: Ramp metering can enhance the highway's overall throughput by removing pointless stops and preserving a smoother traffic flow, enabling more vehicles to pass through at any moment.

2.3.2 Congestion charging

Congestion charging also known as congestion pricing and value pricing is a way of changing the high demand on highways by shifting road users to use other transportation modes and off-peak periods. The Federal Highway Administration (FHWA), (2008) underscored that congestion pricing is a sustainable strategy for decreasing congestion. Selmoune et al. (2020) stated that this strategy ensures that there is complete utilisation of the existing road network. The authors further stated that the revenue collected can be used to improve road infrastructure and upgrade of alternative routes and modes such as metro buses (Barwick et al, 2021).

FHWA (2008) highlighted four approaches to value pricing: variably priced lanes, zone-based or cordon charges, variable tolls on entire roadways, and area-wide or system-wide charges. Express lanes and High Occupancy Toll (HOT) lanes are variably priced lanes where Low Occupancy Vehicles (LOV) are charged for driving along these lanes. HOV lanes are permitted to use the lanes at reduced charges or free of charge. For express toll lanes, HOV and LOV vehicles pay a toll fee to use the lanes. Zone-based or cordon charges involve charging drivers commuting in a specific area and the prices vary based on the time of the day. This approach was first implemented in 1975 in Singapore. Variable tolls on roadways involve applying various toll fees based on peak and off-peak periods. This is done to encourage drivers to shift their commute to off-peak periods. Lastly, area-wide or system-wide charges entail charging drivers per mile within a specific area or road network depending on the congestion level.

Congestion charging has advantages for users. There is less delay, because trips will be predictable. There is a decrease in fuel consumption, which lowers vehicle emissions on the highway (FHWA, 2008). Various countries such as Singapore, the United Kingdom, the United

States of America, Sweden etc. implemented this strategy and there were different reactions to its application (Selmoune et al., 2020; K.T. Analytics, Inc., 2008). Singapore was the first country to accomplish congestion charging in 1975 by using a daily license paper system for vehicles entering the business district during peak periods. Phang & Toh (2004) reported that traffic volume decreased by 43% in the charging area. In 1998, Singapore shifted to an electronic scheme which was more advanced as shown in **Figure 2.6**. Santos (2005) underscored that for value pricing to be successful, public transport should be improved. Seven more gantries were added in 2013 which increased bus ridership by 12% (Santos, 2004).

Figure 2.6: Singapore Road Pricing Gantry

Source: Mailer, 2005

Congestion charging was implemented in London, in 2003 after conducting feasibility studies. The number of chargeable vehicles decreased, and the number of accidents reduced by 40% to 70% in the charging area. Santos (2009) mentioned that the revenue collected was used to improve bus services that would reduce traffic congestion. Cycling increased by 66%, bus ridership increased by 6%, and private vehicle use decreased in the charging area (Pike, 2010). In 2006, Stockholm implemented value pricing. Accessibility was enhanced and travel time decreased in the city six months after the execution. Carbon dioxide emissions decreased by 14% (Hugosson & Jonas, 2006). The FHWA (2008) reported that traffic volumes were reduced by 18% in Sweden, which increased the average vehicle speed by the same amount. Public transport use improved between 6% and 9%.

2.4 Microscopic Simulation in Traffic Studies

Microscopic simulation is a useful tool for analysing and controlling traffic flows. It enables an in-depth analysis of specific car movements, offering perceptions of intricate traffic dynamics. The production of high-quality traffic modelling simulations has increased in demand and has enabled better decision-making (Krogscheepers & Kacir, 2001)

2.4.1 Evolution and Importance

The development of microscopic simulation reflects the need for more in-depth traffic analysis and technological advancements. Planning, designing, and running transport systems depend on this tool. Microscopic simulations are used to simulate how different components of a complex system, Including the road network and its users, behave and interact, such as cars, drivers, pedestrians, and traffic signals. Microsimulation models can assess the effects of various policies or interventions, such as traffic management, road design, or intelligent transportation systems. Comprehensive and realistic insights into the performance, efficiency, safety, and sustainability of traffic can be produced (Van As, 2000).

Raju & Farah (2021)conducted a review of the evolution of traffic microsimulation and discovered that Webster (1958) initially attempted to use a computer simulation approach to optimise the signal time of intersections. Over time researchers (Zheng, 2014; Saifuzzaman & Zheng, 2014) have established and incorporated mathematical models, such as Lane Changing (LC) and Car Following (CF) models that consider human behaviour. Zheng (2014) mentioned that LC and CF are two fundamental tasks seen in traffic flow. Raju & Farah (2021) stated that microsimulation models are categorised into continuous space and discrete time phenomena. Improvements in computing technology have led to upgrades of microscopic simulation packages. The author further highlights that it is risky to rely on empirical results from traffic data analysis alone, hence, microsimulation assists with various solutions to comprehend traffic characteristics. Lane changing, ramp metering, traffic safety, signal control, traffic emission etc. have been incorporated into models to provide realistic and feasible solutions.

The FRESIM model and CORSIM model by the Federal Highway Administration (Jiménez, 2017) and the MITSIMLab model by Yang (1997) are examples of the very first models that were developed in the traffic engineering industry. The advent of new applications and technologies in the 2000s and 2010s, like big data, smart mobility, and Connected and Automated Vehicles (CAVs), presented opportunities and new challenges for microscopic simulation in traffic studies. These technologies and applications necessitated the creation of new techniques and instruments, including co-simulation, agent-based modelling, and data-driven modelling, as well as the integration of several domains and disciplines, including communication, control, artificial intelligence, and machine learning (Wang et al., 2020; Talebpour & Mahmassani,2016; Li et al., 2023). The AIMSUN model by Barceló et al., (2002), the VISSIM model by Fellendorf & Vortisch (2010), and the SUMO model by Krajzewicz et al. (2002) are a few examples of these techniques and instruments.

The numerous uses and advantages of microscopic simulation in traffic studies attest to its significance. Aspects of traffic systems, including flow, speed, density, travel time, delay, queue length, emissions, fuel consumption, safety, and comfort, can be examined and assessed using microscopic simulation. Additionally, scenarios and alternatives can be tested and compared using microscopic simulation, including traffic demand, network configuration, traffic management, road design, and policy measures. Additionally, decision-making and planning procedures like traffic signal control, route guidance, traffic assignment, and traffic forecasting can be supported and optimised by microscopic simulation (Barceló et al., 2002; Rao et al., 2015; Berg, 2022; Krogscheepers & Kacir, 2001).

The potential effects and ramifications of emerging technologies and applications, such as big data, smart mobility, and CAVs, on traffic performance, efficiency, safety, and sustainability can also be investigated and understood using microscopic simulation (Chen et al., 2021; Berg & Balac, 2023). Microscopic simulation can overcome some of the drawbacks of other techniques, such as expense, time, risk, or ethical concerns, and can produce comprehensive and realistic results that can be added to or supplemented by other approaches like surveys, field experiments, or analytical models (Barceló & Ferrer 2002; Singh & Kumar, 2016). Nonetheless, there are certain restrictions and difficulties with microscopic simulation in traffic studies that must be resolved. A few of the difficulties and restrictions concern the models, data, computation intensity, validation, calibration, and interpretation.

The availability, calibre, and representativeness of the data required to construct, calibrate, and validate the microscopic simulation models are referred to as the data challenge and limitation. The efficacy and legitimacy of the model may be impacted by incomplete, erroneous, out-of-date, or biased data (Alghamdi & Mostafi, 2022; Chowdhury et al., 2000). The authors further state that the intricacy, authenticity, and scope of the microscopic simulation models are referred to as model challenges and limitations. The models may not accurately depict the fundamental or realistic aspects of the traffic phenomena, because they are either overly basic or overly sophisticated. Additionally, the models may be overly general or specific, failing to take into consideration the variability or transferability of the traffic phenomena.

The estimation, choice, and modification of the parameters of the microscopic simulation models are referred to as the calibration challenge and limitation (Alwosheel & Chand, 2016). The sensitivity and accuracy of the model may be impacted by several correlated or uncertain parameters. Additionally, subjective, inconsistent, or inefficient calibration may have an impact on the models' robustness and dependability. The verification, comparison, and assessment of the outcomes of the microscopic simulation models are the subjects of the validation challenge and limitation. Erroneous, inconsistent, or incomparable results could compromise the models' applicability and validity (Wang et al., 2014; Sun & Liu, 2016). The models' acceptability and confidence may be influence by an inadequate, capricious, or deceptive validation.

The time, money, and scalability of the microscopic simulation models are the computation challenge and limitations (Fellendorf & Vortisch, 2001). The models' applicability and feasibility may be impacted by their resource-, time- or scalability-intensive nature. Additionally, the computation may be unstable, untrustworthy, or incompatible, which could affect how well the models function and are maintained. The comprehension, justification, and dissemination of the outcomes of the microscopic simulation models are the subjects of the interpretation challenge and limitation. The interpretation and implications of the models may be affected by the results, which may be complicated, unclear, or uncertain. Inaccurate, partial, or biased interpretations can also influence how the models are used and disseminated (Barceló, 2017; Punzo & Simonelli, 2023; Park & Qi, 2019).

In addition, microscopic simulation is a strong and adaptable method for studying traffic, and it has developed and improved over time to meet the complex and ever-changing requirements of traffic systems (Punzo & Simonelli, 2023). Microscopic simulation can assess the effects of various policies or interventions, such as traffic management, road design, or intelligent transportation systems, and can offer comprehensive and realistic insights into the performance, efficiency, safety, and sustainability of traffic. Nevertheless, certain obstacles and constraints with microscopic simulation must be addressed and surmounted (Zheng et al., 2017). These include issues with data, models, calibration, validation, computation, and interpretation.

Future research on microscopic simulation in traffic studies should create new techniques and tools that improve data availability and quality, model complexity and realism, parameter estimation and selection, results accuracy, consistency verification, computation efficiency, scalability, result comprehension and communication. By doing this, microscopic simulation can enhance and optimise the processes involved in traffic system planning and decision-making, and make traffic analyses and evaluations more efficient, dependable, and valuable (Punzo & Simonelli, 2023).

PTV Vissim is a microsimulation and behaviour-based tool used to assess congestion and traffic volumes in corridors. It was developed by PTV Group in Germany in 1994. Vissim simulates traffic flows by accounting for vehicle lane allocation, composition and detection. The software is used by transport planners to compare scenarios and interventions to produce the best option through capacity analysis (Goyal & Bhugra, 2021). Tianzi et al. (2013) highlighted that Vissim allows for the assessment of multiple what-if scenarios, which assists with decision-making.

2.4.2 Comparative Analysis with other Models

Several factors, including the degree of realism, flexibility, data requirements, computational cost, and applicability of the models, can be used to compare microscopic simulation in traffic studies with alternative models (Zhao & Chien, 2004).

The granularity and resolution of the model representation and output affect the level of detail. Since they simulate the actions and interactions of individual components, such as cars, drivers, pedestrians, and traffic signals, in a complex system like a road network, nanoscopic simulation models offer the highest level of detail. Potucek (2013) discussed problems and solutions related to nanoscopic simulation. The simulation type requires a large volume of calculations, hence, the suggestion of integrating nanoscopic and microscopic models for study areas. Therefore, combining the two approaches can enhance the level of detail if required. Nanoscopic microsimulation can focus on aspects, such as safety and the analysis of vehicle technologies.

Since macroscopic models use mathematical equations to model traffic dynamics, they have less detail (Zhao & Chien, 2004). These equations relate the aggregate traffic variables, like flow, density, and speed. Macroscopic models, which can be solved analytically or numerically, can capture the key elements of traffic flow, such as capacity, shock waves, and congestion (Garber & Hoel, 2002). Mesoscopic models represent traffic as a collection of discrete entities, like vehicles or platoons, moving along predefined paths following probabilistic or deterministic rules, and have an intermediate level of detail (Krogscheepers & Kacir, 2001). Mesoscopic models can be solved using simulation or optimisation techniques, and they can capture the stochastic and dynamic aspects of traffic, such as lane changing, gap acceptance, and car following (Leclercq et al., 2016)

The validity and accuracy of the model's output and representation are referred to as its realism (Barceló, 2017). The most realistic simulation models are microscopic models because they can include the effects of various factors like artificial intelligence, machine learning, communication, control, and different vehicle types. They can also capture the heterogeneity, variability, and complexity of traffic, including driver characteristics, vehicle types, road geometry, traffic control, and environmental conditions. Emergent and nonlinear traffic phenomena, like oscillations, stop-and-go waves, and ghost jams, can also be replicated using microscopic simulation models (Zheng et al., 2017).

Vanderschuren (2006) reported that there is an interaction between road users and planners concerning decision-making. Operational, tactical and strategic choices are made by road users. This information is illustrated in **Figure 2.7**

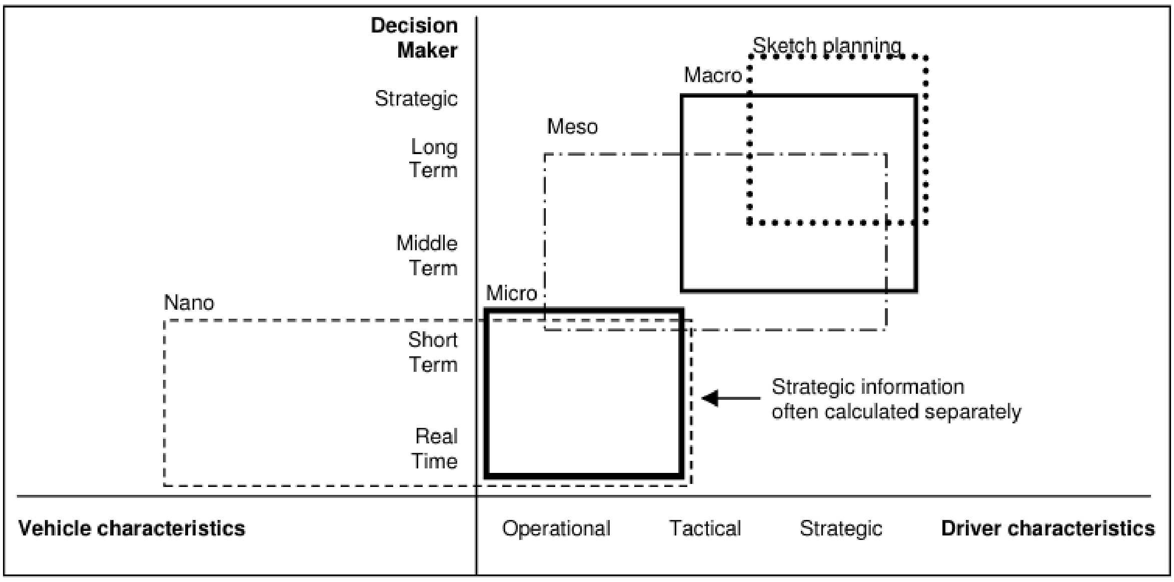


Figure 2.7: Relationships between model types and decision horizon

Source: Vanderschuren, 2006

Strategic choices are made before using the road network, tactical decisions are made whilst using the road and operational choices involve changing lanes, decelerating and accelerating. Planning models were developed by considering the planning horizon of decision makers (Short, middle, long and strategic) and road users. and advantages and disadvantages of the models are shown in **Table 2.1.**

Table 2.1: Advantages and Disadvantages of Simulation types

Model Simulation type	Advantage	Disadvantage
Nanoscopic	Highest level of detail and accuracy, Models vehicle components	Difficult to validate and execute. Expensive to compute the mathematical models,
Microscopic	Intricate interactions between road users and the infrastructure can investigated. Individual vehicle and driver behaviour can be assessed to the highest detail	Detailed input data required. Expensive to compute the mathematical models.
Mesoscopic	The hybrid model offers the benefit of using both microscopic and macroscopic simulation models.	Accuracy level lower than nanoscopic and microscopic model. Intricate calibration required. May not represent detailed information such as driver behaviour and vehicle components. Not suitable for microscopic analysis
Macroscopic	Appropriate for policy planning. Traffic flow trends can be modelled. Works well for large-scale simulations.	Individual driver behaviour is not modelled. Unable to produce intricate interactions between road users and the infrastructure. Inappropriate for small -scale analysis

Sources : Zhao & Chien,2004; Leclercq et al., 2016; Fellendorf & Vortisch, 2001; May 1990; Lighthill & Whitham, 1955, Daganzo, 1994

2.4.3 Previous Studies and Findings

Microscopic simulation has been used in many studies to address several aspects of traffic congestion (Chowdhury et al., 2000). According to these studies (Park & Qi, 2019; Zhao & Chien, 2004; Barceló, 2017; Zheng et al, 2017), simulation is (1) useful for planning infrastructure projects, assessing the effects of traffic management strategies, and forecasting traffic; (2) application and evaluation of microscopic simulation models and methods for various traffic systems, scenarios, units, policies, or interventions; (3) comparison and integration of microscopic simulation models and methods with other models and methods of traffic simulation, such as macroscopic and mesoscopic models; and (4) opportunities and challenges of microscopic simulation models and methods for future research.

The development and refinement of microscopic simulation models and techniques, such as the modelling and representation of traffic units, behaviour, and interactions; the validation and calibration of model parameters and variables; the automation and optimisation of model solution and output; and the integration and adaptation of new features and functions, like automated and connected vehicles, smart mobility, or big data, are the main areas of focus for the first category of studies (Toledo et al., 2003; Park and Qi, 2005; Al-Ghamdi, 2019).

Ahmed & Rakha (2000) examined the effects of various traffic demands, network configurations, and traffic management scenarios on traffic flow, speed, and safety. They applied and evaluated a microscopic traffic simulation model (FRESIM) for motorway traffic systems. Ahmed & Rakha (2000) tested and compared various traffic signal control, route guidance, and traffic assignment strategies on traffic performance, efficiency, and sustainability. The authors also applied and evaluated a microscopic traffic simulation model (MITSIMLab) for urban traffic systems. To simulate and evaluate various vehicle types, driver behaviour, and traffic control scenarios on traffic flow, speed, and emissions, Barceló et al. (2010) applied and evaluated a microscopic traffic simulation model (AIMSUN) for multimodal traffic systems.

The third category of studies compares and integrates microscopic simulation models and methods with other traffic simulation models and methods, like macroscopic and mesoscopic models. It also addresses the benefits and drawbacks of each model, as well as its applicability, trade-off, and complementarity for various traffic study contexts and goals. In their study, Fellendorf and Vortisch (2001) compared the level of detail, realism, flexibility, data requirements, computational cost, and applicability for various traffic analysis, evaluation, testing, or design tasks between macroscopic and mesoscopic models and microscopic simulation models (VISSIM).

The studies in the fourth category concentrate on the difficulties and prospects associated with microscopic simulation models and techniques for upcoming study and application. These include issues with data accessibility and quality, model complexity and realism, parameter estimation and selection, accuracy and consistency of the results, computation efficiency and scalability, and comprehension and communication of the results. The use of new data sources, such as connected and automated vehicles, smart mobility, or big data, and the application of new data methods, such as data fusion, data mining, or machine learning, are just a few of the opportunities and challenges that Park and Schneeberger (2003) identified for the collection and analysis of data using microscopic simulation models.

The difficulties and possibilities of using microscopic simulation models for model calibration and validation were highlighted by Balakrishna et al. (2007). These included the use of novel techniques for both calibration and validation, such as genetic algorithms, simulated annealing, or Bayesian inference, as well as sensitivity, error, or confidence interval analysis. Antoniou et al. (2010) identified the opportunities and challenges of using microscopic simulation models for model application and evaluation. These included the use of evaluation techniques like cost-benefit analysis, multi-criteria analysis, or stakeholder analysis, as well as the use of new application domains like traffic safety, emissions, or equity.

Consequently, prior research and discoveries regarding microscopic simulation in traffic studies have demonstrated the development and significance of microscopic simulation as a potent and adaptable method for traffic analysis and assessment, as well as some of the obstacles and constraints that must be addressed and surmounted. A critical evaluation of these studies can highlight the benefits and drawbacks, gaps and requirements, trends, and future directions of microscopic simulation in traffic studies. It can also offer helpful suggestions and insights for further study and application.

Furthermore, Chong et al. (2015) examined the degree of realism, flexibility, data requirements, computational cost, and suitability for various traffic estimation and control tasks by contrasting macroscopic models (METANET) and microscopic simulation models (SUMO). The researchers created a simulation-based optimisation method that uses genetic algorithms and field data to calibrate microscopic traffic models. They tested the precision and effectiveness of the calibrated microscopic model on a Singaporean motorway network. The calibration procedure was quick and reliable, and the microscopic model could replicate the patterns and features of traffic flow seen in the field data. Additionally, they discovered that, although the microscopic model was more realistic, flexible, and detailed than the macroscopic model, it also required more data and computational power and was less useful for long-term, large-scale traffic analysis.

Ciuffo and Punzo (2016) compared mesoscopic models (DYNASMART) and microscopic simulation models (VISSIM), discussing the applicability for various traffic assignment and evaluation tasks and their degree of detail, realism, flexibility, data requirements, and computational cost. They conducted a case study of a sizeable urban network in Rome, Italy, and examined the advantages and disadvantages of the two types of models. An assessment of the sensitivity and robustness of the models to various input parameters and scenarios was conducted and compared to the outcomes of the two models in terms of traffic flow, speed, travel time, and emissions. They discovered that, while the mesoscopic model was less suitable for medium-scale and medium-term traffic analysis, the microscopic model was more realistic, flexible, and detailed than the mesoscopic model. However, it also required more data and computational resources.

For traffic flow modelling and analysis tasks, Van Wageningen-Kessels et al. (2015) integrated microscopic simulation models with macroscopic models and Lighthill-Whitham-Richards (LWR) showed the advantages of combining the aggregate and detailed approaches. A technique was developed and implemented on a Dutch motorway network to connect the SUMO microscopic traffic simulation model with the LWR macroscopic traffic flow model. The accuracy and effectiveness of the integrated model were evaluated by contrasting the output with that of the standalone models in terms of traffic flow, speed, and density. They discovered that the integrated model could accurately represent both the diversity and variability of traffic, including lane changes, gap acceptance, and car following, as well as the primary characteristics of traffic flow, such as shock waves, congestion, and capacity. Furthermore, the integrated model also outperformed the microscopic model in terms of efficiency and scalability and outperformed the macroscopic model in terms of accuracy and realism.

Work et al. (2008) demonstrated the benefits of merging discrete and stochastic approaches for traffic state estimation and prediction tasks by integrating microscopic simulation models with mesoscopic models, such as Cell Transmission Model (CTM). They suggested utilising the Ensemble Kalman filter (EnKF) technique to integrate the data from the VISSIM microscopic traffic simulation model with the data from the CTM mesoscopic traffic flow model. They used a motorway network in Atlanta, Georgia, to test their approach. The accuracy and dependability of the integrated model with the standalone models' results in terms of traffic flow, speed, and density were assessed. The integrated model could represent both the aggregate and simplified characteristics of traffic, like flow, density, and speed, as well as the stochastic and dynamic aspects, like lane changing, gap acceptance, and car following. Compared to the microscopic and mesoscopic models, the integrated model was more detailed, realistic, accurate, and dependable.

The benefits and drawbacks of using microscopic simulation models for traffic network modelling and optimisation were highlighted by Zhou & Mahmassani (2007). These included the use of novel network models, such as dynamic network loading, dynamic network equilibrium, or dynamic network control, and novel optimisation techniques, like dynamic programming, genetic algorithms, or bi-level programming. Using the DYNASMART mesoscopic traffic simulation model, a dynamic traffic assignment model for large-scale evacuation networks was created and implemented on a fictitious network in Chicago, Illinois.

The effectiveness of the evacuation network in terms of travel time, delay, and clearance time was evaluated. Tests and comparisons of various evacuation strategies were done, such as pre-defined routes, real-time information, or optimal control. Zhou & Mahmassani (2007) discovered that the dynamic traffic assignment model could simulate the behaviour of evacuees in terms of route choice and traffic flow, and it could also optimise evacuation plans by applying various optimisation techniques. Additionally, they discovered that the dynamic traffic assignment model outperformed the microscopic simulation model in terms of efficiency and scalability and outperformed the macroscopic model in terms of flexibility and realism.

The challenges and opportunities of using microscopic simulation models for traffic signal control and transit signal priority were noted by Park and Schneeberger (2003), the authors included the use of novel models for signal control, such as adaptive, coordinated, or actuated signal control, and for signal priority, such as conditional, unconditional, or queue jump. The VISSIM simulation model was used to develop a method for calibrating and validating a microscopic traffic simulation model, which they then implemented in a coordinated actuated signal system located in Fairfax County, Virginia. The precision and coherence of the model outputs were assessed after calibrating and validating the model's variables and parameters using field data and optimisation methods.

2.5 Research Gap Identification

Identifying the research gaps in microscopic simulation for traffic studies was based on previous studies. The modelling of automated driving in microscopic traffic simulations lacks a common framework and terminology, which makes it challenging to compare and assess the findings of various studies and models. The vehicle automation level, penetration rate, communication mode, control mode, and interaction mode are factors that were suggested by Chong et al. (2015) when modelling automated driving. However, these factors are not commonly accepted or standardised in the literature.

Park and Schneeberger (2003) discovered that the calibration and validation procedure was quick and reliable and that the microscopic traffic simulation model could replicate the features and patterns of traffic flow and signal control seen in the field data. Comparing macroscopic to mesoscopic models, they also discovered that the microscopic traffic simulation model was more realistic, flexible, and detailed, however, it also required more data and computational resources and was less suitable for long-term and large-scale traffic analysis. Furthermore, the calibration and validation of microscopic traffic simulation models lack empirical data and validation techniques, particularly for novel and emerging traffic phenomena like big data, connected and automated vehicles, or smart mobility. Field data and genetic algorithms were used by Liu et al. (2011) and Park and Schneeberger (2003) to calibrate the driver behaviour parameters of microscopic simulation models, however, the methods for calibration and validation are frequently ad hoc or subjective, and the availability and quality of such data are limited or uncertain.

Jobanputra & Vanderschuren (2012) stated that the transportation industry has not established a universal approach for calibrating microsimulation models. This is because it is a complex process that involves numerous parameters specific to the scope and study area. The authors focused on using the Paramics modelling tool to assess how the model of an arterial road in Cape Town can be calibrated and simulated. The authors found that it is essential to properly calibrate models to ensure that accurate data represent real-time traffic conditions. There is no standardised method of calibrating and validating data, and it is difficult to compare results from various studies due to how models are calibrated.

Furthermore, the performance, effectiveness, sustainability, safety, and units of various traffic systems, scenarios, units, policies, or interventions using microscopic traffic simulation models are not well-evaluated, nor are systematic and thorough evaluation criteria and methods available. The effects of various traffic scenarios and interventions on traffic flow, speed, travel time, and emissions were assessed by Yang & Koutsopoulos (1996) and Barceló et al. (2010) using a variety of indicators and measures. However, the choice and weighting of these indicators and measures are frequently arbitrary or inconsistent, and the trade-offs and synergies among them are often disregarded.

Moreover, there is a lack of coordination and integration between microscopic traffic simulation models and other traffic simulation models, like mesoscopic and macroscopic models, as well as other traffic analysis tools and techniques, like surveys, field experiments, and analytical models. Although Ben-Akiva et al. (2004) integrated microscopic simulation models with analytical models, Knoop et al. (2008), Zheng et al. (2011) and Ben-Akiva et al. (2004) integrated microscopic simulation models with macroscopic and mesoscopic models. However, the benefits and limitations of each model and method are frequently unclear or unknown, and the integration and coordination of various models and methods are frequently difficult or incomplete.

These research gaps point to areas that should be pursued in future studies and practice, as well as the need for and potential for further development and improvement of microscopic simulation in traffic studies. Based on the findings from Jobanputra & Vanderschuren (2012), this study modelled the N2 highway, and the data collected was calibrated and validated to attain real-world traffic conditions in PTV Vissim.

2.6 Study Area Introduction

This section provides a general overview of Cape Town, setting the context for the study. It outlines the city's significance as a major urban centre in South Africa, introduces traffic congestion issues, and highlights the importance of the selected study area in the study.

2.6.1 Geographic and Demographical Overview of Cape Town

Cape Town topography and weather conditions

Cape Town is located on the southwestern coast of South Africa and has the most diverse geographical landscapes (mountains, oceans, endemic vegetation, built infrastructure and attractive beaches) in the country depicted in **Figure 2.8**. The Table Mountain range consists of Lion’s Head, Devil’s Peak and Signal Hill is considered a protected area and has not been developed because of the steep topography. The low-altitude areas have developed extending between the mountain and the bay and open spaces serve as conservation and recreational areas. (Goodness & Anderson, 2013).

Figure 2.8: Geographical landscape of Cape Town

Source: Kautsky/Azote, 2013

Mucina and Rutherford (2006) highlighted that the Cape Town region has wet winters and dry, hot summers. The average rainfall varied between 13.92 mm (in January and February) and 88.99 mm (in August) in 2023. The lowest average temperatures were 11.48 °C and 11.97 °C in July and August respectively and the highest temperature was 20.35 °C in January 2023 (Africadatahub, 2024). This climate enables the most diverse fauna and flora to thrive (Goodness & Anderson, 2013).

Cape Town Demographics

The City of Cape Town (CCT) (2023) reported that the population was recorded as 4.68 million in 2021. Some 70% of the population is between 15 and 64 years old, which falls within the working age as indicated in **Table 2.2**. The report suggests that since most of the households fall under low and low-medium-income groups, individuals depend on public transportation to travel to work.

Table .2.2: Population Profile of Cape Town based on Age, Education and Income

TOTAL POPULATION (2021)	4 678 900	
POPULATION BY INCOME (MONTHLY HOUSEHOLD INCOME, 2019/2020)[5]	R0 – R1 500	12%
	R1 501- R 3 500	13%
	R3 501 – R10 000	33%
	R10 001 – R15 000	10%
	R15 001 – R22 000	8%
	>R22 000	24%
POPULATION BY AGE (2021)[6]	0 - 14	24%
	15 - 64	69%
	65+	7%
POPULATION BY EDUCATION (2020, ADULT EDUCATION AGED 20 YEARS AND OLDER)[7]	No schooling	0,2%
	Some primary	5,0%
	Completed primary	2,9%
	Some secondary	32,7%
	Grade 12	36,7%
	Higher	19,8%
	Other	1,1%
	Unknown	1,6%

Source: CCT Research Branch, Policy and Strategy Department, 2023

The City of Cape Town (CCT, 2023) underscored that vehicle ownership in the city has increased gradually as shown in **Table 2.3**, with a maximum of 230 vehicles per 1 000 people in 2018. Vehicle ownership decreased in 2021, due to the economic impacts of the COVID-19 pandemic.

Table 2.3: Cape Town Car Ownership Information

	2003	2013	2018	2021
Private vehicles	570 000	853 646	995 971	999 773
Vehicles per 1 000 people*	178	220	230	214

Source: Stats SA, 2021

2.6.2 Transport Infrastructure in Cape Town

Overview of the Road Network

The Comprehensive Integrated Transport Plan (CITP) drafted by the CCT (2013) detailed that the transport network consists of the road and rail network. The road network caters to pedestrians, cyclists, private vehicles, public transport and freight. The road network is illustrated in **Figure 2.9.** According to the CITP, the Cape Town Road network has a total length of 9 836 km with Class 1, 2 and 3 roads adding up to 1 804 km. Class 4 and 5 roads add up to 81% of the network length (8032 km). The N2 Road connects the Airport to the CBD. **Tables 2.4** and **2.5** show the pavement surfacing types by distance and percentage for the city and the road class with bituminous surface material respectively. **Table 2.4** shows that 95.5% of the road is made of bitumen.

Table 2.4: Surfacing type of the Cape Town roads

Surface type	Distance (km)	Percentage of total
Bituminous	9 392	95.5%
Block paving	107	1.1%
Concrete	123	1.3%
Gravel	214	2.2%
TOTAL	9 836	100%

Source: CCT, 2013

Table 2.5: Length of road classes with bitumen surfacing

Functional Class	Distance (km)	Percentage of total
Freeway (Class 1)	133	1.4%
Expressway (Class 1)	213	2.3%
Primary Arterial (Class 2)	553	5.9%
Secondary Arterial (Class 3)	983	10.5%
Tertiary Roads (Class 4)	1 443	15.4%
Minor Roads (Class 5)	6 067	64.6%
Private Roads	Not available	Not available
Total	9 392	100%

Source: CCT, 2013

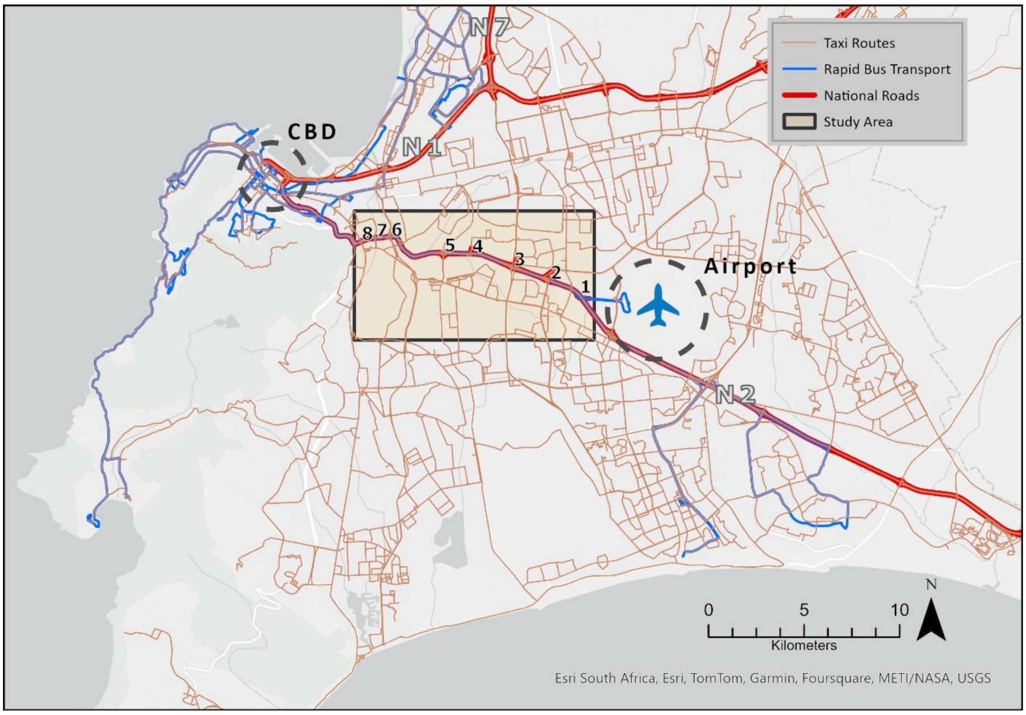


Figure 2.9: City of Cape Town Transport Network and study area[1]

In 2007, the city started implementing an Integrated Rapid Transit (IRT) system to enhance public transport and encourage intermodality. MyCiTi bus services were first introduced in 2010 during the FIFA World Cup. The route has extended throughout the city and together with GABS and Sibanye Bus Service, over 325 000 passengers use the BRT system. Cape Town has dedicated Bus-Minibus Taxi (MBT) lanes along the N2 road to the CBD (CCT, 2013). Vanderschuren et al. (2021) highlighted that unscheduled MBTs assist the transport system by filling transit gaps or deserts, based on the transit deserts theory, which was first defined by Hulchanski (2010). Transit deserts are areas with no access to transport. Vanderschuren et al. (2021) stated that since the MBT system has fragmented management, the mode offers services to the population with no private cars. Transport and Urban Development Authority Cape Town (TDACT) (2018) highlighted that 12% of the morning peak trips are by MBTs.

An analysis was conducted based on the National Household Travel Survey (NHTS), 2020 for work trips. The pie chart in **Figure 2.10** shows the modal split of these trips. 58% of the

[1] The numbered intersections are as follows: 1-Airport On-Ramp, 2- Duinefontein Road, 3- Jakes Gerwel Drive, 4- Langa, 5- Jan Smuts Drive, 6- Raapensberg Road, 7-Black River Parkway, 8-Main Road

households take trips to work using private cars. This information indicates that 33% of commuters depend on public transport with 22% using MBT.

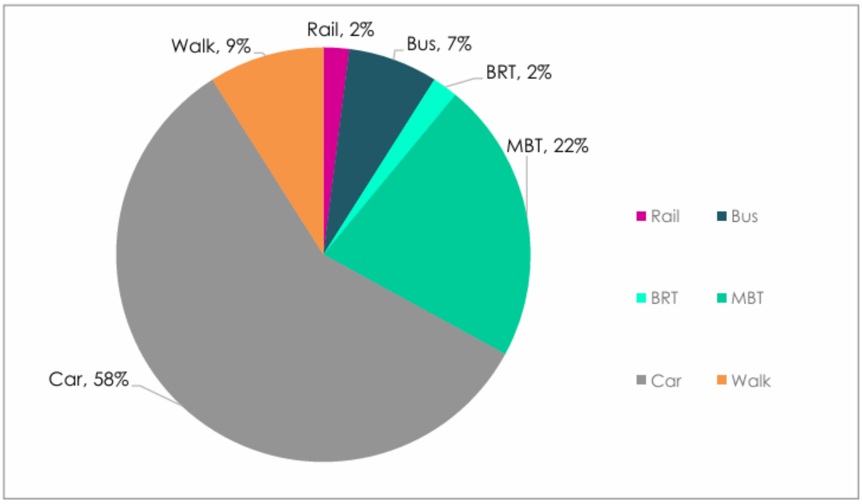


Figure 2.10: Modal Split for work trips

Source: NTHS, 2020

The modal split in the city has changed over time, as shown in **Table 2.6.** Rail ridership has decreased gradually from 18% to 2% over a 7-year period. The use of the GABS bus service fluctuated from 6% to 7% with the highest use in 2018. MyCiTi ridership remained constant while the number of private cars increased from 53% to 58% in 2020. CCT (2023) highlighted that road public transport use has increased from 20% in 2013 to 31% in 2020, since commuters have shifted from rail to road. Another contributing factor to the increase in private car ridership is the use of e-hailing services which is a private car-hiring transport service used in Cape Town.

Table 2.6: Modal split of work trips in the City of Cape Town over the years

Mode	**2013** (EMME model)	**2018** (Cordon counts, rail ticket sales)	**2020** (NHTS 2020)	**2020** (Vehicle population for MBT and private vehicles, ticket sales for BRT and rail)
Rail	18%	13%	3%	**2%**
Bus (GABS)	6%	11%	9%	**7%**
BRT (MyCiTi)	2%	2%	2%	**2%**
MBT	12%	21%	26%	**22%**
Private car	53%	51%	56%	**58%**
Walk	9%	2%	4%	**9%**
Cycle	n/a	n/a	n/a	Tbc

Sources: NHTS, 2020; CCT CITP, 2017

2.6.3 Traffic Congestion: Current Issues and Challenges

Identifying Congestion Hotspots

The Google Maps Traffic Layer (2024) was used to assess congestion hotspots in Cape Town**.** **Figure 2.11** shows the typical traffic during Tuesday's AM peak periods.

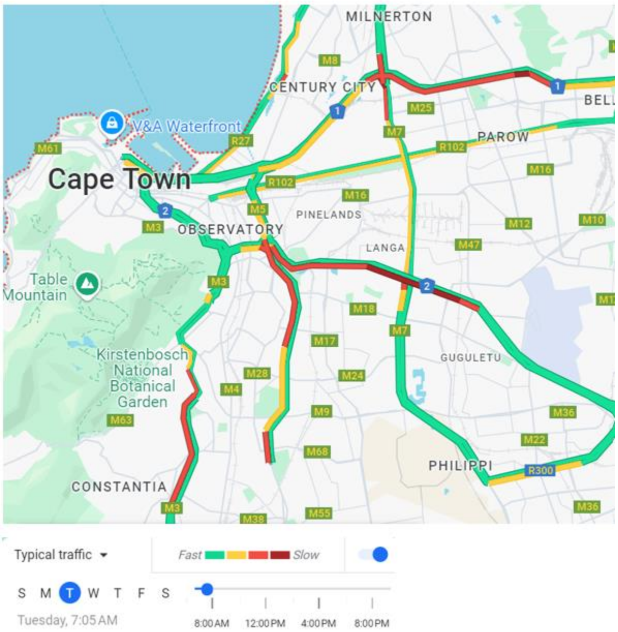


Figure 2.11: Congestion Hotspots for the weekday AM Peak period

Source: Google Maps Traffic Layer, 2024

The traffic data shows that the most congested roads are as follows:

1. M3 highway in proximity to Kirstenbosch National Botanical Garden
2. N1 highway heading into the CBD
3. N2 corridor heading to the CBD from the Cape Town International Airport.

2.6.4 Study Area

The field analysis was done on a section of the N2 National Road. Out of the 183 km of Class 1 National Road in Cape Town (CCT, 2023), a 9.8 km road section, which runs from the Cape Town International Airport on-ramp westbound to the Main Road off-ramp was selected as the study area, as shown in **Figure 2.12.** The land use pattern of the corridor is mixed, with buildings lining the roads that are institutional, commercial, and residential. The airport approach road is a two-lane road, which merges with the N2 road and consists of two lanes for all traffic and a bus/minibus taxi HOV lane. The freeway consists of segments with three lanes per direction and another with a third lane used as an HOV lane. The road section snapshot taken during the data collection process is displayed in **Figure 2.13.**

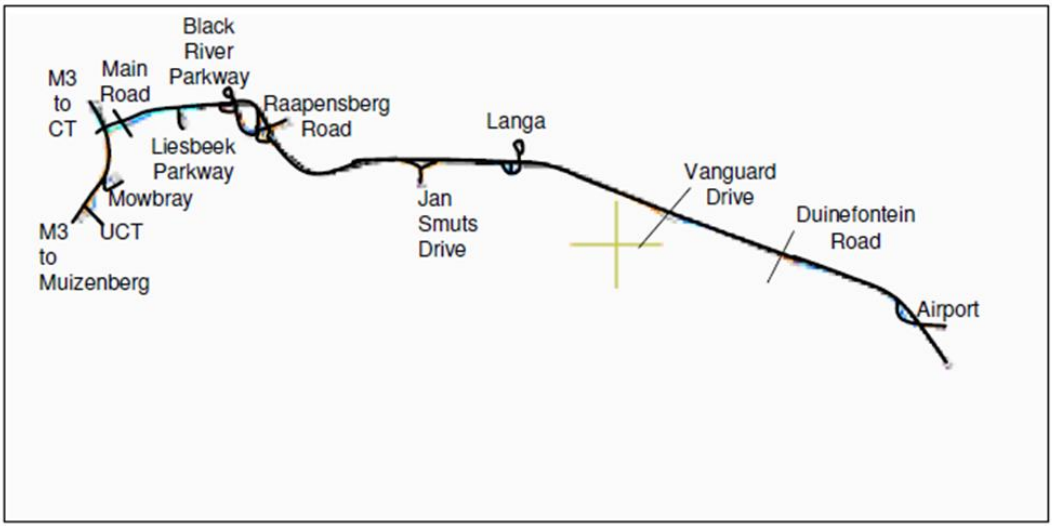


Figure 2.12: N2 Corridor in Cape Town, South Africa

Source: Vanderschuren, 2006

Figure 2.13: Data collection on the N2 National Road

2.7 Résumé

Traffic congestion is a significant issue in urban areas worldwide that negatively impact people's quality of life, the environment, and economy. Factors contributing to traffic congestion include population and vehicle fleet growth, migration to urban areas, insufficient road capacity, inadequate public transportation, and inefficient use of time and space spreading on roads. Traffic congestion has numerous negative effects, including raising the price of goods and transportation, wasting money, time, and fuel, lowering economic productivity and competitiveness, increasing greenhouse gas and air pollution emissions, and negatively impacting road safety, public health and the environment.

Microscopic simulation is a valuable tool for understanding traffic dynamics and planning, designing, and running transport systems. It allows for in-depth analysis of specific car movements, providing insights into intricate traffic dynamics. However, microscopic simulation faces challenges, such as data, model, calibration, validation, computation, and interpretation. Despite these challenges, microscopic simulation is a robust and adaptable method for studying traffic systems, offering comprehensive insights into performance, efficiency, safety, and sustainability. Comparing microscopic simulation with alternative models can be done using factors, such as the degree of detail, flexibility, data requirements, computational cost, and applicability. Nanoscopic simulation models offer the highest level of detail but require more data and computational power. Macroscopic models have the lowest computational cost but provide the least detail. Mesoscopic models provide an intermediate level of detail and computational cost. Previous research has demonstrated the benefits and drawbacks of microscopic simulation, and future research should focus on addressing the challenges and gaps in the field.

3. METHODOLOGY

This chapter provides information on how traffic data was collected and collated to compare the 2005 and 2023 records from the N2 national road segment, which was selected as the study period. The metrics collected from the field analysis include travel time, vehicle class, average speed, and traffic volume. This data is then used to develop a Vissim model. The method by which data was prepared for microsimulation analysis is also shown in this chapter. The organisation of the information in the proceeding chapters is represented in the flowchart in **Figure 3.1.** The detailed flowchart is illustrated in **Figure B1.1** in **Appendix B.**

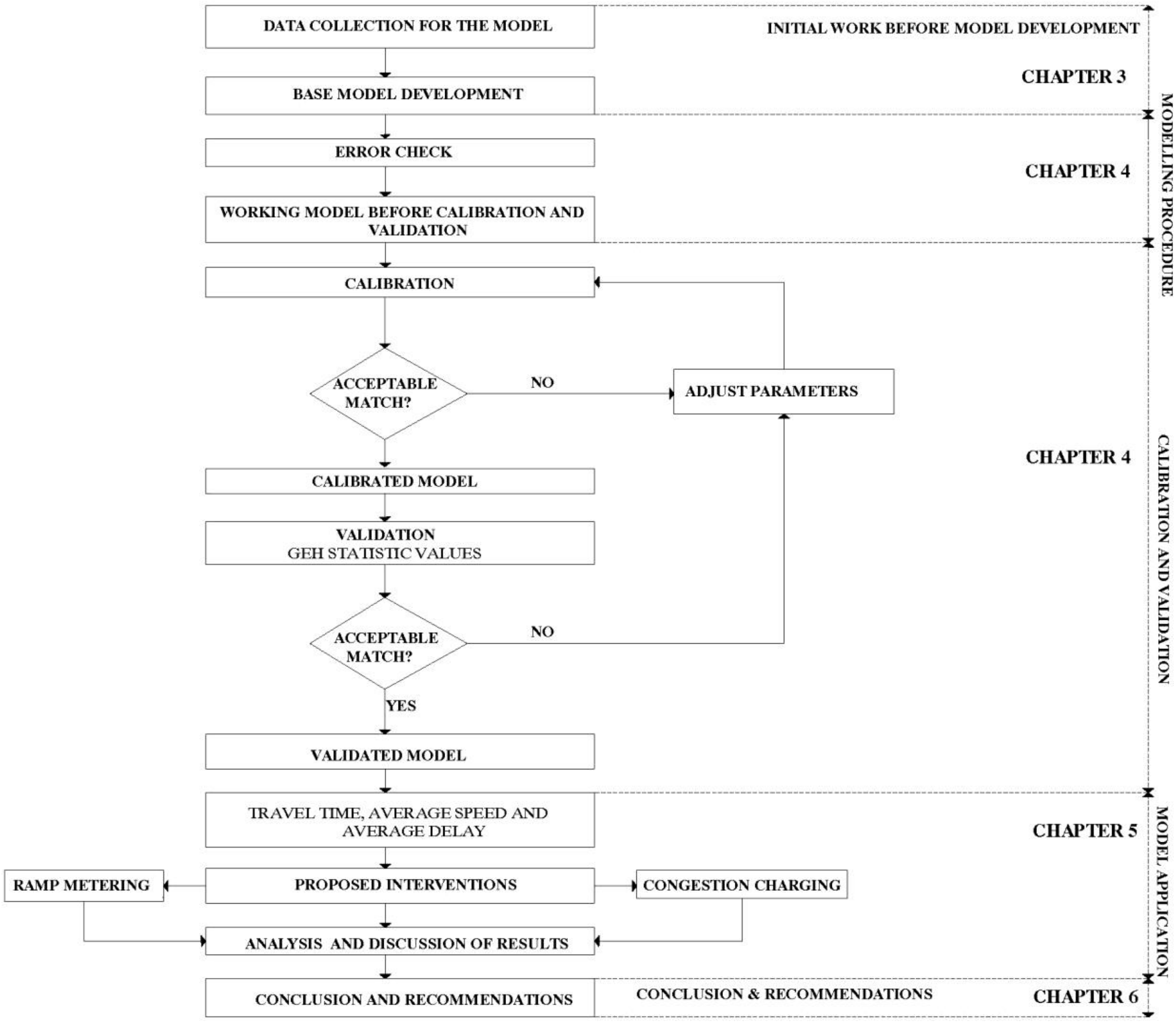


Figure 3.1: Flow chart for data collection, model development and application

3.1 Data collection for the model

The Vissim model in this study needs the following as the input:

1. Network area to be defined within the model interface.

2. Traffic Volumes to be defined at every start of the links.
3. Speed limits to be defined as part of the calibration process.
4. Driver behaviour parameters.
5. Measured travel times for calibration and validation. This study uses the 2005 data to build the 2023 model. The model produced by Vanderschuren (2006) was close enough to the measured travel times, hence, the 2023 model must yield similar measurements.

3.1.1 Vehicle Inputs

Vehicle classification, speed and traffic volume were collected from SANRAL loop data. Dual loops were used in this study. These detectors can measure vehicles, categorising them based on length and quantifying speed and traffic volume (Klein et al., 2006). **Figure 3.2** shows the typical information provided by SANRAL collected from 10 detection stations along the N2 road segment. The data is presented in seven columns: Province, Detector, Date, Time of the day (Hour), Vehicle Class, Traffic Volume and Speed. The raw data was sorted, and **Figure 3.3** shows the processed data based on time intervals.

Province	Detector	Date	Hour	Class	Volume	Speed
WC	DS WTRNX 144A IB	2023-03-27	0	3	86	55.36
WC	DS WTRNX 269B S	2023-03-27	0	1	21	81.16
WC	DS VDS 229 IB	2023-03-27	0	3	3	105.65
WC	DS VDS 116 OB	2023-03-27	0	3	18	102.57
WC	DS WTRNX 204 OB	2023-03-27	0	2	1	87.35
WC	DS VDS 130 IB	2023-03-27	0	3	25	106.79
WC	DS VDS 229 IB	2023-03-27	0	1	53	105.65
WC	DS VDS 123 OB	2023-03-27	0	1	73	100.43
WC	DS VDS 121 IB	2023-03-27	0	3	27	100.9
WC	VDS 203 IB	2023-03-27	0	1	360	88.36
WC	DS VDS 505 South	2023-03-27	0	3	6	86.33
WC	DS VDS 109 IB	2023-03-27	0	3	22	107.38
WC	DS VDS 224 IB	2023-03-27	0	2	3	106.03
WC	DS VDS 209 OB	2023-03-27	0	2	10	99.88
WC	DS VDS 504 North	2023-03-27	0	3	5	88.46
WC	DS VDS 217 OB	2023-03-27	0	3	3	97.6
WC	DS VDS 309 North	2023-03-27	0	2	9	111.39
WC	DS VDS 217 IB	2023-03-27	0	3	6	103.12
WC	DS VDS 913 IB	2023-03-27	0	1	56	85.52
WC	VDS 203 OB	2023-03-27	0	1	487	86.7
WC	DS VDS 107 IB	2023-03-27	0	3	24	101.72
WC	DS WTRNX 405A OB	2023-03-27	0	1	315	84.31
WC	VDS 705 SB	2023-03-27	0	2	1	99.04
WC	DS WTRNX 139 IB	2023-03-27	0	1	19	99.75
WC	DS VDS 222 OB	2023-03-27	0	3	6	105.58
WC	DS VDS 109 OB	2023-03-27	0	2	6	96.2

Figure 3.2: Raw loop data

Source: SANRAL, 2023

Province	Detector	Date	Hour	Class	Volume	Speed
WC	DS VDS 214A OB	2023-03-29	6	2	18	92.27
WC	DS VDS 214A OB	2023-03-29	6	1	668	92.27
WC	DS VDS 214A OB	2023-03-29	6	3	12	92.27
WC	DS VDS 214A OB	2023-03-29	7	3	31	88
WC	DS VDS 214A OB	2023-03-29	7	2	50	88
WC	DS VDS 214A OB	2023-03-29	7	1	1042	88
WC	DS VDS 214A OB	2023-03-29	8	2	71	90.2
WC	DS VDS 214A OB	2023-03-29	8	1	850	90.2
WC	DS VDS 214A OB	2023-03-29	8	3	26	90.2
WC	DS VDS 214A OB	2023-03-29	9	2	56	89.76
WC	DS VDS 214A OB	2023-03-29	9	3	28	89.76
WC	DS VDS 214A OB	2023-03-29	9	1	802	89.76
WC	DS VDS 214A OB	2023-03-29	10	1	51	89.54
WC	DS VDS 214A OB	2023-03-29	10	2	1	89.54
WC	DS VDS 214A OB	2023-03-29	10	3	1	89.54

Figure 3.3: Processed SANRAL Loop data

Data preparation for Vissim Microsimulation Modelling

The data provided by SANRAL categorised vehicles from Classes 1 to 3. The road agency classifies Class 1 vehicles as motorcycles and light motor vehicles with or without a trailer. Class 2 vehicles carry medium loads which are minibuses and light trucks. Class 3 vehicles consist of buses and heavy trucks, with three or more axles. The SANRAL vehicle classification was converted to Person Car Equivalent (PCE) to model the vehicles counted during data collection. The following PCE factors were assumed for the conversion based on these sources (Rashid & Ahsan, 2014; Bosman, 2019) as shown in **Table 3.1**.

Table 3.1: PCE Conversion Factors

Vehicle Class	Conversion Factor
Class 1	1
Class 2	1.6
Class 3	3

Sources: Rashid & Ahsan, 2014; Bosman, 2019

Turning Movements

Vehicle routes determine the direction a vehicle takes at intersections or junctions on the road in PTV Vissim. Each vehicle route starts at a routing decision point, located on a link. Multiple vehicle routes can originate from this routing decision and end on various links. Each vehicle is assigned a route upon reaching a routing decision if no route has been previously assigned. The number of vehicles that follow a specific vehicle route may be determined by estimating the fraction of all vehicle routes that originate from a routing choice. During a routing decision, cars are neither created nor eliminated from the network. **Figure 3.4** shows a typical vehicle route definition in Vissim.

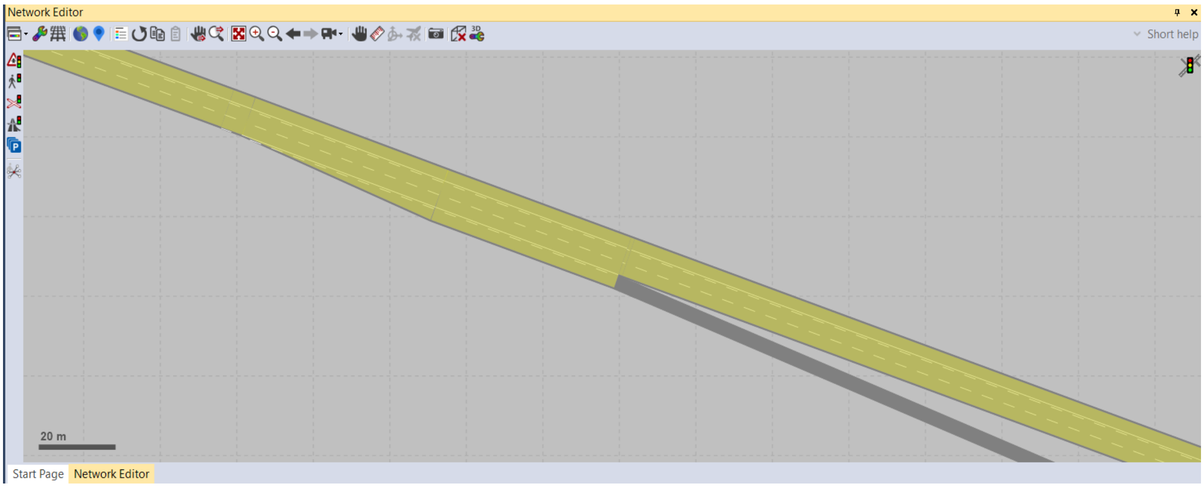


Figure 3.4: On-ramp Vehicle Route

3.1.2 Speed Limits

Within a Vissim network, it is possible to establish the preferred speed of cars by considering the curve of the road. Speed control in Vissim may be automated by either Vissim itself or by using network objects, such as ‘Reduced Speed Areas’ and ‘Desired Speed Decisions’ placed strategically within the Vissim network. While automated speed control in curves triggers the vehicle to respond to each point with a certain radius and initiates brakes promptly if needed, limited speed regions apply to the fully modelled area for which they are designated. **Figure 3.5** shows the typical definition of reduced speed areas, especially towards intersections.

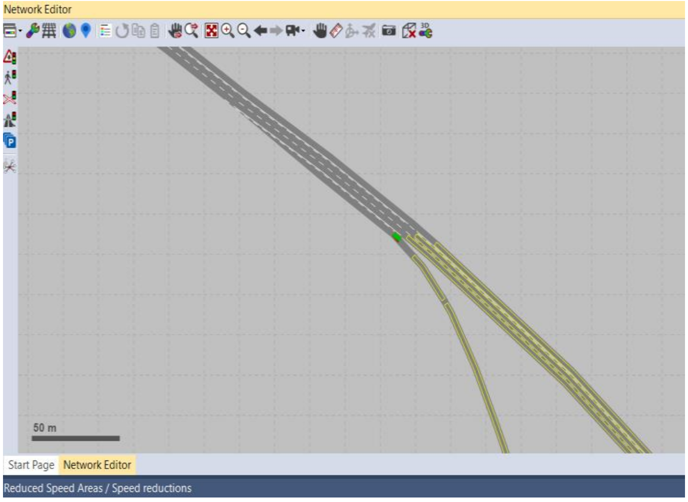


Figure 3.5: Reduced Speed Areas

The default setting in the Network parameters is to enable automatic speed decrease for cars when moving forward in curves. This option eliminates the need to manually modify the intended speed of vehicles following any alterations to the connection geometry.

3.1.3 Measurement of Travel Time

Travel time data was collected on the N2 road on 24 October 2023. **Figure 3.6** shows the locations where the enumerators started and stopped the stopwatch. The travel time between the fixed locations was recorded.

Figure 3.6: Map of nine selected locations[2]

[2] Data collection points are as follows: 1- Petrol Station, 2- Airport On-ramp, 3- First M10 Bridge, 4- First M7 Bridge, 5- Langa Bridge, 6- M17 Bridge, 7- M52 Bridge, 8- M5 Bridge, 9- Main Road Off-Ramp

A weekday was selected, because it represents a normal traffic day that is not influenced by school or public holidays. No major event influenced traffic flows significantly. The field team consisted of 14 members: 7 field enumerators and 7 drivers. The drivers were instructed to drive like average drivers abiding by the road rules and speed limits. This enabled driver behaviour to be controlled. Enumerators were tasked to observe the drivers by measuring the time it takes to travel from the Cape Town International Airport on-ramp to the Main Road off-ramp. Each pair (driver and enumerator) from the team started the survey at ten-minute intervals.

3.2 Base Model Development

Base model development involves several steps that are termed the calibration process. The calibration process is shown in **Table 3.2**. The primary aim is to develop a model simulation that resembles real-world traffic flows. This involves adjusting default parameters through an iterative process until an acceptable match is achieved.

Table 3.2: Procedure of the calibration process

Model	Action
Default Parameters	Conduct multiple runs using default parameter values to determine if they provide acceptable results.
Adjustment	Systematically adjust parameters, focusing first on those affecting capacity, followed by those affecting route choice.
Iteration and Comparison	Iteratively compare model outputs with observed data, adjusting parameters as necessary to reduce discrepancies.

The specific steps in the calibration process include:

- *Capacity Calibration*: Adjusting global parameters to match observed traffic flows and fine-tuning specific links.
- *Route Choice Calibration*: Modifying global route choice parameters, followed by local adjustments.
- *System Performance Calibration*: Comparing overall system performance, such as travel times and queue lengths, with observed data.

3.2.1 Calibration Targets

Setting calibration targets is crucial for evaluating the model's accuracy. These targets assist in reducing the amount of time and effort it takes to reduce error (FHWA, 2004). Typically, the following targets are included in a freeway microsimulation model:

1. Hourly Flows: Ensuring individual link flows are within 15% of observed values.
2. Travel Times: Achieving travel times within 15% of observed values.
3. Visual Audits: Conducting visual checks to confirm realistic representation of queues and traffic distribution (Vanderschuren, 2006).

This study makes use of the Wisconsin Department of Transport calibration and validation guidelines indicated in **Table 3.3**. This criterion can be used to calibrate freeways in PTV Vissim models.

Table 3.3: Calibration and Validation Criteria

Criteria and Measures	Calibration Acceptance Targets
Hourly Flows, Model Versus Observed	
Individual Link Flows	
Within 15%, for 700 veh/h < Flow < 2700 veh/h	> 85% of cases
Within 100 veh/h, for Flow < 700 veh/h	> 85% of cases
Within 400 veh/h, for Flow > 2700 veh/h	> 85% of cases
Sum of All Link Flows	Within 5% of sum of all link counts
GEH Statistic < 5 for Individual Link Flows*	> 85% of cases
GEH Statistic for Sum of All Link Flows	GEH < 4 for sum of all link counts
Travel Times, Model Versus Observed	
Journey Times, Network	
Within 15% (or 1 min, if higher)	> 85% of cases
Visual Audits	
Individual Link Speeds	
Visually Acceptable Speed-Flow Relationship	To analyst's satisfaction
Bottlenecks	
Visually Acceptable Queuing	To analyst's satisfaction

Source: FHWA, 2004

3.2.2 Model Parameters

To account for observed driving patterns in the study, parameters related to driver behaviour were modified. As a result, the model accurately represents the subtleties of human decision-making while driving. These are:

- Acceleration/deceleration rates,
- Lane-changing models, and
- Car-following models.

These parameters will be adjusted during the calibration and validation process.

3.2.3 Driver Behaviour Parameters

Oregon Department of Transportation (ODOT), (2016) provided Lane Change (LC) and Car Following (CF) parameters and stated that ten Wiedemann 99 parameters are used for Vissim calibration based on driver behaviour types. Default driver behaviour parameters were not altered, however, some of the CF and LC parameters were adjusted based on recommended values from ODOT (2016). The recommended values are represented in **Table C.1** and **Table C.2** in **Appendix C,** respectively. The Vissim model was simulated with default values and was adjusted based on whether the model satisfies the calibration criteria. The adjusted values in the Vissim are shown in **Appendix B** (**Figures B1.1 to B1.4).**

3.3 Running The Simulation and Analysing Interventions

The model is set to run with default parameters to assess whether the simulation runs without errors. The parameters are then adjusted during calibration and the results will be presented. After calibration, ramp metering and congestion charging are implemented in the base model to evaluate the changes.

3.3.1 Ramp Metering

Ramp Metering is implemented for three scenarios. It is applied to identified congestion hotspots causing instabilities in the freeway traffic flows. A ramp meter is applied to the Langa onramp as the first scenario. Two ramp meters are then applied to the Langa and Raapenberg on-ramps as a second scenario. Five ramp meters are then implemented on Duinefontein, Jakes Gerwel Drive, Langa, Jan Smuts and Raapenberg on-ramps as a third scenario.

3.3.2 Congestion Charging

Eliasson et al. (2017) stated that traffic volumes in Stockholm, Sweden reduced by 5% at peak periods in 2017. FHWA (2008) highlighted that traffic volumes decreased by 18% in Stockholm after implementing congestion. These values were used to assess the congestion charging scenarios in the Vissim model. The three scenarios investigated are 5%, 10% and 15% traffic volume reductions.

3.3.3 Key Performance Indicators

The Key Performance Indicators (KPIs) used in this study are the attributes that reflect the dynamic changes in traffic flows during morning peak times. The KPIs are simulated for each scenario and compared with the base scenario to ascertain the degree of change. These consist of the overall travel time, average travel time, total delay, and average delay for every vehicle in the network (Nalic, Pandurevic, Eichberger, Fellendorf, & Rogic, 2021). These KPIs show the degree of traffic congestion and the dependability of travel times. This study focuses on travel times, average delay, Level of Service (LOS), and average speed. Average delay is selected as the KPI for the implemented scenarios. Average delays are directly related to the Level of Services as detailed in the Highway Capacity Manual (2010). The LOS definitions are shown in **Table 3.3**. LOS A represents the best operating conditions with minor or no delays, while LOS F represents the worst conditions with serious delays. This LOS criteria were used for the base model, ramp metering and congestion charging interventions.

Table 3.3: LOS Criteria

Level Of Service (LOS)	Description	Average Delay (Signalized)	Average Delay (Unsignalized)
A	Excellent	≤10seconds	≤10seconds
B	Very Good	>10 and ≤20seconds	>10 and ≤15seconds
C	Good	>20 and ≤35seconds	>15 and ≤25seconds
D	Acceptable	>35 and ≤ 55seconds	>25 and ≤35seconds
E	Poor	> 55and ≤ 80seconds	>35 and ≤50seconds
F	Unacceptable	>80seconds	>50seconds

Sources: Transportation Research Board, 2010; Highway Capacity Manual, 2010

3.4 GEH STATISTICS

Model calibration and validation involve using GEH statistics, which measures the difference between observed and simulated traffic volumes, calculated using **Equation 1**. This is a critical parameter used in the calibration and validation process to compare modelled and observed traffic volumes. This parameter is used to show how traffic volumes compare (FHWA, 2004).

$$GEH = \sqrt{\frac{2(m-c)^2}{m+c}} \qquad \textbf{Equation 1}$$

Where:

m =output traffic volume from the model simulation

c =input traffic volume

Table 3.4 shows different categories of GEH values that are used in model validation. The GEH value must be less than 5 for an acceptable model (Federal Highway Administration, 2004).

Table 3.4: GEH Statistic Ranges

GEH Value	Interpretation
GEH < 5.0	Acceptable fit
5 ≤GEH≤10.0	Caution: possible model error or bad data
GEH>10.0	Unacceptable

Source: Federal Highway Administration, 2004

3.5 Résumé

This chapter detailed the methodology of the data collection process and data preparation for Vissim microsimulation. The data was collected from SANRAL loops and travel time was measured on the 9.8 km road section of the N2 national road. This 2023 data was compared to the 2005 data to assess the change in traffic flows in **Chapter 4.** Travel time, average speed, and average delay are the Key Performance Indicators that were selected for this study, and they were used to assess the level of traffic congestion and measure the performance of the traffic system on the road.

4. BASE MODEL DEVELOPMENT

This chapter outlines the development of the base model, calibration, and validation processes used to develop a reliable representation of the study area. The focus was adjusting model parameters for simulation outputs to align closely with observed traffic data. Before model development, this chapter also gives a measured comparative background of 2005 and 2023 travel time and speeds.

4.1.1 Comparative Analysis of Traffic Congestion Growth: 2005 vs 2023

This section compares the measured travel time and speeds.

Analysis of Travel Time

Figure 4.1 compares the measured travel times in 2005 and 2023 during the morning peak on the N2 highway from the airport on-ramp to the main road off-ramp. The travel time in 2005 is remarkably consistent and shorter during the morning peak period.

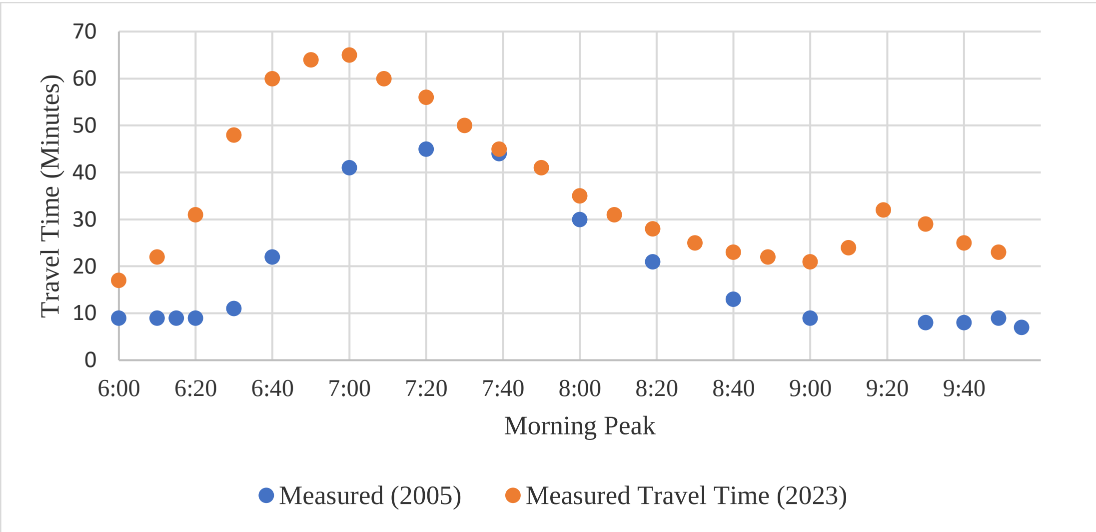


Figure 4.1: Comparison of measured travel time

In 2005, travel time increased starting at 06:40, when the 10-minute free-flow travel time increased to 20 minutes. At 07:00, the travel time increased to 40 minutes. Between 7:00 and 7:40, the travel time remained constant over 40 minutes in 2005. The travel time decreased from 07:40 to 09:40.

The data in 2023 presented more severe congestion. At 6:00, the travel time was already, marginally longer than the 10-minute free-flow travel time. At 6:20, the travel time was 30 minutes in 2023, compared to 10 minutes in 2005. At 6:40, the travel time in 2023 was approximately 60 minutes, compared to just over 20 minutes in 2005, a 40-minute increase. At 7:00, the travel time increase stagnates at 65 minutes. This is about 25 minutes more than the travel time, at the same time, in 2005. By 7:40, the travel time in 2005 and 2023 is identical and the decrease is similar, especially when the effect of the road incident is ignored. The base travel time in 2023 plateaued at approximately 20 minutes.

Travel times in 2005 and 2023 showed a decreasing trend after 7:40. By 8:00, travel times in 2005 decreased to 35 minutes, while in 2023, the reduction is slower, remaining around 55 minutes. Between 8:00 and 8:20, travel times in 2005 decreased steadily to 25 minutes, while in 2023, they only start to decline significantly after 8:20, falling to 45 minutes. By 9:00, travel times in 2005 had decreased to 20 minutes, nearly returning to free-flow conditions. However, 2023 did not approach free-flow conditions due to an incident that temporarily increased travel times to 30 minutes. By 9:40, travel times stabilised at 10 minutes, while in 2023, they stabilise around 20 minutes, indicating a higher base level of congestion compared to 2005.

In conclusion, the 2023 data highlights a much slower recovery from the morning peak, and the effects of an incident post-09:00 increased the travel times, making them noticeably worse than in 2005. Comparing the two years (2005 and 2023), the graph illustrates an increase in travel time. **Table 4.1** presents a comparative analysis of travel time between the two years. The measurements indicate that the overall travel time has seen a 51% increase.

Table 4.1 Travel Time Percentage Increase Calculation[3]

Time	Measured Travel time (Minutes) (2005)	Measured Travel time (Minutes) (2023)	Travel Time Difference	Percentage Increase
6:00	9	17	8	47%
6:10	9	22	13	59%
6:20	9	31	22	71%
6:30	11	48	37	77%
6:40	22	60	38	63%
6:50				
7:00	41	65	24	37%
7:10				
7:20	45	56	11	20%
7:30				
7:39	44	45	1	2%
7:50				
8:00	30	35	5	14%
8:10		31	31	
8:20	21	28	7	25%
8:30		25	25	
8:40	13	23	10	43%
8:50				
9:00	9	21	12	57%
9:10				
9:20				
9:30	8	29	21	72%
9:40	8	25	17	68%
9:50	9	23	14	61%
	Total	584	296	
	Overall percentage change	51%		

Analysis of Average Speeds

Figure 4.2 compares the average speed measured both in 2005 and 2023. These measured speeds give insights into what has changed and the current reality of traffic patterns.

Speed in 2005

[3] **Table 4.1** has empty cells due to missing data. Nevertheless, the existing data was sufficient to draw definitive conclusions regarding the increase in travel time.

The speed starts high at around 80 km/h from 6:00 to 6:20 AM. There is a sharp decrease in speed after 6:20 AM, reaching levels as low as 10 km/h around 7:00 to 7:40 AM. The speed gradually increases after 7:40 AM, with some fluctuations, and then peaking at 80 km/h by 9:20 AM.

Speed in 2023

The speed starts at around 40 km/h at 6:00 AM and decreases gradually to about 10-20 km/h from 6:20 to 7:00 AM. The speed remains relatively low and stabilises between 10 and 20 km/h from 7:00 to 8:40 AM. There is a slight increase in speed after 8:40 AM, reaching around 30km/h by 9:40 AM.

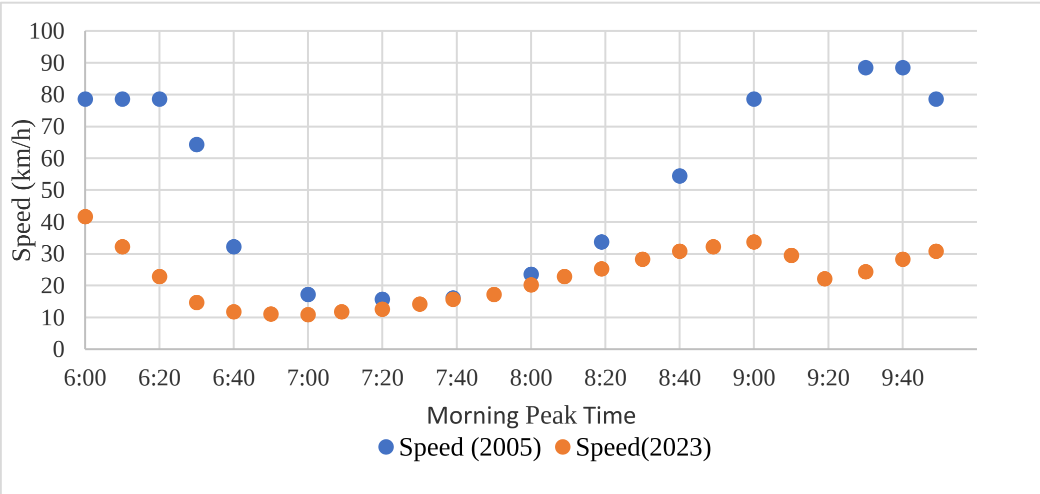


Figure 4.2: Comparison of 2005 and 2023 average speed based on field measurements.

Comparative Analysis

During the early morning (6:00 to 6:20 AM), the speed was at its maximum around 80 km/h making it the free-flow speed in 2005. Compared to 2023 the free flow speed is around 40 km/h. During morning peak (6:20 to 7:40 AM); both years show a decline in speed, but the decline is more pronounced in 2023, reaching very low speeds (around 10 km/h). In 2023, the speed decreases more gradually and stays relatively low but stable (around 10-20 km/h). In 2005 post-peak, there is a noticeable recovery in speed with fluctuations, eventually reaching high speeds (80 km/h) again. In 2023, the speed shows a gradual and modest increase, peaking at around 30 km/h by 9:40 AM.

4.1.2 Model Configuration

As mentioned in **Section 3.2.1**, The Vissim model was developed by matching the road geometry and physical features using Google Maps and field observations. Average delay, average speeds, and travel times were measured over four hours at five-minute (300-seconds) intervals between 6:00 AM and 10:00 AM. The model interface and the parameters used during model development are depicted in **Figures 4.3** to **4.5.**

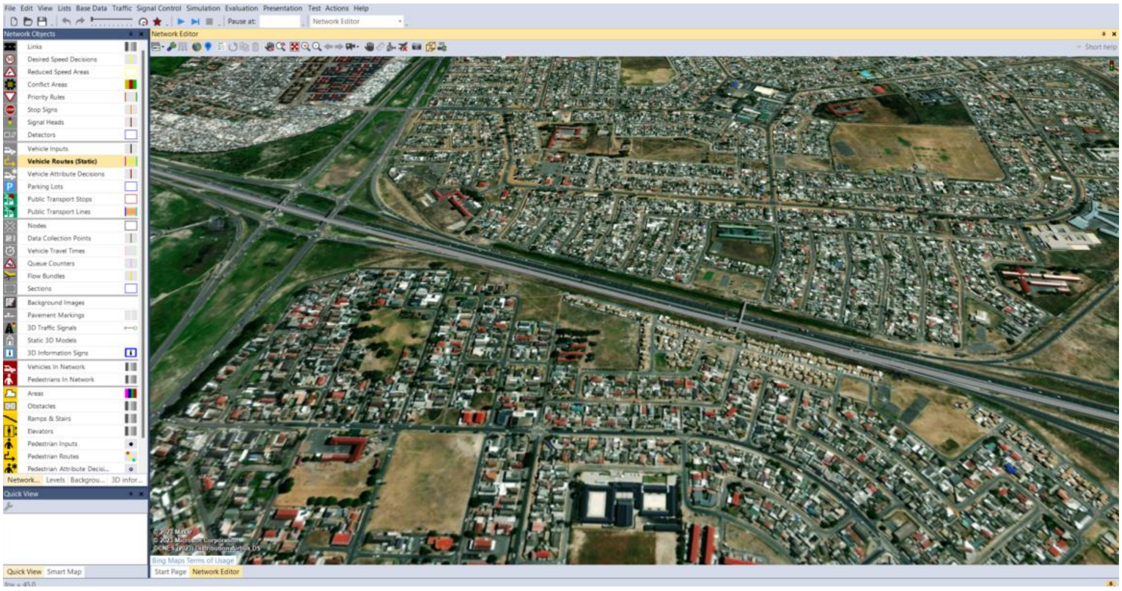


Figure 4.3: General interface layout of the model with the background maps and network objects

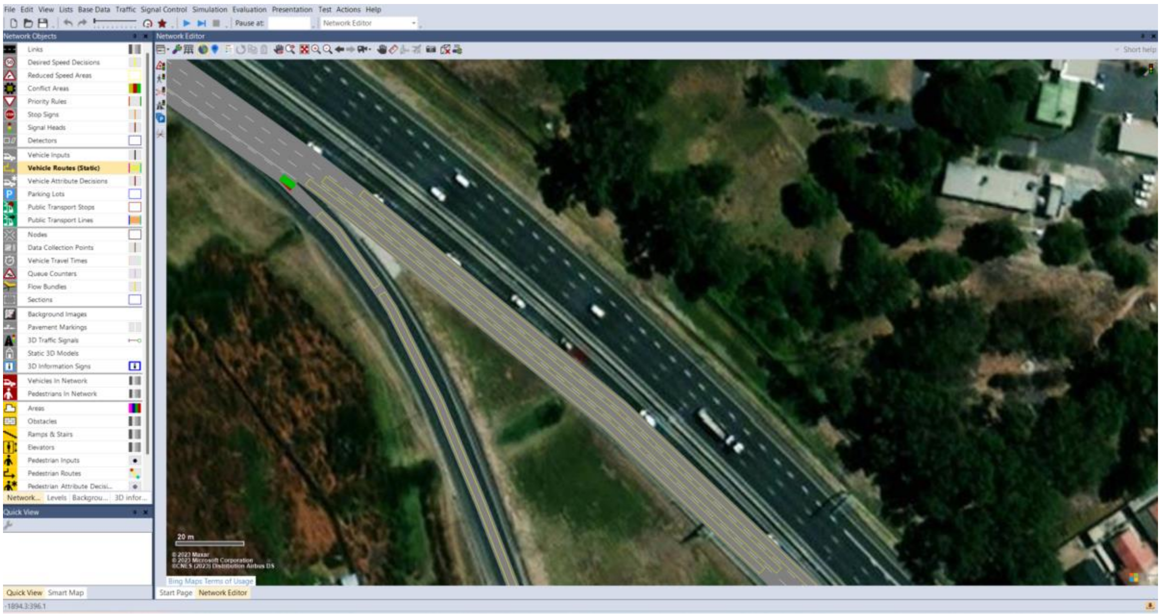


Figure 4.4: Lane insertion of the N2 road section

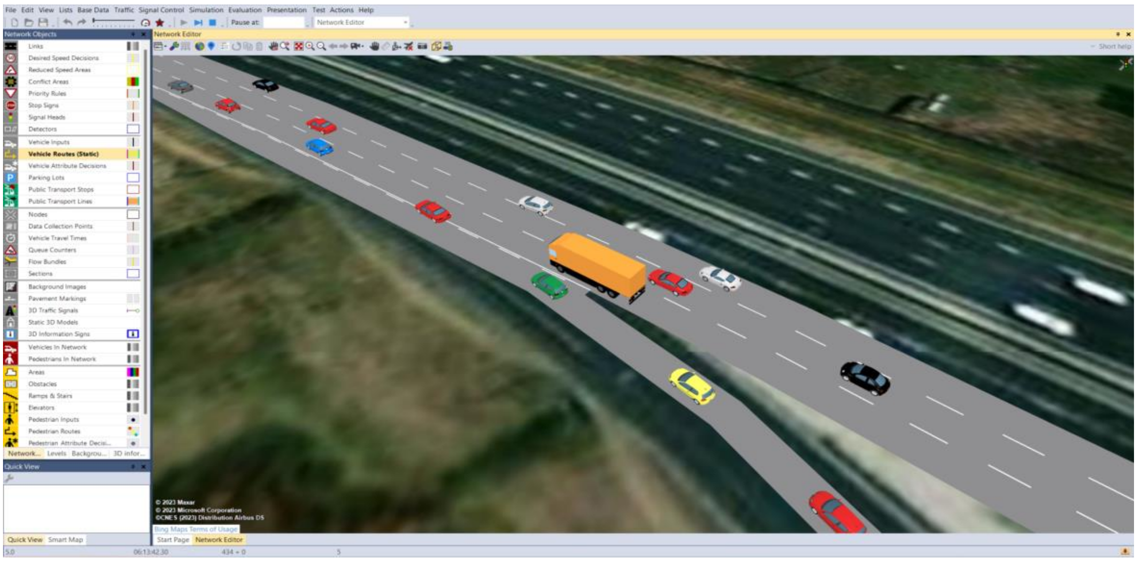


Figure 4.5: Vehicle type based on SANRAL classification system

Table 4.1 shows the objects used to set up the network in the PTV Vissim.

Table 4.2: PTV Network objects

Network objects	Representation	Function
	Links	Connecting two points in a roadway
	Desired speed decision	Used to set the speed limit on a link
	Conflict areas	Point of intersection of links in roadway
	Stop signs	Road sign for stopping
	Detectors	To identify oncoming vehicles passing through
	Vehicle inputs	For inserting input volumes
	Vehicle routes	To define vehicle routes
	Vehicle travel times	Calculation of travel time
	Pavement markings	Assisting vehicles on the direction to follow

Source: Adopted from PTV Vissim, 2023

4.2 Model Parameters

Before adjusting these parameters: desired speed, acceleration, deceleration, headways and lane-changing behaviour; the model was set to run with default values described in **Section 3.3**. **Table 4.4** shows the values that were adopted for the base model. Simulated travel times were compared with observed data, and parameters were iteratively adjusted to minimise errors.

Table 4.3: Parameters and Values for the Base Model

Simulation Parameter	Value
Simulation Period	4 Hours or 14400 Seconds
Time Period	06:00:00 - 10:00:00
Simulation Resolution	10 Time step (s) per simulation second
Random Seed	17 , 22 , 29 , 37 , 42
Driver Behaviour Model	Wiedemann 99
Desired Speeds	15 to 120 km/h
Headway	0.5 seconds
Maximum Acceleration	3.0 m/s^2
Desired Acceleration	2.0 m/s^2
Maximum Deceleration	4.5 m/s^2
Desired Deceleration	2.5 m/s^2
Curve Speed	50-80 km/h (depending on specific curve characteristics)

The final parameters used for the calibration of Lane Change (LC) and Car Following (CF) models are indicated in **Tables 4.5 and 4.6**.

Table 4.4: Car Following Calibration Parameters

Wiedemann 99 Model Parameters	Default	Basic Freeway	Ramps/Loops	Freeway Weave	Freeway Major Merge	Freeway Merge Dropped Lanes
CC0 (Standstill Distance) (m)	1.50	1.50	1.50	1.50	1.50	1.50
CC1 (Headway Time) (s)	0.90	0.90	0.90	0.90	0.90	0.90
CC2 ('Following' Variation) (m)	4.00	4.00	4.00	4.00	4.00	4.00
CC3 (Threshold for Entering Following) (m/s^2)	-8.00	-8.00	-8.00	-8.00	-8.00	-8.00
CC4 (Negative 'Following' Threshold) (m/s^2)	-0.35	-0.35	-0.35	-0.35	-0.35	-0.35
CC5 (Positive 'Following' Threshold) (m/s^2)	0.35	0.35	0.35	0.35	0.35	0.35
CC6 (Speed Dependency of Oscillation) (m)	3.49	3.49	3.49	3.49	3.49	3.49
CC7 (Oscillation Acceleration) (m/s^2)	0.82	0.82	0.82	0.82	0.82	0.82
CC8 (Standstill Acceleration) (m/s^2)	3.50	3.50	3.50	3.50	3.50	3.50
CC9 (Acceleration at 50 mph) (m/s^2)	1.50	1.50	1.50	1.50	1.50	1.50

Table 4.5: Lane Change Calibration Parameters

Lane Change Parameters	Default	Basic Freeway	Ramps/Loops	Freeway Weave	Freeway Major Merge	Freeway Merge Dropped Lanes
Max. Deceleration (own) (m/s^2)	-13.12	-13.12	-13.12	-13.12	-13.12	-13.12
Max. Deceleration (trailing) (m/s^2)	-9.84	-9.84	-9.84	-20	-20	-9.84
-1 m/s^2 per Dist. (own) (m)	60.96	60.96	60.96	60.96	60.96	60.96
-1 m/s^2 per Dist. (trailing) (m)	60.96	60.96	60.96	60.96	60.96	60.96
Accepted Deceleration (own) (m/s^2)	-3.28	-3.28	-3.28	-3.28	-3.28	-3.28
Accepted Deceleration (trailing) (m/s^2)	-1.64	-1.64	-1.64	-1.64	-1.64	-1.64
Wait Time Before Diffusion (s)	18.29	18.29	18.29	18.29	18.29	18.29
Min. Headway (front / rear) (s)	0.5	0.5	0.5	0.5	0.5	0.5
To Slower Lane - Collision Time Above (s)	0	0	0	0	0	0
Safety Distance Reduction Factor	0.6	0.4	0.6	0.2	0.15	0.15
Max. Deceleration for Cooperative Braking (m/s^2)	-9.84	-9.84	-9.84	-9.84	-9.84	-9.84
Overtake Reduced Speed Areas	Off	Off	Off	Off	Off	Off
Advanced Merging	On	On	On	On	On	On
Consider subsequent static routing decisions	On	On	On	On	On	On
Cooperative Lane Change	Off	Off	Off	On	On	Off
Lateral Correction of Rear-end Position	Off	Off	Off	Off	Off	Off

Speed decisions

Modelling of vehicle speed was required for the Vissim program. Free flow speed decisions and reduced speed areas shown in **Tables 4.7** and **4.8** were used in the model when vehicles passed through speed points. This simulates areas where the free flow speed changes, because of speed limit signage. Reduced speed zones are usually used for turning movements**. Figure 4.6** shows the speed profile of the N2 highway.

Table 4.6: Free flow speed limits

Class	Posted Speed Limit (km/h)	Minimum Speed (km/h)	Maximum Speed (km/h)
Class 1: Light Motor Vehicles	120	100	140
Class 2: Medium Vehicles	100	80	120
Class 3: Heavy Vehicles	80	60	100

Table 4.7: Reduced speed for right and left turn movements

Location	Vehicle Types	Minimum Speed (km/h)	Maximum Speed (km/h)
Right Turns	Class 1, 2, 3	15	20
Left Turns	Class 1, 2, 3	20	25

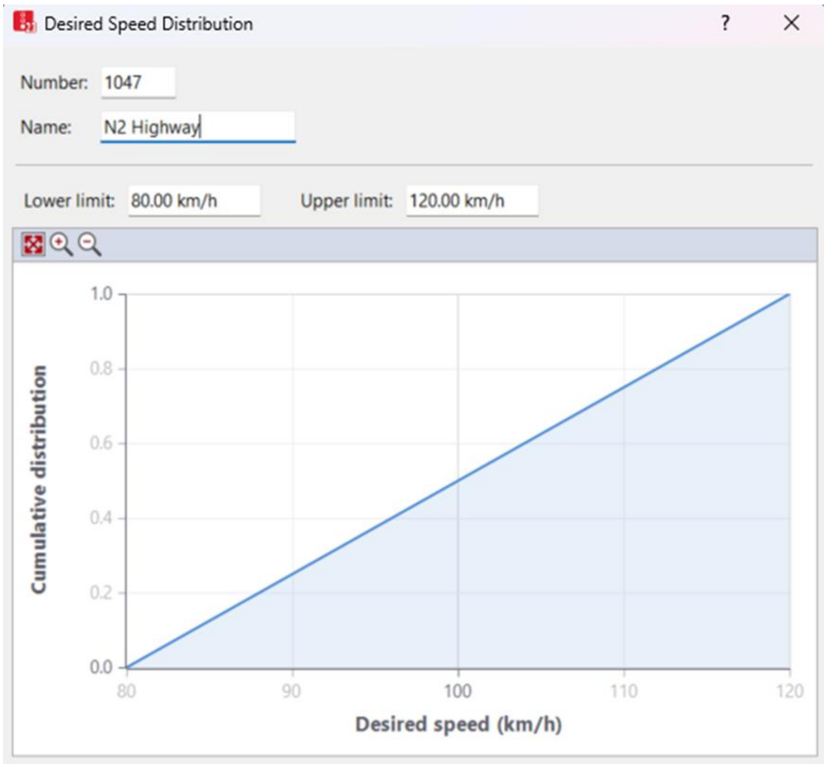


Figure 4.6: Desired speed profile for the N2 National Road

4.3 Calibration of Travel Times

The model calibration and validation make use of 2005 data. The 2023 model results are compared with the 2005 model results which were validated by the 2005 actual measured travel times.

4.4 Calibration and Validation Results

The validation of the model is based on analysing the statistical models and the visual audits. Travel time, average speed, and traffic volume are inputs added to the model to simulate field conditions. The comparison of the results between the model and the data collected from the field is reported. **Figure 4.7** shows a snippet of the model after calibration. Visual audits are conducted to identify simulation errors and to analyse whether the model replicates real-world traffic flows.

Figure 4.7: Visual Audits

4.4.1 Analysis of Paramics and Vissim Travel Time Simulations

The initial stage of model calibration involved loading the 2005 data into the Vissim model to replicate the travel times generated by the Paramics model. **Figure 4.8** displays the outcomes obtained from the two models.

These simulated travel time findings exhibit a strong correlation despite their modest discrepancies. The percentage variance between the two graphs was computed as 4.17% (or equivalently, 95.83% similarity) as indicated in **Table B1.1** in **Appendix B**. The first model met all the requirements, and as a result, it was adopted for measurements.

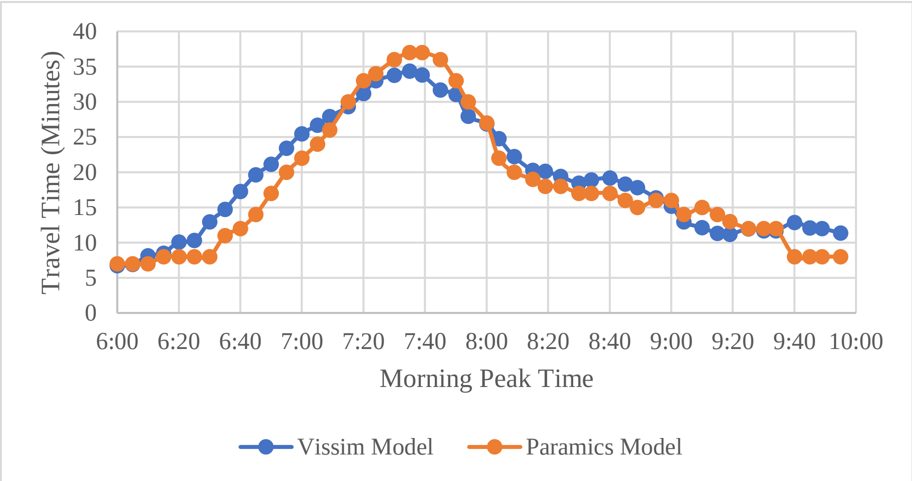


Figure 4.8: Vissim and Paramics Simulated Travel Times (2005)

Table 4.9 presents the results of the comparison between travel time data collected in 2005 and those modelled using Paramics and Vissim. The findings demonstrate that Vissim accurately models travel times, achieving a calibration match of 95.83%, well above the accepted threshold of 85%. As a result, the Vissim model is validated for use as the base for analysing the 2023 data and subsequent interventions.

Table 4.8: Comparison of Paramics vs Vissim Travel Time

Vissim travel time(Min)	Paramics travel time (Min)	Percentage of observed value	Threshold met?
8	7	-14%	Yes
8	7	-14%	Yes
8	7	-16%	Yes
9	8	-13%	Yes
10	8	-26%	Yes
10	8	-29%	Yes
13	8	-62%	Yes
15	11	-34%	Yes
17	12	-44%	Yes
20	14	-40%	Yes
21	17	-24%	Yes
23	20	-17%	Yes
25	22	-16%	Yes
27	24	-11%	Yes
28	26	-7%	Yes
29	30	2%	Yes
31	33	5%	Yes
33	34	3%	Yes
34	36	6%	Yes
34	37	7%	Yes
34	37	9%	Yes
32	36	12%	Yes
31	33	6%	Yes
28	30	7%	Yes
27	27	0%	Yes
25	22	-13%	Yes
22	20	-11%	Yes
20	19	-7%	Yes
20	18	-12%	Yes
19	18	-8%	Yes
18	17	-8%	Yes
19	17	-11%	Yes
19	17	-13%	Yes
18	16	-14%	Yes
18	15	-19%	Yes
16	16	-2%	Yes
15	16	5%	Yes
13	14	7%	Yes
12	15	19%	No
11	14	19%	No
11	13	14%	Yes
12	12	0%	Yes
12	12	3%	Yes
12	12	3%	Yes
13	8	-61%	Yes
12	8	-51%	Yes
12	8	-50%	Yes
11	8	-42%	Yes
		46	
		48	
Threshold satisfied for travel time >85%		95.83%	

4.4.2 GEH Statistic values

Table 4.11 indicates the outcome obtained from the statistical analysis. The Vissim model had 10 major links, as shown in the table, and 79 minor links, which were connectors along the 9.8 km road.

Volume Differences

The differences between the observed peak hour traffic volumes and the Vissim model volumes range within ±2% for most links, indicating a close match between simulated and measured volumes.

Table 4.9: GEH Statistic Results for the Vissim Model

Vissim Link Number	Location	Hour	Peak Hour Count Volume	VISSIM Model Volume (vph)	Difference	Within 15% vph	Criteria Met	GEH Statistic	Criteria Met
10010	Highway	5400-9000	2797	2751	-46	-2%	YES	0.87	YES
10014	Airport	5400-9000	1855	1872	17	1%	YES	0.40	YES
10017	Duinefontein	5400-9000	3658	3696	38	1%	YES	0.62	YES
10022	Vangaurd	5400-9000	3928	3814	-114	-3%	YES	1.83	YES
10027	Langa	5400-9000	3870	3812	-58	-1%	YES	0.93	YES
10030	Jan Smuts	5400-9000	4476	4391	-85	-2%	YES	1.27	YES
10032	Pinelands	5400-9000	3029	3081	52	2%	YES	0.95	YES
10035	Rapensberg	5400-9000	2969	2913	-56	-2%	YES	1.03	YES
10038	Kromboom	5400-9000	3086	3044	-42	-1%	YES	0.76	YES
10041	Liesbeek	5400-9000	3958	3992	34	1%	YES	0.54	YES

Total No. of Links	Links within Criteria (GEH< 5)	Criteria	Percentage Compliant	Criteria Met
89	85	85%	96%	YES

GEH Statistic

The GEH statistic for most links is below the threshold of 5, with values ranging from 0.40 to 1.83. The low GEH values indicate that the model meets the calibration criteria. The model complies with the GEH criterion for 96% of the links, and 85 out of 89 links meet the GEH ≤5 requirement, which translates to an 85% compliance rate across the entire model.

Criteria Compliance

As indicated, 96% of the locations comply with the 15% volume difference threshold. This implies that the traffic volumes estimated by the Vissim model are within acceptable limits compared to the measured data. Following compliance with the set criteria, the model can reliably replicate the observed traffic flows across the study area.

4.5 Résumé

This chapter discussed the stages and steps that were taken to calibrate and validate the model using comparisons between the two models: Paramics and Vissim. Microscopic traffic simulation is an effective tool for long-term traffic control. GEH statistic was used to assess how well the model fits the observed data. Through modelling, researchers and traffic engineers can confidently evaluate the possible effects of different traffic management strategies in the simulation environment when using a calibrated model. Modelling shows a comprehensive and dynamic picture of traffic flow, potential solutions can be assessed before implementation.

5. ANALYSIS AND DISCUSSION OF RESULTS

This chapter details an analysis of the 2023 model results. Ramp metering and congestion charging interventions are implemented as measures to enhance the efficiency of traffic flows. Furthermore, the outcomes of the model are thoroughly examined and discussed. An analysis is conducted on travel times, average speed, and average delays before and after the suggested interventions.

5.1 Analysis of 2023 Simulated Travel Time

The base model was set to simulate travel time and speed based on the 2023 data. This is illustrated in **Figure 5.1**. The graph displays comparable patterns of the observed travel times, showing a peak in the early morning and a slow decline as the peak period ends. The simulated travel time during the morning peak period starts at 6:00 AM with a slight increase, indicating some congestion levels. By 6:30 AM, it increases to 31 minutes, peaking at 61 minutes by 6:55 AM.

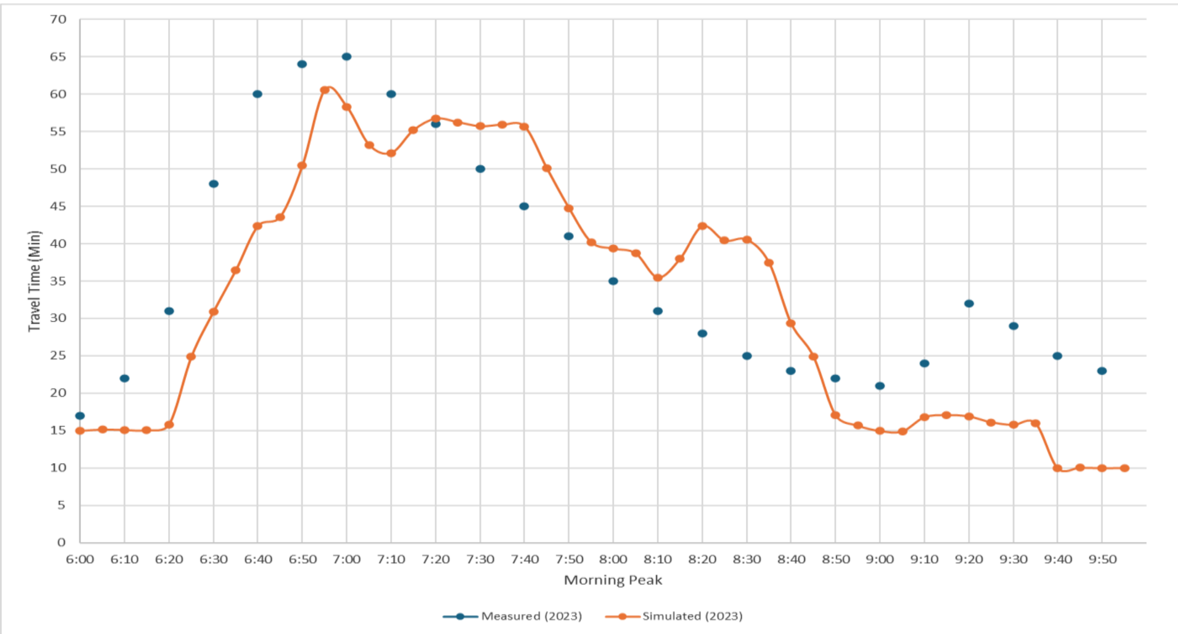


Figure 5.1: Simulated Travel Time (2023)

The simulated travel time remains high between 7:00 AM and 7:30 AM, indicating heavy congestion. After 7:40 AM, it decreases to 39 minutes by 8:00 AM. By 8:10 AM, it drops to 35 minutes, with some fluctuations. These fluctuations could be attributed to the instabilities in traffic flows predicted by the model due to high traffic volumes in 2023. By 9:00 AM, it drops to 10 minutes, nearing normal travel times. By 9:35 AM and 9:50 AM, the simulated travel time stabilises at around 10 minutes, indicating that the road conditions have returned to normal.

The observed differences between simulated and measured travel times can be attributed to several factors. Firstly, microscopic traffic simulation models, such as the one developed using PTV Vissim, rely on assumptions about driver behavior, vehicle characteristics, and network conditions. While these assumptions are calibrated to match real-world conditions, they cannot fully replicate all variations in human driving patterns, weather conditions, and road incidents that may affect travel time in reality.

Additionally, discrepancies may arise due to limitations in the accuracy of input data. Traffic volumes, and road geometry used in the simulation may not perfectly align with real-world conditions at the time of measurement.

5.1.1 Base Model Simulated Speeds

Figure 5.2 shows the simulated and measured speeds in 2023.

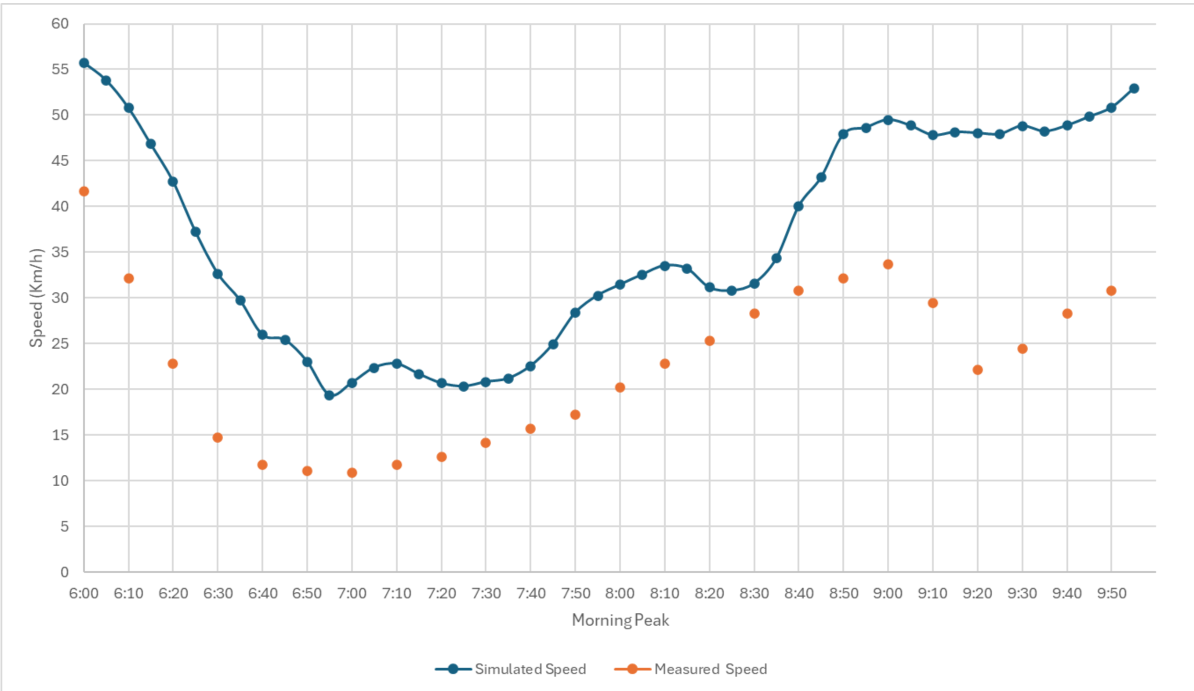


Figure 5.2: Simulated and measured average speeds for 2023

When comparing the simulated and measured average speeds for 2023, the model consistently shows higher speeds than the actual measured values. This discrepancy is recognised, and in order to balance both speed and traffic volumes within the model, this difference is considered acceptable.

The 2023 simulated speeds show mild congestion at 6:00 AM, with traffic building up due to overnight traffic or early commuters. As the morning progresses, congestion intensifies, with speeds dropping to around 40 km/h by 6:30 AM. Between 6:30 and 7:00 AM, simulated speeds decrease to 30 km/h, indicating severe congestion as the road network reaches its maximum capacity. By 7:30 AM, the lowest speeds are recorded, indicating heavy congestion. After 7:30 AM, simulated speeds gradually recover, increasing to 30 km/h by 8:00 AM. Between 8:00 and 8:40 AM, simulated speeds rise to around 40 km/h, suggesting congestion dissipates, but still significantly below free-flow conditions. By 9:00 AM, simulated speeds increase to around 50 km/h, indicating moderate congestion. After 9:20 AM, the measured speed decreases, while the simulated speeds continue to increase. By 9:50 AM, simulated speeds stabilise at around 55 km/h, indicating a return to mild congestion rather than full free-flow conditions.

5.1.2 Base Model Simulated Average Delays

After measuring travel times and speeds, the model was set to measure average delays. These delays are utilised to calculate the Level of Service (LOS) as specified in **Table 3.3. Figure 5.3** displays the base model average delays and LOS.

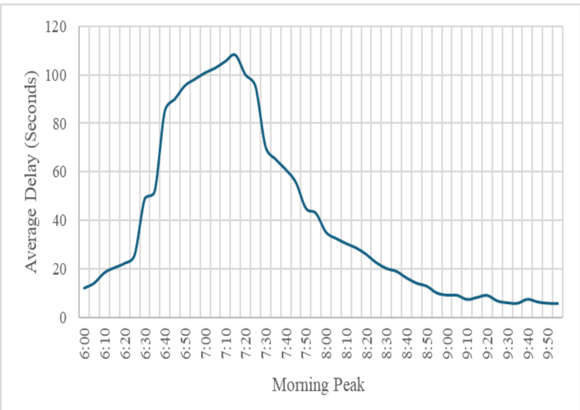
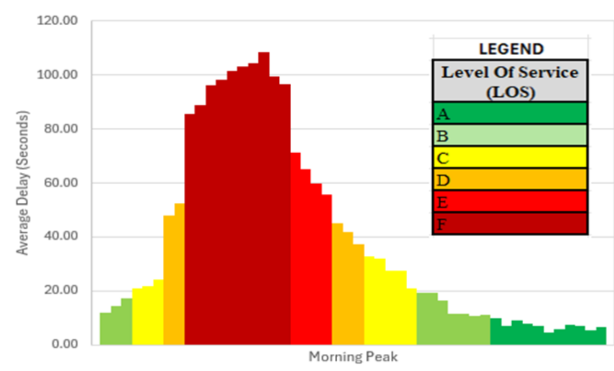
Base Model Average Delay	Base Model Level of Service (LOS)
	

Figure 5.3: Base Model Average Delay and LOS

The Average Delay graph illustrates the fluctuating traffic conditions during the morning peak. The early peak (6:00 AM - 6:20 AM) is marked by relatively low delays, indicating the early stages of congestion. The rapid increase (6:20 AM - 7:10 AM) leads to a sharp rise in average delays, peaking at around 110 seconds by 7:10 AM. The morning peak is the worst period, because the network is highly congested, and vehicles experience the maximum delay. Post-peak recovery (7:40 AM - 9:50 AM) follows, with delays dropping to around 40 seconds, easing congestion, and stabilising at under 10 seconds after 9:30 AM.

The Level of Service (LOS) chart categorises traffic conditions based on average delays in the morning peak, with LOS A-B indicating smooth traffic flow with minimal delays. LOS B-C (6:00 AM - 6:30 AM) transitions into D as delays increase, indicating moderate congestion. LOS E-F (6:30 AM - 8:00 AM) is the most severe, with delays exceeding 80 seconds and reaching up to 110 seconds, indicating highly congested traffic conditions.

After 8:10 AM, the network gradually recovers, transitioning from LOS F back to LOS C-D, and by 9:00 AM, conditions improve to LOS B as delays reduce to below 20 seconds. This analysis highlights the need for potential interventions to reduce peak delays and improve the overall LOS during the busiest times. The following sections detail the proposed ramp metering and congestion charging interventions.

5.2 Ramp Metering Scenario Analysis

This section presents the results obtained from ramp metering interventions. One ramp meter was implemented on the Langa on-ramp, two ramp meters on the Langa and Raapenberg on-ramps, and five ramp meters were placed on the Duinefontein, Jakes Gerwel, Langa, Jan Smuts, and Raapenberg on-ramps. Vehicles on the ramp are held at a signal (visible as a green bar) before merging onto the freeway. **Figure 5.4** is a snippet from a Vissim simulation illustrating ramp metering. The system uses traffic sensors and signals to regulate the inflow of vehicles, preventing a sudden surge of traffic that could cause congestion on the main freeway lanes. **Figure 5.5** displays ramp metering scenario results.

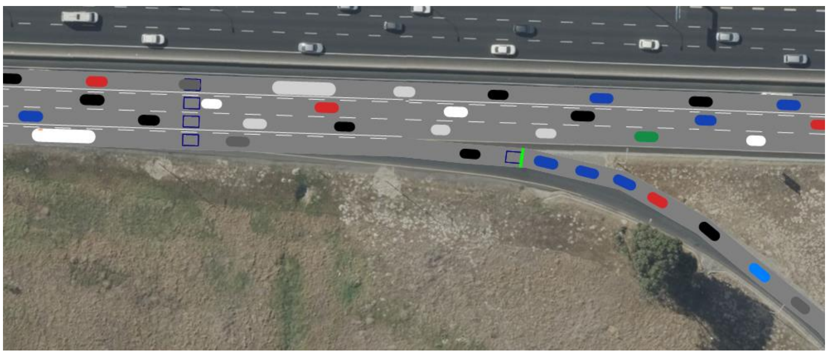
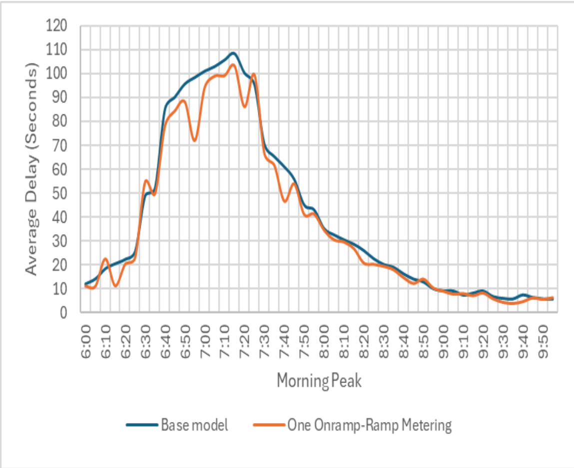
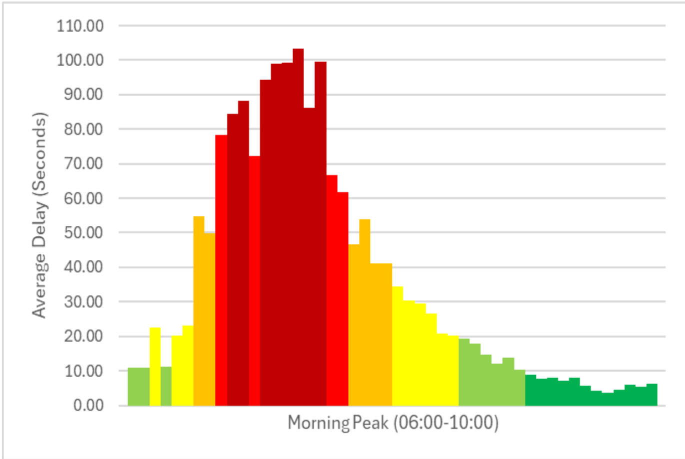
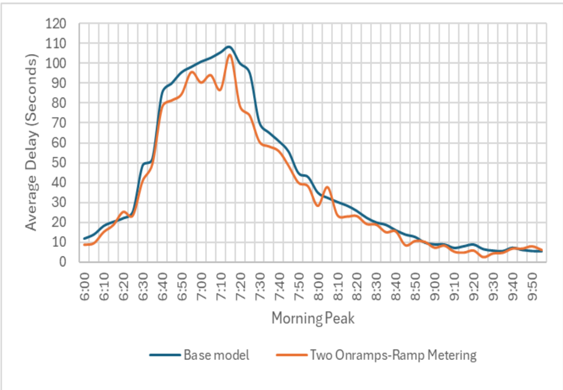
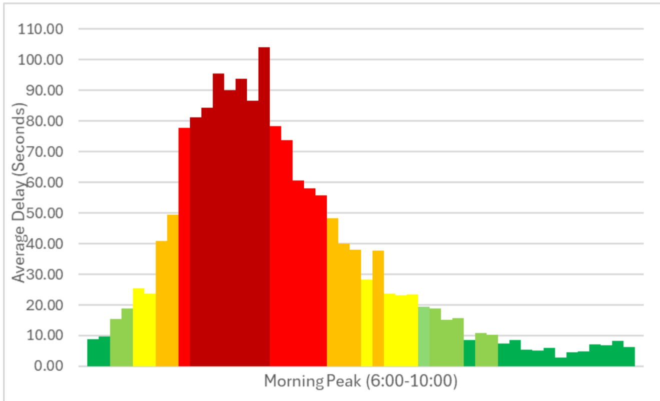


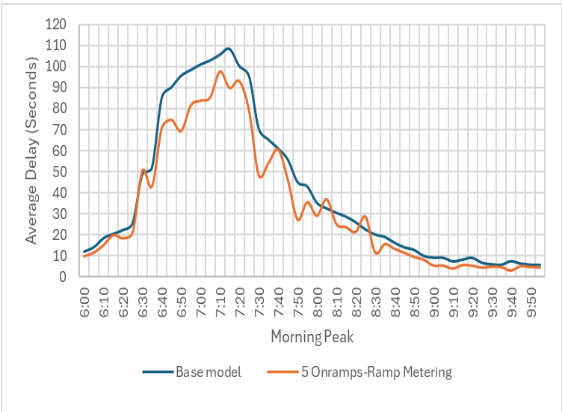
Figure 5.4: Ramp Metering simulation in Vissim

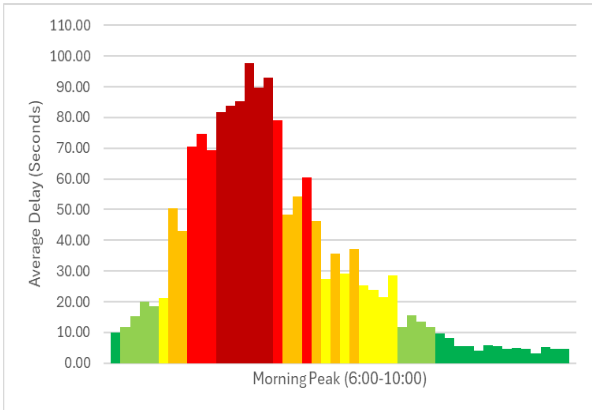
<table>
<tr><th>Scenario</th><th>Base vs Ramp Metering</th><th>Level Of Service (LOS)</th></tr>
<tr><td>1 onramp</td><td>

(a)</td><td>

(b)</td></tr>
<tr><td>2 onramps</td><td>

(c)</td><td>

(d)</td></tr>
<tr><td>5 onramps</td><td>

(e)</td><td>

(f)</td></tr>
</table>

Figure 5.5(a-f): Ramp Metering Scenarios

5.2.1 One On-ramp

A ramp meter was proposed on Langa on ramp and the results are presented in **Figure 5.5 (a and b)**. Implementing ramp metering resulted in reduced delays, particularly during the most congested period between 6:40 AM and 7:40 AM. The maximum delay for the ramp metering scenario remains lower than that of the base model, demonstrating its effectiveness.

The LOS improves by reducing the duration and severity of poor traffic conditions (LOS E and F), shifting the traffic conditions towards LOS C and D for a more extended period, and decreasing the proportion of LOS F. This indicates an overall improvement in traffic flow and reduced congestion during the peak period. **Table D1.1** in **Appendix D** illustrates that the total delays improved by 8% under this ramp metering scenario.

5.2.2 Two On-ramps

Two ramps were proposed on Langa and Duinefontein onramps and the results are presented in **Figure 5.5 (c and d).** Applying ramp metering on two on-ramps resulted in a more significant reduction in delays compared to the one-onramp scenario. Particularly during the peak period (around 6:40 AM to 7:40 AM), the delays in the ramp metering scenario are consistently lower than the base model. Overall, total delays improved by 13% as shown in **Table D1.2** in **Appendix D** due to the addition of ramp metering at two on-ramps, showing a marked improvement over the base model. The Level of Service (LOS) graph shows a clear improvement in traffic flow. The periods with LOS F (severe congestion) are reduced, and the distribution shifts towards better LOS, such as LOS C and LOS D. The decrease in the duration of poor LOS levels (E and F) and the increase in the extent of better LOS levels indicates that ramp metering on two on-ramps has a substantial positive impact on reducing congestion during the morning peak. This scenario demonstrates that extending ramp metering to two on-ramps enhances system performance significantly compared to the base model and even the one-onramp scenario.

5.2.3 Five On-ramps

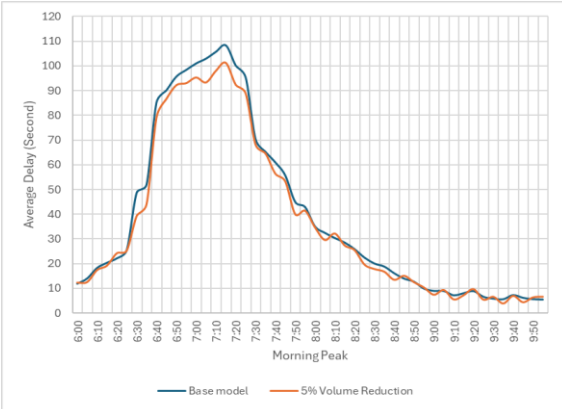
Ramp metering is implemented on these on-ramps: Duinefontein, Jakes Gerwel, Langa, Jan Smuts and Raapenberg and the results are presented in **Figure 5.5 (e and f)**. The results show a significant reduction in delays, especially during the critical peak period (between 6:40 AM and 7:40 AM). The ramp metering reduces the peak delay compared to the base model, indicating that controlling traffic at multiple onramps helps smooth the overall traffic flow. By the end of the morning peak, delays in the ramp metering scenario drop more rapidly than in the base model. Overall, this approach led to a 19% improvement in total delays as shown in

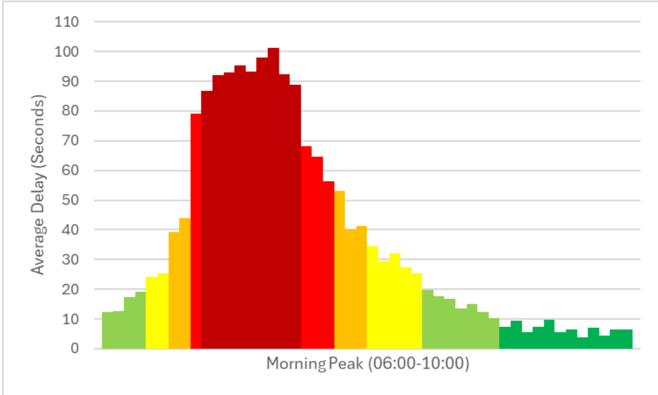
Table D1.3 in **Appendix D**, representing the most significant reduction in delay among the scenarios.

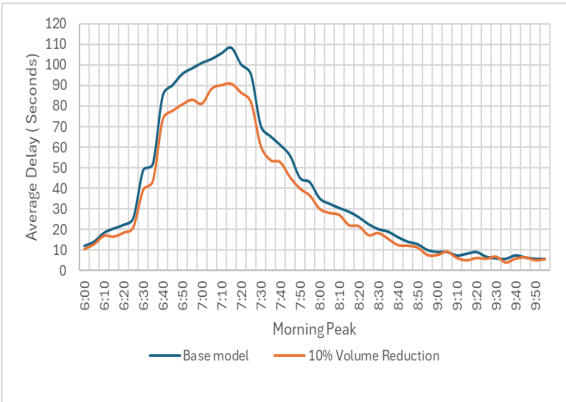
The LOS graph shows that the most congested periods (LOS E and F) are significantly reduced in duration and severity compared to the base model. The extent of LOS A, B, and C interventions indicate increased traffic flow, while the period of LOS F is notably shorter and less severe. This shows that ramp metering on five on-ramps improves traffic conditions by reducing severe congestion and enhancing the overall network performance during the peak period. Travel times were reduced compared to the base model and other ramp metering scenarios. The total average delay with ramp metering is 1 583 seconds, compared to 1 890 seconds in the base model. Ramp metering resulted in an overall delay reduction of approximately 19%. The ramp metering intervention significantly reduces the average delay across the morning peak period.

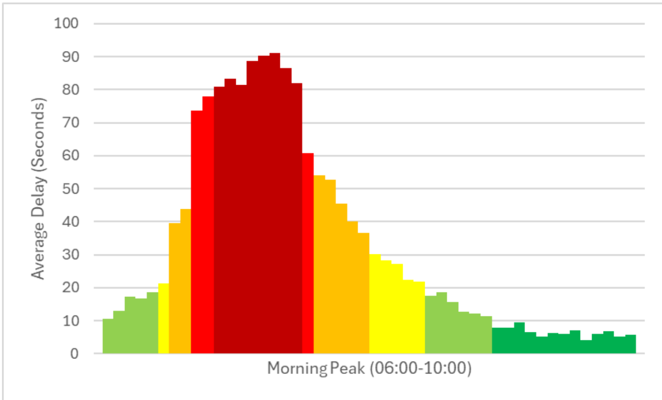
5.3 Congestion Charging

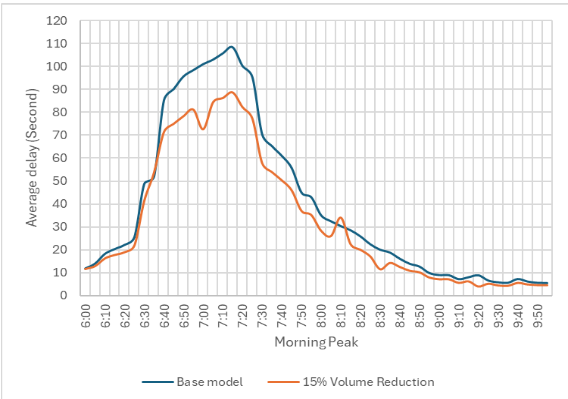
This section discusses the congestion charging results. The assumption is that congestion charging implementation reduces traffic volumes by at least 5%. Volume reductions of 5%, 10% and 15% were investigated and the results are presented in **Figure 5.6**.

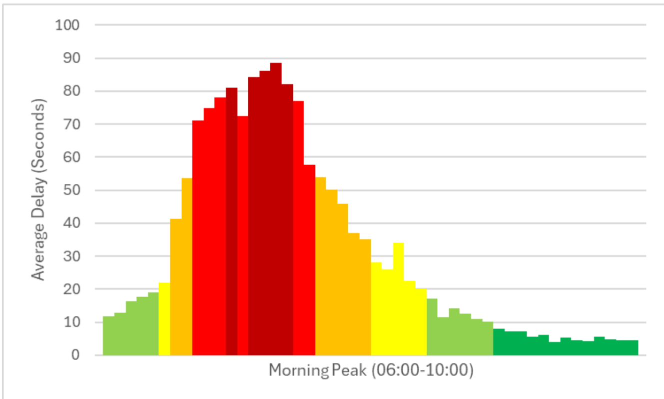
<table>
<tr><th>Scenario</th><th>Base vs Congestion Charging</th><th>Level Of Service (LOS)</th></tr>
<tr><td>5%
Volume
Reduction</td><td>

(a)</td><td>

(b)</td></tr>
<tr><td>10%
Volume
Reduction</td><td>

(c)</td><td>

(d)</td></tr>
<tr><td>15%
Volume
Reduction</td><td>

(e)</td><td>

(f)</td></tr>
</table>

Figure 5.6(a-f): Congestion Charging Scenarios

5.3.1 Volume reduction of 5%

The volume reduction significantly improves delays, especially during the most congested period between 6:40 AM and 7:40 AM. While both lines follow a similar trend, the 5% volume reduction scenario delays remain consistently lower than the base model. By reducing the number of vehicles by 5%, overall congestion decreases, leading to a 7% improvement in total delays as shown in **Table E 1.1** in **Appendix E**. The LOS graph shows a corresponding improvement in traffic conditions. With the 5% volume reduction, the duration and severity of LOS F (indicating severe congestion) are shortened, and the traffic distribution shifts more favourably towards LOS C and LOS D, meaning fewer delays. Additionally, there is a noticeable increase for the LOS A and LOS B extents, representing smoother traffic flow with minimal delays. This scenario demonstrates that even a 5% reduction in traffic volume through congestion charging can significantly improve traffic flow and reduce delays during the morning peak. The network becomes more efficient, with a decrease in extreme congestion, leading to better overall performance compared to the base model without any volume reduction interventions.

5.3.2 Volume reduction of 10%

The decrease in traffic volume by 10% leads to a significant decline in delays, particularly during the most congested period between 6:40 AM and 7:40 AM. The graph illustrates a consistent reduction in delays across the morning peak in the volume reduction scenario, with the average delay decreasing more steeply compared to the base model after 7:30 AM. The overall improvement in total delays is 17% as shown in **Table E1.2** in **Appendix E**, demonstrating that a 10% volume reduction substantially impacts reducing congestion.

The Level of Service (LOS) graph indicates a clear improvement in traffic conditions. The duration and severity of LOS F (severe congestion) are significantly reduced, and there is an increase for the LOS B and LOS C extents, indicating better traffic flow. The volume reduction also results in a more significant shift towards LOS A, representing free-flow or minimal delays for more of the morning peak period. This scenario leads to a substantial improvement compared to both the base model and the 5% volume reduction scenario.

5.3.3 Volume reduction of 15%

The 15% reduction in traffic volume leads to substantial improvements in delays, particularly during the peak congestion period between 6:40 AM and 7:40 AM. Delays in the volume reduction scenario are consistently lower than in the base model, with the volume reduction allowing for a steeper decline in delays after 7:30 AM. The total improvement in delays is 22% as shown in **Table E 1.3** in **Appendix E**, making this scenario highly effective in reducing congestion and improving travel times. The LOS graph highlights significant improvements in traffic conditions. The volume reduction resulted in shorter periods of LOS F (severe congestion) and more traffic can be managed within LOS B and C, indicating moderate to good traffic flow. Additionally, there is a noticeable increase for the LOS A and LOS B extents, representing free-flow or very low delays during the morning peak period. This scenario demonstrates a marked shift towards better LOS ratings and more efficient traffic flow during the morning peak compared to both the base model and lower volume reduction scenarios.

5.4 Résumé

The chapter examined morning peak travel time patterns using a microsimulation model on the N2 highway in Cape Town using the 2023 data. The results from the base model showed that simulated travel time exhibited similar trends to the actual measured travel times. The average delay was used to quantify LOS and was analysed for the morning peak period in this study. Ramp metering and congestion charging discussed in the literature review were investigated and traffic flows on the highway improved by at least 7% for both interventions. **Chapter 6** discusses the implications of these findings.

6. CONCLUSION AND RECOMMENDATIONS

This chapter examines the observations and implications of the measured and simulated outcomes. The discussion includes recommendations for both short-term and long-term measures, which are derived from the measured and simulated outcomes, as well as relevant literature. Furthermore, the study also includes suggestions for further research. The chapter also reflects on (1) traffic congestion and the use of microscopic simulation in traffic congestion, (2) the development of the PTV Vissim model for the N2 highway in Cape Town (from the airport on-ramp to the Main Road off-ramp), (3) the calibration and validation of the model using the 2005 and 2023 data (measured traffic volumes and travel times), (4) data collection procedure and the identification of the changes between 2005 and 2023, (5) running the simulation and collecting the data, (6) comparison of the traffic behaviour and ascertaining the changes and propose interventions for improving traffic flow.

6.1 Conclusion

This section presents the concluding observations derived from the study's findings. The results are further supported by the literature as noted.

6.1.1 Traffic congestion and the use of microscopic simulation

According to the literature about the study area, Cape Town ranks number three on the most congested towns in Africa with an average speed of 33 km/h in peak hour time based on **Table 1.1**. **Figure 2.11** shows that the N2 is one of the most congested hotspots in Cape Town, which has been caused by the population and economic growth of the country, which has also increased private car ownership. Private car use has the highest modal split and has increased by 5% between 2013 and 2020 according to **Table 2.6**. Microscopic simulation was used, as it provides a detailed analysis of individual car movements. Traffic flow tasks, such as car following and lane changing were observed upon adding the inputs into the model. Multiple scenarios were assessed which provide insights on reducing traffic.

6.1.2 Changes in Travel Time Peak Periods

The peak congestion times in 2023 have shifted slightly later in the morning than in 2005. This shift may result from altered work patterns, such as flexible work schedules or modified work schedules that affect when parents and students are on the road. Transport planners should be aware of these developments, as they can enhance their traffic management strategies. The shift in the peak congestion times indicates a change in commuter behaviour. Different lifestyle choices, flexible work schedules, or staggered school start times could be the cause. To guarantee seamless operation during morning peak hours, traffic management and infrastructure must be adjusted to consider these changes.

6.1.3 The Value of Extended Analysis

An examination of traffic data over a long period, such as the 18 years under consideration, provides valuable insights into the shifts in traffic congestion patterns. By adopting a long-term perspective, hidden patterns become apparent and are uncovered. Tracking changes in travel times over an extended period allows for the identification of underlying trends. Additionally, studying traffic patterns concerning larger urban and economic developments enables transport planners to gain a deeper understanding of the long-term impact of these developments on traffic congestion.

This also assists in the development and implementation of strategic plans. Long-term data analysis provides planners with crucial information necessary for developing comprehensive plans that account for the evolving transport needs of the city.

6.1.4 Overall Trend in travel times

Between 2005 and 2023, the morning peak travel time has generally increased. This demonstrates the rise in traffic congestion over the years. Potential contributing factors include increased traffic volumes, urban development (growing city areas lead to more people commuting), and infrastructure issues (roads not upgraded enough to meet demand) (Liu et al 2017; Nečoska et al 2018). The growing trend in travel times highlights the urgency of alleviating traffic congestion.

6.1.5 Variations in Speed and Perspectives on Road Safety

Speed variations were observed from the results, which show implications for road safety. Transport authorities around the world continue to place a high priority on traffic safety. Studies conducted in 2008 by the Monash University Accident Research Centre highlighted fluctuations in speed, a crucial element that is frequently disregarded. Their results showed a strong link between speed fluctuations and traffic safety, especially on highways like the N2 in this study.

For efficient management and accident prevention tactics, it is essential to comprehend how speed variations affect traffic flows. Vissim and other traffic simulation tools assist in this case. The model results and safety research offer insightful information that can help with important policy choices about speed limits, tactics for enforcing them, and even the layout of roads (Elvik, 2005).

6.1.6 Trends in Traffic Volume

The N2 highway has a significant increase in vehicles during the study period. This increase is consistent with the growing urban population observed. As Cape Town City grows, more commuters rely on the N2 highway for daily travel. Economic growth also necessitates the need for mobility. Furthermore, traffic patterns may be impacted by changes in land use and urban development.

6.1.7 Congestion Hotspots

Most of the on-ramps are the primary locations for traffic congestion. Traffic congestion occurs on the on-ramps, resulting in long queues as shown in Vissim. Ramp metering techniques are recommended in these locations to maintain smooth traffic flow on highways while facilitating the trickle entry of cars through the on-ramps. This aligns with the assertion that congestion occurs at certain points within the transportation system. **Figure 6.1** shows an on-ramp congestion hotspot from the model.

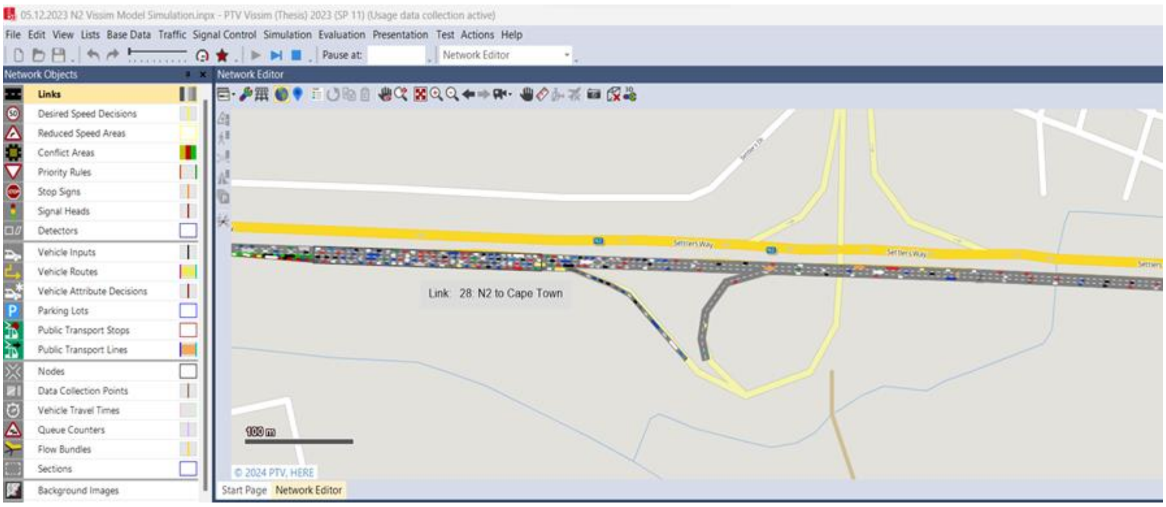


Figure 6.1: Langa on Ramp congestion hotspot

6.1.8 Bottleneck and Congestion

One of the bottlenecks on the N2 highway is shown in **Figure 6.1**. These bottlenecks were caused by high travel time. Congestion at certain locations impacted the overall traffic flow, particularly during peak hours. In today's transport systems, traffic congestion is a major problem that causes financial losses, environmental harm, and annoyance among drivers (Fattah et al., 2022). To reduce congestion and improve traffic flow, it is essential to locate and fix bottleneck locations in a network where traffic flow is extremely limited.

PTV Vissim and other traffic simulation software are useful tools for analysing bottlenecks and congestion in transportation networks. This data-driven strategy is essential for maximising traffic flow, reducing congestion, and building a more effective and sustainable transportation network. Ramp metering was introduced to improve traffic flows on the freeway by regulating the vehicles entering the on-ramps.

The findings of this study support several key insights from the literature reviewed in Chapter 2. Prior research has highlighted the inherent challenges of accurately modeling real-world traffic conditions using microscopic simulation tools (Xie et al., 2018). These tools, while powerful, are sensitive to calibration parameters and input data quality. The observed discrepancies between simulated and measured travel times align with the findings of Xie et al. (2018), who noted that achieving exact matches between simulated outputs and real-world measurements is often constrained by data limitations and stochastic variations in traffic flow.

Furthermore, the study's findings reinforce the importance of continuous model calibration and validation to improve simulation accuracy. As highlighted by Piao & McDonald (2020), incorporating real-time traffic data and adaptive calibration techniques can help reduce discrepancies and enhance the reliability of simulation outputs. Future research could explore integrating these advanced techniques to further improve model accuracy.

6.2 Recommendations

Drawing from an analysis of traffic congestion in the study area, the following suggestions are put forth to address the issue and enhance commuter mobility in general. This section provides recommendations based on the measurements and sustainable solutions based on the literature.

6.2.1 Ramp Metering

This study examined ramp metering as a viable and sustainable option to enhance the traffic flow on highways. The results showed a minimum 8% enhancement in traffic flow. The implementation of ramp metering can, significantly, alleviate congestion on highways by regulating the entry of vehicles onto the main traffic flow. This method uses traffic signals on highway on-ramps to control the rate at which vehicles enter the highway, preventing the over-saturation of the main roadway and reducing the stop-and-go driving conditions that contribute to traffic jams.

Integrating ramp metering with advanced traffic management technologies can lead to an effective system. These technologies include real-time traffic monitoring, adaptive signal control, and communication systems that provide drivers with real-time information about traffic conditions. Additionally, it is crucial to conduct an extensive analysis of the characteristics and needs of each highway segment to determine the optimal ramp metering strategies. Ramp metering has proven to be an effective measure for enhancing highway traffic flow by potentially improving congestion and travel times. Including his intervention in traffic management strategies is highly recommended based on the promising results of this study.

Although the primary focus of this study was on congestion reduction, road safety is a critical factor that should be considered when implementing ramp metering strategies. Future research could include KPIs such as the reduction in collision rates, average vehicle speeds, and the frequency of sudden braking incidents at onramps and downstream freeway sections. The inclusion of such KPIs would provide a more comprehensive assessment of the safety benefits or drawbacks associated with ramp metering.

6.2.2 Congestion Charging

Congestion charge is a thoroughly studied approach in traffic management, designed to discourage unnecessary travel during peak periods and encourage alternate transportation methods. This study assumed volume reductions based on relevant research, as the PTV VISSIM model does not directly facilitate the simulation of congestion charging. Reductions of 5%, 10%, and 15% were implemented to model the impacts of congestion charge, yielding notable enhancements in traffic flow of 7%, 17%, and 22%, respectively. These assumptions illustrate the prospective advantages of congestion charge, even in the absence of direct modelling, indicating how pricing systems might alleviate congestion, enhance traffic flow, and optimise route use, particularly during peak times. Further investigation into practical applications may enhance these estimations and validate their efficacy on the N2 highway.

6.2.3 Speed limit regulations

The author states that variations in speed have the following effects on these crucial elements of road safety:

- Enforcing suitable speed limits is essential to preserving a safe and effective traffic flow. It is possible to identify places where current speed limits might not be sufficient by analysing speed variations in a traffic simulation. By adjusting the limits based on this data, travel times and safety can be maximised.
- Targeted enforcement strategies can be developed by considering the patterns of speed variations. Enforcement efforts can be most effectively directed towards areas where notable deviations take place to discourage risky driving practices. For example, stepping up police presence in areas where speeding is common could be a targeted strategy.
- Flow and crash risk are impacted by the basic design of a road. Decisions on lane widths, median barriers, and intersection design can be influenced by analysing speed variations in a traffic simulation. For instance, wider lanes may promote a more fluid traffic flow, and median barriers may physically stop risky manoeuvres.

Transport experts can better understand the factors influencing road safety by including speed variations in their analysis of traffic patterns. Vissim gives policymakers insights to design data-driven policies and infrastructure upgrades that reduce accidents and make transport systems safer for everyone by supplying data that accurately depicts real-world traffic dynamics.

As speeds in the research corridor are already low, no simulation scenarios were developed. Unfortunately, it cannot be concluded that traffic has become safer, as the additional volume inherently leads to additional conflicts, potentially with vulnerable road users on before and after corridor parts of the network.

6.2.4 Demand Management Strategies

The Cape Town transport system has a variety of public transport systems. Therefore, encouraging the use of public transport by putting policies and programmes into place can assist in shifting modes. This might entail subsidising the cost of public transport, coordinating schedules with commuter needs, and improving accessibility and information at transport hubs. Promoting sustainable transport by constructing bike lanes, pedestrian walkways and carpool parking spaces can encourage people to walk, cycle and carpool. Policies that encourage carpooling, like toll exemptions or designated lanes, can be implemented to reduce the number of cars on the road. Implementing flexible work arrangements by companies and organisations, enabling staff members to work remotely or modify their commute times to avoid periods of high traffic play a significant role in reducing traffic flows.

A few other strategies that can be applied to the transport system in Cape Town are as follows:

6.2.5 Flexible Work Hours and Remote Work Options:

During peak hours, traffic congestion can be reduced by encouraging alternate commuting schedules such as:

- **Flexible Work Hours**

  Employers can set up flexible work schedules that let workers begin and end work at various times, which helps to distribute the day's traffic demand. Employees can travel outside of traditional peak hours to reduce overall traffic volume during these periods of congestion.

- **Options for Telecommuting and Remote Work**

  Allowing workers to work from home during peak hours drastically lowers the number of cars on the road.

By carefully implementing the measures, organisations can indirectly lessen traffic congestion and its detrimental effects by providing remote work options.

6.2.6 Incident Management

Accidents and vehicle breakdowns are common events that worsen traffic congestion. Managing incidents quickly and skillfully is essential to reducing the disruption of these occurrences. These include clearing lanes faster by reducing the length of lane blockages requires prompt incident response times. The availability of tow trucks, effective emergency services, and well-organised response procedures are needed. Restoring traffic flow and reducing the ripple effects of incidents depend on clearing blocked lanes as soon as possible.

6.2.7 Managing Shifts in Vehicle Class Distribution

With more people using public transport, there is a need to modify traffic laws and road designs because a higher proportion of larger vehicles are now on the road. Larger vehicles have distinct operating characteristics and can have an overall negative impact on traffic flow. Enacting weight restrictions or designating special lanes for large vehicles during peak hours could mitigate their impact on traffic congestion (Button et al., 1993). Reducing heavy vehicles during peak hours helps preserve the roads, lowering the need for repairs and road closures, which can exacerbate traffic congestion. Heavy vehicles are more likely to cause wear and tear on road surfaces than lighter vehicles. Again, larger vehicles tend to move more slowly than smaller ones. Traffic flow can be made smoother and faster for other vehicles by restricting their use during peak hours.

6.2.8 Infrastructure Investment

Extend Road Network: To boost capacity and enhance traffic flow, carefully add lanes or build bypasses on the N2 highway and other important arterial routes. This needs to be implemented after thorough planning and assessment of the environmental effects. Furthermore, it also has to be kept in mind that we cannot build our way out of congestion.

Upgrade Public Transport Infrastructure: Make investments in the development and upkeep of public transport systems, such as those for trams, trains, and buses. This includes expanding the reach and frequency of public transport options to serve commuters better and make them more convenient.

6.2.9 Long-Term Planning

Continuous Data Collection and Analysis: To track the efficacy of solutions put into place and make necessary strategy adjustments, maintain long-term data collection and analysis of traffic patterns. This will enable decision-makers for future infrastructure development and transport planning to stay ahead of changing trends and make data-driven choices.

By applying these recommendations, the traffic on the N2 highway can lessen traffic and ultimately improve travel times, reduce pollution, and create a more effective and sustainable transportation system for the city.

6.2.10 Area of Further Research

Although the current analysis offers insightful information about traffic congestion on the N2 highway, there are a few areas that warrant further investigation to obtain a complete picture and create even better solutions:

Integration of Public Transport Prioritisation into Ramp Metering Systems

Given that public transport can reduce congestion by decreasing the number of private vehicles on the road, it would be beneficial to evaluate what percentage of traffic at onramps comprises public transport vehicles and whether these vehicles can be given priority during ramp metering operations. Public transport prioritisation could involve adaptive traffic signal control to minimise delays for buses and taxis, thus encouraging more commuters to shift from private vehicles to public transport. This approach aligns with sustainable traffic management practices and promotes equitable transport

Ramp Metering Effects on Adjacent Minor Road Networks

A long-term approach is essential to fully understand the trends and impacts of ramp metering over time. While this study focused on specific freeway sections, it is necessary to consider the broader network impacts to ensure that traffic diverted from freeways does not cause congestion on minor roads. Future studies could employ a corridor-based approach that incorporates network-wide traffic analysis, including minor roads and adjacent arterials. Such an approach would provide insights into policies required to mitigate potential negative impacts on surrounding road networks. Additionally, strategies such as dynamic route guidance systems and traffic redistribution measures could be explored to optimise network-wide performance.

Analysis of Origin-Destination Data

Gaining knowledge about the origin-destination patterns of commuters utilising the N2 highway could offer insightful information about the reasons behind trips and possibly identify particular routes or areas that most heavily contribute to traffic. The data could assist in providing areas of focus regarding infrastructure upgrades or changes to public transport routes.

This analysis was not investigated, as the study did not focus on origin and destination surveys of road users. The data collected was aggregated traffic volumes and vehicle speed from dual loops.

Analysis of Multimodal Transport

Opportunities for improved integration and modal shift tactics can be found by examining how various modes of transportation, such as walking, cycling, and public transportation, interact with automobile traffic. Examining the first- and last-kilometre connectivity between public transportation hubs and residential or commercial areas may be one way to do this.

Impacts on the Economy and Land Use

Researching the connection between land-use patterns, economic activity, and traffic congestion can help understand how traffic flow can be impacted by urban development policies. This could entail researching ways to support sustainable and balanced development patterns and the locations of employment hubs, residential neighbourhoods, and commercial zones along the N2 highway.

Public Views and Actions

Effective demand management strategies can be developed by researching commuter behaviour and public perception of traffic congestion. Surveys, focus groups, or real-time data collection can be conducted to understand the factors influencing travel decisions and can assist in finding potential incentives for using alternative modes of transportation.

Technological Progress

Plans for controlling traffic flow and congestion can be informed by investigating the possibilities of cutting-edge technologies like autonomous vehicles, intelligent transportation systems, and vehicle to vehicle communication. Evaluating the possible effects of such technologies on traffic management and overall transportation efficiency may entail pilot projects or feasibility studies.

6.3 Overall Benefits

These potential solutions offer a range of benefits that can contribute to a more efficient and sustainable transportation system:

- *Lessening of Congestion*: These strategies can significantly lessen traffic congestion by promoting public transportation, controlling traffic demand, and rewarding carpooling.
- *Environmental Impact*: Reducing the number of automobiles on the road decreases greenhouse gas emissions, which helps maintain a cleaner environment.
- *Economic Benefits*: By generating revenue through congestion pricing, infrastructure upgrades can be made, improving the transportation network even more.
- *Work-Life Balance*: Employees with flexible work arrangements have more control over their schedules, which may enhance work-life balance.

6.4 Reflection

Cape Town, South Africa, is one of the urban areas globally that consistently struggle with traffic congestion. A trend has been identified which is a cause of concern. There has been an increase in morning traffic congestion over almost two decades.

The analysis identifies several important variables that are causing the congestion to worsen. Firstly, the current infrastructure is severely strained by the growing number of cars on the road, due to an increase in car ownership. Secondly, as more people move into the N2 highway service area an ongoing urban sprawl continues to occur, and the number of commuters increases. Infrastructure upgrades have not kept up with the growth in population and economic activity, which has left it unable to manage the ever-increasing demand for transport.

Fascinatingly, the data points to a shift in peak congestion periods, which might reflect shifts in commuter behaviours like altered school schedules or flexible work arrangements. This emphasises how dynamic traffic patterns are and how flexible solutions are required. To tackle the increasing traffic congestion, a comprehensive strategy is needed. Implementing sustainable traffic management improves mobility while ensuring that the safety of road users is fostered. By adopting a long-term perspective, one can discern underlying trends and understand the implications of significant urban and economic developments, so informing strategic planning for viable solutions.

A thorough plan that tackles the underlying causes of the issue is required considering the escalating traffic congestion on the Cape Town N2 highway. Authorities can work towards reducing traffic and developing a more effective and sustainable transport system for Cape

Town by investing in infrastructure, enhancing public transportation, and encouraging sustainable transportation practices.

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APPENDIX A: ETHICS CLEARANCE LETTER

UNIVERSITY OF CAPE TOWN
IYUNIVESITHI YASEKAPA • UNIVERSITEIT VAN KAAPSTAD

2024/04/18

EBE/00656/2024

RE: Research Ethics Committee Project Approval Letter

Dear Mpumelelo Zhou,

Your application for ethics review of your project titled

Impact Assessment Through Microscopic Simulation: A Sustainable Approach to Improving Traffic Congestion

has been reviewed and evaluated by the Engineering & Built Environment Committee.

You may proceed with your research project titled:

Impact Assessment Through Microscopic Simulation: A Sustainable Approach to Improving Traffic Congestion

Please note that should:

(i) any serious or adverse effects to participants occur and/or,

(ii) aspect(s) of your current project change and/or

(iii) any unforeseen events that might affect continued ethical acceptability of the project occur then you should immediately report this to the approving REC. You may be required to submit an amendment to this application, in order to determine whether the changed aspects increase the ethical risks of your project.

Based on the information supplied your application has been successful and is approved.

Please note the following additional conditions associated with this approval:

(i) This research did not need to undergo full ethics review as there are no human subjects involved. (Research assistants are not research subjects.) As such, this approval constitutes not an approval per se, but rather an exemption from full ethics review. No work involving human subjects may be done under this exemption.

Regards,

Engineering & Built Environment Committee.

APPENDIX B: METHODOLOGY ADDITIONAL INFORMATION

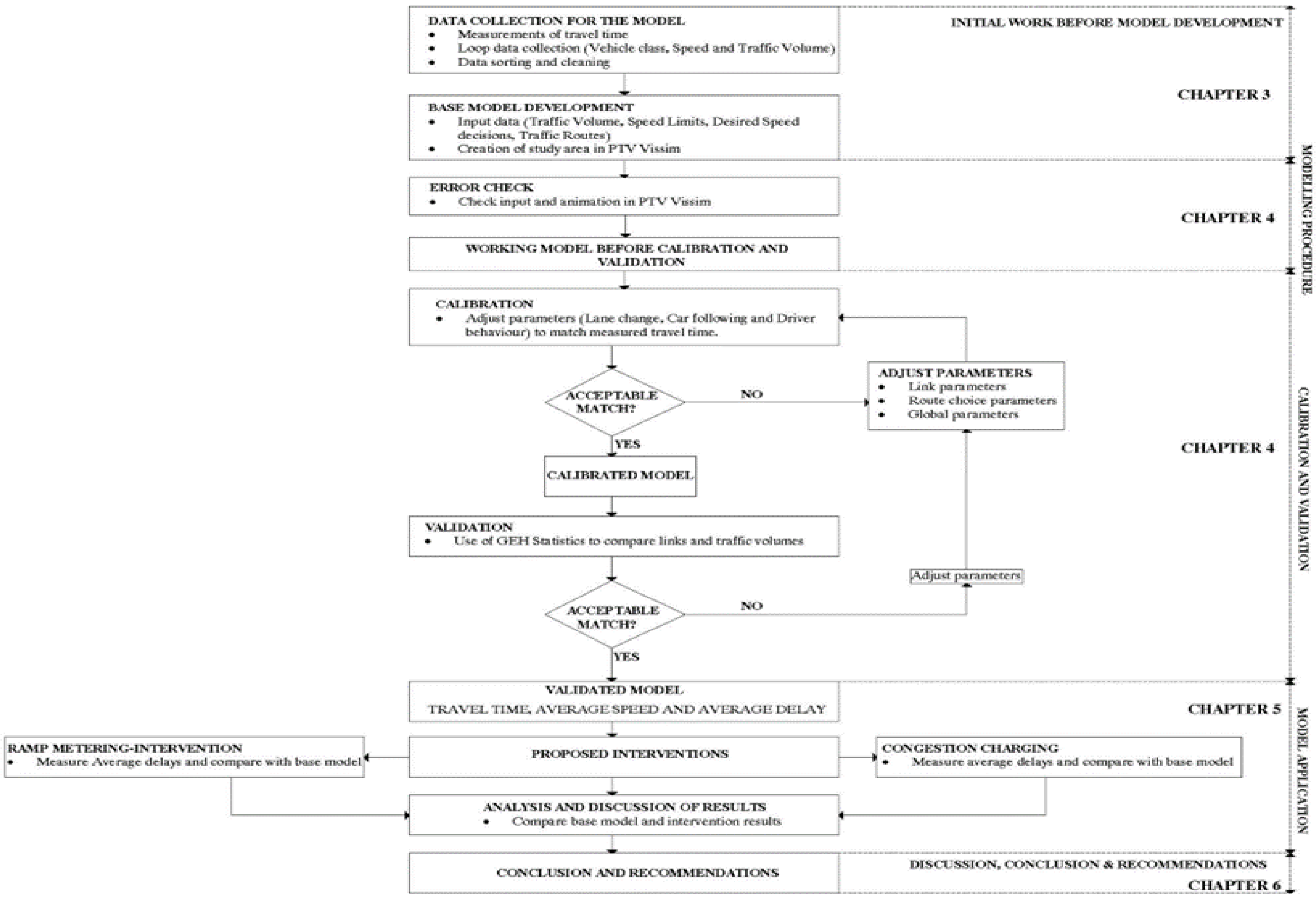


Figure B1.1: Detailed flow diagram

APPENDIX C: MODEL PARAMETERS

Table C.1: Car Following recommended values

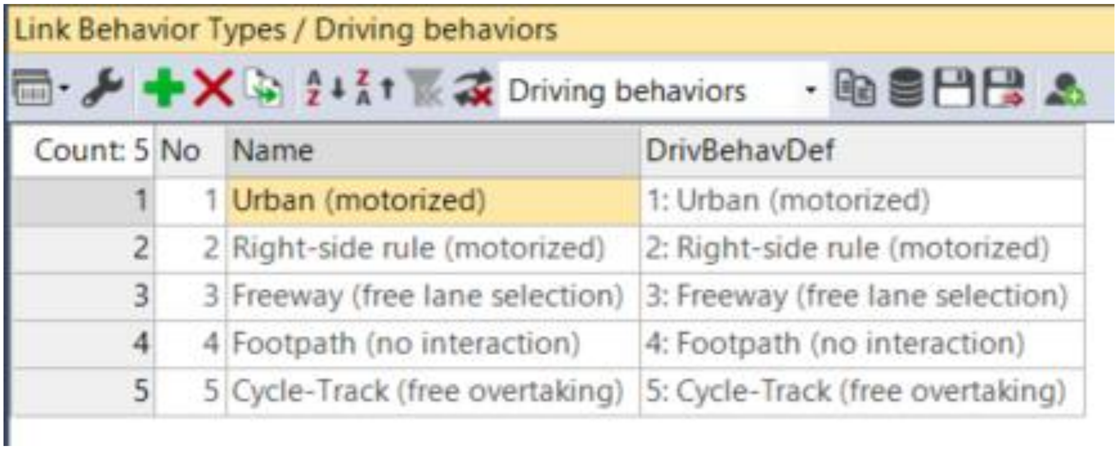
Parameter	Default (m or s)	Suggested Range Basic Segment (m or s)	Suggested Range Merging / Weaving (m or s)
CC0 (Standstill Distance) (m)	1.5	1.37-1.68	>1.50
CC1 (Headway Time) (s)	0.9	0.85-1.05	0.90-1.50
CC2 ('Following' Variation) (m)	4	2.00-7.00	4.00-12.00
CC3 (Threshold for Entering Following)	-8	Use default	Use default
CC4 (Negative 'Following' Threshold)	-0.35	Use default	Use default
CC5 (Positive 'Following' Threshold)	0.35	Use default	Use default
CC6 (Speed Dependency of Oscillation)	11.44	Use default	Use default
CC7 (Oscillation Acceleration) (m/s^2)	0.25	Use default	Use default
CC8 (Standstill Acceleration) (m/s^2)	35	Use default	Use default
CC9 (Acceleration at 80.5 km/h) (m/s^2)	1.5	Use default	Use default

Source: ODOT, 2016

Table C.2: Lane Changing recommended values

Defaults				
General Behavior Necessary Lane Change (route)	**Free Lane Selection Own**	**Unit**	**Trailing Vehicle**	**Unit**
Maximum deceleration	-4.02	m/s²	-3	m/s²
Accepted deceleration	-1	m/s²	-0.5	m/s²
Waiting time before diffusion			60	s
Minimum Headway (front/rear)			0.5	m
Maximum deceleration for cooperative braking			-3	m/s²
Suggested Ranges				
General Behavior Necessary Lane Change (route)	**Free Lane Selection Own**	**Unit**	**Trailing Vehicle**	**Unit**
Maximum deceleration	-4.02	m/s²	3.66 to 2.44	m/s²
Accepted deceleration	-1	m/s²	0.46 to 0.76	m/s²
Waiting time before diffusion			60	s
Minimum Headway (front/rear)			1.5 to 2	s
Maximum deceleration for cooperative braking			2.44 to 4.57	m/s²

Source: ODOT, 2016


Link Behavior Types / Driving behaviors

Driving behaviors

Count: 5	No	Name	DrivBehavDef
1	1	Urban (motorized)	1: Urban (motorized)
2	2	Right-side rule (motorized)	2: Right-side rule (motorized)
3	3	Freeway (free lane selection)	3: Freeway (free lane selection)
4	4	Footpath (no interaction)	4: Footpath (no interaction)
5	5	Cycle-Track (free overtaking)	5: Cycle-Track (free overtaking)

Figure C1.1: Driver behaviour types relevant to the study

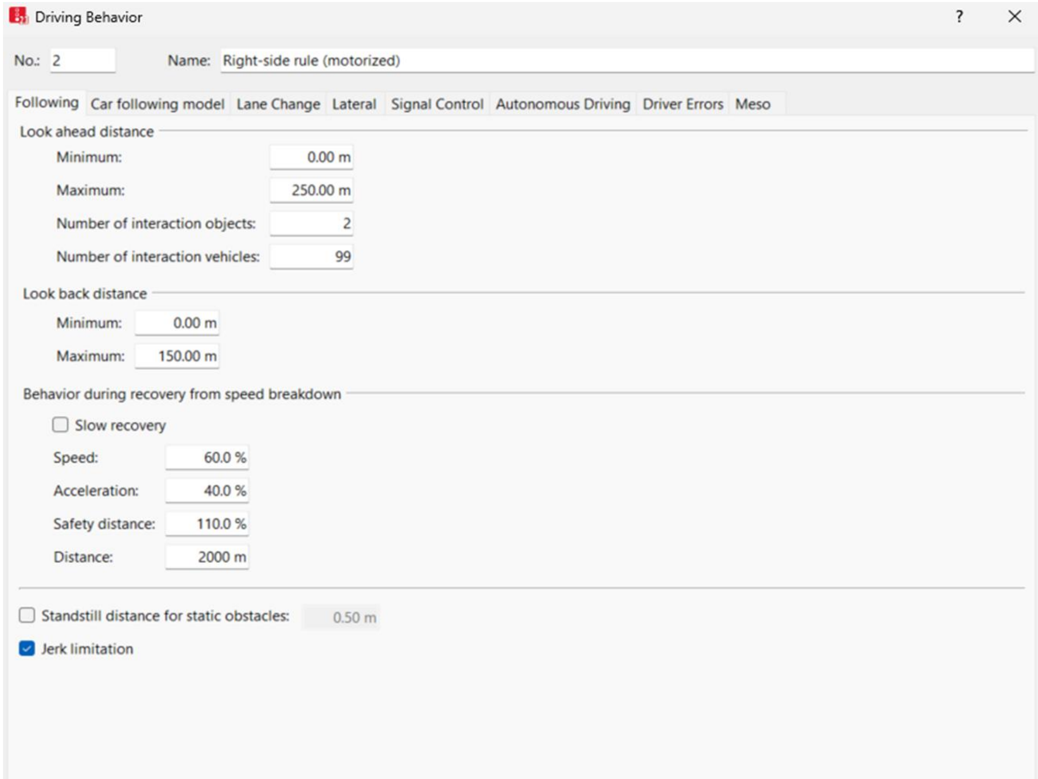


Figure C1.2: Driver behaviour parameters adjusted in the Vissim model

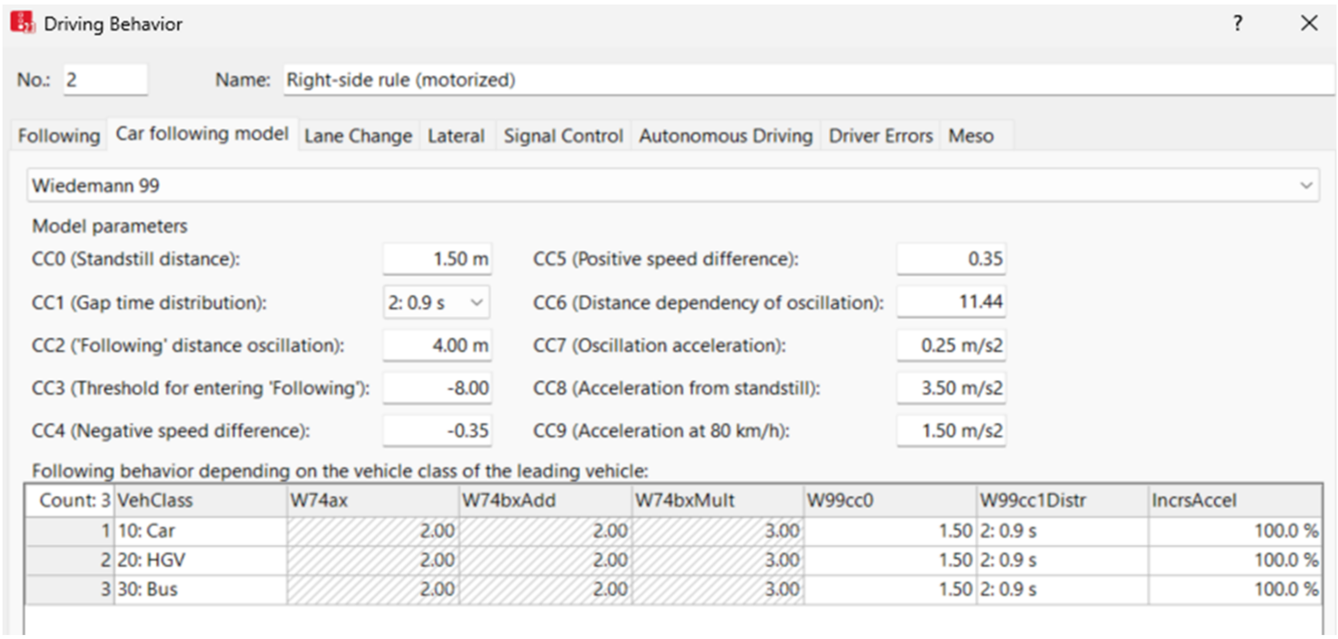


Figure C1.3: Wiedemann 99 parameters adjusted in the Vissim model

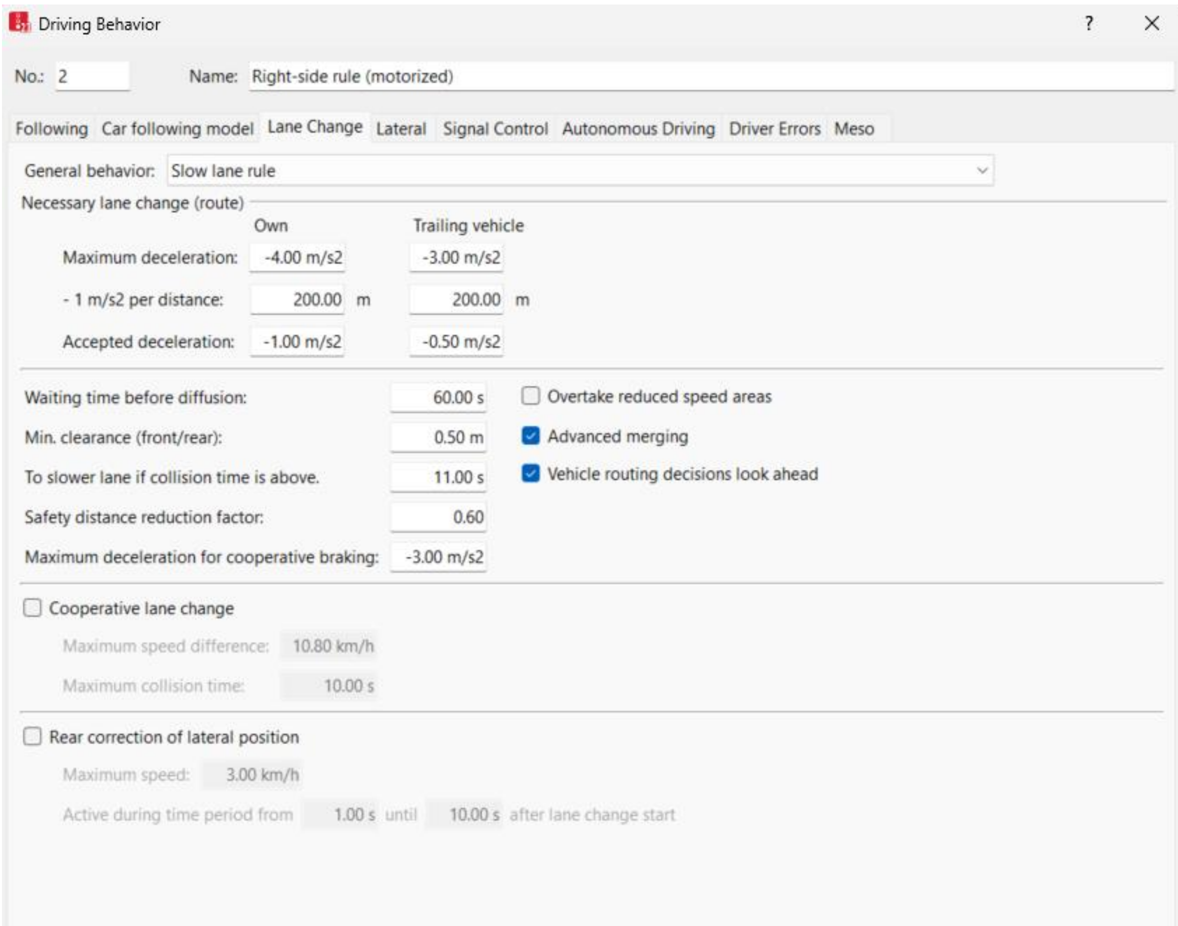


Figure C1.4: Lane change parameters adjusted in the Vissim model

APPENDIX D: RAMP METERING CALCULATIONS

Table D 1.1: One On Ramp Scenario

Time	Base model	One Onramp-Ramp Metering	Average Delay Difference (Seconds)	Percentage Change
6:00	12.01	11.01	-1.00	-9%
6:05	14.12	11.02	-3.10	-28%
6:10	18.37	22.43	4.06	18%
6:15	20.46	11.18	-9.28	-83%
6:20	22.25	20.32	-1.93	-9%
6:25	25.62	23.05	-2.57	-11%
6:30	48.76	54.65	5.89	11%
6:35	52.03	49.82	-2.21	-4%
6:40	85.13	78.28	-6.85	-9%
6:45	90.09	84.53	-5.56	-7%
6:50	95.61	88.25	-7.36	-8%
6:55	98.32	72.09	-26.23	-36%
7:00	100.94	94.36	-6.58	-7%
7:05	102.88	99.08	-3.80	-4%
7:10	105.64	99.33	-6.31	-6%
7:15	108.25	103.32	-4.93	-5%
7:20	100.11	86.21	-13.90	-16%
7:25	95.28	99.56	4.28	4%
7:30	70.36	66.59	-3.77	-6%
7:35	65.23	61.68	-3.55	-6%
7:40	60.97	46.65	-14.32	-31%
7:45	55.72	53.90	-1.82	-3%
7:50	45.02	41.07	-3.95	-10%
7:55	42.95	41.24	-1.71	-4%
8:00	35.12	34.53	-0.59	-2%
8:05	32.53	30.47	-2.06	-7%
8:10	30.44	29.52	-0.92	-3%
8:15	28.61	26.72	-1.89	-7%
8:20	25.94	20.71	-5.23	-25%
8:25	22.53	20.15	-2.38	-12%
8:30	20.15	19.34	-0.81	-4%
8:35	18.92	17.85	-1.07	-6%
8:40	16.22	14.56	-1.66	-11%
8:45	14.05	12.16	-1.89	-16%
8:50	12.82	13.94	1.12	8%
8:55	10.01	10.20	0.19	2%
9:00	9.12	8.92	-0.20	-2%
9:05	9.07	7.68	-1.39	-18%
9:10	7.34	7.91	0.57	7%
9:15	8.19	7.04	-1.15	-16%
9:20	9.02	8.14	-0.88	-11%
9:25	6.73	5.69	-1.04	-18%
9:30	5.98	4.25	-1.73	-41%
9:35	5.76	3.76	-2.00	-53%
9:40	7.42	4.55	-2.87	-63%
9:45	6.31	6.10	-0.21	-3%
9:50	5.77	5.48	-0.29	-5%
9:55	5.63	6.20	0.57	9%
	Total	1745.49	-144.31	
	Overall percentage change	-8%		

Table D 1.2: Two On Ramps Scenario

Time	Base model	Two Onramps-Ramp Metering	Average Delay Difference (Seconds)	Percentage Change
6:00	12.01	8.91	-3.10	-35%
6:05	14.12	9.71	-4.41	-45%
6:10	18.37	15.30	-3.07	-20%
6:15	20.46	18.85	-1.61	-9%
6:20	22.25	25.39	3.14	12%
6:25	25.62	23.64	-1.98	-8%
6:30	48.76	40.83	-7.93	-19%
6:35	52.03	49.35	-2.68	-5%
6:40	85.13	77.79	-7.34	-9%
6:45	90.09	81.26	-8.83	-11%
6:50	95.61	84.36	-11.25	-13%
6:55	98.32	95.43	-2.89	-3%
7:00	100.94	90.19	-10.75	-12%
7:05	102.88	93.87	-9.01	-10%
7:10	105.64	86.63	-19.01	-22%
7:15	108.25	104.01	-4.24	-4%
7:20	100.11	78.40	-21.71	-28%
7:25	95.28	73.67	-21.61	-29%
7:30	70.36	60.57	-9.79	-16%
7:35	65.23	58.17	-7.06	-12%
7:40	60.97	55.77	-5.20	-9%
7:45	55.72	48.45	-7.27	-15%
7:50	45.02	40.05	-4.97	-12%
7:55	42.95	38.16	-4.79	-13%
8:00	35.12	28.42	-6.70	-24%
8:05	32.53	37.77	5.24	14%
8:10	30.44	23.83	-6.61	-28%
8:15	28.61	23.07	-5.54	-24%
8:20	25.94	23.29	-2.65	-11%
8:25	22.53	19.35	-3.18	-16%
8:30	20.15	18.98	-1.17	-6%
8:35	18.92	15.20	-3.72	-24%
8:40	16.22	15.62	-0.60	-4%
8:45	14.05	8.66	-5.39	-62%
8:50	12.82	10.80	-2.02	-19%
8:55	10.01	10.32	0.31	3%
9:00	9.12	7.43	-1.69	-23%
9:05	9.07	8.47	-0.60	-7%
9:10	7.34	5.46	-1.88	-34%
9:15	8.19	4.98	-3.21	-64%
9:20	9.02	6.00	-3.02	-50%
9:25	6.73	2.72	-4.01	-147%
9:30	5.98	4.56	-1.42	-31%
9:35	5.76	4.90	-0.86	-18%
9:40	7.42	7.01	-0.41	-6%
9:45	6.31	6.95	0.64	9%
9:50	5.77	8.15	2.38	29%
9:55	5.63	6.32	0.69	11%
	Total	1667.02	-222.78	
	Overall percentage change	-13%		

Table D 1.3: Five On Ramps Scenario

Time	Base model	5 Onramps-Ramp Metering	Average Delay Difference (Seconds)	Percentage Change
6:00	12.01	9.97	-2.04	-20%
6:05	14.12	11.72	-2.40	-20%
6:10	18.37	15.25	-3.12	-20%
6:15	20.46	19.98	-0.48	-2%
6:20	22.25	18.47	-3.78	-20%
6:25	25.62	21.26	-4.36	-20%
6:30	48.76	50.47	1.71	3%
6:35	52.03	43.18	-8.85	-20%
6:40	85.13	70.66	-14.47	-20%
6:45	90.09	74.77	-15.32	-20%
6:50	95.61	69.36	-26.25	-38%
6:55	98.32	81.61	-16.71	-20%
7:00	100.94	83.78	-17.16	-20%
7:05	102.88	85.39	-17.49	-20%
7:10	105.64	97.68	-7.96	-8%
7:15	108.25	89.85	-18.40	-20%
7:20	100.11	93.09	-7.02	-8%
7:25	95.28	79.08	-16.20	-20%
7:30	70.36	48.40	-21.96	-45%
7:35	65.23	54.14	-11.09	-20%
7:40	60.97	60.61	-0.36	-1%
7:45	55.72	46.25	-9.47	-20%
7:50	45.02	27.37	-17.65	-65%
7:55	42.95	35.65	-7.30	-20%
8:00	35.12	29.15	-5.97	-20%
8:05	32.53	37.00	4.47	12%
8:10	30.44	25.27	-5.17	-20%
8:15	28.61	23.75	-4.86	-20%
8:20	25.94	21.53	-4.41	-20%
8:25	22.53	28.70	6.17	21%
8:30	20.15	11.72	-8.43	-72%
8:35	18.92	15.70	-3.22	-20%
8:40	16.22	13.46	-2.76	-20%
8:45	14.05	11.66	-2.39	-20%
8:50	12.82	9.64	-3.18	-33%
8:55	10.01	8.31	-1.70	-20%
9:00	9.12	5.57	-3.55	-64%
9:05	9.07	5.53	-3.54	-64%
9:10	7.34	4.09	-3.25	-79%
9:15	8.19	5.80	-2.39	-41%
9:20	9.02	5.49	-3.53	-64%
9:25	6.73	4.59	-2.14	-47%
9:30	5.98	4.96	-1.02	-20%
9:35	5.76	4.78	-0.98	-20%
9:40	7.42	3.16	-4.26	-135%
9:45	6.31	5.24	-1.07	-20%
9:50	5.77	4.79	-0.98	-20%
9:55	5.63	4.67	-0.96	-20%
	Total	1582.534	-307.266	
	Overall percentage change	-19%		

APPENDIX E: CONGESTION CHARGING CALCULATIONS

Table E 1.1: Volume Reduction of 5%

Time	Base model	5% Volume Reduction	Average Delay Difference (Seconds)	Percentage Change
6:00	12.01	12.31	0.30	2%
6:05	14.12	12.53	-1.59	-13%
6:10	18.37	17.37	-1.00	-6%
6:15	20.46	19.19	-1.27	-7%
6:20	22.25	24.21	1.96	8%
6:25	25.62	25.28	-0.34	-1%
6:30	48.76	39.28	-9.48	-24%
6:35	52.03	44.01	-8.02	-18%
6:40	85.13	79.04	-6.09	-8%
6:45	90.09	86.63	-3.46	-4%
6:50	95.61	92.14	-3.47	-4%
6:55	98.32	92.99	-5.33	-6%
7:00	100.94	95.27	-5.67	-6%
7:05	102.88	93.27	-9.61	-10%
7:10	105.64	97.99	-7.65	-8%
7:15	108.25	101.21	-7.04	-7%
7:20	100.11	92.34	-7.77	-8%
7:25	95.28	88.83	-6.45	-7%
7:30	70.36	68.12	-2.24	-3%
7:35	65.23	64.53	-0.70	-1%
7:40	60.97	56.36	-4.61	-8%
7:45	55.72	53.24	-2.48	-5%
7:50	45.02	39.99	-5.03	-13%
7:55	42.95	41.40	-1.55	-4%
8:00	35.12	34.63	-0.49	-1%
8:05	32.53	29.52	-3.01	-10%
8:10	30.44	32.17	1.73	5%
8:15	28.61	27.33	-1.28	-5%
8:20	25.94	25.41	-0.53	-2%
8:25	22.53	19.59	-2.94	-15%
8:30	20.15	17.81	-2.34	-13%
8:35	18.92	16.71	-2.21	-13%
8:40	16.22	13.44	-2.78	-21%
8:45	14.05	15.06	1.01	7%
8:50	12.82	12.45	-0.37	-3%
8:55	10.01	10.31	0.30	3%
9:00	9.12	7.40	-1.72	-23%
9:05	9.07	9.31	0.24	3%
9:10	7.34	5.52	-1.82	-33%
9:15	8.19	7.22	-0.97	-13%
9:20	9.02	9.67	0.65	7%
9:25	6.73	5.41	-1.32	-24%
9:30	5.98	6.56	0.58	9%
9:35	5.76	3.86	-1.90	-49%
9:40	7.42	6.96	-0.46	-7%
9:45	6.31	4.38	-1.93	-44%
9:50	5.77	6.34	0.57	9%
9:55	5.63	6.59	0.96	15%
	Total	1771.18	-118.62	
	Overall percentage change	-7%		

Table E 1.2: Volume Reduction of 10%

Time	Base model	10% Volume Reduction	Average Delay Difference (Seconds)	Percentage Change
6:00	12.01	10.64	-1.37	-13%
6:05	14.12	13.07	-1.05	-8%
6:10	18.37	17.13	-1.24	-7%
6:15	20.46	16.73	-3.73	-22%
6:20	22.25	18.67	-3.58	-19%
6:25	25.62	21.36	-4.26	-20%
6:30	48.76	39.47	-9.29	-24%
6:35	52.03	43.91	-8.12	-18%
6:40	85.13	73.71	-11.42	-15%
6:45	90.09	77.88	-12.21	-16%
6:50	95.61	80.99	-14.62	-18%
6:55	98.32	83.27	-15.05	-18%
7:00	100.94	81.36	-19.58	-24%
7:05	102.88	88.66	-14.22	-16%
7:10	105.64	90.34	-15.30	-17%
7:15	108.25	90.98	-17.27	-19%
7:20	100.11	86.60	-13.51	-16%
7:25	95.28	82.01	-13.27	-16%
7:30	70.36	60.81	-9.55	-16%
7:35	65.23	53.91	-11.32	-21%
7:40	60.97	52.83	-8.14	-15%
7:45	55.72	45.48	-10.24	-23%
7:50	45.02	40.08	-4.94	-12%
7:55	42.95	36.68	-6.27	-17%
8:00	35.12	30.21	-4.91	-16%
8:05	32.53	28.25	-4.28	-15%
8:10	30.44	27.29	-3.15	-12%
8:15	28.61	22.33	-6.28	-28%
8:20	25.94	21.81	-4.13	-19%
8:25	22.53	17.44	-5.09	-29%
8:30	20.15	18.50	-1.65	-9%
8:35	18.92	15.64	-3.28	-21%
8:40	16.22	12.60	-3.62	-29%
8:45	14.05	12.28	-1.77	-14%
8:50	12.82	11.41	-1.41	-12%
8:55	10.01	7.81	-2.20	-28%
9:00	9.12	7.77	-1.35	-17%
9:05	9.07	9.42	0.35	4%
9:10	7.34	6.40	-0.94	-15%
9:15	8.19	5.25	-2.94	-56%
9:20	9.02	6.37	-2.65	-42%
9:25	6.73	5.99	-0.74	-12%
9:30	5.98	7.02	1.04	15%
9:35	5.76	4.15	-1.61	-39%
9:40	7.42	6.10	-1.32	-22%
9:45	6.31	6.66	0.35	5%
9:50	5.77	5.28	-0.49	-9%
9:55	5.63	5.81	0.18	3%
	Total	1608.36	-281.44	
	Overall percentage change	-17%		

Table E 1.3: Volume Reduction of 15%

Time	Base model	15% Volume Reduction	Average Delay Difference (Seconds)	Percentage Change
6:00	12.01	11.66	-0.35	-3%
6:05	14.12	12.89	-1.23	-10%
6:10	18.37	16.25	-2.12	-13%
6:15	20.46	17.75	-2.71	-15%
6:20	22.25	18.95	-3.30	-17%
6:25	25.62	21.89	-3.73	-17%
6:30	48.76	41.25	-7.51	-18%
6:35	52.03	53.67	1.64	3%
6:40	85.13	71.23	-13.90	-20%
6:45	90.09	74.87	-15.22	-20%
6:50	95.61	78.20	-17.41	-22%
6:55	98.32	81.02	-17.30	-21%
7:00	100.94	72.51	-28.43	-39%
7:05	102.88	84.22	-18.66	-22%
7:10	105.64	86.11	-19.53	-23%
7:15	108.25	88.50	-19.75	-22%
7:20	100.11	82.10	-18.01	-22%
7:25	95.28	77.12	-18.16	-24%
7:30	70.36	57.71	-12.65	-22%
7:35	65.23	53.82	-11.41	-21%
7:40	60.97	50.23	-10.74	-21%
7:45	55.72	45.90	-9.82	-21%
7:50	45.02	36.93	-8.09	-22%
7:55	42.95	35.12	-7.83	-22%
8:00	35.12	28.25	-6.87	-24%
8:05	32.53	26.00	-6.53	-25%
8:10	30.44	34.00	3.56	10%
8:15	28.61	22.42	-6.19	-28%
8:20	25.94	20.00	-5.94	-30%
8:25	22.53	17.10	-5.43	-32%
8:30	20.15	11.56	-8.59	-74%
8:35	18.92	14.27	-4.65	-33%
8:40	16.22	12.52	-3.70	-30%
8:45	14.05	10.87	-3.18	-29%
8:50	12.82	10.20	-2.62	-26%
8:55	10.01	7.92	-2.09	-26%
9:00	9.12	7.20	-1.92	-27%
9:05	9.07	7.15	-1.92	-27%
9:10	7.34	5.60	-1.74	-31%
9:15	8.19	6.25	-1.94	-31%
9:20	9.02	4.01	-5.01	-125%
9:25	6.73	5.22	-1.51	-29%
9:30	5.98	4.48	-1.50	-33%
9:35	5.76	4.31	-1.45	-34%
9:40	7.42	5.58	-1.84	-33%
9:45	6.31	4.92	-1.39	-28%
9:50	5.77	4.60	-1.17	-25%
9:55	5.63	4.55	-1.08	-24%
	Total	1548.88	-340.92	
	Overall percentage change	-22%		

APPENDIX F: TRAVEL TIME CALIBRATION

Table B1.2: 2023 Simulated and measured travel times comparison

Time	Measured travel time (2023) (min)	Simulated travel time (2023) (min)	Percentage of measured value	Threshold met?
06:00	17	15.0	12%	Yes
06:10	22	19.0	14%	Yes
06:20	31	27.0	13%	Yes
06:30	48	45.0	6%	Yes
06:40	60	53.0	12%	Yes
06:50	64	60.0	6%	Yes
07:00	65	62.0	5%	Yes
07:10	60	55.0	8%	Yes
07:20	56	56.7	-1%	Yes
07:30	50	55.7	-11%	Yes
07:40	45	55.7	-24%	Yes
07:50	41	44.8	-9%	Yes
08:00	35	39.3	-12%	Yes
08:10	31	35.5	-14%	Yes
08:20	28	42.3	-51%	Yes
08:30	25	12.0	52%	No
08:40	23	29.4	-28%	Yes
08:50	22	17.1	22%	No
09:00	21	19.0	10%	Yes
09:10	24	22.0	8%	Yes
09:20	32	30.0	6%	Yes
09:30	29	33.0	-14%	Yes
09:40	25	29.0	-16%	Yes
09:50	23	19.0	17%	No
			21.00	
			24.00	
	Threshold satisfied for travel time >85%		0.875	