Vehicle-to-Vehicle Connectivity for Real-time Traffic Incident Detection on Motorways: A Traffic Microsimulation Study

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Abstract

The rapid pace of urbanisation and advancements in Intelligent Mobility (IM) bring both opportunities and challenges. While improved mobility options enhance convenience, they also contribute to traffic congestion and increased incident risks. Innovations in artificial intelligence—such as machine learning, big data, and image recognition—have transformed vehicles from mechanical systems into intelligent, connected entities. Connected Vehicle (CV) technology, which includes vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication, enables real-time data exchange, improving traffic safety and efficiency.

Addressing traffic congestion and incidents—two key transport issues—requires advanced solutions. Incident Detection (ID) algorithms, supported by V2V connectivity, offer real-time alerts to road users, helping mitigate congestion and reduce accident risks. This study developed a V2V-based ID algorithm, evaluated using indicators like vehicle delay, queue length, macroscopic fundamental diagrams (MFDs), and conflict numbers. Using VISSIM traffic microsimulation and real-world data from the M1 motorway, scenarios with varying vehicle types and CV market penetration rates (MPRs) from 0% to 100% were assessed.

Simulations revealed that CV integration significantly improves traffic flow and safety. At 100% MPR, average delays dropped by 50%, and conflicts decreased by 55–70%, depending on incident duration. Five incident scenarios with different lane closures and durations further demonstrated that higher CV penetration leads to reduced disruption and better traffic performance.

The study also analysed 2019 traffic data on the M1 to explore incident and congestion patterns, revealing notable correlations. The findings support the potential of CV-enabled incident detection to enhance real-time traffic management and safety. This research provides a robust framework for integrating CV technology into existing infrastructure, aiding transport planners and policymakers in reducing incidents and improving congestion strategies.

Keywords: Traffic Incident detection; Motorways; Traffic Microsimulation; Vehicle-to-vehicle (V2V) connectivity; Real-time traffic operations

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"The measure of intelligence is the ability to change" – Albert Einstein

True intelligence is not just about acquiring knowledge; it's about the ability to adapt and evolve with new challenges and information. The world is constantly changing, and those who can keep up with it are the ones who will go forward. I wish all of us would strive for true intelligence in all aspects of our lives, not just in our careers.

To my mom and dad,

the unseen heroes of my life.

Thank you for all that you have done for me, I love you so much!

I would never be the person I am without you!

Μαμά, Μπαμπά σας αγαπάω πολύ!

(Mom, Dad, I love you so much!)

Declarations

Statement of Originality

I hereby declare that the research outcomes and analyses presented in this thesis result from my own scholarly endeavours, except where specific contributions from other sources have been properly referenced.

Copyright Declaration

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List of Abbreviations

The following is a list of abbreviations and associated definitions for terms appearing throughout this this first-year report:

Abbreviation	Definition
ACC	Adaptive Cruise Control
ADAS	Advanced Driver Assistance Systems
ADS	Advanced Driver Systems
AMoD	Automated Mobility-on-Demand system
AI	Artificial Intelligence
AVs	Autonomous Vehicles
BS	Bike Sharing
CAV(s)	Connected and Autonomous Vehicle(s)
CAS	Collision Avoidance System
CFM	Car-Following Models
CACC	Cooperative adaptive cruise control
CCAM	Cooperative, connected and automated mobility
CCAV	Centre for Connected and Autonomous Vehicles (UK)
C-ITS	Co-operative Intelligent Transport Systems
CV	Connected Vehicle(s)
CS	Car Sharing
DLL	Discretionary Lane Changing
DfT	Department for Transport
DSR	Demand-side response
DSRC	Dedicated Short-Range Communications
FV	Following Vehicle
GEH	The GEH statistics formula gets its name from Geoffrey E. Havers, who invented it in the 1970s
GHG	Greenhouse Gas
GPS	Global Positioning System
HGVs	Human Goods Vehicles
HIL	Hardware-in-the-loop simulation
EU	European Union
EVs	Electric Vehicles
I2I	Infrastructure to Infrastructure
I2V	Infrastructure to Vehicle
ICC	Intelligent Cruise Control
ICTs	Information and Communication Technologies
ILDs	Inductive Loop Detectors
IM	Intelligent Mobility
INS	Inertial Navigation Systems
IRR	Incidence Rate Ratio
IVC	Inter-Vehicle Communication
IoT	Internet of Things
ITS	Intelligent Transport Systems
KPI	Key Performance Indicators
LCM	Lane Changing Models
LCV	Lane Changing Vehicle
LIDAR	Light Detection and Ranging

LV	Lead Vehicle
MaaS	Mobility as a Service
MLC	Mandatory Lane Changing
MOE	Measures of Effectiveness
RCC	Regional Control Center
ROC	Regional Operational Center
NB	Negative Binomial
NHTSA	National Highway Traffic Safety Administration
NMS	New Mobility Services
SEM	Simultaneous Equation Models
TET	Time Exposed Time-to-collision
TERCRI	Time Exposed Rear-end Crash Risk Index
TFM	Traffic Flow Models
TIT	Time integrated time-to-collision
TNCs	Transport Network Companies
PT	Public Transport
QGIS	Quantum Geographic Information System
RADAR	Radio Detection and Ranging
RENB	Random Effect Negative Binomial
SAVs	Shared Autonomous Vehicles
SEM	Simultaneous Equation Models
SIL	Software-in-the-loop simulation
SRN	Strategic Road Network
SSAM	Surrogate Safety Assessment Model
SSCR	SideSwipe Crash Risk
VIL	Vehicle-in-the-loop simulation
VISSIM	"Verkehr In Städten - SIMulationsmodell" (German for "Traffic in cities - simulation model")
V2I	Vehicle-to-infrastructure
V2V	Vehicle-to-vehicle
V2X	Vehicle-to-everything
VKT	Vehicle Kilometers Travelled
VMS	Variable Message Sign
VMT	Vehicle Miles Travelled
WAVE	Wireless Access in Vehicular Environment
WebTRIS	Website for Traffic Information System

Chapter 1: Introduction

1.1 Background

We live in a time of remarkable change in the transport system. Changes in the nature of working and shopping, new technologies and behaviours – such as automation, connectivity, and vehicle electrification – are already having an impact on how the system functions, while the intersection of the physical and digital realms is changing with respect to how transport is planned and used (Becker et al., 2019). These developments bring exciting possibilities which, if grasped, will bring significant social benefits. The government has an excellent opportunity to capitalise on these, particularly through the future of mobility industrial strategy grand challenge (Jittrapirom et al., 2017).

With the projected growth in transport demand, the need for innovative services that could encourage seamless mobility and a shift from car ownership to usership is crucial. More specifically, global passenger demand is projected to more than double from 50,000 to 120,000 billion passenger-kilometres between 2015 and 2050 (ITF Transport Outlook, 2017) . An emerging trend supporting this transformation is the integration of on-demand transport modes – such as ridesharing, bike-sharing, and Mobility-as-a-Service (MaaS) – with traditional public transport systems. This integration represents a shift toward Intelligent Mobility, defined as a system of interconnected technologies and services that enable efficient, safe, and sustainable transportation solutions tailored to the needs of users, infrastructure, and the environment, where technology-enabled solutions enhance connectivity, accessibility, and efficiency in transport networks (Mulley et al., 2018). To this end, Intelligent Mobility Vehicles are well-placed to drive this vision to another outstanding improvement in the industry (Elliott et al., 2019). Automation is seen as a key driver for Intelligent Mobility and an area which is on the brink of revolutionising the way people and of course, goods are moving (Casner et al., 2016). Driverless cars, connected vehicles, autonomous trains, unscrewed aerial vehicles, and autonomous pods and shuttles are examples of this technology.

Over the past few decades, autonomous and connected driving has been the subject of great research efforts (John Bradburn, David Williams, Rob Piechocki, 2017a; Talebpour & Mahmassani, 2016a). Driving is an exclusionary achievement of human function. The automobile and technology industries have made a significant jump in bringing computerisation into driving (Fagnant & Kockelman, 2015). Despite human's huge development in driving throughout the years, the human errors are a notable cause of road accidents and fatalities (Dai et al., 2022). Furthermore, road congestion causes inefficiency in daily commutes and other aspects of road transport (C. Wang et al., 2013). It is envisaged that a transport system that is less reliant on human drivers will allow all the passengers to use their travelling time better and is associated with fewer road accidents (Guanetti et al., 2018). Automation technology is improving at a high pace, and connected features are already offered on current vehicle models. Consequently, the idea of a driverless car is no longer a distant possibility. Moreover, thinking of a broadened horizon, the entrance of intelligent mobility will be pledged to the connectivity between transport with more safety, convenience, and energy efficiency.

As an efficient, sustainable transport system is based on Intelligent Mobility, the benefits should be obvious (Atkins, 2019b; Mandžuka, 2020). As urban areas grow and challenges such as pollution, traffic congestion, and inefficient transport networks intensify, it is evident that a transformative shift is required in how mobility is planned and delivered (Treiber & Kesting, 2018). Intelligent Mobility reduces pollution, congestion and spending on infrastructure development while enabling more reliable, faster journeys and decreasing the burden on those who are car-dependent (G. Arnaout & Bowling, 2011). However, achieving these gains will not be easy, and an uncoordinated and slow approach could hinder the outcome. A shared vision between industry, academia, and government is critical if it aspires to be at the forefront of innovation.

It is widely known that Intelligent Mobility technologies are transformative technologies that have great potential for reducing traffic accidents, enhancing quality of life, and, finally improving the efficiency of transport systems (Elliott et al., 2019). As analysed in detail below in Chapter 2, Intelligent Mobility Technologies can be categorised into three main groups: a) Shared Mobility/On-Demand Mobility and Mobile Applications, b) Mobility as a Service, and c) Connected and Autonomous Vehicles.

Depending on these technologies, in the future some years from now, the roads will look completely different. Conventional vehicles will be replaced all by connected vehicles, automated vehicles, zero-emission vehicles, and other intelligent mobility vehicles, such as autonomous shuttle buses. Looking at the future, all of the above will no longer be a rarity and “drivers” will be seen working, watching a movie, or even facing away from the direction of travel.

The CV is an innovative project that aims to create "intelligent vehicles" and is set to become the next significant advancement in travel technology. This exciting new technology will offer a range of benefits, including increased capacity for existing transport networks and improved road safety measures. The CV is an innovative project that aims to create "intelligent vehicles" and is set to become the next significant advancement in travel technology. This exciting new technology will offer a range of benefits, including increased capacity for existing transport networks and improved road safety measures. An "intelligent vehicle", as a CV, is emerging as the next wave of technology to empower travellers further. Among other advantages, this technology will provide for increased capacity of existing transport networks in addition to increased roadside safety (Jadaan et al., 2017).

1.2 Research Importance

Recent advancements in technology, connectivity, and dynamic mapping will revolutionise the way people interact and utilise transport infrastructure. Future mobility will be more human-centric, interconnected, intelligent, sustainable, and resilient (Docherty et al., 2018). These systems will optimise infrastructure use, offer on-demand ubiquitous mobility, and tackle traffic congestion and safety concerns. Intelligent mobility, enabled by vehicle connectivity automation, cloud computing, artificial intelligence, and the Internet of Things, will gather and analyse a vast amount of data, minimising the impact of traffic incidents on network performance (Outay et al., 2021). This data-driven approach will enable us to mitigate the impact of traffic incidents on network performance and transform the economy and society in the coming decade.

Current transport systems lack economic efficiency, environmental friendliness, and safety due to the influence of human factors. Human error is responsible for 94% of road traffic collisions (Singh Bhupendra, 2015). However, breakthroughs in artificial intelligence, sensor fusion, connected capabilities, and software algorithms are leading to the development of CVs. CVs can communicate with other vehicles and infrastructure, sharing real-time information about traffic conditions, hazards, and incidents. This enhanced connectivity improves situational awareness and enables cooperative driving strategies, promising significant impacts on safety, mobility, and society(Abdelkader et al., 2021). Particularly, CVs offer a crucial advantage in terms of improved road safety, especially when a traffic incident occurs on a network, such as breakdowns, as CV technology can potentially achieve real time detection, mitigating its effects on traffic efficiency and safety (X. Li et al., 2023).

Existing studies have explored on-demand mobility, Mobility-as-a-Service (MaaS), and CVs in detecting abnormal traffic patterns and their impact on road safety (Hörl et al., 2019a; Pandey et al., 2019a; Rahman & Abdel-Aty, 2018a; Virdi et al., 2019a) . However, limited research on using CV technology to address traffic incident consequences exists. While V2V technologies primarily concentrate on efficient traffic information dissemination (Nadeem et al., 2004) and route guidance (Claes et al., 2011), its comprehensive evaluation in incident-prone scenarios is limited. Leveraging the potential of CVs' route choice coordination system (Claes et al., 2011) and the online environment (Du et al., 2014), these technologies can effectively handle issues such as predicting link travel time. Therefore, robust V2V communication is vital for connected transport systems (Dey et al., 2016), enabling CVs to exchange data, enhance situational awareness, reduce congestion, and improve road safety for a convenient and safe travel experience.

The significance of this research is strongly connected with intelligent mobility capabilities, particularly in the context of the Strategic Road Network (SRN). The SRN experiences a significant number of incidents every year, with research indicating that over half a million such incidents occurred in 2019 alone. These incidents caused significant delays and disruptions, costing the UK government £3 billion. From the analysis of incident data from 2017 to 2019, it was found that an annual average of 600,000 to 800,000 incidents occurred on the SRN of UK motorways. These incidents included breakdowns, traffic obstructions, collisions, fires, and pedestrian-related incidents. It's crucial to address these challenges as they pose a threat to human lives.

Detecting traffic incidents on high-speed road networks is crucial to responding and resolve promptly, thereby restoring safe traffic flow within acceptable timeframes (Farag & Hashim, 2017). However, there is a research gap in quantitatively assessing the influence of CVs in the event of an incident. To address this, a traffic simulation framework is required, capable of modelling both CVs and conventional vehicles in various predefined scenarios.

The study aims to detect incidents in real time and quickly share this information with other road users. It also addresses the scarcity of real-world data on V2V connectivity in motorway settings. By overcoming these challenges, traffic performance will be maximised, and highway road safety will be enhanced by integrating CVs. The main contribution is evaluating the effectiveness of CVs' V2V technologies as an intelligent incident detection and mitigation method under representative incident scenarios. This will enable decision-makers to define the best-operated technique when dealing with motorway incidents.

1.3 Problem statement and research challenges

Inserting integrated V2V connectivity technologies to enhance traffic incident detection is a complex endeavour that demands cutting-edge technologies to manage various uncertainties and limitations. These uncertainties can include forecasting the behaviour of other vehicles, gathering accurate data from the manoeuvres of the following vehicles in case of an incident and correctly informing the following vehicles and Regional Operating Centers (ROC) in real-time.

The primary objective of this research is to minimise the aforementioned challenge and enhance traffic performance by leveraging a novel V2V communication protocol to automatically detect traffic incidents. By implementing this innovative approach, the aim is to significantly reduce the occurrence of incidents and mitigate their impact on the SRN. Such advancements hold promise for enhancing not only the efficiency of traffic management systems, but also overall road safety and minimising disruptions. Thus, the findings of this study have the potential to contribute substantively to the advancement of intelligent mobility strategies and the optimisation of transport infrastructure within the UK and beyond.

The current incident detection situation on SRN involves reliance on automated incident detection systems deployed by National Highways. These systems, until now, leverage a combination of sensors, CCTV cameras, and radar to identify incidents, supplemented by incident reports from road users. Upon detection, notification is routed to the Regional Operational Center, initiating confirmation and response procedures, which include determining the location of stopped vehicles and activating warning notifications on Variable Message Signs (VMS). However, literature studies have indicated that this process can be time-consuming, with previous research suggesting detection delays of up to 16 minutes, particularly under either adverse traffic or temporal and weather conditions. Consequently, a primary objective of this research is to address this challenge by integrating vehicle-to-vehicle (V2V) connectivity, an emerging disruptive technology, to accelerate incident response times.

The secondary challenge in this research endeavour lies in leveraging V2V connectivity to smooth incident management processes. Direct real-time communication among vehicles equipped with V2V capabilities can facilitate immediate distribution of incident location information to nearby vehicles. This paradigm shift aims to enhance situational awareness among road users, enabling prompt and adaptive responses to unfolding incidents. By harnessing V2V communication protocols, the framework seeks to revolutionise the efficacy and efficiency of incident detection and response mechanisms on the SRN, thereby advancing the overarching goals of road safety and traffic management optimisation. So, when an incident occurs, the vehicles involved will communicate with the following vehicle, informing them about the location of the incident by V2V connectivity, as shown in Figure 1.1 below.

Figure 1.1: Vehicle-to-vehicle connectivity

The third significant challenge concerns the insufficiency of empirical data regarding the implementation of V2V connectivity. The implementation and efficacy of V2V connectivity in motorway environments still need to be explored due to several limitations in empirical data. One major challenge is the need for large-scale deployment of V2V-enabled vehicles, making it difficult to study their real-world interactions and impacts on traffic management (Frenzel, 2018; Muhammad & Safdar, 2021). Existing studies often rely on small-scale pilot projects or simulations that, while insightful, may not fully capture the complexities of dense, high-speed traffic on motorways.

Additionally, variations in in-vehicle communication protocols, data transmission reliability, and environmental factors such as weather conditions further complicate the ability to draw comprehensive conclusions about V2V performance (Nadeem et al., 2004; H. Sharma et al., 2024). Empirical data on how V2V technologies integrate with existing infrastructure and incident management systems is also scarce, leaving gaps in understanding their scalability and practical applicability. Addressing this challenge requires a concerted effort to implement extensive field trials, gather real-world data, and refine simulation models to validate the benefits and limitations of V2V technologies in motorway contexts. This research aims to fill these gaps using a microsimulation platform that combines real-world data and simulated scenarios to evaluate V2V connectivity under diverse incident conditions.

In summary, the challenges facing incident management on the Strategic Road Network (SRN) can be categorised into two primary areas. The first challenge revolves around the necessity for real-time incident detection and the prompt distribution of relevant information to key stakeholders such as the ROC, VMS, and emergency services. This involves the seamless transfer of data regarding incident location and cruciality to enable swift and effective response measures. The second challenge concerns the insufficiency of empirical data regarding the implementation and efficacy of V2V connectivity, specifically within the context of motorway environments.

Nevertheless, despite these obstacles, V2V connectivity holds considerable promise in expanding incident detection capabilities on the SRN. By facilitating real-time detection and response, V2V connectivity stands to enhance road safety by promptly alerting nearby road users and enabling proactive measures such as rerouting. Furthermore, the timely distribution of incident information among road users has the potential to mitigate the effects of incidents, thereby minimising disruption and alleviating congestion on affected routes. Thus, despite the existing challenges, integrating V2V connectivity technologies offers a substantial pathway toward enhancing the efficiency and efficacy of incident detection strategies on the SRN.

Given the absence of empirical CV data, a simulation-based methodology has been adopted to address this limitation. This approach involves utilising the COM API interface of VISSIM software to simulate the driving behaviour of connected vehicles and generate simulated traffic incidents on the motorway under investigation. By leveraging this simulation framework, researchers can model various scenarios and assess the impact of CVs on incident management strategies despite the dearth of real-world data. Through this simulation-based approach, insights into the potential efficacy of CVs in mitigating incidents and optimising traffic flow can be gleaned, thereby informing future deployment and operational strategies within motorway environments.

In conclusion, additional potential challenges warrant consideration in integrating V2V technology within incident detection strategies. Firstly, the gradual pace of progress in V2V technology development poses a notable obstacle, potentially slowing down its swift adoption and deployment within operational frameworks. Secondly, the market penetration rates of connected vehicles (CVs) must surpass the critical threshold of 50% to yield significant reductions in vehicle delays and enhance the effectiveness of incident detection measures, as the research below showed. Lastly, the utilisation of artificial intelligence (AI) -based V2V algorithms introduces complexities, particularly when compared to traditional 'kinematics '-based approaches. These challenges underscore the need for comprehensive planning and strategic initiatives to overcome barriers and maximise the potential benefits of V2V technology in advancing incident detection capabilities on the road network.

1.4 Research Questions, Aim and Objectives

As highlighted, this study aims to assess the impact of Vehicle-to-Vehicle (V2V) connectivity for real-time traffic incident management on motorways. To achieve its scope, all Intelligent Mobility (IM) capabilities on highway traffic performance need to be examined, explaining their contribution to the existing transport systems. V2V connectivity as part of IM is a very promising solution, as it can achieve a great impact via Connected Vehicles (CVs) in real-time traffic incident management. To this end, with the use of an integrated mobility simulation platform, the opportunity to network operators is given to carry out a sensitivity analysis in designing real-time traffic control strategies and, secondly, creating impact assessment models to identify the optimal scenarios to introduce future mobility services involving fleets of Connected Vehicles (CVs), in the traffic incident management.

This aim will be fulfilled by developing, applying, and verifying various statistical and artificial intelligence techniques and algorithms to make predictions, taking optimal decisions and actions that are rigorous and scientific in the face of uncertainties. The study aims to detect incidents in real time, including assessing their severity (e.g., the impact on traffic flow, vehicle safety, and lane closures) and disseminating this information promptly to other road users. To address the scarcity of real-world data on V2V connectivity in motorway settings—given the current limitations in the widespread deployment of Connected Vehicles (CVs)—the research leverages advanced traffic microsimulation software. Using tools like VISSIM, the study creates realistic traffic scenarios replicating real-world conditions, combining Inductive Loop Detectors (ILDs) field data with simulated CV driving behaviours. This hybrid approach enables the evaluation of V2V technologies under controlled, scalable conditions, providing insights into their potential effectiveness even in the absence of extensive empirical data.

The output would be valuable for designing and implementing real-time traffic incident management, operations and control strategies aimed at enhancing overall traffic conditions, reducing delays and traffic collisions, and improving the traffic performance of motorways. The main contribution is developing and evaluating the effectiveness of CVs' V2V technologies as an intelligent method for incident detection and mitigation, tested under representative incident scenarios. The three research questions arising from the aim of the study are the following:

1. How do IM technologies affect the current and future network-level road conditions?
2. How and when are the benefits of V2V connectivity for real-time traffic incident detection going to be maximised?
3. How can an algorithm leveraging V2V connectivity be developed, implemented, and evaluated to detect incidents in real-time and mitigate their impacts on traffic flow, safety, and congestion at a network level?

The aim is to enhance the management of motorway incidents by implementing real-time vehicle-to-vehicle connectivity. By fostering communication between vehicles in real-time, this approach seeks to improve overall incident response and motorway detection. Moreover, the utilisation of advanced connectivity technologies can hold the potential to streamline communication, facilitate quicker responses, and enhance coordination among vehicles, contributing to a more efficient and effective incident management system. To fulfil the aim of this study, the following research objectives have been formulated:

1. To identify existing IM, traffic management systems and traffic incident management services and their characteristics with respect to network performance
2. To investigate existing techniques, via IM, for incident modelling and Vehicle-to-Vehicle Connectivity for real-time traffic incident management

3. To assess underlying factors affecting the occurrence of traffic incidents
4. To build an integrated simulation platform, which combines a microscopic traffic simulation model with an External Driver Model that can incorporate connected vehicles (CVs) and mixed traffic
5. Construct traffic incidents within the integrated simulation and develop an incident detection method using Vehicle-to-Vehicle Connectivity

A summary of the research agenda including the objectives and how each component is interdependent together is presented in Figure 1.2.

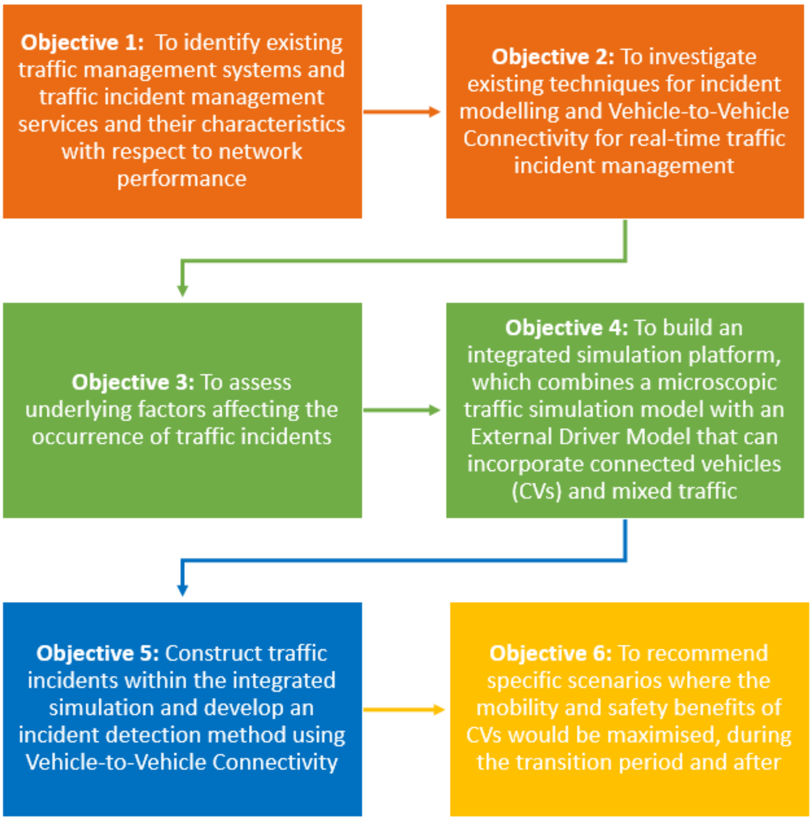

Figure 1.2: Research agenda

1.5 Research Design

The aim of this thesis is divided into six pre-dominant objectives which are achieved through the methods and data presented in Table 1.1.

Table 1.1: Research Aim and Objectives

Aim: Enhancing Motorway Incident Detection through Real-time Vehicle-to-Vehicle Connectivity				
Objective	Method	Chapter	Data Required	Outcome
To identify existing IM, traffic detection systems and traffic incident management services and their characteristics with	Literature Review on Traffic Management and Traffic Incident	Chapter 2	Academic/Grey Literature; Commercial Publishers; Stakeholders	A set of Intelligent Mobility Services

respect to network performance				
To investigate existing techniques for incident modelling and Vehicle-to-Vehicle Connectivity for real-time traffic incident management	Literature Review on Intelligent Mobility, Incident Modelling and Simulation, V2V simulation	Chapter 2	Academic/Grey Literature; Commercial Publishers; Stakeholders	Identify the impact of IM on Highways Traffic Performance
To assess underlying factors affecting the occurrence of traffic incidents	Development of statistical models capable of handling the interlink between traffic incidents and traffic variables, especially congestion index	Chapter 3 and Chapter 4	Real World Data	A descriptive exploration in the interlink of incidents and congestion to allow network operators to carry out sensitivity analysis in designing real-time traffic control strategies
To build an integrated simulation platform, which combines a microscopic traffic simulation model with an External Driver Model that can incorporate connected vehicles (CVs) and mixed traffic	Development of an integrated CV simulation algorithm and implementing it in a calibrated traffic microsimulation environment	Chapter 3 and Chapter 5	Real World Data	An adaptable simulation platform to allow network operators to carry out sensitivity analysis in designing real-time traffic control strategies
Construct traffic incidents within the integrated simulation and develop an incident detection method using Vehicle-to-Vehicle Connectivity	Development of a simulation technique to generate incidents and a new incident detection technique	Chapter 3 and Chapter 5	Simulated data from VISSIM;	Development of an incident detection method using V2V Connectivity within the integrated simulation platform to evaluate and identify optimal traffic management strategies for future mobility services involving fleets of CVs

To recommend a number of specific scenarios where the mobility and safety benefits of CVs would be maximised, during the transition period and after	Estimation of the mobility and safety benefits per simulation scenario in order to provide recommendations for the real-world implementation of CVs	Chapter 6	Key findings and literature review; scenarios development and testing	A set of recommendations for optimal traffic operations targeting new mobility services

1.6 Report Overview

This thesis comprises a structured exploration into Incident Detection and Management within the domain of road safety, employing a sophisticated approach that integrates traffic microsimulation, incident modelling, and cutting-edge Vehicle-to-Vehicle (V2V) connectivity technologies. This thesis is organised into nine chapters. The first chapter has outlined this research's main aim and objectives. It also includes the research questions to achieve the main aim, the objectives to answer the research questions and the research agenda. The remainder of this report is structured as follows.

In Chapter 2, a comprehensive Literature Review examines five key themes essential for the research. The first section covers traffic flow principles within traffic microsimulation, including Lane-Changing and Car-Following Models. Section second explores the parts of Intelligent mobility while the third section reviews Traffic Incident Detection, contrasting traditional methods with advanced IM approaches. The fourth section analyses IM scenario development, exploring Vehicle-to-Vehicle (V2V) connectivity for real-time incident detection and traffic safety. Finally, the fifth section evaluates simulation tools for modelling IM technologies and connected vehicles.

Chapter 3 intricately delineates the chosen Methodology. Comprising Research Design and Concept & Challenges, this chapter unfolds into three sections: A) Analysing Incidents, B) Simulation Network Model Method and CV driving behaviour and Traffic Incident Detection. These sections include the analytical frameworks, simulation designs, and modelling methodologies that existing in the study.

Chapter 4 introduces practical implementation, expounding upon the Data Collection and Integration Architecture. This section offers a comprehensive exposition of dataset acquisition, encompassing traffic, incident, and field observation data. The ensuing presentation of Exploratory Data Analysis results provides a foundation for incident detection insights.

Chapter 5 adopts a microscopic lens, focusing on Microscopic Simulation Modelling and its Calibration with meticulous attention to Scenario Development. This section methodically outlines the study area, details the calibration and validation processes, and unfolds the creation of representative scenarios for incident detection within the simulated environment.

Chapter 6 is dedicated to the adoption of V2V technologies, providing an in-depth Analysis and Findings related to Incident Detection. The introduction of selected Key Performance Indicators (KPIs), evaluation of effectiveness concerning mobility and safety, and a thorough exploration of connected vehicles' driving behaviour are presented through calibration results and scenario representations.

Chapter 7 includes empirical observations to a Discussion, synthesising findings across chapters, establishing interconnections, and engaging with the broader implications of the research within the academic and practical domains.

Chapter 8 brings the thesis to a conclusive milestone with a perceptive Conclusion. This section summarises key insights, outlines contributions to the field, and suggests avenues for future research, offering a fitting denouement to the comprehensive journey undertaken in this scholarly endeavour.

Chapter 2: Literature Review

The literature review of this study related to the first two objectives as depicted in Figure 2.1. As can be seen, four primary themes have been identified from the literature, and the focus has been given to these themes:

a. Traffic Flow Models
b. Intelligent Mobility
c. Incident Detection
d. Scenarios Development
e. Traffic Micro-simulation

The utilisation of a simulator becomes imperative to evaluate the influence of existing and prospective mobility services on the Strategic Road Network (SRN) and its implications for incident detection. It was crucial to gain a comprehensive understanding of all four themes, as illuminated by the extensive literature review conducted in the initial phases of the research. This foundational knowledge was necessary to pinpoint the research gap and determine the suitable methodology to achieve the overarching goal of the PhD, which is to appraise the impact of incident detection facilitated by Intelligent Mobility, leveraging CVs and V2V communication capabilities, on the traffic performance of highways for enhancing mobility and safety.

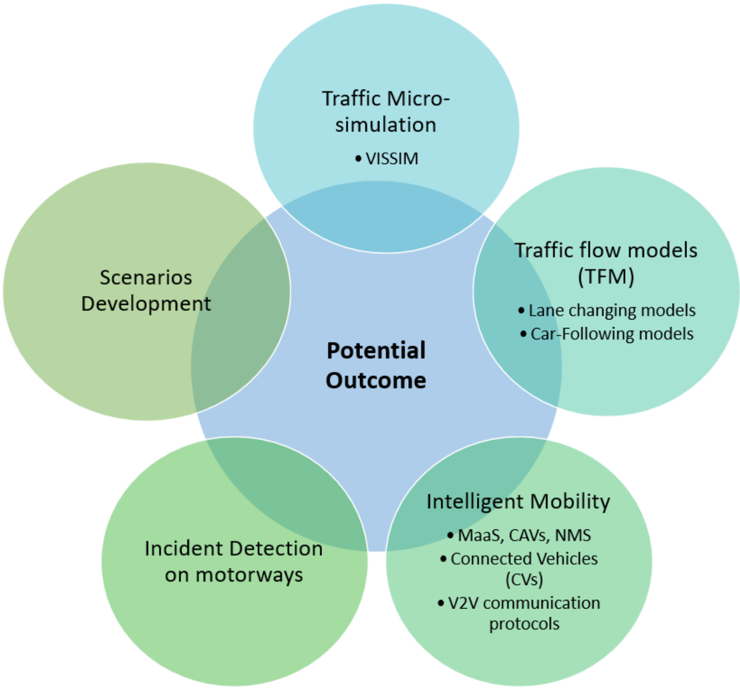

Figure 2.1: Methodology of Literature Review.

To sum up, the literature review consists of five main sections. The aim of each section is briefly presented below:

1. **Traffic Flow Theory.** This first section summarises the two basic traffic flow models: a) Lane Changing Models and b) Car-Following Models to obtain a holistic understanding of the traffic flow pattern. It also includes the categorisation of traffic flow models. This section summarizes

a literature review on different traffic flow models (e.g., macro-, meso- and microscopic), which are used to characterise the behaviour of the complex traffic flow system, which are an essential tool in traffic flow analysis and experimentation.

2. **Intelligent Mobility.** The second section of the Literature Review presents the three major parts of Intelligent Mobility and evidence of their impact on safety, traffic, the environment, etc. It identifies the possible issues which are currently occurring. Intelligent Mobility is summarised in three sections: a) Background, b) Intelligent Mobility definitions, c) New Mobility Technologies, which are divided into i) Shared Mobility/OnDemand Mobility, ii) Mobility as a Service and New Mobility Services, iii) Connected and Autonomous Vehicles, and Connected Vehicles each one of them has been analysed in-depth below.
3. **Incident Detection:** The Literature Review's third section emphasises the crucial role of incident detection on motorways for ensuring road safety and minimising traffic disruptions. Intelligent Mobility, incorporating technologies like Connected Vehicles and V2V communication, emerges as a promising solution to enhance incident detection. These technologies allow real-time vehicle communication, facilitating information exchange about incidents and road conditions. This interconnected system improves incident detection accuracy and speed, leading to quicker response times and enhanced traffic management. Incident detection relies heavily on traditional methods like surveillance cameras and roadside sensors without intelligent mobility integration, which may lack timely and dynamic information. The adoption of Intelligent Mobility has the potential to revolutionise incident detection on motorways, contributing to safer and more efficient road networks.
4. **Scenarios Development.** The fourth section of the Literature Review summarises several scenarios implemented, either for short or long-distance trips, to evaluate the impact of IM Technologies on the current and future Highways England's Strategic Road Network. Scenarios Development is summarised in two sections: a) Semi-automated/CAVs scenarios and b) Shared Mobility and MaaS scenarios.
5. **Existing simulation tools and attempts to simulate IM technologies.** The fifth section explains the virtual environment where simulation is relying on virtual agents to generate knowledge about vehicle behaviour without the need for a physical vehicle and actual testing in the real world. Also provides a review of the currently available traffic simulation software to form a shortlist of candidate tools capable of simulating IM. Moreover, attempts to simulate IM, and connected vehicles are also reviewed.

2.1 Motivation

Undoubtedly Intelligent Mobility is a technology that is continuous, the last decade, under the microscope of many researchers. The technological achievements have led to the transmission of mixed messages to the people, both negative and positive, regarding their direct but also the indirect impacts. Regarding the several stories about incidents that include IM technology, none of them managed to provide an exhaustive analysis of the incident regarding environmental conditions, equipment failure, or a specific reason for the incident, which was the lack of IM knowledge. This PhD research aims to give a holistic understanding of why the concept of IM is vital nowadays by providing an assemblage of advantages of IM on highway traffic performance.

Several attempts have been conducted to simulate Intelligent Mobility Scenarios (on-demand mobility, MaaS, CAVs, and CVs), trying to assess the impact of technologies like these on road safety and road mobility (Becker et al., 2019; Elvik, 2001; Katrakazas et al., 2015; Pandey et al., 2019b; Papadoulis et al., 2019; Rahman et al., 2018; Shao et al., 2019; Virdi et al., 2019b) and so far there are not as many as developed scenarios are needed in order to evaluate the impact of IM technologies on the network, concerning Incident Detection using CVs and V2V communication protocols. Thus, the Research Gap is identified as there is a need to quantify the impact of this Intelligent Mobility Technology of CVs enhancing with the V2V in the event of an incident on motorways through the formulation of a traffic simulation framework capable of modelling connected along with non-connected vehicles in a variety of pre-defined scenarios, with regards to maximising the traffic performance on highways, during and after the transition period to assess the impact of them on the SRN, enhancing safety and mobility.

As far as the research design of this research is concerned, a comprehensive development of one IM scenario has been identified that has not been evaluated in-depth through the existing literature on IM and the Scenarios. The scenario centres on simulating incident detection using Vehicle-to-Vehicle (V2V) connectivity to assess its effectiveness in real-time identification and response. So, it will be beneficial to figure out how their development will help Highways England enhance mobility and safety. For the Incident detection through V2V part, to figure out how to detect incidents through IM technologies, using CVs and V2V, there is the chance to minimise congestion and fatalities on Highways' England SRN. The exploration of incident detection through V2V technology, leveraging Connected Vehicles (CVs), aims to elucidate effective strategies for utilising Intelligent Mobility (IM) technologies to detect incidents. By harnessing the capabilities of CVs and V2V communication, the objective is to identify methodologies that have the potential to minimise congestion and reduce fatalities on Highways England's Strategic Road Network (SRN). This research aims to contribute valuable insights into leveraging cutting-edge technologies to enhance incident detection, thereby improving overall highway safety and operational efficiency.

Moreover, it is advantageous to discern, through simulation, the necessary measures to be implemented at a network level. The following sections will provide a concise literature review based on this scenario of this PhD research. Thus, insights into traffic incident modelling and incident detection using simulation for connected vehicles through V2V technologies will be presented below.

2.1 Traffic Flow Theory

It is widely known that traffic processes cause several problems in the motorways. Traffic delays, congestion, fatalities, and air pollution are examples of such problematic areas. Such kind of problems can be reduced rapidly with the appropriate road design and traffic control measure (W. Li & Kamargianni, 2018; Makarova et al., 2018; Noland & Quddus, 2004; Stevanovic et al., 2008; Q. Yang & Koutsopoulos, 1996). It is fundamental, therefore, for the effect of road designs and traffic control measures to be tested before implementing them. To this end, the knowledge of traffic flow theory is needed to be analysed. For this PhD, two general models of Traffic Flow Theory will be analysed: a) Lane Changing Models (LCM) and b) Car-Following Models (CFM).

To start with, traffic flow theory entails the knowledge of the fundamental characteristics of traffic flows and the associated analytical methods (Knoop, 2017). Examples of fundamental characteristics are the road capacities, the relationship between flow and density, and headway distributions. On the other hand, examples of analytical methods are shockwave theory and microscopic simulation models. Nowadays, a look at network dynamics needs to be made through traffic flow operations. To achieve this, both a microscopic and a macroscopic perspective need to be taken into consideration. The microscopic perspective reflects the behaviour of individual drivers interacting with surrounding vehicles, while the macroscopic perspective considers the average state of traffic.

In this respect, managing traffic in congested networks requires a clear understanding of traffic flow operations, i.e., insights into what causes congestion, what determines the time and location of traffic breakdown, how the congestion propagates through the network, etc. are essential. For this purpose, a wide range of traffic flow theories and models have been developed to answer several research questions. These models can be helpful tools in answering questions such as: When do traffic jams emerge? And how long does it take for congestion to be resolved? Additionally, the models can be used to improve road safety, something which is urgent, especially in motorway roads.

Lane changing (LC) and Car following (CF) are two primary models observed in traffic flow and are thus vital components of traffic flow theories (Zheng, 2014)(Zheng, 2014). CF and LC rules describe vehicular longitudinal and lateral interactions on the road, respectively. Although CF has been widely studied throughout years (Gurusinghe et al., 2002; Herman et al., 1958; Mathew, 2014), LC did not receive much attention until recently (Pan et al., 2016; Zhang et al., 2019; C. Zhu et al., 2019). Zheng (2014) supports this argument by stating that there is increasing evidence of (1) LC's negative impact on traffic safety and (2) its linkage to macroscopic traffic flow characteristics.

2.1.1 Lane Changing Models

Lane change is defined as "a driving manoeuvre that moves a vehicle from one lane to another where both lanes have the same direction of travel" (Fitch et al., 2009). Lane changing is usually modelled in two steps: (a) the decision to consider a lane change, and (b) the decision to execute the lane change. In many models, lane changes are classified as either mandatory or discretionary (Pan et al., 2016; Ahmed et al., 1996; Toledo and Zohar, 2007; Yang et al., 2019; Moridpour et al., 2010a). Mandatory Lane Changing (MLC) happens when a driver is forced to leave the current lane, for instance, when merging onto the motorway from an on-ramp or taking an exit off-ramp. Discretionary Lane Changing (DLC) is performed when the driver is not happy with the driving situation in the current lane and wants to have some velocity advantage, for instance, when the driver is obstructed by a slow-moving vehicle (Moridpour et al., 2010a). Toledo et al., 2003a modelled the lane-changing decision as a sequence of three stages: (a) decision to consider a lane change, (b) choice of the target lane and (c) acceptance of a sufficient space gap in the target lane to execute the lane-changing decision. Furthermore, Ahmed (1999) was one of the first researchers to define three categories of lane-changing manoeuvres: MLC, DLC, and forced merging. Forced merging occurs in heavily congested traffic conditions when a gap of sufficient space and time is "created" by drivers to enable them to execute a lane-changing manoeuvre. Gap acceptance models are eventually used to model the execution of lane changes.

2.1.1.1 Lane Change Definitions

Different approaches have been taken in lane-changing studies during the decades. Moridpour et al. (2010) use a classification scheme for lane-changing models, as shown in Figure 2.2, to enhance road capacity and road safety for driving assistance systems (Moridpour et al., 2010a).

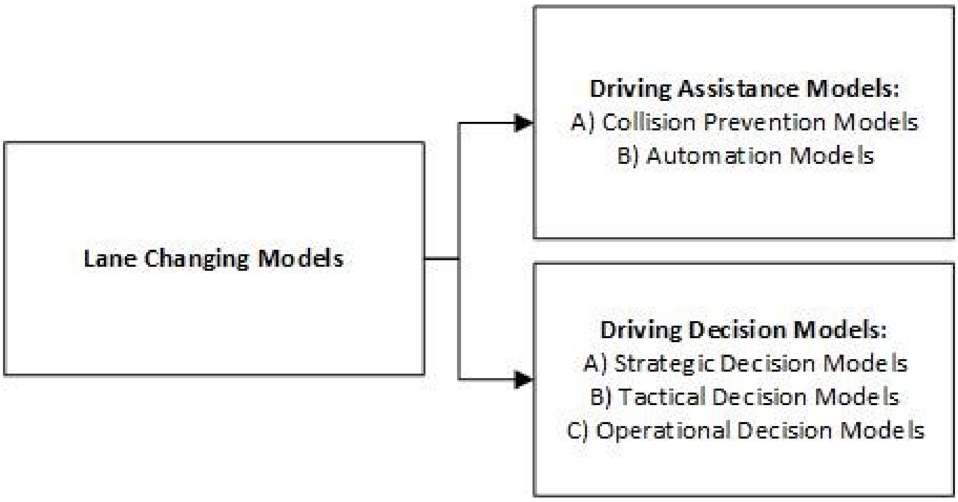

Figure 2.2: Classification of available approaches in lane changing studies. (Adapted from Moridpour et al. 2010)

Moridpour et al. (2010) classified driving assistance models as either collision prevention models or automation models. Both models consider the steering wheel angle and lateral motions to control the lane-changing performance of vehicles. Collision prevention lane-changing models are developed to monitor drivers' lane-changing manoeuvres and assist them in executing a safe lane change, improving road safety. On the other hand, automation models are applied to perform either partially or entirely, the driving tasks. Many different configurations are defined for models in this category, such as lane change or side crash avoidance systems. Those applications involve automotive adjustments to the steering wheel angle of vehicles to control their lateral motion and reduce dangerous lane-changing manoeuvres (Jin et al., 2009; Lygeros et al., 1998; Maerivoet & De Moor, 2005).

The other category of lane-changing models focuses on drivers' lane-changing decisions under different traffic conditions and under different situational and environmental characteristics. While responding to the surrounding environment, drivers' decisions can be classified as strategic, tactical or operational. This classification is based on the required time to execute the decisions.

To illustrate the point, the time required to make and implement the decisions differs depending on each level of the driver's choice. The definitions and the duration of drivers' decisions are analysed in Table 2.1 (adapted from (Moridpour et al., 2010b).

Table 2.1: Analysis of the exact definitions of drivers' decisions.

Classification of drivers' decision	Decision Level	Making/Executing Decisions' Time	Definitions
Strategic level	Highest	>30 sec	Are usually made before the start of a trip and include the goal or purpose of the trip and choice of route. A driver's destination choice, mode choice and route choice are examples of strategic driving decisions
Tactical level	Medium	5-30 sec	While executing the strategic level decisions, a series of tactical decisions are made by the drivers. At the tactical level, manoeuvres are selected to achieve short term objectives such as a decision to pass a slow-moving vehicle or maintaining the desired speed
Operational level	Lowest	<5 sec	Drivers decide about the manoeuvres to control their vehicles. These take place on a time scale of less than five seconds (or near real-time) and include decisions such as whether to accept a gap or not.

To illustrate the advantage of tactical changing decision of a driver, consider the situation presented in Figure 2.3. In this figure, suppose that the driver of the subject vehicle (vehicle A) decides to take the exit off-ramp. The decision to execute a lane-changing manoeuvre to take the exit off-ramp is an operational lane-changing decision. However, the driver is obstructed by a slow-moving vehicle (vehicle B). Vehicle A is planning to use the off-ramp, and Vehicle B is a slow-moving heavy vehicle.

In this example, depending on the distance to the exit off-ramp, the traffic condition and the characteristics of the driver and vehicle, the driver may have two different responses. The first response is remaining in the lane, which is nearest to the shoulder and accepting the speed limitation caused by the slow-moving vehicle to stay on the correct lane to take the exit off-ramp. The alternative is executing a lane-changing manoeuvre to pass the slow-moving vehicle and then taking the exit off-ramp.

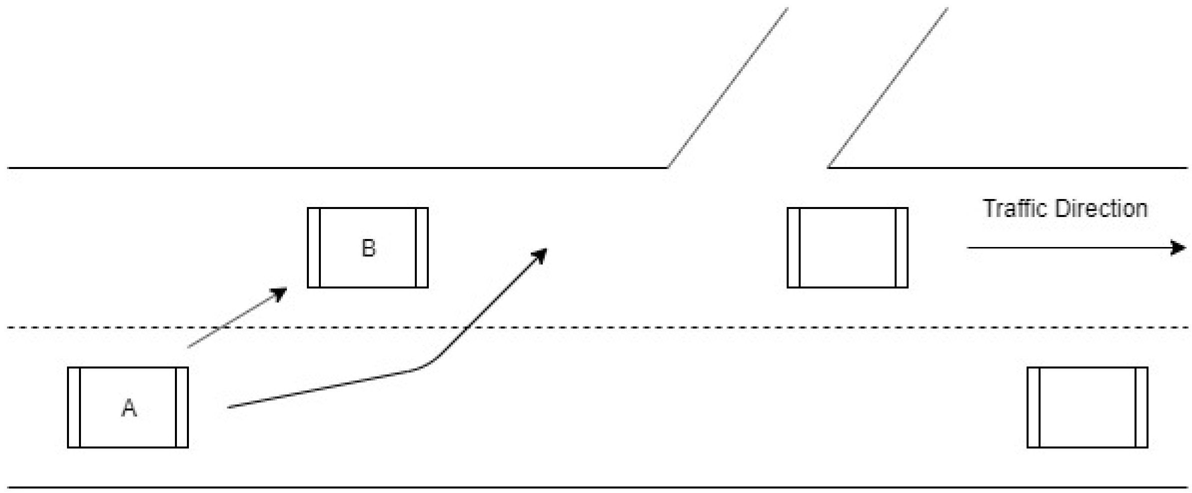

Figure 2.3: Lane changing situation illustrating tactical lane changing decision.

In real traffic situations, drivers make tactical and operational decisions for their lane changing manoeuvres mainly based on the current characteristics of the surrounding traffic and their anticipated future components of the surrounding traffic (Eidehall et al., 2007).

2.1.1.2 Structure of Lane Change Scenarios

As (Gipps, 1986) stated, a driver's decision to change lanes is the result of the answers to several composite questions: (a) Is it necessary to change lanes? (b) Is it possible to change lanes?, and (c) Is it desirable to change lanes?

Because of potential conflicts, there is a need to have a clear definition of the factors that influence drivers to change lanes. The following factors and their effects were considered to be most important for general models (Gipps, 1981, 1986; Wilson, 2001).

(a) Whether it is physically possible and safe to change lanes
(b) The location of permanent obstructions
(c) The presence of transit lanes
(d) The driver's intended turning movement
(e) The presence of heavy vehicles
(f) Speed

One of the major problems faced when proposing alterations to a road is to estimate in advance the likely effect of the modifications and to determine possible side effects (Xiaorui & Hongxu, 2013). There are analytical methods of estimation for different highways traffic situation such as when the traffic is so heavy that the lane changing is not possible or can only be performed by slow merging at over-saturated bottlenecks. With lighter traffic, the interaction between various features of the driving environment and the ability to change lanes make analytical techniques impossible in many urban situations. Lane changing and merging occur more frequently in work zones than other roadway conditions due to mandatory and discretionary lane changes that occur in work zones. L. Xiang et al., 2015) research shows that drivers must interact with both roadway and other drivers when changing lanes. Factors such as public transport, turning movements and lane closures interact with one another, and finally, the general traffic and the results of change are difficult to predict.

At the level of the individual driver, the effects of the several features of the traffic and road can produce reactions in two dimensions (Gipps, 1986). The driver can break or accelerate in an effort to maintain his desired speed without running into the vehicle ahead or can change lanes. Modelling the behaviour of a vehicle within its present lane is relatively straightforward, as the only considerations of any importance are the location of the preceding vehicle and speed.

2.1.1.3 Lane Change Model Construction

Lane change models usually are supported by the analysis of kinematics. Many surveys data (i.e. (Xiaorui and Hongxu, 2013) show that the driving behaviour of the drivers on the highway within the lane-changing method has to accelerate or decelerate. Xiaorui and Hongxu, in their analysis, have shown that accelerated lane amendment time usually lasts three to five seconds till it may be outlined the target vehicle moves at a continuing positive acceleration eventually.

Usually, the lane change model can be divided into two components. As Xiaorui and Hongxu, 2013), support the first half is that the method of accelerated lane amendment and therefore, the second half is that the lane-changing vehicle is moving at the target lane. Considering the real lane-changing procedure, once the lane-changing vehicle enters the target lane, the drivers change the velocity to ensure its safety with the leading vehicles of the target lane. At an equivalent time, the subsequent vehicle arranges speed to be safe with the lane-changing vehicle.

Consequently, to confirm that the second half is implemented safely, it is mandatory to ensure the lane-changing vehicle and, therefore, the leading vehicle of the target lane keeps an appropriate distance, as will be explained in the following example.

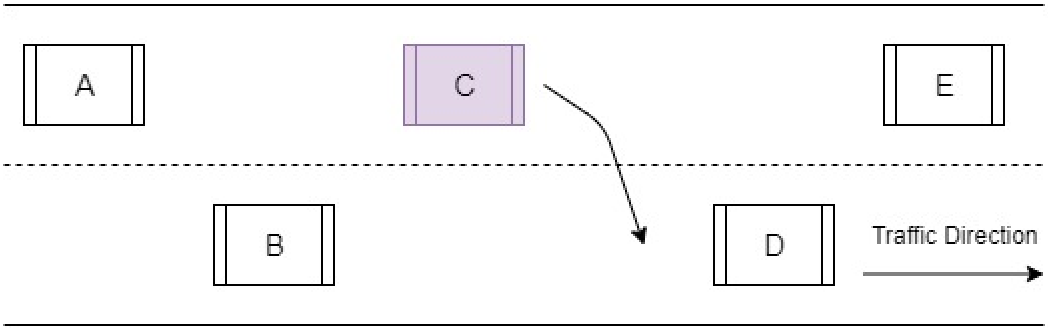

Figure 2.4: Complete lane change scenario.

In Figure 2.4, Vehicle C is the target vehicle aiming to make a lane change. In contrast, Vehicle A and Vehicle E are the following and leading vehicles in the same lane as Vehicle C, respectively, and Vehicle D and Vehicle B are the leading and following vehicles in the target lane. Vehicle C switches to the target lane between Vehicle B and Vehicle D from its lane between Vehicle E and Vehicle A. This example generally focuses on the importance of vehicle B, vehicle D and vehicle E upon vehicle C in the case of accelerated lane change (from low-speed lane to high-speed lane to make a lane change).

The process of accelerated lane change can be divided into the following three steps:

1. Determine the distance between subject vehicle C and vehicle E to ensure a safe lane change.
2. Whether the subject vehicle C can change lane from the space between vehicle B and vehicle D mainly depends on the distance relationship with vehicle B.
3. The safe distance between vehicle D should be considered when vehicle C arrives at the target lane.

Vehicle C can only change lanes when all three steps are carried out. After Vehicle C arrives at the target lane, Vehicle C adjusts its speed to guarantee the safety of Vehicle D. Vehicle B accordingly adjusts its speed to ensure the safety of Vehicle C.

2.1.1.4 Gap Acceptance

Gap acceptance is an essential element in most lane-changing models.(Gipps, 1986) considered a necessity, desirability and safety in the first lane change model in 1986. Since the late 90s, many researchers have modelled lane changing acclimated for traffic microsimulation software; but in each model, gap acceptance is a crucial element for the decision-making process. Throughout the execution of a lane change, the driver evaluates the positions and velocities of the lead and lag vehicles in the target lane and decides whether the gap between them is acceptable to accomplish the lane change. For instance, they evaluate whether the longitudinal gaps between the examined vehicle and the vehicles in the target lane are satisfactory or not. The target gap is separated into the lead gap, the longitudinal distance between the lead vehicle in the target lane and the lane changing vehicle; and the lag gap, the distance between the following vehicle and the lane changing vehicle (Toledo et al., 2003b). In Figure 2.5, there are being pictured the definitions of lead, front and lag vehicles and their relations with the subject vehicle.

Gap acceptance models are being developed as binary choice problems, during which drivers decide whether or not to accept the available gap by comparing it with the critical gap (minimum acceptable gap). To seizure the variation in the behaviours of various drivers (even for the same driver sometimes), critical gaps are modelled as random variables.

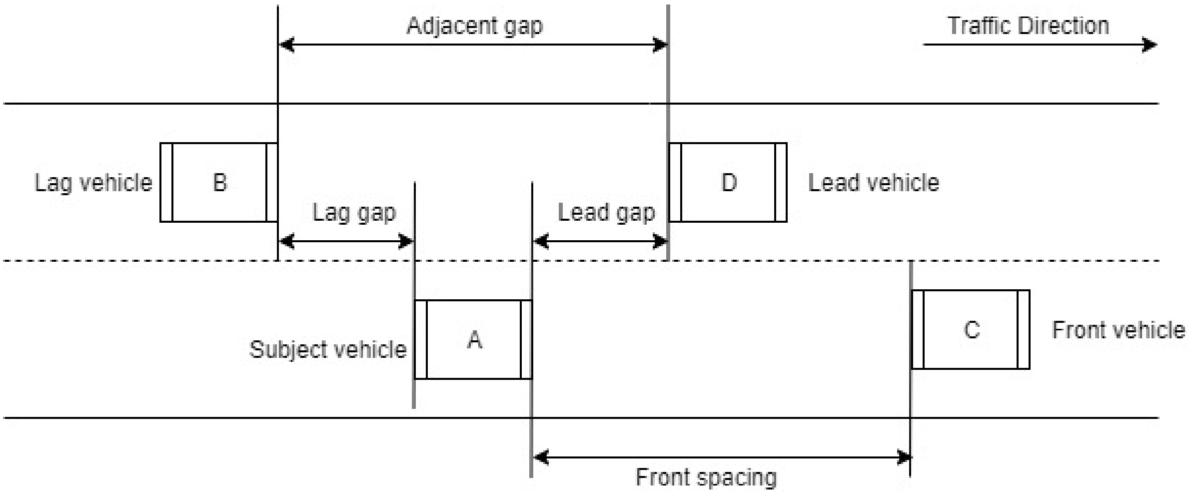

Figure 2.5: Definition of front, lead and lag vehicles and their relations with the subject vehicle.

2.1.1.5 Lane change duration

Duration measures the length of the lane change execution stage, which starts when the vehicle which tends to change lane, initiates its intention to change lane by a movement toward the target lane and ends when it has stabilised itself in the target lane. (Yang et al., 2019) support that lane change duration has a significant effect on traffic flow and consequences in the simulation outputs, too. For example, the Lane Change Vehicle (LCV) adjusts acceleration according to its perception of the needed duration; the Following Vehicle (FV) also adjusts acceleration directly after it notices the initiation of the LCV.

Consequently, the acceleration of the LCV and FV may, in turn, affect duration (Toledo & Zohar, 2007). Lane change duration research has found values ranging from 1 to 16 s (Hanowski et al., 2000), but few studies have assiduously examined the influencing variables (Moridpour et al., 2010b; Salvucci & Liu, 2002). Despite the duration's broad value range and its importance in lane changing, most existing microsimulation tools discard it; instead, lane change behaviour is generally considered as an almost spontaneous event or given a fixed period (Toledo & Zohar, 2007). Nonetheless, most duration studies have been based on driving simulator data. While simulator research is useful for many objectives, this shortcoming may distort the realism of the simulated driving experience and the fidelity of the data collected(K. Singh & Li, 2012; Toledo & Zohar, 2007).

2.1.1.6 Impact of lane changes

A lane change event inevitably impacts the following vehicle. For instance, Ahmed et al. (1996) developed a forced merging model. They found that in congested traffic where gaps meeting the minimum acceptable length are scarce, drivers change lanes either through the FV's courtesy yielding or through forcing the FV to slow down. Lane changing also impacts traffic flow. An abrupt lane change that results in the FV's hard braking or excessive acceleration contributes not only to emissions and wasted fuel but also to traffic waves or stop-and-go oscillations (Sultan et al., 2002). Oscillations are problematic because they trigger a drop-in road capacity and increase the risk of rear-end crashes. Mauch and Cassidy (2002) found that oscillations tended to form near freeway interchanges, sites of frequent lane changing. These manoeuvres have been considered to enlarge the capacity drop phenomenon (Srivastava & Geroliminis, 2013). Yet, despite the effect of lane change impact on traffic safety, its analysis has received less attention than lane change decision-making and execution.

2.1.2 Car-Following Models

Car-following is a typical driving behaviour and has been extensively researched all over the world, the development of which starting during 1960. Many scientists and scholars devoted to research in this field (Gurusinghe et al., 2002; Koutsopoulos & Farah, 2012; Newell, 1961; Papathanasopoulou & Antoniou, 2015; Wen-Xing & Li-Dong, 2018; W. X. Zhu & Zhang, 2018). The progress of car-following models, which define the processes by which drivers follow each other in the traffic stream, have been studied for over half a century, including driving safety. Car-following models have become an extensive topic in many fields, like car emissions and traffic congestion (Tang et al., 2015; X. Zhao & Gao, 2006). During the 1960s, research efforts focused on the follow the leader (as they called) models. These models are based on supposed mechanisms describing the process of one vehicle following the another. Four types of car-following will be analysed, namely:

i. Stimulus-response models
ii. Intelligent driver models
iii. Safe distance models
iv. Psycho-spacing models

2.1.2.1 Stimulus-response car-following models

Car-Following Model (CFM) is an important type of microscopic models, which describes the longitudinal interaction between vehicles, usually based on ordinary differential equations (Xiong et al., 2019). Car-following models firstly proposed by (Pipes, 1953) termed the stimulus-response model, and it was generally used to characterize the moving behaviour of a stream of the moving vehicles. Drivers who follow try to conform to the behaviour of the preceding vehicle. This car-following process is based on the following principle (S. P. Hoogendoorn, 2001) :

Response = sensitivity * stimulus

Stimulus-response models regarded the action of the preceding vehicle as directly related to the action of the following vehicle and proposed that the driver always attempted to maintain the same velocity as the preceding vehicle and included the reaction delay of the driver during this speed adjustment. In the model of (Gazis et al., 1961), the behaviour of following drivers is modelled very unrealistically: when the distance headway is substantial, drivers still react to velocity differences.

(Gazis et al., 1961) support that when the traffic is presumed to be homogeneous, all model parameters are equivalent for all user classes and all lanes of the roadway. Lane changing cannot be easily described so car-following models have been chiefly applied to single-lane traffic, such as tunnels (Mathew, 2014) and for analysing traffic stability. For example, car-following models can be used to evaluate the stability of traffic flow by examining conditions under which small disturbances (such as a sudden reduction in speed) are absorbed or amplified as vehicles follow one another. This allows researchers to assess both local stability (how an individual vehicle reacts to a disturbance) and asymptotic stability (how the overall traffic flow recovers from a disturbance over time)(Amini et al., 2019; Gazis et al., 1961). Herman et al., 1958 proposed to apply a stochastic term which represents the acceleration noise outlining the difference between actual acceleration and the ideal acceleration and determined the relationship between the acceleration of the relative speed and the following vehicle, based on the stimulus-response model and calibrated and determined the parameters according to a field test.

This process is the prototype of the General Motors (GM) Model. General Motors models are in a family of models refined by a team of scientists in the community of General Motors, from which pioneering work has been done that broke the ground for traffic flow theory. A general formulation of General Motors model has been proposed by (Gazis et al., 1961).

After that several studies focused mainly on the calibration of the sensitivity of the model of the general motor by using a big dataset of driving behaviour ((Kim et al., 2003; Brackstone et al., 2002; Treiber et al., 2000). Based on classical car-following models, an autonomous intelligent cruise control system for automatic vehicle following to examine its effect on traffic flow and to compare the performance with the manual driver vehicle was developed Martin (Martin, 1993) followed by several researchers (Björnberg, 1994; Magdici & Althoff, 2017; Touran et al., 1999). The classical car-following model was improved by Bando by incorporating an optimal speed function to describe the evolution of the traffic congestion (Bando et al., 1995).

2.1.2.2 Intelligent driver models

For almost half a century, researchers have modelled traffic-utilizing continuous in-time microscopic models (car-following models) (Bando et al., 1995; Brackstone & Mcdonald, 2000; Gipps, 1981). (Treiber et al., 2000) proposed a new stimulus-response model, called the intelligent driver model (IDM) both for single-lane and multilane traffic, including lane changes. Treiber' s framework determined that the acceleration behaviour of the following vehicle was affecting by the gap, speed and relative speed. That has been widely used in adaptive cruise control (ACC) and connected adaptive cruise control (CACC) (Magdici & Althoff, 2017) concerning the actual systems. (Rahman and Abdel-Aty, 2018) used micro-simulator and Surrogate Safety Assessment Models (SSAM) to a calibrated intelligent driver model to emulate the behaviour of CAVs. In their subsequent research, Rahman (Rahman et al., 2018) used Intelligent Driver Model (IDM) in the simulation of CACC, pointing out that IDM is the simplest model and can provide the most realistic deceleration and acceleration behaviour during car-following. Previous findings in applying IDM in ACC (Kesting et al., 2008), pointing out that using ACC with IDM can mitigate traffic congestion.

2.1.2.3 Safe-distance model

In addition to the stimulus-response model, the safety distance model (also known as the safe-distance model) is examined to play a critical role, where the following vehicle should keep a secure distance from the preceding vehicle when the driver cannot determine the driving behaviour of the preceding vehicle (Björnberg, 1994; Fu et al., 2019a; Touran et al., 1999). To be more specific, safe-distance models outline the dynamics of a single vehicle concerning its predecessor. In this respect, a simple model is Pipes' rule (Pipes, 1953) "A good rule for following another vehicle at a safe distance is to allow yourself at least the length of a car between you and the vehicle ahead for every ten miles an hour of speed at which you are travelling". A more refined model describing the spacing of constrained vehicle in the traffic flow is the one that Leutzbach discusses in his book, where he states that the overall reaction time T consists of three components:

a. Perception time: time needed by the driver to recognise that there is an obstacle ahead
b. Decision time: time needed to decide to decelerate and
c. Braking time: time needed to apply the brakes.

These components are directly related to safe distance in traffic flow. The safe distance between vehicles must account for the total reaction time (TTT) to ensure that a driver has sufficient time and space to perceive, decide, and react effectively to avoid a collision. This spacing is critical for maintaining traffic stability and minimising rear-end collisions, as it provides a buffer proportional to the speed and reaction capability of the driver and vehicle system.

Gipps developed a new safety distance model which divided the car-following process into three stages (Gipps, 1981) depending on the drivers' desired speed: a) keeping desired speed, b) accelerating and c) decelerating to the desired speed. The total safety distance model assumes that drivers consider braking distance large enough to allow them to stop without causing a rear-end collision with the preceding vehicles if the latter vehicle come to a stop instantaneously. Apparently, many researchers tried to improve the safety distance model using simulation by calibrating the Gipps model (Papathanasopoulou & Antoniou, 2015; Punzo et al., 2012; Punzo & Simonelli, 2005; Vasconcelos et al., 2014). One safety distance model, which takes into consideration the speed of the leading vehicle and the subject vehicle, as well as the reaction times of the driver and the vehicle is the Mazda model (X. Xiang et al., 2014).

2.1.2.4 Psycho-spacing models

Literature on car-following models can be classified into streams, a)Newtonian, which are based on physical principles like acceleration and deceleration, and b)psycho- physiological models, which incorporate human perception, reaction, and decision-making processes (Brackstone et al., 2002; Pariota & Bifulco, 2015). ver more than 70 years of development, these two streams have increasingly converged, as psycho-physiological processes have been embedded into traditional engineering-based Newtonian models. This integration has led to a deeper analytical understanding of driver behaviour and traffic flow dynamics(Brackstone et al., 2002; Pariota & Bifulco, 2015; Wagner, 2011).

However, the focus of these modelling efforts has often been uneven and limited in scope, particularly with regard to human factors. While significant progress has been made in modelling driver behaviour, these efforts sometimes overlook the fundamental purpose of car-following models: to explain traffic flow phenomena and propose strategies to alleviate congestion. Wiedemann's psycho-spacing model. Treiber, 1974 advanced the field by refining earlier approaches to incorporate the spacing and interaction dynamics between vehicles. These models now serve as the foundation for many contemporary microscopic traffic simulation tools, enabling realistic analysis of traffic behaviour and flow.

The primary behavioural rules of psycho-spacing models are, according to (S. P. Hoogendoorn, 2001):

i. At large spacings, the following driver is not influenced by velocity differences.
ii. At small spacings, some combinations of relative velocities and distance headways do not yield a response of the following driver, because the relative motion is too small.

2.1.3 Categorisation of Traffic Flow Models

Traffic congestion is one of the fundamental economic and societal problems related to transport in industrialised countries. Traffic flow displays many attractive phenomena, such as traffic breakdown and capacity drop, hysteresis and metastability, formation of phantom jams and growth of oscillations. Traffic flow models can be classified according to various criteria (level of detail, operationalisation, representation of the processes.) In this respect, managing traffic in congested networks demands a fully understanding of traffic flow operation, i.e., insights into what causes delays or congestion, what determines the location and time of traffic breakdown, how does the delay/congestion inseminate through the network, etc. are essential. To explain more the reasons for these phenomena, a wide range of traffic flow theories and a large number of simulation models have been refined, based on which mathematical analyses have been performed.

2.1.3.1 Traffic simulation

Traffic operations on the roadway can be revised by field experiments and research in order to understand real-life traffic flow fully. However, there is not only the problem of reproducing such experiments but also the costs and safety which play a role of dominant importance as well. Analytical approaches may not provide to the researchers the desired results, due to the complexity of the traffic flow system. Therefore, traffic flow simulation models designed to characterize the behaviour of the complex traffic flow system have become an essential tool in traffic flow analysis and experimentation.

Depending on the type of model, the application of these traffic flow models is very comprehensive. (S. P. Hoogendoorn, 2001) depicted the application area as follows:

a. Evaluation of alternative treatments in (dynamic) traffic management.
b. Design and testing of new transport facilities (e.g., geometric designs);
c. Operational flow models serving as a submodule in other tools (e.g., model-based traffic control and optimization and dynamic traffic assignment);
d. Training of traffic managers

Hoogendoorn and Bovy, however, support that the description of observed phenomena in traffic flow is not self-evident. There are several mathematical models aimed to describe this behaviour by using the following approaches (Papageorgiou, 1998):

a. Purely deductive approaches whereby known accurate physical laws are applied.
b. Purely inductive approaches where available input/output data from real systems are used to fit generic mathematical structures.
c. Intermediate approaches, whereby first basic mathematical model structures are developed, after which a specific structure is fitted using real data.

Traffic flow models can be divided according to the following categories:

a. Scale of the independent variables (continuous, discrete, semi-discrete).
b. Level of detail (sub-microscopic, microscopic, mesoscopic, macroscopic).
c. Representation of the processes (deterministic, stochastic).
d. Operationalization (analytical, simulation).
e. Scale of application (networks, stretches, links and intersections).

2.1.3.2 Scale of the independent variable

Almost all traffic models are described as dynamical systems, so a natural classification is the timescale. Researchers have distinguished two timescales: continuous and discrete. A continuous model describer how the traffic system's state changes continuously over time in response to continuous stimuli. On the other hand, the discrete model assumes that state changes occur discontinuously overtime at discrete time instants (S. P. Hoogendoorn, 2001). Besides time, other independent variables can also be described either continuous or discrete variables such as position, velocity, or desired velocity. Researchers, as (Smulders, 1990) have proposed mixed models (both continuous and discrete).

2.1.3.3 Level of detail

Traffic flow simulation models can be divided into four categories according to the level of detail with which they represent the traffic systems:

i. Macroscopic;
ii. Mesoscopic ;
iii. Microscopic;
iv. Sub-microscopic.

This categorisation can be operationalised by considering the distinct traffic entities and their level in the respective flow models.

The macroscopic models are based on hydrodynamic method and are codified by partial differential equation or equations (Papageorgiou, 1998). Macroscopic flow models can be classified according to the number of partial differential equations that frequently underlie the model and their order. They describe traffic at a high level of aggregation as a flow without distinguishing its constituent parts, and they are mostly used for planning applications, and operations control design, involving large networks and long periods (Moridpour et al., 2010a).

Mesoscopic models provide a middle ground with their ability to model large networks with limited calibration effort and network coding, while providing a better representation of the traffic dynamics and individual travel behaviour than their macroscopic counterparts (S. P. Hoogendoorn, 2001). Mesoscopic models are used for both real-time operations and planning (Burghout et al., 2006). They are a lot more flexible than macroscopic models for modelling essential elements, such as travel behaviour like route choice. For instance, a lane-change manoeuvre might be represented for an individual vehicle as an instantaneous event, where the decision to perform a lane change is based on, such as speed differentials (M. Yang et al., 2019). Some mesoscopic models are derived in analogy to gas kinetic theory, which describer the dynamics of velocity distributions (Gurusinghe et al., 2002).

Although mesoscopic and macroscopic models seize the traffic dynamics of large networks in less detail without the problems of calibration and application of microscopic models, microscopic simulation models require a detailed representation of the traffic process (Arem & Vos, 1997). The microscopic models aim to describe driving behaviour based on the driver's perception of the nearby driving condition (Brockfeld et al., 2003). As (Gunay, 2007) pointed out, microscopic flow models capture the behaviour of vehicles and drivers in detail, as well as their interactions among vehicles, lane changing, the response to incidents, and the behaviour at merging points (at a high level of detail). For instance, for each vehicle in the stream, a lane change is described as a detailed chain of drivers' decisions (Punzo & Simonelli, 2005).

Similar to microscopic simulation models, the sub-microscopic simulation models depict the characteristics of individual vehicles on the traffic stream (Vasconcelos et al., 2014). Apart from a detailed description of driving behaviour, vehicle control behaviour in correspondence to prevailing surrounding conditions is also modelled in detail, as well as the functioning of specific parts of the vehicle (Krbálek et al., 2019). S. P. Hoogendoorn, 2001 pointed out that sub-microscopic simulation models describe the functioning of specific parts and processes of vehicles and driving tasks in addition to describing the time-space behaviour of the individual entities in the traffic system

Figure 2.6 depicts the definition of macro-, meso- and microscopic models and some of the most known simulation programmes that the researchers use in their studies.

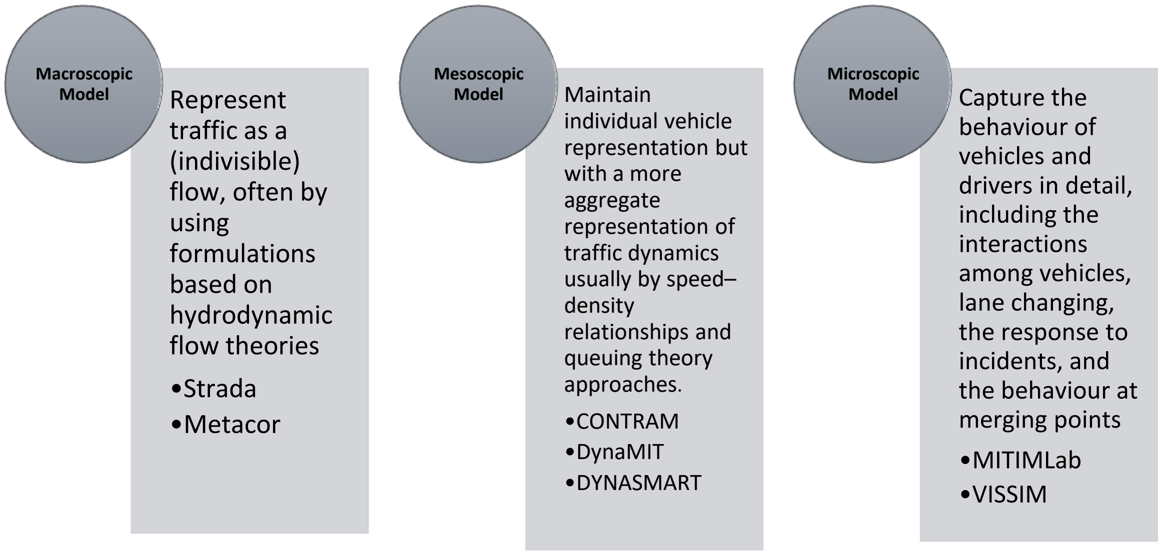

Figure 2.6: Definitions of macro-, meso- and microscopic models and Traffic simulation for modelling of the operations of dynamic traffic systems.

In the Table 2.2 is presenting an overview of some known traffic flow models based on the proposed criteria according to (S. P. Hoogendoorn, 2001).

Table 2.2: Overview of traffic flow models.

Detail level	**Model name**
Sub-microscopic models	Simone Mixic Pelops
Microscopic models	Safe-distance models Stimulus-response models Wiedemann model Psycho-spacing models CA models Fosim Wiedemann model Pedestrian models Intergration
Mesoscopic models	Headway distribution models Reduced/ Multilane/ Improved/Multiclass gas kinetic models Cluster models

Macroscopic models	LWR model Helbing-type models Payne-type models Cell transmission model Semi-discrete model Metanet Master

2.1.3.4 Representation of the process

In this subject, deterministic models have no random variables, involving that all factors in the model are characterised by an exact relationship. On the other hand, stochastic models include processes that include random variates. For instance, as (S. P. Hoogendoorn, 2001) proposed, a car-following model can be formulated as either a stochastic or a deterministic relationship be defining the driver's reaction time as a constant or as a random variable respectively.

2.1.3.5 Operationalisation

Concerning about the operationalisation criterion, models can be operationalised either as a simulation model or as analytical solutions of sets of equations.

2.1.3.6 Scale of application

The application scale demonstrates the area of application of the model. For example, the model can be describing the dynamics of its entities for a single roadway stretch, a corridor, an entire network, or a city, etc. (S. P. Hoogendoorn, 2001).

2.1.4 Conclusion

This section of the literature review has identified and reviewed the most common traffic flow models used in the evaluation of several problems in the highways that traffic processes cause such as traffic delay, fatalities, congestion, and air pollution. All the previous problems can be mitigated, rather than fully solved, with the appropriate road design and traffic control measure so its foundational, their effect to be tested, before implementing these kinds of designs of measures. One of the critical problems faced when proposing alterations to a road is to estimate beforehand the likely effect of the changes, and to determine possible side effects (Xiaorui & Hongxu, 2013). For that reason, functional methods such as Lane Change Models and Car Following Models are appropriate to estimate the different highways traffic situation such as when the lane changing is not possible or can only be performed by slow merging at over-saturated bottlenecks because of the heavy traffic.

Furthermore, traffic operations on the roadway can be improved by field experiments and research to understand real-life traffic flow fully. However, there is not only the problem of reproducing such experiments but also the costs and safety which play a role of dominant importance as well. Analytical approaches may not provide to the researchers the desired results, due to the complexity of the traffic flow system. Therefore, traffic flow simulation models designed to characterise the behaviour of the complex traffic flow system have become an essential tool in traffic flow analysis and experimentation.

In the context of Intelligent Mobility, Connected Vehicles (CVs) have the potential to revolutionise incident detection by enabling real-time communication and dynamic responses to traffic conditions. To fully evaluate these capabilities, it is essential to review existing attempts to simulate Intelligent Mobility technologies and assess the available traffic simulation software. However, before delving into incident detection methods and traffic simulation tools, an in-depth understanding of Intelligent Mobility is required to contextualise its role in modern traffic management systems.

2.2 Intelligent Mobility

2.2.1 Background

Nowadays, new car models increasingly include features such as parking assist systems and adaptive cruise control that allow vehicle to steer themselves into parking spaces (Fagnant & Kockelman, 2015). Many vehicle manufacturers have developed further the autonomous driving by creating autonomous vehicles that can drive themselves on existing roads and can navigate in different road network layouts with almost no direct human input. Such vehicle manufactures are Nissan (NISSAN, 2020), Ford (Ford, 2020), Porsche (Porsche, 2020) and more which their action will be reported below.

The transport sector is at a highlight period of significant disruption, with new technologies, products and services fundamentally shifting customer expectations and opportunities. The market for Intelligent Mobility is rapidly developing as customers, transport authorities, businesses and governments understand the huge potential for unlocking significant opportunities and improving a great range of outcomes by taking a user-centric approach to looking at mobility opportunities for customers as part of a more integrated, comprehensive system (Burrows et al., 2015).

Intelligent mobility is a term that has been used extensively in the existing literature and original equipment manufacturer's documents. However, differences are observed between definitions found in industrial and academic reports. This report will investigate not only the different definitions of intelligent mobility provided by manufacturers, academic researchers, government agencies and industry but also the new mobility services technologies to achieve a full understanding of Intelligent Mobility (IM).

The potential network-level outcomes of these new technologies are to ease congestion, reduce crashes, reduce parking needs improve fuel economy and bring mobility to those unable to drive. According to (Fagnant and Kockelman, 2015), these new intelligent technologies can dramatically change the nature of world travel with quantifiable and real benefits. Based on their research, the annual economic benefits could be approximately in the range of $27 billion with only 10% market penetration, and CAVs have the potential to save the United States economy roughly $450 billion per year (Fagnant & Kockelman, 2015). Assuming that these technologies become available and successful to the mass market, the transport network will have the potential to be changed dramatically. It is compulsory though to understand the potential impact of autonomous driving and the hurdles for transport manufactures and policymakers. But prior to that, it is necessary to define Intelligent Mobility as it is the new future of transport and define the underpinning technologies.

The development of road vehicles is advancing at full speed, and disciplines such as Electronics, Communication and Control have increasingly essential roles in this advance. This has opened numerous fields of development and research that, although they end up being interconnected, correspond to very diverse areas. As a result, there is a lack of an integrated and comprehensive vision of the Intelligent Transport Systems (ITS).

Although transport has a link with economic development, the considerable growth of mobility in recent years, and above all, the preponderance of the mode of road transport over the others, has led to some adverse effects in different areas such as accidents, congestion, and pollution.

To this end, technological and social evolution has led to higher demand for transport, safety, comfort, reliability, performance, efficiency, etc., that have grown exponentially in recent years. In particular:

- In the European Union, at 2023, approximately 20,400 people were killed in road accidents across the EU, marking a 1% decrease compared to 2022 (ROAD SAFETY Annual Statistical Report on Road Safety in the EU, 2024)
- Approximately 10% of the main road network is affected by daily congestion (Jimenez, 2017) .
- Transport is the sector that has grown mostly in energy demand in all sectors, 27% of which corresponds to road transport, which in turn has a direct relationship with CO_2 emissions (Aminzadegan et al., 2022).
- Vehicles are the primary source of air pollution in cities, and 20% of cities have unacceptable levels of noise (Afifa et al., 2024).

The concept behind Intelligent Mobility is the use of new technologies in the world of road transport to reduce the above major problems through innovative solutions. Within Intelligent Mobility, intelligent vehicles are one of the critical elements, involving task of sensors, processors, and transmitters of information to conceive driving as an automated and cooperative driving.

Generally, Intelligent Mobility is about moving people and goods around in a more efficient, more accessible, and more environmentally friendly way (Aquino Santos et al., 2019). Intelligent mobility refers to the optimised movement of people and goods, but it is intentionally vague about what mode – or modes – of transport might be used to achieve that. One thing that should be made clear, though, is that Intelligent Mobility should address complete end-to-end journeys. It uses new ideas and new technologies to look beyond traditional, infrastructure-heavy approaches to transport and to instead come up with innovative ways to improve mobility and make journeys better and accessible to all.

This part of the literature review on Intelligent Mobility aims to describe the essential steppingstones of the transport system in the following core sectors:

1) Intelligent Mobility Definitions by road network operators, manufacturers, and industries
2) New Mobility Services Technologies:
    - Shared Mobility / On-demand Mobility and Mobile Applications
    - Mobility as a Service (MaaS)
    - Connected and Autonomous Vehicles (CAVs)
    - **Connected Vehicles (CVs)**

2.2.2 Intelligent Mobility Definitions

Intelligent Mobility definition often is used as a buzzword: manufacturers, researchers and companies talk about it, but it seems that there has been a lack of clarity and some confusion on what this actually includes, and how, for instance, this differs from the 'smart city' concept or the Intelligent Transport Systems. Transport Systems Catapult, one of eleven elite technology and innovation centres, support that Intelligent Mobility uses emerging technologies to enable the more efficient, smarter and greener movement of people and goods worldwide (Catapult, 2018). Highways England in their report "Roadmap for Scotland Contents & foreword" and "Mobility 2030: Transforming the mobility landscape" added in this definition and the encompasses everything from autonomous vehicles to seamless journey systems and multi-modal modelling software (Scotland, 2019; Simpson et al., 2019).

Intelligent Mobility is about taking a contrasting approach to the challenges that have traditionally beset the transport sector, whether it be pollution, congestion, or the lack of "joined-up" thinking between different means of transport. It goes further than that, however, by also helping the transport industry to address broader societal trends – including climate change, a growing and ageing global population, increasing urbanisation and the rapid depletion of our traditional energy resources.

In order to meet these massive and multiple challenges, Intelligent Mobility has to cut across and go beyond the traditional transport sector. Intelligent Mobility focuses instead on new and emerging technologies that make it possible to achieve more for less (Catapult, 2018).

Furthermore, Atkins supports that Intelligent Mobility involves innovation and a shift in perspective, driven by the new opportunities technology offers (Atkins, 2019b). Intelligent Mobility can be defined as the integration of advanced technologies and applications designed to improve the efficiency, safety, and sustainability of transportation systems. These technologies include real-time data analytics, connected and autonomous vehicles (CAVs), Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication, Mobility-as-a-Service (MaaS) platforms, and advanced traffic management systems. Actions under Intelligent Mobility leverage these tools to provide seamless travel experiences, reduce congestion, and enhance road safety (Atkins, 2016):

- Enhance current transport systems, by making them not only more efficient and less costly (e.g., electric vehicles, wireless induction charging) but also more convenient (e.g., contactless payment, City Mapper, Autopilot from Tesla); and
- Provide opportunities to move around, e.g., self-service bike-sharing scheme, Uber, Drive Now from BMW.

Some will disagree and support that Intelligent Mobility includes the focus on needs of the user and a real personalisation of the journey. Transport has always been focused on meeting user needs and putting the user at the centre of the journey somehow. Thus, what is more personalised than the private car?

Particularly, Intelligent Mobility is about innovation and thinking differently about how to connect people, places and goods across all transport modes, based on the new opportunities' technology brings us. Intelligent Mobility combines a strong focus on putting the customer at the heart of the service offering with the requirement of integrating all transport opportunities into a whole system. (Atkins, 2019a; UK Department for for transport, 2019).

However, it is fundamental to note that the concept of sharing resources, whether cars or bicycles or partnering with a party from another discipline (e.g., Airbnb with Tesla) to develop a new business model or create new solutions are first of all founded on human intelligent ideas and secondly, amplified by technology. In the Appendix, the tables for the definition of Intelligent Mobility as described by different governmental and industrial sources and the perspective of four major car companies regarding Intelligent Mobility and how they are going to encourage it in the future are presented.

Taking all the above into consideration, Intelligent Mobility represents a forward-thinking approach to connecting people, goods, and places across all transport modes. As Atkins concludes in their report on mobility, it involves leveraging a combination of technology, systems thinking, and data integration across transport networks to enable behavioural change and support informed decision-making(Atkins, 2015). Intelligent Mobility emphasizes prioritizing the customer experience while integrating all transport options into a cohesive, efficient system. As technologies continue to evolve, policymakers and funders are increasingly focusing on Intelligent Mobility as a transformative approach to addressing transportation challenges in the United Kingdom and globally.

Definition: Intelligent Mobility is the application of advanced technologies, real-time data, and integrated systems to create a seamless, efficient, and sustainable transport network that prioritises user experience, reduces congestion, and enhances safety across all modes of transport.

2.2.3 New Mobility Services Technologies

The transport sector is already at the beginning of a term of significant disruption, with brand-new technologies, services and products fundamentally shifting customer expectations and opportunities (Burrows et al., 2015). The market for Intelligent Mobility is promptly developing as customers, businesses, transport authorities, and governments understand the great potential for unlocking major opportunities and improving a great range of outcomes by taking a user-centric approach to looking at mobility opportunities for customers as part of a broaden, integrated system (Davies, 2018). Thus, the rise of the sharing economy, mobility services on-demand, access over ownership, the convergence of modes and types of transport, the blurring line between public and private transport, the arrival of new entrants challenging the market and regulators should be able to respond to a new innovative world (Burrows et al., 2015). Plus, great opportunities and challenges for industries and stakeholders arise everyday with the introduction of intelligent vehicle technologies, such as private companies providing new mobility services such as car-sharing and ride-hailing services.

Planners, policymakers, and industry adopt the concept of mobility to describe the systems that allow people to move in a network. Actually, this shift from transport to mobility represents a shift in thinking about how a transportation system is best designed and managed (Spulber & Dennis, 2016). As it was mentioned, Mobility is a user-centric concept recognizing that transport products and services must be responsive to the habits, preferences and the needs of travellers and society.

Plenty new passenger transport options, collectively called new mobility services (NMS), have been developed during the past 20 years (Utriainen & Pöllänen, 2018). These services offer transport as a shared mobility and an on-demand shared service, enabling users to have access to a vehicle (automobile, van, bicycle, etc.) for on an as-needed and short-term basis. New mobility services frequently blur the lines between private and public transport, and between what is shared and what is owned (Spulber & Dennis, 2016).

2.2.3.1 Shared Mobility / On demand Mobility and Mobile Applications

New mobility services are enabled by wireless connectivity and emerging technologies that allow for more efficient, convenient, and flexible travel (De Sanctis et al., 2019). New mobility services have been characterised as more predictable, reliable, efficient, convenient, accessible, and seamlessly connected compared to established means of transport, as well as offering easier options for payment (Storme et al., 2021). Carsharing, ride-hailing, ridesharing, micro-transit, bike sharing, and mobility-as-a-service are among the most noteworthy new mobility services currently being developed (Atkins, 2019a). Public transport, or mass transit, as well as newer schemes such as car-sharing, bike-sharing and ride-sharing, are all types of shared mobility. Each has its own underlying service characteristics and business model. Some paradigms of shared and on-demand mobility are:

1. ***Ride hailing:*** Ride hailing services rely on mobile apps to connect paying passengers with drivers who provide rides in their private vehicles (for a fee), services that can be shared as well. Transportation Network Companies (TNCs) design and operate these online platforms. Most TNCs

function as digital marketplaces linking self-employed drivers with customers, while collecting a fee for making the connection.

2. ***Ride sharing/Carpooling:*** Ride sharing is a type of carpooling that uses private vehicles, arranging shared rides on short notice between travellers with a common origin and/or destination. Travelers share trip costs in these systems, that organize either short- or long-distance ridesharing.
3. ***Car sharing:*** Car sharing is a short-term car rental, often by the hour. Electronic systems allow unattended access to vehicles. Insurance and gasoline are included in this type of service. These characteristics distinguish carsharing from traditional car rental. Carsharing can be round-trip or one-way, free-floating or station based.
4. ***Bike sharing:*** Bike sharing is a system that provides free or affordable access to bicycles for short-distance trips, mostly in urban areas. Most programs are organized either by local non-profit organizations or by public agencies.
5. ***Microtransit:*** Microtransit is a big category encompassing miscellaneous private transit services that use small buses and develop flexible routes or schedules (or both) based on customer demand. Microtransit bridges the gap between single user transportation and fixed-route public transit and resembles current route-deviation services.
6. ***Micro mobility:*** The use of small mobility devices, designed to carry one or two people, or ‘last mile’ deliveries. E-scooters and e-bikes are examples.
7. ***Mobility as a Service:*** Mobility as a Service (MaaS) is a mobility distribution model in which a person’s transport needs are met over one interface and are offered by a service provider. In general, transportation options (mass transit, carsharing, ride hailing, etc.) are bundled and the combined solution is presented to the user through a smartphone app and is paid through a single account.
8. ***Shared autonomous vehicles:*** Shared autonomous vehicles (SAVs) are fully self-driving vehicles that do not need human operation, other than providing information regarding the destination of the trip.

In the Table 2.3 there are some examples of New Mobility Services [Adapted from: Atkins, 2019a; Becker et al., 2019; Spulber & Dennis, 2016; Wong et al., 2019)]

Table 2.3:Examples of New Mobility Services.

Service	**Examples**	**Markets**
Ride hailing	1. Uber 2. Lyft 3. Didi 4. Ola 5. Gett	More than 75 countries globally. Uber and Lyft the two biggest operators
Ride sharing/Car pooling	1. BlaBlaCar 2. vRide 3. Commutr	Europe is the primary market globally. The biggest operator, BlaBlaCar, has 25 million members across 22 European and South American countries.
Car sharing	1. Zipcar 2. Car2go 3. Enterprise CarShare	26 countries in North/South America, Europe, Asia, and Oceania.
Bike sharing	1. Motivate 2. DecoBike 3. Zagster	Almost 1000 cities worldwide.
Microtransit	1. Bridj 2. Chariot 3. Via 4. Citymapper	Many developments exist in Europe, where the concept was developed. In the United States, service currently is limited to six major cities
Micro mobility	1. E-scooters 2. E-bikes	All-over the world. UK and Europe use them a lot, especially in big town centres.
Mobility as a Service	1. MaaS Global 2. UbiGo 3. Transloc 4. Xerox 5. Moovel	Pilot and in-service projects in Europe and the United States.
Shared Autonomous Vehicles	1. Google 2. EasyMile 3. Uber 4. Ford 5. Nissan 6. Yandex 7. Porsche	Technology remains in-development. Some companies are testing their technology, especially via private shuttles on campuses.

The increasing adoption and expansion of new mobility services are already prompting vehicle manufacturers not only to think twice their existing business models but also explore new ones. The mainstreaming of new mobility services is an opportunity for automakers more than it is a threat. As transport preferences slowly evolve, the automotive industry is trying to show customers they understand the shift toward on-demand shared mobility and have relevant new products and services to offer. Building relationships with New Mobility Services is an opportunity for vehicle manufacturers to diversify their activities and, particularly, to strengthen their market share in urban areas and with the younger generations (Spulber & Dennis, 2016).

2.2.3.2. Mobility as a Service (MaaS)

The growing pressure on passenger transport systems has increased the demand for new and innovative solutions to increase its efficiency (Ong et al., 2019). One critical approach to tackle this challenge has been the steady and slow shift towards shared mobility services (car-, bike-sharing etc.)(Becker et al., 2019). Building on these new modes and of course the developments in information technologies, the concept of "Mobility as a Service" (MaaS) has come to light and offers convenient door-to-door transport without the need to own a vehicle (Kamargianni et al., 2016). The term - Mobility as a Service (MaaS) stands for buying mobility services based on consumer needs. In recent years, various MaaS schemes have arisen around the world. The main goal of MaaS is to make transport more sustainable through mobility plans created for educational and municipal institutions, and companies in specific city-regions all over the world. In order to reach this aim, a worldwide roadmap has to been established, including current situation analysis, collection of mobility incentives, review of the situation of stakeholder involvement, and assessment of problems and opportunities of mobility planning (Karlsson et al., 2019).

The increasing number of transport services provided in cities have introduced an innovative Mobility as a Service (MaaS) concept. This MaaS Concept merges different transport modes to offer a tailored mobility package, related to a monthly mobile phone contract and involves other complementary services, such as trip planning, reservation, and payments, through a single interface (Hietanen, 2014).

The concept of Mobility as a Service (MaaS) focuses to break the determining role of car ownership and scale down the use of them in the everyday life. Instead, travellers are presented plenty of travel options tailored to their respective needs, either as a subscription package or in a pay-per-use approach, by an integrated mobility provider (Jittrapirom et al., 2017; Kamargianni et al., 2016; Mulley et al., 2018)

2.2.3.2.1 Definition of MaaS

Additionally, although several MaaS schemes have been implemented all over the world, there is always a lack of assessment framework that classifies their unique characteristics in a systematic manner as the technology grows up every year. "What constitutes a MaaS concept?"

Mobility as a Service (MaaS) is a mobility concept which has been developed quite recently. It can be thought of as a new idea for conceiving mobility, a phenomenon or as a new transport solution, merges all the available transport modes and mobility services). The first inclusive definition of MaaS is offered by (Hietanen, 2014). Their study describes MaaS as a mobility distribution model that transfer users' transport needs through a single interface of a service provider. It combines varied transport modes to offer a tailor-made mobility package such as an annual mobile phone contract. This interpretation encompasses some of the core characteristics of MaaS: customer's need-based, service bundling, cooperativity and interconnectivity in transport modes and service providers. (Cox, 2015) adds to this definition, by emphasizing the similarity with the telecommunication sector. Being based on the same definition, (Finger, M., Bert, N., & Kupfer, 2015) envisioned MaaS to integrate transport models through the internet.

(Holmberg, P.-E., Collado, M., Sarasini, S., & Williander, 2016) in their research, emphasized the role of subscription in MaaS, giving the user the possibility to plan his/her journey, in terms of booking and paying the several transport modes that might be required, all in one service. To access the service, travellers will be asked to register or make an account. With a first glance, this is to make payment and of course booking easier, as the concept envisions a 'seamless' combination of all transport modes and a 'Mobility Aggregator' that gathers and sells every service through a single smartphone app, allowing easy fare payment and one-stop billing (CIVITAS, 2016). Based on the traveller's needs, people can have the choice of 'pay-as-you-go' or pre or even post pay, considering people's registration and an annual subscription. At a second stage, subscription results in personalisation, framing mobility services around traveller's preferences, which is one important advantage that is absent from conventional public transport services and thus not covering passenger's needs which might result in inconvenience (Atasoy et al., 2015).

More specifically, tailoring the assortment to the heterogeneous needs of the subscribers is advantageous for both users and transport providers usually referred to as collaborative customisation or personalisation (Hietanen, 2014; Kamargianni et al., 2016). In addition to the definitions above, which emphasise the bundling and subscription aspects of MaaS, there are various other interpretations of the term that under- score other aspects. (Atkins, 2015) defines MaaS as a new way to provide transport, which facilitates the users to get from A to B by joining mobility options and presenting them in a completely combined manner. Therefore, it is possible to consider MaaS as mobility service that is flexible, personalised and on-demand. Evidently, MaaS essential characteristic is the user-centric vision which frames the mobility service provision, a view which many authors strongly emphasise. (Nemtanu, F., Schlingensiepen, J., Buretea, D., & Ior- dache, 2016) considering the Information and Communication Technologies (ICTs) as the main component of MaaS systems, they mention that the collection, transmission, process, and presentation of the information are obligatory for identifying the best transport solution for user's needs.

Information and Communication Technologies (ICTs) also play a vital part in information integration and convergence between users, providers, and services. The emergent notion in the Internet of Things (IoTs), which further accentuate the connectivity between physical objects and virtual data, is a vision of Smart transport systems to support the Smart City vision (Sherly, J., & Somasundareswari, 2015). In the context of MaaS, similar emphasis stressing the importance of integrations between transport data, data infrastructure and physical transport infrastructure can also be observed (Hietanen, 2014). In Melis, Prandini, 2016 interpretation, IoTs acts as an enabler for the integration of private and public transport. Similarly, (Giesecke R., Surakka T., 2016) also considered an intelligent use of ICTs as the basis for transporting persons through the combination of different means.

Interestingly, (Giesecke R., Surakka T., 2016) conceptualise MaaS as a socio-technical phenomenon with sustainability as a critical aspect, thus shedding the light on the sociological level and the sustainability dimensions of the concept. This highlights the importance of users' acceptance and adoption to MaaS, as well as its roles to transform their habits and behaviours to meet their travel needs in a sustainable way. Accordingly, other authors consider sustainability and user perspective as the core elements of MaaS concept. In the interpretation of (König, D., Eckhardt, J., Aapaoja, A., Sochor, J. & Karlsson, 2016) MaaS offers need-based and customized mobility solutions for the users with the goal of achieving a more sustainable transport. This change of focus considers the social context to fulfil users' needs and environmental aspect while addressing the challenge of urban mobility. Implementing and delivering innovative services like MaaS will help to enhance accessibility and equity through a shift from ownership-based to access-based transportation. More specifically, a wide range of alternative modes and customiSed mobility ser- vices is expected to have societal value, increasing accessibility in reaching places and in the ability to utilize transport modes. Exploring the current use of shared mobility, it is believed that these options can be the solutions for residents of low-density areas, as well as an affordable solution for low-income households (CIVITAS, 2016).

As mentioned above, the Mobility as a Service (MaaS) model target to provide seamless trips over one interface by combining different transport services and modes through the next generation technologies. To this end, mobility services and sustainable transport modes have to be able to provide a higher service level to attract new users. The successful new MaaS utilisation is expected to be able to increase the use of sustainable transport modes and decrease the use of private cars even further in the near future (Wong et al., 2019).

2.2.3.3. Connected and Autonomous Vehicles and Connected Vehicles

A Connected and Automated Vehicle (CAV) is defined as a vehicle that is capable of automated driving and connectivity with other vehicles, road users, the road infrastructure, and the cloud (Guanetti et al., 2018), whilst CV is defined as a human-driven vehicle that is equipped with communication devices and technologies that allow it to communicate with other vehicles, infrastructure, and external systems as well. The communication capabilities of CVs enable them to share information about their speed, position, and other relevant data with nearby vehicles, traffic signals, and transport infrastructure. This communication helps enhance road safety, optimise traffic flow, and enable various applications such as real-time traffic updates and warnings. Thus, CAVs are distinguished by connectivity and driving automation; powertrain control is not a peculiarity of CAVs, but it is essential for applications oriented to energy efficiency improvement. There are crucial economic and social benefits associated with the adoption of CAVs, including reduced congestion, increased safety, and reduced emissions. The challenge exists for transport agencies, companies and cities in order to understand what the impact of CAVs and CVs will be and how the opportunities that they will bring to better manage networks today and, in the future, will be maximised (John Bradburn, David Williams, Rob Piechocki, 2017b). Connected and Autonomous Vehicles as well as Connected Vehicles are acting, and they will continue to act, as an enabler for supporting and development of Intelligent Mobility. One example of such CAVs enablers are the autonomous shuttles around the world (for example in Australia, England, and Netherlands), which are allowing people, especially the seniors, using an app to order a bus. It can accommodate multiple passengers plus it has no set route (Mulley et al., 2019). Instead, it uses artificial intelligence in order to determine its most efficient path based on real-time pick-up and drop-off requests. The use of self-driving buses and cars is part of the growing demand of Mobility as a Service, which uses Artificial Intelligent to enable ridesharing and transport on-demand (Waytz et al., 2014).

Simply stated, connected vehicle (CV) technologies allow vehicles to communicate with each other and the world around them, the vehicle is likely already more connected than anybody could realise. Navigation systems already include connected vehicle capability, such as dynamic route guidance. A GPS-based system receives information on congestion in the road ahead through cellular signals (4G LTE or 3G) and suggests an alternative route as it’s shown in Figure 2.7.

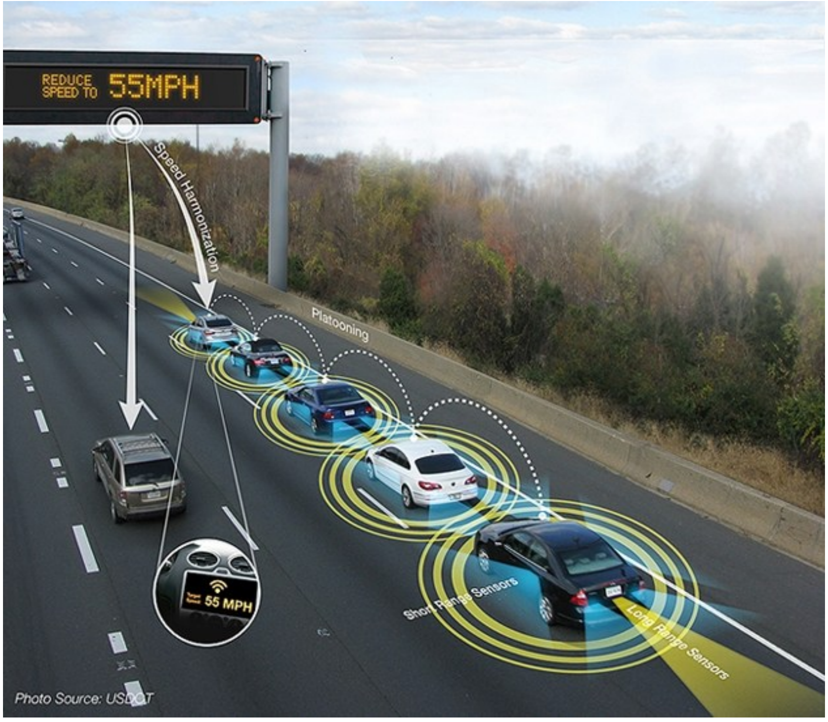

Figure 2.7:GPS-based system on connected vehicle(USDOT, 2018).

The CV concept is about supplying valuable information to a vehicle or a driver to help the driver make more informed and safer decisions. The use of a "connected vehicle" does not imply that the vehicle is making any kind of choices for the driver. Moderately, it supplies information to the driver, including potentially dangerous situations to avoid.

On the other hand, some vehicles are already being deployed with autonomous functionality, such as self-parking or auto-collision avoidance features (Magdici & Althoff, 2017). But it is not a true autonomous vehicle (AV), until a vehicle can drive itself independently. A fully autonomous vehicle does not require a human driver-rather, they are computer-driven. Many manufacturers will phase in various levels of autonomy until fully autonomous vehicles are widely tested and accepted by the general public. Autonomous vehicles don't need connected vehicle technology to function since they must be able to independently navigate the road network as (Rahman and Abdel-Aty, 2018) pointed out. However, CV technologies provide beneficial information about the road ahead—allowing rerouting to rely on new information like an obstacle or a lane closure on the road. By incorporating CV technology, AVs will be faster, safer, and more efficient.

Furthermore, virtually, every autonomous vehicle will require some form of connectivity to ensure data sets and software are current (John Bradburn, David Williams, Rob Piechocki, 2017b). As autonomous vehicles rely on knowing the traffic roadway they are traveling on, alterations to the roadside such as new construction or development will require the type of real-time exchange of information that CV technology provides.

Fu et al., 2019a supported that autonomous vehicles will probably be part of normal traffic in most countries within a few years. But will their introduction contribute to better traffic flow when mixed into traffic with conventional vehicles? Previous research, mostly based on microsimulation studies, suggests that traffic solely composed of autonomous vehicles will flow better and that traffic volumes will be lower than today (Guanetti et al., 2018). However, in the future, a more realistic scenario is that there will be a mixture of autonomous and traditional vehicles.

To facilitate the evaluation of the impact of CAVs, it is important to understand the main features of the vehicles, the systems, sensors, and the basic elements that define them. This part of the literature review aims to describe the most important steppingstones of a CAV in the following sections:

1) Definition and Equipment of Connected and Autonomous Vehicles
2) Level of Automation
3) Potential Impact and Issues of Connected and Autonomous Vehicles
4) Barriers to Implementation

2.2.3.3.1 Definition and Equipment

Autonomous vehicle (AV) technologies represent a switch in responsibility for the task of driving to machine from human. There are a diverse range of automated technologies, from relatively simple driver assistance systems to fully automated vehicles. Generally, an autonomous vehicle is one in which there is no human driver, and the levels of automation are higher.

A fully autonomous vehicle does not require a steering wheel, accelerator, or a brake pedal as anyone can see in the Figure 2.8. All functionality for driving is handled through on-board computers, maps, radar, software, and sensors etc., as they are depicted in Figure 2.9. The majority of traffic crashes are caused by human error, so the benefits provided by Autonomous vehicles are compelling. Furthermore, other potential benefits are related to congestion mitigation, air pollution, greenhouse gas reduction (GHG) and mobility enhancement for underserved population such as low-income people, elder people, and persons with disabilities.

Figure 2.8:Interior of a fully self-driving vehicle (Automotiveplastics, 2018).

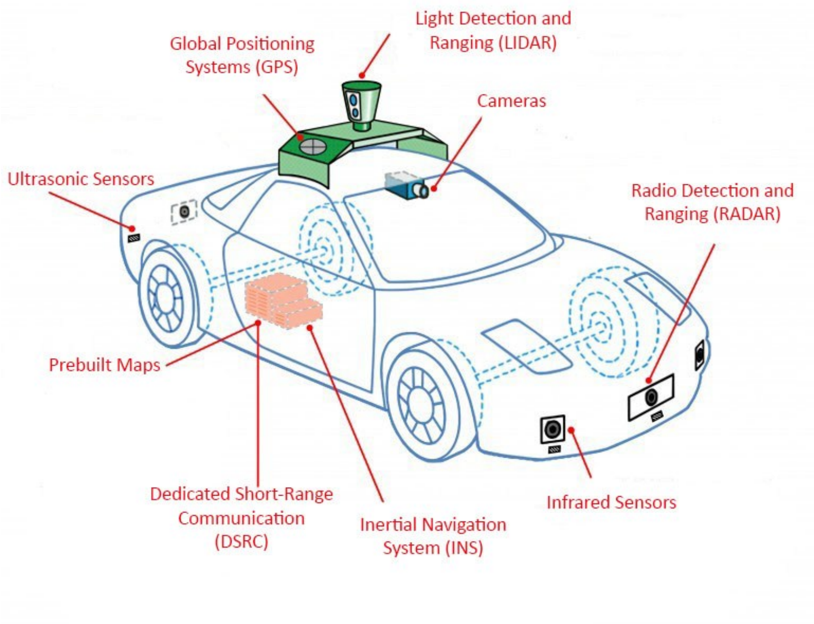

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Figure 2.9:Automated vehicle technologies (css.umicj.edu, 2018).

According the Figure 2.9 the technologies of an automated vehicle are:

1. **Global Positioning Systems (GPS):** Locate the vehicle by using satellites to triangulate its position. Although GPS has improved since the 2000s, it is only accurate within several meters.
2. **Light Detection and Ranging (LIDAR**): A 360-degree sensor that uses light beams to determine the distance between obstacles and the sensor.
3. **Cameras:** Frequently used inexpensive technology, however, complex algorithms are necessary to interpret the image data collected.
4. **Radio Detection and Ranging (RADAR):** A sensor that uses radio waves to determine the distance between obstacles and the sensor.
5. **Infrared Sensors:** Allow for the detection of lane markings, pedestrians, and bicycles that are hard for other sensors to detect in low lighting and certain environmental condition.
6. **Inertial Navigation Systems (INS):** Typically used in combination with GPS to improve accuracy. INS uses gyroscopes and accelerometers to determine vehicle position, orientation and velocity.
7. **Dedicated Short-Range Communication (DSRC):** Used in Vehicle to Vehicle (V2V) and Vehicle to Infrastructure (V2I) systems to send and receive critical data such as road conditions, congestion, crashes, and possible rerouting, DSRC enables platooning, a train of vehicles that collectively travel together.
8. **Prebuilt Maps:** Sometimes utilised to correct inaccurate positioning due to errors that can occur when using GPS and INS. Given the constrains of mapping ever road and drivable surface, relying on maps limits the routes an AV can take.
9. **Ultrasonic sensors:** Provide short distance data that are typically used in parking assistance systems and backup warning systems.

Autonomous vehicles can be further distinguished as being connected or not. Furthermore, connectivity is seen by many to be a major enabler for driverless vehicles in the medium term (Guanetti et al., 2018).

On the other side, a connected vehicle has internal devices that enables it to communicate wireless with other vehicles, as in vehicle-to-vehicle communication, or even with an intelligent roadside unit as in V2I communication (Davies, 2018). Data communications that enable real-time driver advice and warnings of threats and hazards on the roadway are the foundation of a connected vehicle.

To summarise the AVs, encompass a range of automated technologies, from relatively simple driver assistance systems to fully autonomous or self-driving vehicles and CVs have internal devices that connect to other vehicles, other road users or back-end infrastructure.

2.2.3.3.2 Level of Automation

The National Highway Traffic Safety Administration (NHTSA, 2016) has adopted a framework for automated driving developed by (SAE International, 2016) that has categorised automation into six levels, ranging from vehicles which are not equipped with automated control systems at all (automation level 0), to fully automated vehicles (automation level 5). More specifically:

Vehicles with level 0, 1, 2 technologies are already available for private ownership and are currently operating on public roadways. Level 0, 1 and 2 are defined as follows:

Level 0 – No-Automation. The driver is in full control of the driving task. Vehicles that are equipped with driver support/convenience systems, also known as Advanced Driver Assistance Systems (e.g., Collision warning systems), are also considered as “level 0”. Example: Classical Buses

Level 1 – Driver Assistance. In this level of automation, the vehicle can automatically assume limited authority over one primary control (such as adaptive cruise control). The driver still has overall control and is solely responsible for safe operation but can choose to hand limited authority over a primary control to the vehicle. Example: Park Assist

Level 2 – Partial Automation. Vehicle has combined automated functions, like steering and acceleration, but the driver should remain engaged with the driving task and monitor the surroundings at all times. The driver is responsible to monitor the roadway and safety operation and is expected to be available to take over the driving task and any given time on short notice. Example: Traffic Jam Assist

NHTSA categorises vehicles with level 3, 4 and 5 technologies as automated driving systems. Such vehicles are still developing, and automakers and technology firms are testing them on public roads. Level 3, 4 and 5 are defined as follows:

Level 3 – Conditional Automation. Driver is an essentiality but is not required to monitor the surroundings. The driver should be ready to take the control of the vehicle at all times with notice. Vehicles can monitor these conditions and can require transition back to driver control. The driver is expected to be available to occasionally take over the driving task. The major difference between level 2 and level 3 is that at level 3, the driver is not expected to continuously monitor the roadway while the vehicle is driving. Example: Highway Patrol

Level 4 – High Automation. Vehicles at this level of automation are capable of performing all safety-critical driving functions and monitoring roadway conditions for an entire trip. They require the driver to input the destination of the trip but not to be available to take control at any time during the trip. Example: Urban Automated Driving

Level 5 – Full Self-Driving Automation. The vehicle is able of performing all driving functions under all conditions. Also, the driver may have the option to control the vehicle. Example: Full end-to-end journey

Intelligent vehicles are a broader category of vehicles that are equipped with perception, reasoning and actuating devices that automate the driving task. The Figure 2.10 below provides an overview of the different levels of driving automation. Also indicates the levels at which a driver may be required to take control and intervene as compared to the levels where the car could be fully autonomous (Scotland, 2019).

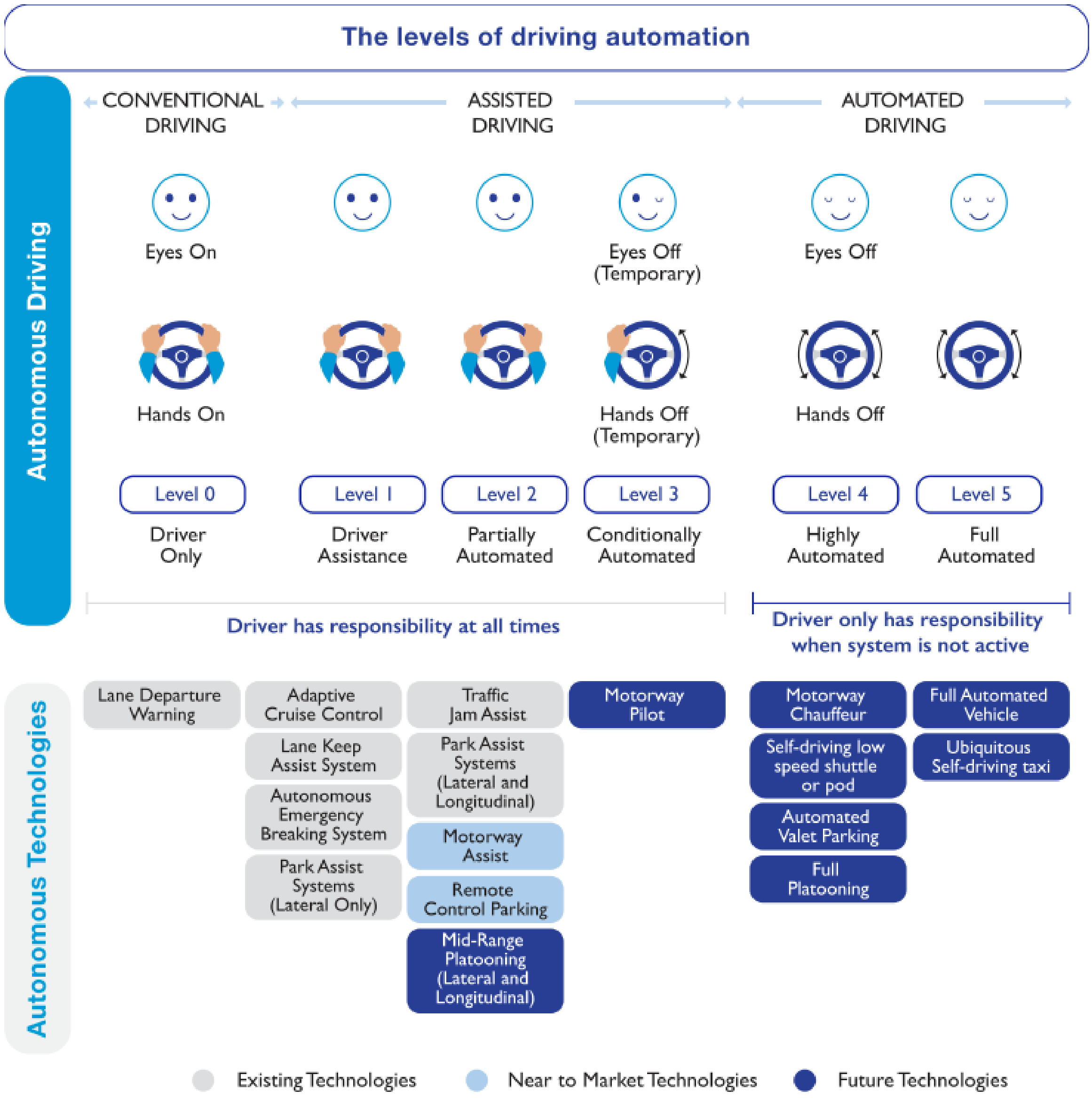


Figure 2.10:SAE Levels of Driving Automation (Adapted from the Society of Automotive Engineers 13016: Standard and UK Centre for Connected and Autonomous Vehicles).

The emergence of CAVs will bring change to the automotive industry all over the world. More than 18 million automated vehicles are forecasted to be added to the global motor parc by 2030, undoubtedly changing the way people commute (Simpson et al., 2019). A global overview of CAVs development made from the literature review is summarised in the Table 2.4. The term "automated road miles" refers to the proportion of total vehicle miles travelled that are driven under some level of automation, typically involving autonomous or self-driving technology. It quantifies the extent to which autonomous systems are used in real-world conditions.

Table 2.4:Global overview of CAV development.

Country	CAVs development
United Kingdom	**Test Beds:** Four major CAV test beds and 3 additional test sites for highways, parking and rural **Self-Driving Testing Approval:** ✓ **Automated Road Miles:** 1 in miles
Netherlands	**Test Beds:** None **Self-Driving Road Testing Approval**: ✓ **Automated Road Miles:** 1 in 10 miles
France	**Test Beds:** Multiple OEM test beds **Self-Driving Road Approval:** ✓ AD testing is permitted on the autoroutes **Automated Road Miles:** 1 in 12 miles
Germany	**Test Beds:** Multiple OEM test beds **Self-Driving Road Testing Approval:** ✓ AD testing is permitted on the autobahns **Automated Road Miles:** 1 in 10 miles
USA	**Test Beds:** 10 government authorised test beds **Self-Driving Testing Approval:** ✓ **Automated Road Miles:** 1 in 8 miles
South Korea	**Test Beds:** 1 dedicated test bed for AD testing. **Self-Driving Testing Approval:** ✗ **Automated Road Miles:** 1 in 20 miles
China	**Test Beds:** 3 cities based restricted AD test trials with testing permitted on specific public roads. **Self-Driving Testing Approval:** ✗ **Automated Road Miles:** 1 in 12 miles

2.2.3.3.3 Potential Impact of Connected and Autonomous Vehicles

Theoretically, a CAV is a technological tool which holds great promise for future transport systems. CAV operations are inherently different from human-driven vehicles and a CAV can be programmed to not break traffic laws. Their reaction times are faster, and they can be optimised to smooth traffic flows, reduce emissions, and improve fuel economy(Fagnant & Kockelman, 2015). They can deliver unlicensed travellers and freight to their destinations. In this section some of the largest potential benefits that have been identified in existing research will be examined so as to achieve a better understanding of CAVs' impact. The potential benefits and obstacles in the way of CAVs are not explicitly proven and quantified yet with scientific methods.

2.2.3.3.3.1 Safety

CAVs have the potential to dramatically reduce crashes as they do not drink and drive so autonomous vehicles. Many research about automobile crashes have been taking place the last decades (Fagnant & Kockelman, 2015; X. Wang et al., 2018; K. Yang et al., 2018) and all of them indicates sources of driver error that may disappear as vehicles become increasingly automated.

Over 40% of fatal crashes involve some combination of distraction, alcohol, drug involvement and/or fatigue as Fagnant and Kockelman indicate in their research (Fagnant & Kockelman, 2015). Self-driven vehicles would not fall prey to human failings, suggesting the potential for at least a 40% fatal crash-rate reduction, assuming automated malfunctions are slightest and everything else remains constant (such as the levels of long-distance, night-time, and poor-weather driving). The main reason for over 90% of all crashes is believed to be the driver error (NHTSA, 2008). Even when the crucial reason behind a crash is attributed to the roadway, vehicle or environment, additional human factors like inattention, speeding or distraction are regularly found to have contributed to the injury severity and crash occurrence.

Designing a system that is able to perform that can perform safely in nearly every situation is a big challenge, (Campbell et al., 2010). For example, the recognition of humans and other objects in the roadway is critical and more difficult for AVs to be recognised than human drivers (Economist, 2012; Fagnant & Kockelman, 2015; Matei et al., 2018). A person in a roadway may be large or small, standing, siting, walking, riding a bike– all of which complicate AV sensor recognition. Furthermore, bad weather, such as heavy rain, fog and snow, and ice create other challenges for driving operations and sensors (Böcker et al., 2016; De Palma & Rochat, 1999). Furthermore, evasive decisions should depend on whether an object in the vehicle's path a large cardboard box or a large concrete block is, and computer vision has much higher difficulty than people in identifying material composition. To illustrate it more, when a crash is unavoidable, it is critical that AVs recognise the objects in their path and so may they act accordingly (Fagnant & Kockelman, 2015). So, for these incidents, a major concern should be liability and should be a substantial impediment to implementation.

2.2.3.3.3.2 Traffic/Congestion

The impact of AVs on congestion is not straightforward, as it depends on various factors, including induced traffic, which poses a significant challenge. Induced traffic refers to the increase in travel demand resulting from the improved convenience and reduced costs of travel facilitated by AVs. While researchers are focused on enhancing vehicle safety, developing ways for AV technology to mitigate congestion and fuel consumption is equally critical. CAVs have the potential to reduce traffic congestion through several mechanisms. For example, AVs can sense and anticipate braking and acceleration patterns of lead vehicles(Fagnant & Kockelman, 2015), enabling smoother braking and finer velocity adjustments among following vehicles. This reduces fuel consumption, brake wear, and the propagation of traffic-destabilizing shockwaves (Traffic, 2012). Vs can optimise lane and intersection usage by allowing shorter gaps between vehicles in coordinated platoons and enabling more efficient route choices. Many features, such as adaptive cruise control (ACC), are already being incorporated into conventional vehicles, demonstrating benefits even before the full deployment of AVs(Kesting et al., 2008).

Several studies have explored the potential for AVs to alleviate congestion under various adoption scenarios. These studies suggest that with higher levels of AV penetration, measures such as traffic monitoring systems and ACC can smooth traffic flows by minimising accelerations and braking in freeway settings. However, the potential for AVs to generate additional travel demand, due to the increased attractiveness of driving, may offset some of these benefits. Therefore, it is crucial to investigate and account for induced traffic effects in planning and evaluating the deployment of AV technologies.

More reliable travel times are being produced by gap reductions coupled with near-constant velocities– an essential factor in trip generation, routing decisions and timing. Similarly, shorter headways and start-up times between vehicles at traffic signals mean that AVs could more effectively handle green time at signals, considerably improving intersection capacities. Many of these congestion-saving improvements depend also on cooperative abilities through vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication. (Fagnant & Kockelman, 2015).

Over the long term, examples for signal control such as autonomous intersection management could use AVs' powerful capabilities. Several evidence shows that advanced systems could nearly eliminate intersection interruption while reducing fuel consumption. In order to implement such technologies, Dresner and Stone estimated that a 95% or more AV-market penetration may be required, leaving several years before deployment (Dresner, Peter Stone, 2008). Of course, until high AV shares are present such benefits may not be realised.

2.2.3.3.4 Barriers to implementation

Connected and Autonomous Vehicles present many opportunities and benefits as well as challenges, whilst ushering in behavioural changes that effect how travellers interact with transportation systems. Furthermore, there are some unusual risks in their implementation particularly from security and privacy standpoints. Some of the barriers for the implementation of CAVs are of course the vehicle cost, as well as not everybody is able to have one and the litigation and liability of CAV. AV capabilities requires special research efforts. This section outlines some barriers that AVs face.

Vehicle Cost: First of all one of the biggest barriers to large scale market adoption is the cost of CAV platforms, and well as the technology needed for a CAV includes the addition of new sensors, communication technology and software for each vehicle. (Silberg et al., 2013) notes that as AVs migrate from custom retrofits to mass-produced designs, it is possible that these costs could fall somewhere close to $3000 mark, and eventually just $1000 to $1500 more per vehicle. Nevertheless, cost remains big. Therefore, it is a key implementation challenge, due to the unaffordability of even some of the basic technologies.

Litigation and liability: Once AVs become certified for safe operation, many new insurance and liability issues will arise, including persuading insurance providers that the technology will work properly, in all driving environments (Fagnant & Kockelman, 2015). There could be instances where a crash is unavoidable, even with near-perfect autonomous driving. For example, if an animal jumps in front of the car, does the AV hit the animal or run off the road? How do actions change if there is another car, a motorcyclist, bicyclist, or pedestrian instead of an animal? With a split second for decision-making, human drivers typically are not held at fault, regardless of whether their decision was the best, when responding to circumstances beyond their control, On the other hand, AVs have sensors, visual interpretation software, and algorithms which enable them to potentially make more informed decisions. Decisions that may be questioned in a court of law, in case of incident. More philosophical questions arise as well, such as what should owners be allowed to adjust such settings?

Some extra barriers that concern a lot the government and the transport policymakers, auto manufacturers and future CAV drivers are the security and the privacy of CAVs. Computer hackers, disgruntled employees, terrorists may target Intelligent Transport System generally by causing harm and different level traffic disruption (Fagnant & Kockelman, 2015; GOV.UK, 2017). Moreover, providing CAV travel data, such as routes, destinations, and times of day, to centralised and controlled systems is likely more controversial, specifically if the data is recorded and stored. Without the proper safeguards, this data could be misused by government employees, for example, for tracking individuals and provided to law enforcement agencies for unchecked monitoring and surveillance.

2.2.3.4 Proposed Connected Vehicle concept and challenges.

One limitation of all research conducted, simulating CV alongside conventional vehicles, is that the examined area of them all were in the capital's cities of the countries, with no researches appearing to exist concerning Connected Vehicles and Motorways to detect incident in real-time. Also comparing with CAVs or Avs, CVs were not fully deployed in the literature review on motorways, and not a specified CV driving behaviour has been directly assigned to this type of vehicle. On the other hand, today is witnessing the initial deployment of technology that promises to redefine the meaning of traveling by automobile and reshape the auto's future role in transport networks. Research like these above should have been already started for highways also. A world of connected driving is likely to be a world where individual car ownership drops off due to risk avoidance in the initial adoption of this technology. CVs would improve incident detection, enhancing communication between vehicles without causing congestion or a secondary incident following the initial one. Additionally, through their future potential to connect city-to-city trips, integrating CVs with public transport systems could increase synergies between transit and vehicles. The use of them in highways could shield the cities from oil and climate vulnerability, as CVs provide accessibility to auto-dependent locations during times of energy and climate disruption.

A limitation in the existing body of research on simulating CVs alongside conventional vehicles lies in its predominantly urban-centric focus, primarily centered in the capital cities of various countries. Moreover, the literature review highlights a relative scarcity of comprehensive studies pertaining to CAVs' full deployment on motorways, but particularly lacking a specific CV driving behaviour designation (Anagnostopoulos & Kehagia, 2020; John Bradburn, David Williams, Rob Piechocki, 2017a; L. Zhao & Sun, 2013; Zhong et al., 2020). In contrast, contemporary developments signal the initial deployment of transformative technologies poised to redefine automobile travel and reshape the vehicle's role in transport networks. Noteworthy is the absence of dedicated research initiatives for highways, especially given the anticipated benefits of CVs, such as enhanced incident detection and improved communication among vehicles without inducing congestion or secondary incidents. The prospect of a connected driving landscape may witness a decline in individual car ownership, driven by risk avoidance during the technology's initial adoption. CVs, with their potential to connect city-to-city trips, could foster synergies between transit and vehicles, offering resilience against oil and climate vulnerabilities and providing accessibility to auto-dependent locations during periods of energy and climate disruption, as less disruptions, weaving and brakes will be occurring in a system where vehicles can be connected to each other.

Moving forward, Figure 2.11 shows the proposed dynamic traffic microsimulation model that can be followed to simulate the driving behaviour of connected vehicles in the incident detection scenario.

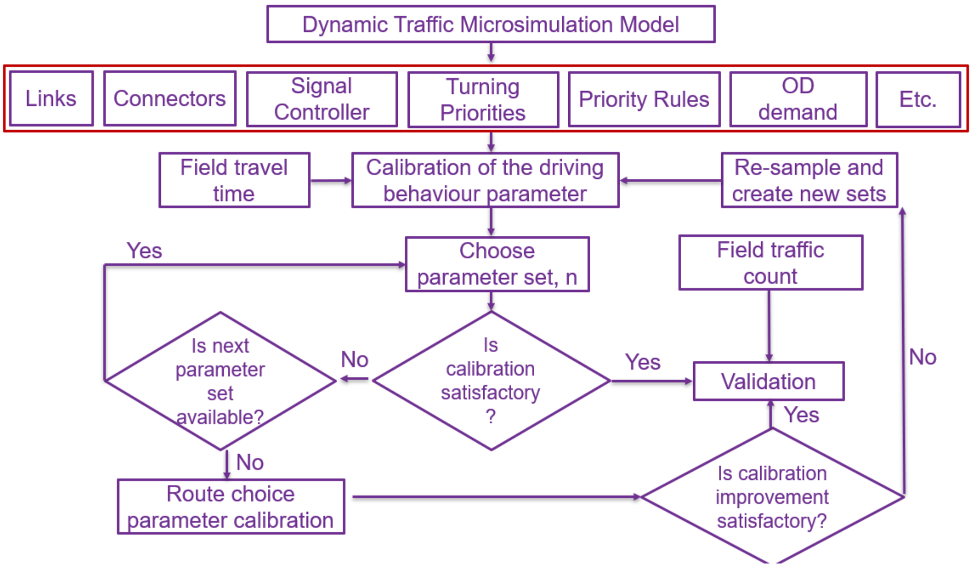


Figure 2.11: Proposed dynamic traffic microsimulation model for the CVs scenario development.

In the proposed model, a valid area will be chosen as the test area, where M1 motorway will be used. All the links, the connectors, the signal controllers, the priority and turning rules, the origin and destination demand will be considered for the accurate illustration of the area. Traffic flow data from the tested area will be considered for analysis of the traffic demand needed for the simulation. The scenario could be used to specify the connected vehicle driving behaviour in an event of an incident.

The simulation will certify the choice of operational policy, which will establish vehicle-customer assignment and reposition of connected vehicles, which heavily affects system performance, for example, travelling times and cost actually meaning congestions. This aspect will probably be regarded as an essential factor in the interpretation of existing and future simulation studies for Highways England's Strategic Road Network (SRN).

The deployment of it will be studied simultaneously with the simulation testing of the Incident Detection scenario. Chapter 3 analyses the methodology followed, proposed concept and challenges of the incident detection scenario, whilst Chapters 4 and 5 have information concerning the data acquisition that will be need and the simulation process of it, respectively, followed by the data results in Chapter 6.

2.2.4 Conclusion

In this literature review section, up to date and long-term effects of Intelligent Mobility have been reviewed. The first section includes a background on IM and the IM definitions. Over the past few decades, autonomous driving has been the subject of great research efforts. Hence, the automobile and technology industries have made significant leaps in bringing computerisation into driving (Fagnant & Kockelman, 2015). Despite human's huge development in driving throughout the years, the human errors are a prominent cause of road accidents and fatalities. Nowadays, the market for Intelligent Mobility is rapidly developing as customers, businesses, transport authorities and governments understand the great potential for unlocking primary opportunities and improving a broad range of outcomes by taking a user-centric approach to looking at mobility opportunities for customers as part of a broader, integrated system (Burrows et al., 2015). As it is mentioned above, IM definition often is used as a buzz word. Fundamentally, Intelligent Mobility is about innovation and thinking differently about how to connect people, places, and goods across all transport modes, based on the new opportunities' technology brings us. Thus, it is about utilising a combination of systems thinking, technology and data across the transport network to inform decision making and implement behavioural change. Intelligent Mobility integrate a strong focus on putting the customer at the heart of the service offering with the requirement of integrating all transport opportunities into a whole system. (Atkins, 2019a; Catapult Transport System, n.d.; UK Department for transport, 2019).

The next section includes the studies that have been on the section of New Mobilities Technologies, including Shared Mobility, On Demand Mobility, MaaS and CAVs, which tend to result in well-supported outcome. The last category includes studies making speculations and predictions about the impact of CAVs in some cases based on the implementation of other transport technologies (Shladover et al., 2012).

In conclusion, a study clearly measuring the impact of NMS on highways SRN does not yet exist. This might be because access to real world autonomous vehicle data is limited and an integrated/robust/validated method for NMS, and especially CAVs evaluation has not been formulated in order to clearly assess their impacts. Alternative appropriate methodologies, previously applied to other Intelligent Transport Technologies, should be reviewed to see whether they can be applied to the evaluation of the use of these NMS on highways strategic road network. For that reason, it is compulsory to evaluate their impact through different scenarios that it is needed to be developed, both at CAV and MaaS section.

2.3 Traffic Incident Detection

The third section of the Literature Review summarises the importance of incident detection. Incident detection on motorways is a critical aspect of ensuring road safety and minimising traffic disruptions (Chen & Pan, 2021; E. Chung & Rosalion, 1999). Intelligent Mobility, incorporating advanced technologies such as Connected Vehicles and V2V connectivity, has emerged as a promising solution for enhancing incident detection capabilities. Utilising these technologies enables real-time communication among vehicles, facilitating the swift exchange of information about incidents, road conditions, and potential hazards (Frenzel, 2018; Frtunik et al., 2021; Muhammad & Safdar, 2021). This interconnected system enhances the accuracy and speed of incident detection, allowing for quicker response times and improved traffic detection . On the other hand, without the integration of Intelligent Mobility, incident detection relies heavily on traditional methods, such as surveillance cameras and roadside sensors, which may not provide as timely and dynamic information (Fleming, 2008; Y. et al., 2017). The adoption of Intelligent Mobility can revolutionise incident detection on motorways, contributing to safer and more efficient road networks.

Traffic incident detection is one of the crucial research areas of intelligent transport systems (Ren et al., 2016). During the last decades, many capital cities suffer from congestion (D. J. Lee, 2018). In many cases, traffic incidents have been proven to be a major cause of road congestion. Monitoring traffic flow is very important for the early and accurate detection of traffic incidents but is challenging too, due to the nature and the characteristics of a traffic incident. In order to avoid traffic incidents, reliable detection is the key. The reliable detection of traffic incidents and congestion could provide useful information for enhancing traffic safety and could indicate the characteristics of traffic incidents, traffic violations, driving patterns, etc. (Steenbruggen et al., 2016a).

Traffic safety, reduction of traffic congestion and improvement of traffic management can be provided through Intelligent transport systems (ITS) who integrates wireless communication technology with the transport networks. Hence, ITS draw a great deal of attention from researchers with its wireless and communication technology background (Sheikh et al., 2020a). For instance, many concerns raised daily to the transport authorities because of the large number of vehicles on the road causing traffic incidents, congestion, road bottlenecks, etc., that need to be managed.

In this context, for an ITS, early detection of incidents is necessary to investigate and implement the traffic strategy. Early incident detection can alleviate traffic congestion and hence improve the traffic flow for real-time traffic monitoring system in ITS (Yuan & Cheu, 2003). It is crucial to mention that the transport operation can be affected easily as well as the traffic conditions on the road can rapidly become severe. To be more specific, it is known that people are using multiple modes of transport, such as private cars, taxis and on-demand ride services as well as buses, to commute to their preferable destination. All of the above modes of transport need to be examined on how they affect the traffic condition in case of a traffic disruption (Luk et al., 2010a).

It is worth mentioning that there are different events that can lead to a temporary reduction in traffic capacity and traffic congestion. All these events can be classified according to the type of cause of the trouble (Nikolaev et al., 2017). It is essential though, to mention the definition of the incident and clarify the difference between an incident and an accident as accident and incident are usually confused when they approach their usage. These two words, incident and accident, have some interesting facts to offer. A traffic incident is referred to as an abrupt change in traffic flow, which reduces the road capacity and increases traffic congestion (Sheikh et al., 2020a). Literally, an incident does not involve a loss of human life or any casualty. On the other hand, an accident is used to express 'a happening or an event that takes place all of a sudden' (Zummack, 2018). Unlike an incident, an accident usually involves the loss of human life or casualty. This is the main difference between the two words. Either way, an accident is constantly unexpected or unintentional. Conversely, an incident is an extensive term that refers to any event, whether big or small, positive or negative, unintentional or intentional.

The aim of any incident detection strategy is the elimination of the emerged incident as soon as possible. Such management strategy should include the following steps: the detection of an incident, response to the occurred incident, the restoration of normal traffic conditions (Samant & Adeli, 2000b).

Historically, analysing traffic incidents has been challenging due to the complex nature of heterogeneous incidents, which is difficult to detect quickly. Such a kind of complexity can cause the failure of the transport management system. Therefore, there is an engagement for designing an integrated system, which is able to predict and detect traffic incident quickly.

2.3.1 Individual Incident Detection

Traffic management systems have the ability to conduct automatic incident classification (AIC) to evaluate different types of incidents (L. L. Wang et al., 2018). Traditionally, the means of detection have been patrols operated by police, by the state highway department or by contact to private groups. Roadside emergency call box and telephone systems have also been used to report incidents.

Nowadays, highways agencies use stationary observers and television surveillance to detect incidents in strategic locations along the highway, such as in tunnels and more. Furthermore, the advent of vehicle detection systems such as loop detectors kindled interest in automating incident detection from the early 60s (Profile, 2020). The automation involved monitoring the highway continuously by collecting traffic flow data through vehicle detectors spaced at intervals along the highway. Specific incident detection algorithms then operate on the collected data to produce indicators of the probable presence of an incident.

Technological advancements in mobile communication in combination with the rising interest in solving travel problems using advanced technologies continue to create new opportunities for further improving incident detection on highways. Drivers can report incidents to highway agencies by voice or digital messaging either directly using cellular telephones or indirectly through roadside beacons using transponders installed in their vehicles (known as E-Call systems) (Thales, 2023) .

Three performance measures are generally used to measure the performance of an incident detection method:

- Time to Detect (TTD): The time interval between the occurrence of an incident and its detection by the system. Shorter detection times are critical for timely responses and minimising traffic disruption.
- False Alarm Rate (FAR): The proportion of instances where the system incorrectly identifies an incident when none has occurred. A lower false alarm rate indicates higher system reliability.
- Detection Rate (DR): The percentage of actual incidents that are correctly identified by the system. A higher detection rate reflects the system's ability to identify incidents accurately.

A straightforward comparison of the achievement of the computer-based algorithms is challenging because both how an incident is defined, and the measures of effectiveness are inconsistent throughout the literature (Kamran & Haas, 2007; Luk et al., 2010b; Parsa et al., 2019; Sheu, 2004; Weil et al., 1998).

A way to achieve the desired aim is through individual incident detection development. To attain better incident detection, surveillance cameras are placed on the road to detect the traffic incident and properties of traffic flow dynamics under incident by using floating data gathered from GPS have been examined. Incident detection and classification are a crucial aspect of the traffic management system, with the main challenging issue to obtain an early and accurate detection of traffic incident (Asakura et al., 2017; Srinivasan et al., 2004). Authorities are currently detecting incidents via different technologies such as loop detectors, CCTV and radar. Some of this sensor technology will be analysed below, giving emphasis to the in-road sensors, providing some advantages and disadvantages and also highlighting the main issues.

In the past, many methods have been proposed which are used to collect data from the detectors, such as loop detector, radar detector, video detector, etc. (C. Lu, 2018; Rossi et al., 2015; Steenbruggen et al., 2016b). Thus, it is still necessary to find a better way to detect a stationary vehicle on highways faster and more accurately. The primary focus would be to reduce 'time to detect' (TTD). For this scope, a V2X communication system will be used to collect data from vehicles to detect traffic incidents. V2X communication is a robust system, which is considered an important component of Intelligent Transport Technologies (J. M. Chung et al., 2011; Milanés et al., 2012). The collected data will be processed by AID algorithms, which can generate incident alerts in case of any traffic incident and traffic violations.

2.3.2 Problem and Aim

As Automatic Incident Detection (AID) has been considered a method for quickly detecting potential incidents, research, development, and testing have been conducted to identify a suitable technology and its underpinning algorithms. Over the last few decades, many incident detection algorithms and methods were developed. Classic AID systems, such as those relying on inductive loop detectors or fixed roadside cameras, have faced substantial challenges in real-world deployment. One major issue is the high rate of false alarms, which can overwhelm traffic operations centers and lead to these systems being deactivated or abandoned. Additionally, some systems exhibit poor detection rates, rendering them unreliable as a primary method of incident detection. These limitations are particularly problematic when detecting critical incidents like stopped vehicles on roadways—scenarios that can quickly escalate into severe accidents if not promptly addressed.

Due to the variability of on-road driving environments, vehicle detection may face different problems and challenges. A disadvantage of the existing ways of detecting is that it takes a long time to detect an incident (Hawas et al., 2020a). It has been proven that approximately sixteen minutes are needed for a stopped vehicle to be detected by emergency services (GOV.UK, 2019), RCC and other drivers, and this time can be much longer in case of low-density traffic flow and night driving. Secondly, the false alarm rate is quite high. To illustrate, consider the typical true- and false-alarm duration probability distributions shown in Figure 2.12 (Tsai & Case, 1979a). The considerable overlap of the two distributions intimates that there is poor pattern separability if one relies entirely on alarm duration to distinguish between true and false alarms. These findings underscore the need for more accurate and timely incident detection methods to enhance roadway safety and efficiency.

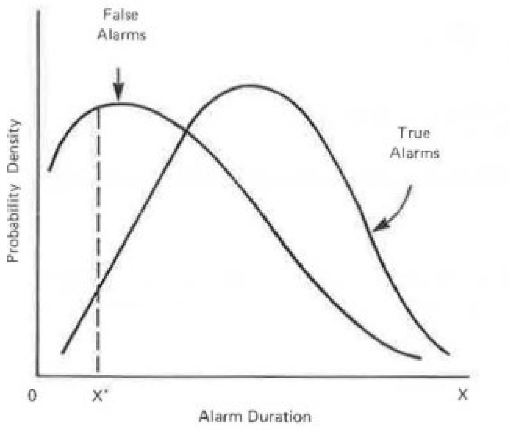


Figure 2.12: Typical alarm duration probability distributions (Source: Tsai and Case, 1979).

The results of the number of false alarms (FAR) are also changing depending on the algorithm effectiveness (Nikolaev et al., 2017). Nikolaev et al. (2017) showed that the maximum values observed for the two algorithms: Bayes algorithm and advanced algorithms based on fuzzy logic-100%. Besides, the SND algorithm has a great indicator above 90%. California and McMaster have the most insignificant values, below 70%. The number of false alarms (FAR) of his research has been showing below in Figure 2.13.

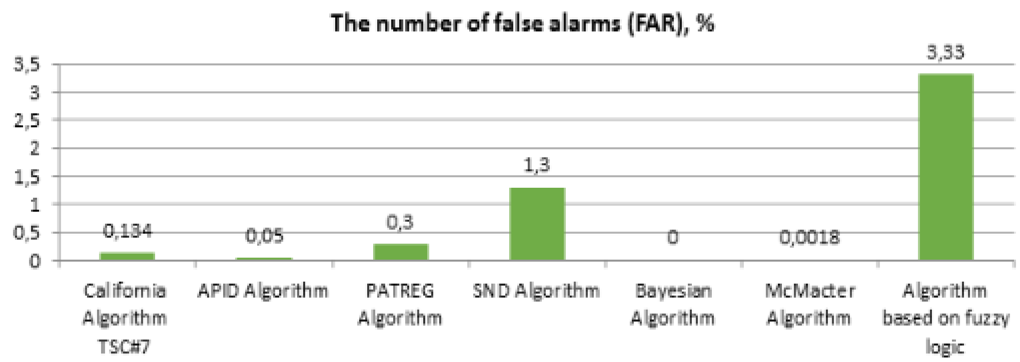


Figure 2.13: The result of the research (Nikolaev et al., 2017) *- number of false alarms.*

Thirdly, the cost of installing and managing the hardware is enormous, having an entire nationwide price tag of $160 billion (Guerrero-Ibáñez et al., 2018), and there are additionally extra costs from the quite often malfunctions of roadway sensor. In order to eliminate these, other alternatives need to be explored.

In this research, in case of a stopped vehicle on highway motorways, all the following vehicles instantaneously will be informed either from the stopped vehicle or from the surrounding vehicles and the roadside units. This will have as result, firstly, quick detection: The stopped vehicle will be detected sooner. Either the stopped vehicle will inform RSU and the following vehicles via V2I and V2V communication, or the surroundings vehicle will do the same in case that the stopped vehicle will not have this capability. Secondly, more time for drivers to react: Drivers will be informed faster for the stopped vehicle ahead, so they will have more time to decrease their speed and be ready for taking evasive actions such as braking, swerving or changing lanes.

As a consequence, the aim of this work is to implement and test various scenarios via an integrated simulation platform in order to reduce the consequences of stopped vehicles on the SRN. This is going to be accomplished by detecting a stopped vehicle using V2X communication and define the right approach to test the concept through a simulation approach.

2.4 Scenarios Development

According to the above sections, the development of Intelligent Mobility technologies has established connected vehicle (CV) technologies, in which vehicles communicate with other vehicles (V2V), roadway infrastructure (V2I), pedestrians (V2P) and vehicle to everything (V2X) in real-time (Rahman & Abdel-Aty, 2018b). Intelligent Mobility and its components are regarded as one of the most promising methods to improve traffic performance including safety, congestion, fatalities etc. Hence, the future traffic environment will consist of a mixture of AVs, CVs, CAVs and conventional vehicles, and their interactions will influence the performance of all of them (Bhavsar et al., 2017a; W. X. Zhu & Zhang, 2018). This new mixture of traffic flow is much closer to be achieved than people can be expected. According to the NHTSA, at a full V2V adoption, CV technology will annually prevent maximum 615,000 crashes (NHTSA, 2016) decreasing that way the fatalities and injuries on highways but also increasing safety on traffic performance. Many researchers have evaluated the efficiency of CV technologies which is heavily decided by the CV full market penetration rate (MPR) (J. Lee et al., 2013; Paikari et al., 2014; Talebpour & Mahmassani, 2016b; K. Yang et al., 2016) . Compared with full market penetration of CVs, car-following safety will be impaired in mixed traffic (Rahman & Abdel-Aty, 2018b).

In mixed traffic situations, irregular driving behaviour such as cut-ins of conventional vehicles will significantly influence the car-following behaviour of the CV and AV. In various cut-in situations, the constant car-following model will result in uneven car-following behaviour, degrading the car-following safety of CVs, impairing the comfort of passengers, and decreasing driver trust and acceptance of AVs (Hartwich et al., 2018a) . To improve the safety and acceptance of CVs and AVs, many researchers have suggested that such vehicles should drive according to human driving behaviour (S. Park et al., 2017; Waytz et al., 2014). Thus, it is necessary to understand driver behaviour and expectation in different driving situations so as to evaluate the impact of intelligent mobility on traffic performance. An effective way to achieve the above is via the implementation of different scenarios in simulation software such as VISSIM. To be more specific different scenarios can be implemented for Intelligent Mobility in mixed traffic. In the following section a literature review on these categories will be taking place.

2.4.1 Semi-automated/CAVs/CVs Scenarios

This section explores the integration of CVs and semi-automated vehicles into existing traffic systems, particularly during the transition period before full market penetration is reached. It highlights the challenges associated with mixed traffic environments, where conventional vehicles coexist with CVs and semi-automated vehicles, and evaluates their impact on traffic flow and safety. The discussion reviews key studies that analyse vehicle interactions and assesses the effectiveness of automation technologies in improving highway efficiency. By understanding these scenarios, this section offers insights into the gradual evolution of transportation systems towards greater automation and connectivity.

As mentioned above, one of the greatest issues facing CVs popularisation accomplices it with the market penetration rate (MPR). Also, the full market penetration of CVs might not be associates recently. Accordingly, traffic flow will be composed of a mix of conventional vehicles and CVs. In this context, the study of CV MPR is worthwhile in the CV transition period.

The recent advances in technology have propelled efforts to automate vehicles in order to achieve safe and efficient use of the current highway system. Fully automated vehicles that are able to operate autonomously in a highway environment are not anymore so a long-term goal. On the other hand, partially or semiautomated vehicles designed to operate with current manually driven vehicles in today's highway traffic are seen as a more near-term objective. Their gradual penetration into the current highway system ushered the stage of mixed traffic where semiautomated vehicles coexist with manually driven ones (Bose & Ioannou, 2003b).

Bose and Ioannou, 2003b examined the effect of semiautomated vehicles on the transient behaviour of traffic flow at the microscopic level when they operate together with manually driven vehicles. In their analysis, they considered a human driver car-following model and a model of a semi-automated vehicle. These models were used to analyse the transient behaviour during vehicle following for three different cases (case 1: all vehicles are manually driven, case 2: all vehicles are semi-automated and case 3: manual and semiautomated vehicles are mixed). They used the Pipes model (Pipes, 1953) to simulate manual vehicle dynamics and examine the effect of mixing manually driven and semiautomated vehicles on the traffic-flow characteristics during transients. The semiautomated vehicle was modelled using an Intelligent Cruise Control (ICC) design developed in previous research of Ioannou that is free of slinky-type effects and is designed to provide smooth driving at all times with the exception of emergencies.

The analysis with mixed traffic shows that a "smooth" acceleration manoeuvre exhibited by a lead vehicle propagates upstream and gets amplified leading to the slinky effect phenomenon, where the semiautomated vehicles did not contribute to the slinky effect since they are designed to respond to any smooth acceleration/velocity response in an accurate manner. When the lead vehicle exhibited a "rough" acceleration manoeuvre, the semi-automated vehicle in a mixed traffic situation acts as a filter by converting the "rough" acceleration response to a smooth response in an effort to maintain smooth driving. This was done at the expense of larger position, velocity, and acceleration errors and sometimes at the expense of falling far behind the vehicle ahead. Finally, they have shown that these characteristics of the semiautomated vehicles have a very beneficial effect on fuel economy and pollution that is significant during rapid acceleration transients. It is worthwhile to show the same with CAVs and not only with semi-automated vehicles cause the outcome of the model would be more efficient than the (Bose and Ioannou, 2003b) model. In their research, by analysing and simulating mixed manual/semi-automated traffic, they found out that: a) Semi-automated vehicles in mixed traffic do not contribute to the slinky-effect phenomena during smooth transients. b) Semi-automated vehicles in mixed traffic smooth traffic flow by filtering the response of rapidly accelerating lead vehicles, and c) The presence of semiautomated vehicles in mixed traffic improves air pollution levels and fuel savings during transients without adverse effects on the traffic flow rate.

With the continuous evolution in computing, sensing, and communication technologies the semi-automated vehicles gave their place to the performance of autonomous vehicles. As it was mentioned in the previous chapter autonomous vehicles have the potential to become a safe, sustainable, yet personal, mode of transport, but despite the significant benefits of autonomous vehicles, they must be evaluated before mass deployment on SRN because the new combination of autonomous automotive and electronic communication technologies will present new challenges, such as interaction with other nonautonomous vehicles.

Paikari et al., 2014, utiliSed PARAMICS traffic micro-simulation software to study the impact of deploying Connected Vehicles (CV). They had implemented a V2V, Assisted V2I system for PARAMICS. It uses Dedicated Short-Range Communication (DSRC) protocol to acquire traffic data, calculate and compare important traffic safety and mobility parameters and their impacts on CV by testing five scenarios differentiated by the percentage of 0% to 40% market penetration of CVs. Despite of previous studies which focused on upstream traffic, in their study they demonstrated effect of considering DSRC, re-routing guidance and advisory speed for upstream and downstream traffic. Their study demonstrated that the CV technology can enhance traffic safety and mobility in freeways, if the percentage of CVs is significant (e.g., 30-40%) and the CV technology is accompanied by advisory speed reflected on Variable Message Signs (VMS) on both upstream and downstream of the incident location using DSRC range. In other words, equipping freeways with VMS, to use V2I communication, complements the CV technology, improves CV efficiency, and leads to higher safety and mobility enhancement in freeways.

In addition, cooperative driving with the connected vehicles is regarded as a promising driving pattern to significantly improve transportation efficiency and traffic safety (Jia & Ngoduy, 2016a). Nevertheless, also introduce packet loss and transmission delay had been introduced by unreliable vehicular communications when vehicular kinetic information or control commands are disseminated among vehicles. This brought more challenges in the system modelling and optimization.

As there are not many data yet available for the validation and calibration of a model for ITS, and most research has been only conducted only in theory, (Jia and Ngoduy, 2016) focused on the (theoretical) development of a more general (microscopic) traffic model which enabled the cooperative driving behaviour via a so-called inter-vehicle communication (IVC). To this end, they designed a consensus-based controller for the cooperative driving system (CDS) considering (intelligent) traffic flow that is comprise of many platoons moving together. To this end, four major components in CDS were supposed to be considered:

1. The vehicle dynamics which inherently characterise vehicle's behaviour stemming from manufacture, e.g., actuator lag
2. The information to be exchanged among vehicles, e.g., the position and velocity of a vehicle.
3. The communication topology describing the connectivity structure of vehicular networks, such as predecessor–follower, leader–follower, and bidirectional.
4. The control law such as sliding-mode control and consensus control to be implemented on each vehicle in order to define the car-following rule in the connected traffic flow.

Finally, they developed a new cooperative driving model based on platooning that includes realistic inter-vehicle communication (IVC). Their theoretical analysis and simulation results showed that having access to information about the leader is essential for stabilising the platoon in cooperative driving systems (CDS) (Wang et al., 2018). An extended car-following model at un-signalized intersections under V2V communication environment. In their study, they compared different communication topologies for vehicle platooning. The general topology involved information being shared among all vehicles in the platoon, while the forward topology only transmitted the leader's information to the following vehicles. The results indicated that the forward topology is more effective for vehicle platooning (Jia & Ngoduy, 2016b), as it not only reduces communication complexity but also maintaining stability and coordination within the platoon. Furthermore, the proposed control algorithm exhibited strong resilience to uncertainties. This is including packet loss and measurement errors, thereby ensuring robust performance even in demanding real-world conditions.

On the other hand, Rahman and Abdel-Aty, 2018 overarching goal was to evaluate longitudinal safety of CV platoons by comparing the implementation of managed-lane CV platoons and all lanes CV platoons (with same MPR) over non-CV scenario. In their survey, the Intelligent Driver Model (IDM) along with the platooning concept were used to regulate the driving behaviour of CV platoons with an assumption that the CVs would follow this behaviour in real-world. They proposed a high-level control algorithm of CVs in a managed-lane to form platoons with 3 joining strategies: rear join, front join, and cut-in joint. Thus, they utilised 5 surrogate safety measures, standard deviation of speed, time exposed time-to-collision (TET), time integrated time-to-collision (TIT), time exposed rear-end crash risk index (TERCRI), and sideswipe crash risk (SSCR) as indicators for safety evaluation. Their results showed that both CV approaches (i.e., managed-lane CV platoons, and all lanes CV platoons) enhance significantly the longitudinal safety in the studied expressway compared to the non-CV scenario.

As concerns the surrogate safety measures, the managed-lane CV platoons significantly outperformed all lanes CV platoons with the same MPR. Also, different time-to-collision (TTC) thresholds were tested and displayed results that were similar to those on traffic safety. Results of their study provide useful insight for the management of CV MPR as managed-lane CV platoons.

Two years before, (Tian et al., 2016) proposed a stochastic model to evaluate the collision probability for the heterogeneous vehicle platooning which can deal with the inter-vehicle distance distribution. Vehicle platooning with CV technology is another key element of the future transportation systems which help us to enhance traffic operations and safety simultaneously. Tian and his team considered the influences of different penetration rates, the stochastic nature of inter-vehicular distance distribution, and the different kinematic criterion related to vehicle and driver. The usability and accuracy of this model had been tested and proved by comparative experiments with Monte Carlo simulations. The results showed great potential in decreasing the chain collisions and alleviating the severity of chain collisions in the platoon at the same time. The platoon-based driving may significantly improve traffic safety and efficiency because a platoon has closer headways and lower speed variations compared to traditional traffic flow. Hence, these results are useful to provide theoretical insights into the safety control of a heterogeneous platoon.

The platoon-based cooperative driving system has been widely studied (Giordano et al., 2019; He & Wu, 2018; Jia & Ngoduy, 2016a; Ma et al., 2019; W. Zhao et al., 2018). However, there have not been many studies that assign managed-lane CV platoons which is highly related to CV MPR. Table 2.5 presents the summary of Bose and Ioannou (2003b), Jia and Ngoduy, (2016), (Tian et al., 2016; Rahman and Abdel-Aty, 2018) scenarios development.

Their results showed that both CV approaches (i.e., managed-lane CV platoons, and all lanes CV platoons) significantly enhanced the longitudinal safety in the examined expressway compared to the non-CV scenario. As concerns the surrogate safety measures, the managed-lane CV platoons significantly outperformed all lanes CV platoons with the same MPR. Also, different time-to-collision

(TTC) thresholds tested and showed similar results on traffic safety and provide useful insight for the management of CV MPR as managed-lane CV platoons.

Furthermore, another scenario development is the vehicle chain collision avoidance. Vehicle chain collision avoidance has attracted several research efforts, and the safety control of automatic vehicle platoons has been modelled as inter-connection systems with wireless vehicular communications. The control policies of vehicle platoons with string stability analysis have been investigating by many researchers (Bose & Ioannou, 2003a, 2003b; Godbole & Lygeros, 1994; Zhou & Peng, 2004). In their control models, the initial speed and the inter-vehicle distance are assumed to be alike. But, generally, the inter-vehicle distance between any adjacent vehicles always pursues a specific stochastic distribution in most traffic scenarios. Namely, the inter-distance in a platoon can be reasonably regarded as an odd variable when exploring the potential chain collisions. Furthermore, deterministic formulations in the form of transfer functions used in the afore-mentioned string ability analysis will be inappropriate to model chain collisions in terms of the stochastic nature of vehicle collisions.

Admittedly, considering the stochastic distribution of vehicles in a platoon, a more effective model to describe the potential chain collisions is the stochastic model. To demonstrate, the evaluation of chain collisions in vehicular communication environments based on stochastic models can be found in (Choi and Swaroop, 2001; Garcia-Costa et al., 2012) . Choi and Swaroop (2001) have considered the random braking in their model. Similarly, Garcia-Costa et al. (2012) has suggested a stochastic model for evaluating all the chances of chain collisions that may occur in a platoon. They developed their model on the basis of the simple and independent equation of motion with constant acceleration. In particular, the authors focus on the theoretical computation of the collision probability and also in the expected collision number. Garcia-Costa et al., in their stochastic model added also a more realistic assumption that the inter-distance between vehicles is a random variable. In addition, in (Garcia-Costa et al., 2012)the kinematic parameters of any one vehicle are assumed to be independent from each other's. Compared to most of the aforementioned work, (Tian et al., 2016) removes the hypothesis that wireless vehicular communications are everywhere required for all the vehicles in a platoon and supply a stochastic model in heterogeneous platoons, in which only the partial vehicles are equipped with inter-vehicle communications, and they are stochastically distributed.

As it was mentioned above, the authors in (Bose and Ioannou, 2003a, 2003b) focused on the automation of vehicles and have studied the consequence of those mixed manual and semi-automated vehicles on the characteristics of general traffic flows. However, as (Chakravarthy et al., 2009) has pointed out, (Bose and Ioannou, 2003a, 2003b) did not adopt the hypothesis of inter-vehicle communications and their goal does not lay in the context of wireless vehicular communications. Chakravarthy et al., 2009 analysis approach adopted in (Chakravarthy et al., 2009) is similar to Bose and Ioannou (2003a,b), the more realistic scenarios where a fraction of vehicles in a platoon equips with inter-vehicle communications are interrogate, and the Laplace transform is used to formulate the transfer function of the heterogeneous platoon system. However, Chakravarthy et al.'s model was failed to describe the chain collisions of vehicles whose inter-distance is considered to follow a stochastic distribution.

From all of the studied microscopic simulators, the models AIMSUN, PARAMICS, CORSIM and VISSIM are found to be suitable for congested arterials and freeways, and integrated networks of freeways and surface streets (Bloomberg & Dale, 2000; Karakikes et al., 2017; Paikari et al., 2014; Papadoulis et al., 2019; S. Park et al., 2017). Also, these models are potentially useful for Intelligent Mobility applications (Paikari et al., 2014). While these packages have many similarities, each has its own specific characteristics that make it more or less suitable for certain modelling purposes. A summary of some Intelligent Mobility scenarios development is presented in Figure 2.5.

Table 2.5: Summary of some Intelligent Mobility scenarios development.

Research	Simulation software	Assumptions / Testbed	Scenarios
(Jia & Ngoduy, 2016a)	They used the **PLEXE simulator**, which consists of the **network simulator OMNeT++/MiXiM** and **the road traffic simulator SUMO**.	This study essentially **explored the relationship between Inter-Vehicle Communication (IVC) and cooperative driving**, which can be exploited as the reference for the CDS optimization and design. They first modelled the traffic dynamics and inter-vehicle communication, respectively, then demonstrated the specifications and assumptions on the proposed platoon based CDS. Finally, they formulated the vehicle platooning into a consensus problem.	The measured traffic flow is composed of three consecutive platoons with an identical platoon size. Three typical traffic scenarios are considered for the system evaluation: **Scenario 1:** an initial phase during which all following vehicles launch from pre-defined positions to finally cooperatively driving at the same constant speed 25 m/s regulated by the leader, **Scenario 2:** a single large perturbation wherein the leader first decelerates from 25 m/s to 5 m/s, then maintains this speed for a period of time, and finally accelerates to the original speed 25 m/s, and **Scenario 3:** the continuous small perturbations wherein the leader experiences a sinusoidal disturbance in speed
(Tian et al., 2016)	**1.** They conduct extensive **Monte Carlo simulations** and perform the comparison between the results of the theoretical computations and the simulations. **2.** All the numerical experiments including simulations are	**1.** Each of the vehicles in a given platoon is moving in the same direction and cannot reverse its motion or change its lane even when it will collide with its preceding or rear vehicle. **2.** Any potential collisions caused by communication device	1. **High Mobility Scenario:** the initial velocity v0 of all vehicles in the platoon is identically set to a relatively high value, i.e., u_0=110 km/h 2. **Low Mobility Scenario:** the initial velocity is set as u_0=60 km/h

	implemented in **MATLAB.**	failures or driver faults are ignored. The model is not limited to the assumption that all the vehicles in a platoon being equipped with vehicular communications.	3. **Model applications:** set up two typical traffic urban scenarios: • one is related to the urban traffic flow during the peak hours and • another is the non-peak hour traffic flow. Generally, the space headway distribution and the mean velocity of the traffic flow are two main parameters to characterize these two traffic scenarios.
(Rahman & Abdel-Aty, 2018b)	**1.** A well calibrated and validated **VISSIM network** replicating the field condition.	The testbed was around 22-miles section of SR 408. The traffic information on the simulation network including, traffic volume aggregated into 5 min intervals, PC and HGV percentages, and desired speed distribution were obtained from the MVDS detectors. The simulation time was set from 6:30 A.M. to 9:30 A.M in VISSIM. After excluding first 30 min of VISSIM warm up time and last 30 min of cool-down time, 180 min VISSIM data was used for calibration and validation. Geoffrey	The CV platoon was deployed in the simulation experiments in a fashion of managed-lane CV platoons and all lanes CV platoons with same MPR of 40%. For the managed lane simulation experiment, CV platoons were dedicated only in the inner lane (close to the median) and all other lanes were implemented as regular vehicles. While the simulation experiment for all lanes, CV platoons were implemented all the lanes of the expressway along with regular vehicles. The main difference between the base scenario and all lanes CV platoons was the car following behaviour. However, all

			lanes CV platoons also considered the platooning concept compared to the base scenario. • **Base condition** • **All lane CV** • **CV managed lane**

In conclusion, the development of scenarios measuring the impact of Connected Vehicles (CVs), semi-automated vehicles, and Connected and Autonomous Vehicles (CAVs) on the Strategic Road Network (SRN) remains an underexplored area, particularly in the context of their integration with V2V communication for incident detection on highways. Significant progress has been made in simulating the impact of these technologies; however, much of the focus has been on urban environments. This leaves a gap in understanding their implications for long-distance safe travel and highway systems. The complexity of mixed traffic scenarios, involving varying levels of automation, along with the challenges of assessing their effects on traffic flow and incident management, highlights the need for further research in this area.

2.5 Existing simulation tools and attempts to simulate IM technologies.

The endeavour to simulate Intelligent Mobility technologies within existing simulation tools marks a pivotal stride toward comprehending and optimising the intricate interplay of these advancements in real-world scenarios. These tools serve as sophisticated platforms designed to replicate and emulate the dynamics of Intelligent Mobility, extending beyond mere incident detection to encompass a broad spectrum of interactions on motorways. As technology continues to evolve, the development of simulation tools capable of accurately modelling these innovations becomes indispensable. Through these simulations, researchers can explore the nuanced complexities of Intelligent Mobility, shedding light on its potential implications for traffic management, safety enhancements, and overall mobility on the road networks.

2.5.1 Simulation

Simulation relies on a virtual environment with constructive agents to generate knowledge for the vehicle behaviour without the requirement for a natural vehicle and actual testing in the real world (Thorn et al., 2018). The base vehicle platform and the underlying Automated Driving System (ADS) components need to be modelled physically and whenever its needed, mathematically to the extent that the behaviour of the virtual system can mimic that of the real system to the desired degree of fidelity (Hartwich et al., 2018b). Similarly, the virtual environment during which the ADS are going to be operational is modelled to the desired degree of fidelity. The upper the fidelity of these models, the more closely they represent the actual nature of the vehicle or environment, which ends up in more substantive data for analysis.

Simulation testing provides several advantages:

- **Controllability:** Simulation affords an unmatched ability to control many aspects of a test.
- **Predictability:** Simulation is designed to run as specified, so there is little uncertainty as to how the test will run, so the calibration/validation and verification is needed to eliminate any uncertainties.

- **Repeatability:** Simulation allows a test to be run many times in the same fashion, with the same inputs and initial conditions.
- **Scalability:** Simulation allows for the generation of a large number and type of scenarios.
- **Efficiency:** Simulation includes a temporal component, which allows it to be sped up faster than real-time so that many tests can be run in a relatively short amount of time.

As Thorn et al., 2018 says, these features are critically for the testing of complex systems. Simulation may also function a relatively a more economical option for initial testing, as opposed to building up more entirely functional test vehicles. Simulation environments are also quicker to deploy and implement and probably be able to check an expansive range of conditions (Fredriksson & Nilsson, 2015). There are multiple approaches to simulation that could be applied to support the validation and verification of ADS according to existing tools.

Several disadvantages exist also in the use of simulation and modelling. It is demanding to model systems and physical properties with loyalty, which will impact how accurately the simulation environment mimics the real world. There is also a big variety of commercially applicable simulation tools with distinctive capabilities and features. This instants challenges that need to be answered, to perform comparisons of results across the different tools.

The literature review showed that traffic simulation had been used extensively to estimate the impacts of Intelligent Transport Technologies. A review of existing Simulation tools and the attempts to simulate Connected and Autonomous Vehicles and other Intelligent Mobility Technologies is taking place in the following sub-section as well as some comparisons of available Traffic Micro-Simulation Software, such as VISSIM, VSimRTI, SUMO and AIMSUN.

In recent years, road vehicle automation has become prevailing and widespread area for imperative research and development in several educational but also industrial domains. Hence, next-generation Intelligent Mobility Technologies, as it is already mentioned above in the previous chapters, contract to deliver phenomenal levels of safety on roads by reducing fatalities, delays, congestions, fatalities, and of course environmental pollution. The vehicles are already converted into a self-automated platforms with various artificial intelligent features integrated into a single large, connected framework equipped with all essential functionalities (Kaur & Sobti, 2018a). Although a design of simulation techniques exists for confirming and evaluating the behaviour of automated vehicles, but still, intelligent driving lacks inherently much smarter techniques to approach them for better safety and quality. Simulations are often used to estimate vehicle applications which are entirely software-oriented (Kaur & Sobti, 2018a). So, it is worldwide known that vehicle simulators are essential to verify and validate new functional components of the automotive industry (Vishnukumar et al., 2018). Many varieties of Intelligent transportation systems (ITS) based applications have been established, and many are still under development and will require comprehensive testing and assessment just before their introduction in real traffic. To evaluate these algorithms, more improved and advanced methods of simulation are required. Nowadays, more and more driving functions are software-based and are designed using neural networks. Therefore, the future simulations must always be a step ahead to test these applications.

2.5.2 Modelling CVs in traffic simulation software

During the previous few years, a continuous sign of progress in wireless communications have opened new analysis fields in computer networking, aimed at extending data networks connectivity to environments where wired solutions are a unit impossible (Härri et al., 2011).

Simulated data can be considered as the least trustworthy source of data. Although, in situations where real-world data are not attainable, like when testing technologies not yet implemented or even widespread, simulated data are the one and only applicable alternative. Real-world data of the few CV trials for example, are not easily reachable, so creating simulation is the only available method to assess the safety impact of them. However, using simulation may be a challenge since the validation of the simulated results can be difficult. Once a CV is simulated in a simulation environment, there are no conflicts. To be additional specific, there are not programmed to collide one another since they are already alert to their surroundings. They have the so-called 'god-knowledge'.

Therefore, arguably, vehicles in a simulation software road network are already autonomous since they need all the convenient data they have. However, the skill to translate the input from its sensors into real-world actions is what makes a connected vehicle diverse from a non-connected. This qualification of the CV has to be the factor to be examined. Hence, most approaches to simulate connected vehicles so far, demonstrate the three dominant elements of a CVs in three different layers of simulation: Traffic simulation, Robotics simulation and Communications simulation. Traffic simulation aims to simulate the traffic flow and the road network, while robotics simulators simulate the vehicle and its sensors. Finally, communications simulators handle the V2V and V2I communication part of the simulation by transmitting data from one vehicle to another or from infrastructure to vehicles and vice versa.

Furthermore, in order to label the test systems (simulation engines), there are four principal classes (Huang et al., 2016):

a. Vehicle Movement simulation
b. Vehicle's Perception simulation
c. Traffic based vehicle simulation
d. Driving based simulation

The first category of test systems is to mimic the vehicle dynamics, for instance, (Fredriksson and Nilsson, 2015). Utilising a model, the test system mimics a vehicle's behaviour closely. VDyna^{TM} is a vehicle simulation software that simulates defence vehicles for virtual testing. The sensing-based simulators such as ProSivic is a test system which deals with perception connected tasks. Its elementary properties are its capacities to recreate physical sensor behaviour like lidar, radar or camera lidar devices. The third test system is depended on traffic environment simulation, which is i established with traffic recreation capacities. SUMO simulation tool clarifies vehicle according to varying conditions of traffic scenarios. As a rule, these sorts of test system assume that the vehicle is a point in the street. VISSIM and PARAMICS are examples of this test system type. The last test system is driving test system or driving simulator, for instance, SCANeR. These test systems endeavour to gather data from the driver behaviours whilst utilizing a simulated vehicle (Kaur & Sobti, 2018b).

The layers specified above of modelling can coordinate on-line using an external platform to form a combined simulation architecture. A variety of divergent software have been used in the literature. Microscopic traffic simulation has been extensively used in connected and autonomous vehicle-related studies due to its cost-effectiveness, risk-free, and high-speed benefits (Ciuffo et al., 2008). Connected and autonomous vehicle technologies, with the help of microscopic traffic simulation models, can be deployed and tested whilst not disrupting the real traffic network. Several microscopic simulation models are widely used, such as AIMSUN, CORSIM, PARAMICS, SUMO, VISSIM, PRESCAN and VSimRTI. Every microscopic traffic simulation model gives default model parameters to define traffic flow characteristics, such as traffic control/operations and driver behaviour. However, the default values have to be calibrated to indicate actual driving behaviour and depict field data more accurately. Due to a big range of each relevant model parameter, the calibration process is defined as an optimization model where the best set of parameters is solved (Liu & Fan, 2020).

Microscopic traffic simulation models are critically applied in conducting the impact analysis of connected and autonomous vehicles. (Atkins, 2016)(Atkins, 2016) used VISSIM to delve into the impact of connected and autonomous vehicles on traffic flow capability. The results showed that road capacity would increase once connected and autonomous vehicles accelerate quicker and keep shorter headways. However, once these new vehicles are more cautious than the existing vehicle fleet, road capacity will decrease by the maximum amount as 40%. (Shelton et al., 2016) in their analysis, they used a multi-resolution model that mixes microscopic, mesoscopic, and macroscopic modelling techniques to test connected and autonomous vehicles in a complex urban roadway network. It was found that the capability could reach 4000 vehicles per hour per lane with 100% market penetration of connected and autonomous vehicles. On the other hand, (Hartmann et al., 2017) used VISSIM to evaluate the impact of automated vehicles on freeway capacity. The simulation results indicated that an increasing share of partially and highly automated vehicles would lead to a capacity decrease up to 7%. Solely with a high penetration rate of connected and automated vehicles that maximizes the cooperative manoeuvring and minimizes the headways, there will be a major increase in road capacity up to 30%.

Shladover et al., 2012 used microscopic simulation to estimate the effect of adaptive cruise control (ACC) and cooperative adaptive cruise control (CACC) vehicles with varying market penetration rates. Their simulation was built on AIMSUN with new driver behavioural models developed in C++ and called by AIMSUN. The results showed that the maximum lane capacity could increase up to 4000 vehicles per hour per lane if all vehicles were CACC vehicles. However, the use of ACCs was unlikely to change lane capacity significantly (G. Arnaout & Bowling, 2011; Bierstedt et al., 2014; Olia et al., 2018).

Five years later, (Lioris et al., 2017) assessed the potential mobility benefits of platoons of connected vehicles. The capacity of a regular four-legged intersection will double if vehicles cross the intersection in platoons with a 0.75 s headway at 45 mph to achieve a saturation flow rate of 4800 vehicles per hour per lane. In the same year, (Auld et al., 2017) used an advanced transport system simulation model POLARIS, including the co-simulation of travel behaviour and traffic flow to review the potential effects of many CAV technologies at the regional level. It was concluded that an 80% increase in capacity change could increase 4% overall vehicle miles travelled (VMT). (Arnaout and Arnaout, 2014) examined the effects of cooperative adaptive cruise control on highway traffic flow characteristics of a multilane highway system by using a microscopic traffic simulator. It was concluded that the CACC impact is not statistically momentous under a low-to-moderate penetration rate. A CACC advantage could be observed with a penetration rate of 40% CACC or more.

In Table 2.6 technologies [adapted from (Liu and Fan, 2020), the vehicle type, the simulation tool, and therefore the impact on capacity in every one of the above studies are summarised and presented. The lack of CV as a vehicle type is quite obvious, necessities the need for exploration CV technologies.

Table 2.6:Summary of literature on study of CAV/CV/CACC/ACC.

Author	Year	Vehicle Type	Tool	Project Purpose	Capacity Impact
Arnaout and Bowling	2011	CACC	-	Traffic performance	Highly increased
Shladover et al.	2012	ACC, CACC	AIMSUN	Lane capacity	4000 vph for CACC
Bierstedt et al.	2014	ACC	VISSIM	Freeway capacity	Minor
Arnaout and Arnaout	2014	CACC	F.A.S.T.	U-shaped four-lane freeway	Large improvement with high penetration rates
Monteil et al.	2014	CV	-	Traffic Flow	Increased traffic flow homogeneity
Atkins	2016	CAV	VISSIM	Traffic Flow Capacity	Decreased by 40%
Shelton et al.	2016	AV	Multi-resolution model	Urban roadway network	4000 vph
Hartmann et al.	2017	CAV	VISSIM	Freeway capacity	Decreased by 7%
Auld et al.	2017	CAV	POLARIS	Travel behaviour	80% increase in capacity can increase 4% VMT
Lioris et al.	2017	CV	PointQ	Four-legged intersection	4800 vph
Olia et al.	2017	CAV	PARAMICS	Highway capacity	6450 vph for CACC, 2046–2238 for
Hajbabaie et al.	2022	CV, AV, CAV	VISSIM	Saturation headway and capacity at signalized intersections	CAVs can reduce saturation headway, increasing intersection capacity by up to 80%; AVs may decrease capacity by 20%

Roy et al.	2024	Autonomous Shuttle	Microscopic Traffic Simulation	Impact on urban road capacity	Increased shuttle frequency raises delay percentages and lowers travel speeds; optimizing shuttle speed improves traffic conditions
Ard et al.	2019	AV	VISSIM	Energy and flow effects in mixed traffic	AVs enhance network capacity in high-volume scenarios; human drivers interacting with AVs experience up to 10% better energy efficiency
Zhao et al.	2019	CAV	Simulation	Traffic impacts of optimally controlled CAVs	Introducing CAVs significantly improves roadway capacity and overall network performance

2.5.3 Comparison of available Traffic Micro-Simulation Software

The literature review showed that traffic simulation had been used extensively to assess the impacts of Intelligent Transport Technologies. As it has been already discussed in-depth at chapter 2.1.3, traffic simulation is divided into four categories, according to its level of detail.

To sum up, from the mentioned chapter, macroscopic simulation relies on mathematical equations simulating the flow of vehicles in a road network, an approach that comes from fluid dynamics. To be more specific, in macroscopic simulation, the road network is charged based on the Origin-Destination matrix and an equilibrium state is reached through multiple steps of calibration, similar to Nash's equilibrium theory of games during which no simulated car can achieve a better travel time by altering its trajectory. From the opposite aspect, a microscopic traffic simulation consists of sets of models like car-following models, driver behaviour models and lane-changing models, simulating individual vehicles behaviour which can basically follow the macroscopic traffic flow. Finally, mesoscopic simulation couples the advantages of both micro- and macro-simulation, whereas sub-microscopic simulation describes the practicality of specific elements of a vehicle.

This section performs a comparative description of the most popular traffic micro-simulation software: AIMSUN (e.g. (Srivastava and Geroliminis, 2013), MITSIM (e.g. (Ben-Akiva et al., 2003), PARAMICS (e.g. (Wilson, 2001), VISSIM (e.g. (Papadoulis et al., 2019), SUMO (e.g.(Wang et al., 2019;

Abdelgadir et al., 2017), MAS-T2er Lab (e.g. (Passos et al., 2011), MATSim (Becker et al., 2019; Hörl et al., 2019b; D. Li et al., 2018), PRESCAN (Fredriksson & Nilsson, 2015; X. Wu et al., 2016) and VSimRTI (e.g. (Queck et al., 2010; Schünemann, 2011). The description of which can be found in Table 2.7.

Table 2.7:Comparative description of the most popular traffic micro-simulation software.

Traffic Micro-Simulation Software	Description
AIMSUN	Developed at 1989-1997, by J. Barcelo and J.L.Ferrer of the Polytechnic University of Catalunya (Barcelona) and is using for operating macro- and micro-simulation. Several driver behaviours models are contained in its micro-simulation such as, car following, lane changing and gap acceptable. It can simulate thoroughly all different components of a road network like detectors, vehicles and traffic lights providing comprehensive statistical outputs. It also can simulate incidents and conflicting manoeuvres. Today, thousands of mobility professionals worldwide in government, research institutions and private companies are successfully using AIMSUN tools and services to model tomorrow’s smart mobility networks.
MITSIM	Developed at the Massachusetts Institute of Technology to capture the real-world interaction between the traffic management centre and the vehicles on the road. It mimics the real-world scenario by separating the simulation of traffic and the traffic management system. Similar to AIMSUN, MITSIM represents individual vehicles in the simulation environment by using car following, lane changing and traffic signal response models. MITSIM can provide real-time sensor data that imitate the surveillance capacities of the traffic management systems in an ITS environment. The MITSIM traffic simulator also has the added flexibility that it can be integrated with other external modules, representing traffic management systems with little extra effort. There has been however no attempt so far making it able to simulate vehicle connectivity or autonomy
PARAMICS	A software developed by SIAS Ltd and Quadstone Ltd of Scotland and is designed for a wide range of applications wherever traffic congestion is a predominant feature. (Plannes, 2009). It includes a sophisticated car-following and lane-changing model for roads. It simultaneously gives every driver/car couple specific characteristic which makes it capable of assessing environmental impacts furthermore as traffic impacts of interventions. Finally, Paramics can model the interaction between drivers and ITS. Similar to MITSIM, there have been no attempts to make it suitable for modelling connected and autonomous vehicles.
VISSIM	A microscopic traffic simulation software developed by PTV in Germany which is time step and behaviour based. Its application ranges from traffic engineering, public transport, urban planning over fire protection to 3D visualisation. Its modules combine to improve usability, integration, and productivity, allowing users and clients to get added value from the modelling process. Through VISSIM, the user can program different traffic

	flow compositions, traffic signals, variable message signs, etc., making it a useful tool to test different scenarios. Further, VISSIM uses a microscopic flux model of discrete, stochastic, and based on time step traffic. This simulator considers as one the pair vehicle/driver, also content a psychophysical model to car-following and lane-changing based on rules. Its results include detailed travel, delay, queue length, signal timing information and speed data. VISSIM also has the capability to simulate vehicle connectivity and ADAS by using its feature - External Driver model.
VSimRTI	Developed to provide the flexibility to exchange simulators, we have developed the Vehicle-2-X Simulation Runtime Infrastructure. The simulation infrastructure offers interfaces for the integration of simulators, e.g., for network, traffic, and environment simulations. It provides the flexibility to exchange them without changing the infrastructure. For the synchronization of and the communication among all components, the implemented infrastructure uses concepts defined in the IEEE standard for modelling and simulation high-level architecture (Queck et al., 2010). Thus, the runtime infrastructure VSimRTI allows a flexible combination of time-discrete simulators for Vehicle-2-X simulations. Finally, based on the requirements of a particular scenario, arbitrary simulators can be plugged onto the VSimRTI and are executed together.
SUMO	A highly portable microscopic simulation software developed by the Institute of Transportation Systems at the German Aerospace Center and can simulate large road networks, and it is licensed under the GPL. SUMO is an open-source and highly editable, and that is the reason why it is widely used by academia and research community. Its features include collision-free vehicle movement, multi-lane streets with lane changing, fast execution speed, dynamic user assignment, and others. SUMO can be connected with external applications through a Transmission Control Protocol (TCP)-based client-server architecture which makes it a suitable tool to simulate autonomous vehicles with the integration of robotics and communication simulators such as NS3 or OPNET.
Mas-T2er Lab	A simulation tool developed by MAS-T2er Lab Group and is an integrated multi-agent system that allows the assessment of ITS for the assessment of today's intelligent transportation solutions through external agents. So, the application domain is conceptualized in terms of agents and three basic subsystems are identified, namely the real world, the virtual domain, and the control strategies inductor
PreScan	An off-line simulation tool which allows the testing of many different traffic scenarios in a virtual environment and is designed to be a development environment for intelligent transport systems. PreScan is the only commercially available software capable of simulating sensor processing and control algorithms within its simulation environment without including

	any external agent. Finally, it is essential to be mentioned that although it has high computational needs, it cannot simulate large traffic flows and road networks.

In Table 2.8 [Adapted from (Passos et al., 2011; Schünemann, 2011; Vision, 2009), there is a summary of the implemented entities of some microscopic traffic simulators. SUMO and MAS-T2er Lab are small academic projects and have a narrow set of entities. SUMO and MITSIM implements cars, buses, and trucks to emulate basic traffic situations. Finally, all of them, except MAS-T2er Lab, have sensors to gather information and signalling to act in the system.

Table 2.8:Implemented entities in the microscopic traffic simulators.

	IM	**Car**	**Bus**	**Truck**	**Train**	**Bicycle**	**Pedestrian**	**Vehicles + Pedestrians**	**Others**
VISSIM	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	TL, PCL, Detectors
PARAMICS	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	TL, PCL, Detectors
AIMSUN	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	TL, Detectors
MITSIM	No	Yes	Yes	Yes	No	No	No	No	TL, IL
SUMO	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	TL, IL
MAS-T2erLab	No	Yes	Yes	No	No	No	No	No	TL

VSimRTI	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	TL, PCL, Detectors
PRESCAN	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	TL, PCL, Detectors

Labels:

- TL: Traffic Light
- PCL: Pedestrian Crossing Light
- IL: Induction Loop
- Detector: IL, Cameras, others

All simulators presented above have the ability to be modelled in a microscopic level. Additionally, VISSIM, PARAMICS, AIMSUM, VSimRTI and PRESCAN have realistic 3D that is great for scenario presentation. Moreover, the Graphical User Interface (GUI) is constantly a different process from the simulator but can be seen as a part of the simulator core. Each one simulator has advanced features, for instance, VISSIM has parameters and function flexibility, AIMSUN provides different forms to extend it, PARAMICS adapts to use all the distributed machine resource available, SUMO architecture flexibility, MITSIM has various types of controllers available for use, and MAS-T2er Lab is originally agent-oriented.

2.5.4 Conclusion

This section of the literature review has been identified and reviewed the most common methodological approaches used in the evaluation of the aforementioned Intelligent Transport Technologies. Traffic systems have been focussing of improvement and commuters have in general witnessed a revolution in the way a trip is planned and of course carried out in strategic road networks, especially nowadays with the development of Intelligent Mobility Technologies. Computer technologies have put intelligent transport solutions in the same level as users, as they now emphasize some degree of intelligence and autonomy as well, and sometimes even deliberating with end-users the first-rate alternative to enhance system's performance. In such a contemporary scenario, ITS-based solutions and users are rival and present a rather social interaction, which brings about new performance measures that must be evaluated somehow. Furthermore, traditional traffic simulation packages decline to model and display all aspects of human behaviour in a particular way.

In this chapter, a first try at evaluating currently existing simulation environments has been carried out, at their ability to simulate and model future transport. Basically, should be taken into consideration that current intelligent transportation systems are able to surprisingly interact with end-users, authorizing them to be slightly accessible, greener, cheaper, more efficient and environment friendly. Moreover, safety and privacy are other essential issues that must be addressed at first hand.

Generally, most simulators pursue a microscopic approach as an attempt to develop the representation either of human behaviour at the road network or the intelligent mobility interface behaviour on a mixed environment. However, a very few arguably implement the concept of agents, although some researchers claim their representation are based on the agent metaphor (Passos et al., 2011). Even so, entities present a fundamental behaviour, being only able to perform car-following and lane-changing interactions. As for speculation and other more cognitive characteristics of the decision-process achieved by humans, they are being neglecting in most packages. Nonetheless, extensibility in a few tools is utterly promising, allowing the user, with outstanding programming skills to enforce the desired features to reinforce Intelligent Mobility Technologies assessment.

There is an important aspect, that should have not been neglecting it, is the necessity to define and enlarge the set of criteria. For example, the extension of communication abilities of entities could be taken its necessary, so standards that are currently applied in transportation such as Vehicle-to-Vehicle, Vehicle-to-Infrastructure will be tested and evaluated accordingly. As for the simulated entities, this aspect will be improved in the chosen simulation software to allow us to consider intelligent infrastructures (mixed realities) and new users' devices. Finally, after having a complete and proper appraisal of those features, the next step is to specify and devise an artificial transport platform based on the agent-oriented paradigm, which is the appropriate way to support Intelligent Mobility Technologies' modelling and assessment in all levels.

2.6 Conclusion, Research Gap, and Research Design

Since the invention of the combustion engine, the vehicles are being the most dominant means of transport and their fleet is being rapidly increasing worldwide. Inevitably, this abrupt growth of the vehicle numbers brought about negative consequences on road congestion, road safety and the environment, by increasing traffic delays, road accidents (incidents/fatalities) and mainly air pollution. Human error is the majority of times the critical cause of crashes, not only in the present but also looking back in the past from the first conventional vehicles. In particular, as (Jimenez, 2017) supported in the European Union every year, there are around 4,000 deaths and 1.7 million injuries in traffic accidents. The concept behind Intelligent Mobility aiming to ameliorate the negative consequences on road safety, road congestion and the environment by getting the driving task out of the hands of the human driver. Generally, the use of new technologies in the world of road transport will reduce the above major problems of this mode of transport, through more innovative solutions.

To meet these challenges, Intelligent Mobility has to cut across and go beyond the transport sector that we are used to. Intelligent Mobility focuses instead on emerging and new technologies that make it possible to accomplish more for less (Catapult, 2018). Furthermore, Intelligent Mobility is about innovating and thinking differently, based of course, on the brand-new opportunities that technology brings us (Atkins, 2019b). These intelligent mobility technologies can be used firstly to enhance current transport systems. This is going to be succeeded by making them more efficient and less costly (for instance electric vehicles, wireless induction charging) and more convenient (e.g., City Mapper, contactless payment) and secondly by providing new opportunities to move around, as for example Uber (Atkins, 2016).

In the past, Intelligent Mobility Technologies have been evaluated with the use of intervention analysis, mathematical/statistical modelling, and traffic simulation. Technologies strongly related to CAVs such as ACC and CACC have been evaluated up to date by using mathematical modelling and traffic simulation mainly, because data including the technology, as a variable, are not handily accessible or available. Traffic simulation and mathematical modelling could assemble the data mentioned above and are the appropriate tools to evaluate CAVs.

Several attempts have been conducted to simulate Intelligent Mobility Scenarios (on-demand mobility, MaaS and CAVs), trying to evaluate the impact of these technologies on the road safety (Becker et al., 2019; Elvik, 2001; Katrakazas et al., 2015; Pandey et al., 2019b; Papadoulis et al., 2019; Rahman et al., 2018; Shao et al., 2019; Virdi et al., 2019b) and so far there are not as many as developed scenarios are needed in order to evaluate the impact of IM technologies on the network. Thus, the Research Gap is identified as there is a need to quantify the impact of Intelligent Mobility Technologies through the formulation of a traffic simulation framework capable of modelling automates along with non-automated vehicles in a variety of pre-defined scenarios, with regards to maximising the traffic performance on highways, during and after the transition period to assess the impact of them on the SRN.

As far as the research design of this research is concerned, one scenario has been identified, that have not been evaluated in-depth, through the existing literature on IM and the Scenarios. Taking into account the aforementioned literature review, the need to analyse a V2V connectivity main scenario depending on Incident detection, using CV is more than necessary. The connectivity capabilities of CVA automatically calls for help and inform following vehicles in case of an incident. A set of data enclosing information about the occurrence, like the geographic location and the vehicle identification is sending through its system. The developments in IP communications and the mobile have imported challenges in emergency services. Moreover, V2V connectivity is designed to be activated automatically, sending proper data, to following vehicles with same capabilities, the infrastructure enables and the emergency services. So, it will be beneficial to figure out how by detect incidents through V2V will help not only National Highways to minimise disruption caused by an incident and decrease congestions and possibly fatalities on Highways' England SRN but also worldwide. Furthermore, it will be advantageous to realise though simulation what kind of measures need to be taken on a network-level, especially now, in the era of CVs.

Chapter 3. Methodology

This study aims to quickly detect traffic incidents, such as vehicle breakdowns, collisions, and stopped vehicles, using CV technology, and exploring strategies to reduce vehicle delays and enhance safety. The study intends to develop methodologies to mitigate delays and increase safety in such events. Previous research shows that a 50% reduction in incident duration can lead to a 75% delay reduction (R. Li et al., 2018). Therefore, real-time incident detection is crucial for effective traffic management, especially on high-traffic areas such as motorways. Given the scarcity of real-world CV data, an approach grounded in simulation was adopted to scrutinise interactions between human-driven vehicles (HV) and CV vehicles during motorway breakdown incidents. To facilitate progression in this endeavour, it is imperative to undertake a comprehensive research initiative to elucidate the impact of traffic data, characterised by various Key Performance Indicators (KPIs), such as traffic congestion, on traffic incidents. By investigating the intricate interplay between incidents and traffic data, a heightened capability for their detection can be attained, thereby fostering a more enhanced and informative discernment.

3.1 Research Design

The objective of this PhD research is to improve the detection of motorway incidents by using real-time V2V connectivity through a traffic microsimulation study. This will be accomplished by creating an integrated mobility simulation platform to help network operators design real-time traffic control strategies and by developing impact assessment models to identify the best scenarios for improving incident detection using fleets of CVs. To achieve this goal, various statistical and artificial intelligence techniques, such as machine learning algorithms (e.g., supervised and unsupervised learning) and neural networks for pattern recognition, will be applied and verified. Reinforcement learning will also be explored to optimise decision-making in dynamic traffic scenarios. These techniques will allow for making predictions, optimal decisions, and actions that are scientifically rigorous in the face of uncertainties. The resulting output will be valuable for designing and implementing effective real-time traffic management and control strategies that focus on improving overall traffic conditions, reducing delays, and minimising traffic collisions.

This research aims to fill the gap in existing studies related to incident detection time by proposing a real-time detection method using V2V connectivity capabilities. Before developing the micro-simulation incident model, it is necessary to conduct incident modelling to understand the complex relationship between incidents and congestion, as well as other factors such as speed, flow, and Vehicles-kilometre-travelled (VKT). This study will include an in-depth analysis to evaluate the influence of various key performance indicators (KPIs) on the occurrence of incidents on motorways. This analytical foundation will guide subsequent phases of the microsimulation process.

The development of the micro-simulation incident model necessitated the acquisition of various types of data. The dataset used included traffic volume, vehicle composition, speed, and travel time; geometric data and route patterns, incorporating lane numbers, width, and road type; as well as incident data, which included the number and type of incidents, their locations, times, and durations. Geometric data elements, such as lane numbers, width, road type, and width, were sourced from National Highways and Google Earth (as cross reference), the government body overseeing England's Strategic Road Network (SRN). Incident data from 2016 to 2019 were analysed to discern incident locations, frequency, and duration across the SRN, thereby contributing to the accuracy of incident detection provided by National Highways. Subsequently, raw traffic data from Inductive Loop Detectors (ILDs) installed at intervals of 500m, referred to as Motorway Incident Detection and Automatic Signalling (MIDAS) data, were used to capture dynamic and static traffic data. The MIDAS data were sourced from Mott MacDonald, a consulting firm (Mott MacDonald).

To achieve the stated aim, five research objectives were formulated and are outlined in Table 1.1. The first two objectives have been discussed and analysed in the literature review in Chapter 2, where a literature review in Traffic Flow Models and Intelligent Simulators took place. This was to explore traffic and incident management, examining their potential impact on National Highways' SRN using the V2V Connectivity and identifying the knowledge gap. The analysed frameworks concerning the methodologies followed, are located alongside the methodology chapter.

3.2 Concept and Challenges

The main focus of this research is to develop an integrated traffic microsimulation platform that will allow us to conduct a sensitivity analysis. The purpose of this analysis is to formulate real-time traffic control strategies that can help mitigate the consequences of stopped vehicles on the Strategic Road Network (SRN). Additionally, the research attempts to develop impact assessment models, focusing on identifying optimal scenarios for detecting stopped vehicles through implementing the V2V connectivity protocol and exploring alternative approaches.

In the research design, critical scenarios are being analysed, which depend on the detection of incidents. Even with technological advancements, incident detection remains a persistent traffic challenge (Chang, 1994; Chassiakos & Stephanedes, 1993; Levin & Krause, 1978; Luk et al., 2010b; Tsai & Case, 1979b; Weil et al., 1998). Incidents can result in delays and conflicts in the motorway network, potentially leading to secondary incidents (Ng et al., 2013). Unfortunately, despite disruptive technologies offering potential improvements in incident detection, their practical deployments remain limited(Sheikh et al., 2020b). Incident detection durations can still extend up to some minutes which exacerbates the problem. National Highways reported that 92% of stopped vehicles were being detected within 20 seconds (Stopped Vehicle Detection Hits Target but 85% of Testing Data Unusable, 2023).

There are two main challenges related to incident detection on the road network. The first challenge is about detecting incidents in real-time, assessing their severity, and quickly informing key stakeholders such as the Regional Operations Centre (ROC), Variable Message Signs (VMS), and emergency services. The second challenge is a lack of real-world data on V2V connectivity on motorways. However, despite these challenges, V2V connectivity has the potential to enhance incident detection on the Strategic Road Network (SRN). This is due to its ability to detect and respond to incidents in real-time, share information with other road users, facilitate rerouting options, and minimise disruptions caused by subsequent incidents and potential congestion.

To improve the way incidents are managed and detect them more effectively, we have developed several scenarios that have been tested empirically. These scenarios have been designed to reduce mobility issues such as vehicle delays, conflicts, and queue lengths. In addition, we can measure the improvement in safety using metrics like average acceleration exceeding 0.5g m/s^2 and the number of conflicts.

The first goal is to optimise incident detection parameters, including the detection rate, time to detect, and false alarm rate, with a focus on the aforementioned KPIs. The forthcoming sections contains details pertaining to the analysis and modelling of incidents, alongside the methodology for incident management and the utilisation of micro-simulation in the context of incident detection scenarios within VISSIM. The overarching methodology is intricately consisting of three principal parts denoted as follows:

1. Part A: Analysing and Modelling Incidents
2. Part B: Simulation Network Model

3. Part C: CV Driving Behaviour and Incident Detection

3.3 Part A: Analysing and Modelling Incidents

This section of the research focussed on the interconnection between traffic incidents and congestion on the M1 motorway in England, aiming to comprehend their collective impact on road safety. The study employed a comprehensive approach, combining exploratory data analysis and statistical models to elucidate patterns and fluctuations in incident rates and traffic-related variables, particularly congestion, speed, flow, and traffic volume but also variables such as direction of driving, day of the month and location (junction segment alongside the network examined). The analysis aims to reveal any disparities existing in traffic congestion and incident occurrence, prompting a focused investigation into the intricate relationship between incidents and KPIs. The outcomes of this research aim to inform transport planners, operators, and policymakers, providing valuable insights into traffic characteristics and facilitating the development of effective road safety measures and incident reduction strategies through congestion management. By understanding how traffic conditions and congestion influence incident occurrence, the study enables the design of targeted road safety measures and real-time traffic management approaches to reduce incidents and their impacts on motorways.

In part A, the methodology is to analyse as mentioned, the relationship between incidents and traffic data, especially congestion focused, on the M1 motorway in the United Kingdom, a critical segment of the Strategic Road Network managed by National Highways. Spanning approximately 292 kilometres in each direction, the M1 serves as a vital link connecting London to Leeds in the northeast and is one of the six major motorways in the UK. The specific stretch under investigation covers 190 kilometres from junction 1 to the east of London to junction 26 northwest of Nottingham. The research based upon two primary datasets: MIDAS provided real-time traffic monitoring data, including speed, volume, and occupancy, while ControlWorks supplied comprehensive incident details. ControlWorks is a National Highways application at the centre of a suite of tools that support the management of incidents across the SRN – capturing and communicating the majority of the key information required to resolve an incident and get the network flowing as safely and quickly as possible. It contains a wealth of information, such as type, location, date, time, duration, and contributing factors. The subsequent data preparation involved methodological extraction, reformatting, and cleaning processes to ensure accuracy and reliability.

The data for March 2019 was extracted from the MIDAS system and then reformatted into CSV files. A 5-minute aggregation was performed, and data were organised into road segments spanning from one junction to the next, considering the different geometric characteristics, if any exist. The averaging of data across days resulted in a monthly daily average, serving as a proxy for recurrent congestion. Concurrently, incidents were extracted, categorised, and analysed by type, location, day, month, and junction segments. The research addressed the central hypothesis that congestion impacts incidents, necessitating the distinction between recurrent and non-recurrent congestion. To achieve this, incident-induced congestion values were identified and excluded from the speed dataset, with a subsequent hypothesis test confirming the lack of a statistically significant difference between recurrent and non-recurrent congestion speed groups. The methodology ensured the accuracy of results and prevented potential overestimation when evaluating the interplay between incidents and congestion on the M1 motorway.

The significance of this research lies in its dedicated pursuit of understanding the intricate and contested relationship between incidents and traffic variables, specifically in the context of congestion. The goal of this investigation is twofold: firstly, to contribute to road safety enhancement, and secondly, to mitigate incident rates. To be more illustrative, the methodology approach followed to evaluate the aforementioned aspects is depicted in Figure 3.1 below. The existing research gap primarily centers on the nuanced interconnection between traffic variables, with a particular emphasis on congestion, and incident frequency. For this reason, the aim of the research is to address and bridge this gap through exploratory data analysis. By utilising robust methodologies, this research aims to provide valuable insights into the dynamics of traffic incidents and variables, ultimately contributing to improved road safety and reduced incident rates.

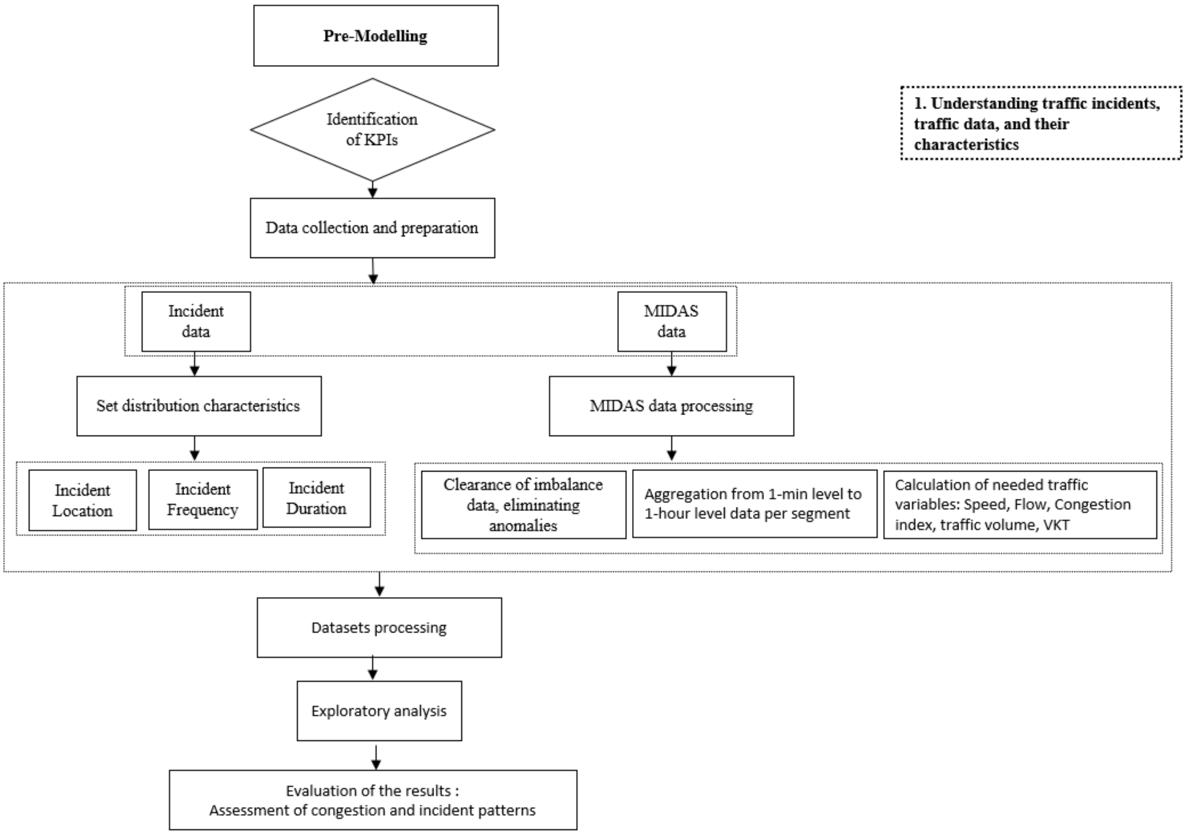


Figure 3.1: Methodological approach followed for analysing and modelling Incidents

The central hypothesis of this research section asserts that congestion impacts incidents. However, as indicated by the literature review, incidents also contribute to congestion from the moment of occurrence until it is cleared (Q. Li et al., 2020; Pasidis, 2019; Skabardonis et al., 2003). It becomes imperative to distinguish between recurrent and non-recurrent congestion to ensure result accuracy and prevent potential overestimation. To achieve this, the locations, and times of incidents across the entire dataset were identified, and corresponding values in the speed data from the incident's initiation to its clearance were omitted. Following that, a need for a statistical test created.

In the methodology, the comparison between average daily speed values, excluding incident-induced congestion, and the complete speed dataset was conducted using a hypothesis test. This analysis was illustrated using southbound data as a representative example. The statistical test employed was a two-sample t-test, and the hypothesis was formulated as follows:

- Null Hypothesis (H0): there is no significant difference between the "recurrent congestion speed" ($\bar{x}_1$) and "non-recurrent congestion speed" ($\bar{x}_2$) groups.
- Alternative Hypothesis (H1): there is a significant difference between the "recurrent congestion speed" ($\bar{x}_1$) and "non-recurrent congestion speed" ($\bar{x}_2$) groups.

The t-test equation used for this comparison is given by equation (3.1):

$$t = \frac{\overline{x_1} - \overline{x_2}}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \quad (3.1)$$

Where, $\bar{x}_1$ and $\bar{x}_2$ represent the sample means of the "recurrent congestion speed" and the "non-recurrent congestion speed" groups, respectively. The variables s_1^2 and s_2^2 denote the sample variances, while n_1 and n_2 represent the sample sizes of the two groups.

Section A focuses on examining incidents and traffic data to understand their intricate relationship on motorways. The main goal is to study the complex connection between incidents and traffic variables, especially congestion, with the aim to enhance road safety and reduce incident occurrence. This effort aims to address the important research gap about how traffic variables, specifically congestion, are linked to the frequency of incidents.

The methodology followed, involved exploratory data analysis, which was utilised to assess congestion patterns and incidents in the year of 2016-2019. This approach aims to unveil disparities in traffic congestion and incident occurrence and to identify any alterations in patterns. 3.4 Part B: Incident Detection through CV technology.

3.4.1 Conceptual Framework: Interconnected Modules and Dependencies

CV technology can be effectively tested and advanced through an integrated simulation scenario, as real-world data on connected vehicles is currently lacking. Using a simulated environment becomes crucial for testing and examining various scenarios. The proposed implementation involves the use of an integrated simulation platform, designed to assess the influence of connected vehicles on mitigating the impact of an incident on the Strategic Road Network (SRN). The proposed conceptual framework relies on four interconnected modules, each serving a distinct role in achieving the overarching objectives. This integrated simulation approach provides a controlled and dynamic environment for thorough testing, offering valuable insights into the potential efficacy of CV technology in addressing challenges related to halted traffic on key road networks. Each module exhibits either one-way or two-way interdependencies with the others, constituting a cohesive system. These modules include:

1. Communication Modules
2. Vehicle Modules
3. Infrastructure Modules
4. Computational Modules

The interrelationships among these modules are visually represented in the flowchart depicted in Figure 3.2 . This schematic illustrates the intricate connections and dependencies that exist between the Communication, Vehicle, Infrastructure, and Computational Modules within the overarching framework.

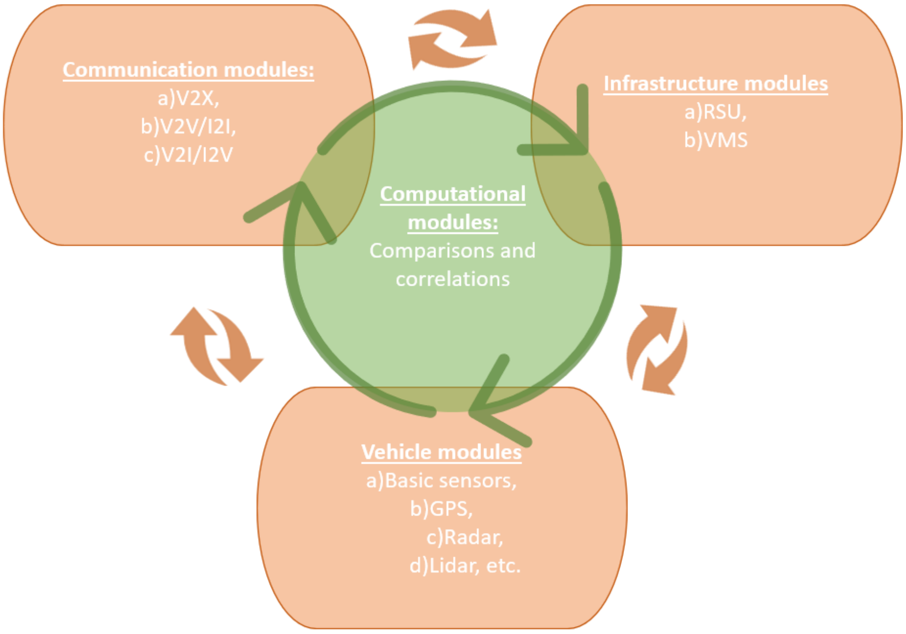


Figure 3.2: Intermodular Correlations: Interdependencies among Modules

The research correlated both four modules by taking account of everything that includes in them. More specifically:

1. Communication Module:

The communication modules are primarily established through V2X, V2I, and V2V communication protocols. A notable challenge in motorway incident detection scenarios lies in the temporal dynamics associated with transmitting critical messages. One of the pertinent communication challenges involves latency, specifically the duration from message initiation to the requisite response from subsequent vehicles. The automotive community, (Silva et al., 2017), has advocated for various communication technologies to facilitate data exchange among vehicles and transmission to the infrastructure.

The principal focus of examination and analysis in this research pertains to V2V communication modules. The access technologies integral to V2V communications will be succinctly examined below to comprehend their operational implications. Contemporary vehicles are equipped with an array of sensors, electronic systems, and in-vehicle communication networks. Diverse protocols and networks facilitate communication among the various sensors and devices embedded within the vehicle. Predominant access technologies for inter-vehicle and vehicle-to-infrastructure communications encompass the IEEE Wireless Access in Vehicular Environment (WAVE) standard, encompassing the Dedicated Short-Range Communications (DSRC) specification, IEEE 802.11p for PHY and MAC layers, and the IEEE 1609 family for upper layers (Bharati & Zhuang, 2013; Dhanya & Martin, 2018; Omar et al., 2013; X. Wu et al., 2013). DSRC enables the exchange of messages among sensors and vehicles within an approximate range of 300 meters (Dhanya & Martin, 2018). Dynamic Spectrum Access (DSA) serves as a complementary technology employed by DSRC to exchange information over unused spectra (Ihara et al., 2013).

Despite the extensive testing of these technologies, their mean latency time, approximately 25 milliseconds, proves insufficient to enable a vehicle to execute collision-avoidance actions (Ghosal & Conti, 2020)(Ghosal & Conti, 2020). Furthermore, potential unlicensed spectrum conflicts may arise due to their transmission frequency. Moreover, the coexistence of these technologies (Wi-Fi, WAVE, DSRC, DSA) may introduce interference, thereby elevating the risk of accidents (Ghosal & Conti, 2020; D. Wang et al., 2019).

Another part of the communication modules involves V2I, which operates on distinct access technologies. V2I entails the wireless exchange of crucial safety and operational data between vehicles and roadside infrastructure to enhance the overall efficiency of transport systems. Several access technologies have been proposed for V2I communications. Notably, 4G/LTE technology provides support for high data rates (up to 129 Mbps), low latency, extensive coverage, and high mobility through soft handoff and seamless switching (Abdelgadir et al., 2017b). Passive magnetic sensors, pneumatic tube sensors, and inductive loops can utilise this technology to disseminate data to vehicles, drivers, or traffic control offices.

Recent research has increasingly explored the advantages of leveraging existing and emerging mobile communication standards, such as LTE-X2 interface and 5G Device-to-Device (D2D), as alternative technologies for delivering automotive applications (Khan et al., 2018; Mohseni-Ejiyeh & Ashouri-Talouki, 2017). The primary objective of V2I is to capitalize on existing telecommunication infrastructures and networks for data collection, offering innovative Advanced Driver Assistance Systems solutions. Wireless technologies exhibit latency times lower than 5 milliseconds, deemed suitable for safety applications (Reyes et al., 2016). However, the primary drawback encompasses the elevated infrastructure costs and the necessity for a subscription or service exchange with carriers for network utilisation (Frenzel, 2018).

2. Vehicle Module:

In the context of this research investigated herein, the detection of potential incidents is primarily entrusted to the vehicle module, which is endowed with Vehicle-to-Vehicle (V2V) capabilities. A pivotal inquiry pertains to the requisite sensors for these vehicles and the essential sensor suite when speed detection is imperative. The fundamental question arises as to whether basic sensors coupled with Global Positioning System (GPS) suffice, or if a more sophisticated array, encompassing radar, lidar, infrared cameras, and vision, is indispensable. Intelligent vehicles are conventionally equipped with storage and computational resources, and embedded sensors to gather diverse and valuable information. The establishment of a network among these intelligent vehicles, where real-time communication and information sharing transpire, holds the potential to actualise the vision of Intelligent Transport Systems (ITS). Such systems support lots of safety-related applications, including traffic management and the timely dissemination of critical emergency alerts.

The vehicle data employed in this research is derived from real-time sources, although not all vehicles have incorporated the latest technological advancements to date. Some vehicles are equipped solely with cameras, others with a combination of cameras and radar, and some lack both. Through microscopic simulation, various vehicles representing distinct levels of autonomy (L1-L5) will be instantiated, ensuring comprehensive coverage of the necessary technological spectrum. The VISSIM platform incorporates classical vehicles and Heavy Goods Vehicles (HGVs), with specific research initiatives undertaken to simulate autonomous vehicles. Pioneering efforts, such as those by CoExist, have formulated profiles for autonomous vehicles on simulation platforms like PreScan and VISSIM. Nevertheless, the integration and testing of connected vehicles remain an area yet to be explored. Subsequently, in future iterations, these diverse vehicle profiles will be amalgamated within a network, each exhibiting varying levels of penetration.

The ensuing sections of this research delve into an in-depth analysis and enhancement of these approaches. Various scenarios will be meticulously crafted to scrutinize the responses and outcomes under different circumstances, employing vehicles equipped with varying degrees of connectivity technologies in the event of an incident on a motorway.

3.Infrastructure Module:

The third module deals with the infrastructure components of a highway segment. It includes all the necessary infrastructure elements, such as Roadside Units (RSU) and Variable Message Signs (VMS). These components are crucial for the proposed experimental framework. VMS and V2I and I2I communications are used to convey information about a stopped vehicle on the SRN. The information is prominently displayed on VMS to expedite the reaction time of subsequent vehicles, thereby preventing potential traffic collisions or more severe incidents after the initial one.

The increased connectivity in modern vehicles has led to concerns about safety. There is a risk of inaccurate or malicious messages being transmitted from Roadside Units (RSUs) or other vehicles, which could cause system failures. For example, a malfunctioning RSU could give wrong directions to a vehicle, leading it to the wrong lane or indicating that a redX signal is inactive when it is actually active. Such incidents can lead to congestion and potential incidents (Siegel & Sarma, 2017). Therefore, it is essential to ensure the accuracy and reliability of data and develop vehicles that can detect and evaluate incoming instructions to ensure that they are safe and do not cause any harm.

Regarding infrastructures and infrastructure-based communications, various applications for Vehicular Ad-Hoc Networks (VANETs) rely on V2V communications, while others necessitate the support of roadside infrastructure to install wireless nodes strategically positioned along highways, providing connectivity to vehicles. Regrettably, owing to the exorbitant deployment costs associated with a pervasive roadside infrastructure, the installation of only a limited number of roadside nodes is anticipated in the near future (S. Sharma & Kaul, 2018). Consequently, it is imperative to endorse both V2V communications (decentralized) and V2I communications, allowing vehicles to leverage the limited resources of roadside units to optimize reaction time in scenarios such as a stopped vehicle on the SRN as investigated in this research.

4. Computational Module

The last part consists of computational modules that contain all the necessary models and algorithms for detecting incidents. The main research task is to successfully integrate these modules into the incident detection framework while ensuring that they are interdependent for the smooth operation of the proposed conceptual framework. There are several challenges that arise during this process, including:

1. The transmission of data from a stopped vehicle to other proximate vehicles, Roadside Units (RSUs), or the nearest Regional Operational Center (ROC) for downstream traffic notification. This necessitates communication capability and basic sensors for incident detection. The efficiency of detection hinges on factors such as communication capability, the presence of basic sensors, distance from RSUs or other communicating vehicles, and environmental conditions (night/daytime, low/high density).
2. Surrounding vehicles endowed with communication capabilities play a crucial role in incident detection. The mode of detection, whether automatic or manual, influences the subsequent reporting to other vehicles, RSUs, or the ROC (as seen in Waze navigation).
3. RSUs function as incident detectors and subsequently relay information to other vehicles, Variable Message Signs (VMS), or the ROC. The drawbacks of this approach in comparison to alternative detection methods are examined, with a focus on speed and feasibility considerations. The

comparative speed and practicality of RSUs in incident detection are explored in contrast to other detection mechanisms.

3.4.2 Proposed Experiment

The proposed experiment included a segment of the M1 motorway at junction 23-26, using the real-time traffic data from 2019 as a baseline case scenario. The motorway developed on the traffic microsimulation software VISSIM, leveraging the cartographic assistance of Google Maps and geographic details sourced from National Highways.

The simulation is created to aid the communication of important information in situations where a vehicle has stopped or when there is an obstacle on the road. Specifically, the simulation allows for the notification of nearby vehicles, RSUs, and VMS about the presence of a stationary vehicle ahead. This feature aims to prompt timely adjustments such as changing lanes or reducing speed limits, resulting in improved traffic management and safety within the simulated environment, and ultimately in the real world.

The experimental design comprises several crucial elements, starting with the utilisation of pre-existing data to establish the baseline scenario for Motorway M1, specifically focusing on the segment spanning Junctions 23-26. Additionally, Roadside Units (RSUs) are strategically deployed along the motorway infrastructure to enhance communication capabilities, complemented by the installation of Variable Message Signs (VMS) in both directions for comprehensive communication and information dissemination. Furthermore, the implementation of V2V connectivity protocols allows surrounding vehicles to relay information to subsequent vehicles, notifying them of the presence of a stopped vehicle ahead.

Data collection is carried out under various conditions including different weather scenarios such as sunny, rainy, stormy, and foggy conditions. Each of these conditions has a unique effect on the simulation process and affects variables such as speed and visibility. The study of traffic dynamics is conducted during both peak and non-peak hours. Peak times are characterised by a high vehicle density and reduced speeds. The study also takes into account varying traffic flow conditions and critical factors such as speed limits, acceleration, and deceleration of vehicles within the network. Scenarios that involve nighttime conditions and low traffic flow are explored to understand the elevated risks and crucial implications that they pose.

The incident detection experiment is a detailed investigation of market penetration rates, particularly in situations where a vehicle has no wireless communication. The study focuses on scenarios with high market penetration rates, especially in low traffic situations, which is a crucial part of the experimental design. This component aims to explore possible outcomes in low traffic scenarios and provide insights into the effectiveness of incident detection mechanisms under varying conditions.

The Market Penetration Rate (MPR) is a critical factor in achieving accuracy and efficiency in the proposed solution. The scenarios are constantly changing, which necessitates the adaptation of approaches. For example, vehicle types are evolving and incorporating new technologies such as cameras, radar, and GPS, which require alternative methodologies for incident detection. An E-call system is also being considered, which would allow drivers to summon assistance during critical situations by pressing an emergency button. It's important to remain flexible during the transitional period to ensure the MPR is adjusted appropriately. Therefore, the MPR undergoes multiple iterations to identify the optimal configuration that aligns with the evolving nature of incident detection scenarios and ensures the best results.

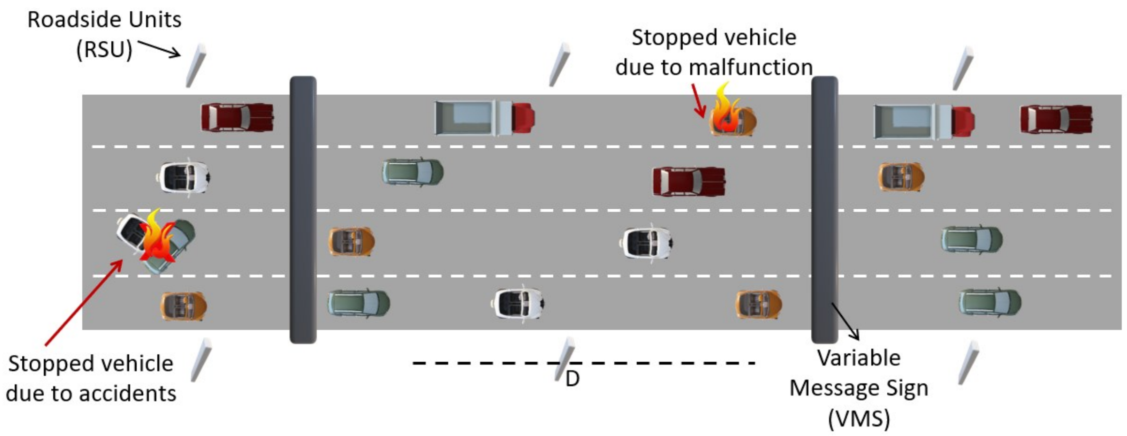


Figure 3.3: Proposed Simulation Experiment.

In the proposed simulation experiment, it is assumed that connected vehicles are equipped with a wireless module. This module serves as a communication tool facilitating interactions between connected vehicles and potentially with RSUs positioned along the roadway (see Figure 3.3). Its primary function is to exchange pertinent traffic-related information with passing vehicles, and crucially, to engage in communication with other vehicles on the road through the utilisation of Vehicle-to-Vehicle (V2V) technologies and Vehicle-to-Infrastructure (V2I). Furthermore, the assumed configuration incorporates the integration of Event Data Recorders (EDR) (Westbrook, 2009), within vehicles. The EDR is deployed to monitor key parameters such as rapid acceleration, speed, and lane information for comprehensive data collection. It is imperative to note that each scenario within the experiment is assigned a specific penetration level, with the penetration level tailored to the unique characteristics under examination in each case. The proposed simulation experiment will take place in case of an incident on the motorway, for instance of an event of a stopped vehicle due to a malfunction or an accident as shown in Figure 3.3.

Figure 3.4 shows the system model of highway traffic flow on the road with the movement of vehicles.

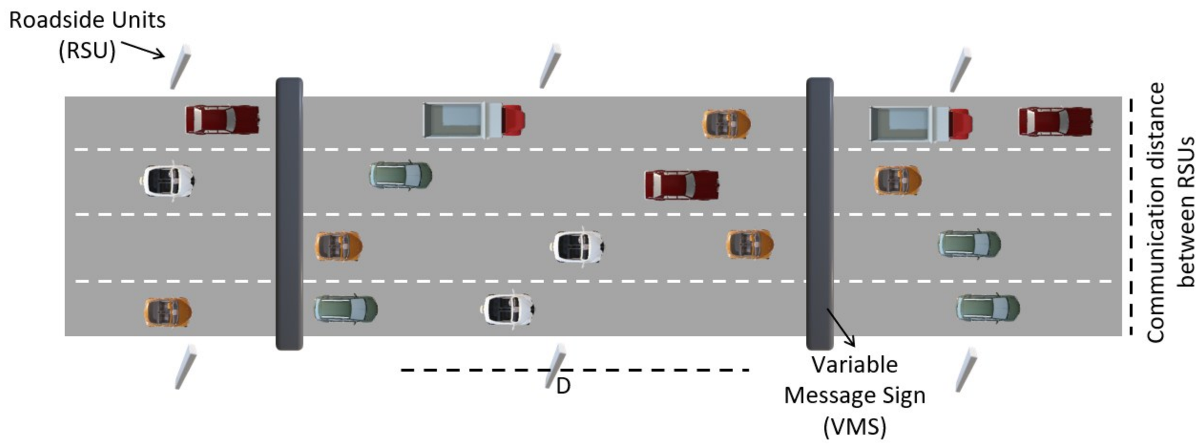


Figure 3.4: Proposed experiment: Individual incident detection through V2X communication.

The ideal is, the signal will be transported either through the roadside unit to other vehicles and VMS, or directly to other vehicles and VMS in the event of incidents. Strategically positioned along the roadway, the RSUs are spaced approximately 1.5 km apart, based on the UK motorways design. This distributed placement serves to ensure uniform coverage within their proximity, situated on both the adjacent and opposite sides of the road to establish a comprehensive infrastructure. Each RSU is equipped with essential components, including a GPS device for precise location determination, a radio transceiver facilitating connections with passing vehicles, and a computing device responsible for processing traffic information data derived from vehicles. This information encompasses crucial parameters such as lane changes, speed, and distance. Figure 3.5 illustrates the intricate systems of and V2I connectivity, while Figure 3.6 provides a visual representation of vehicle-to-roadside communication.

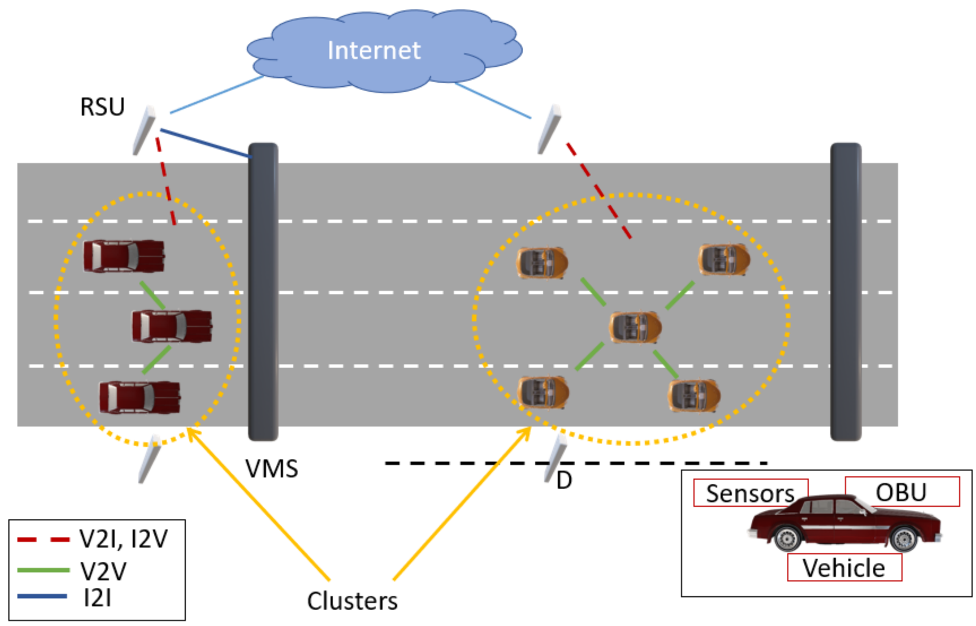


Figure 3.5: V2V and V2I Communication systems.

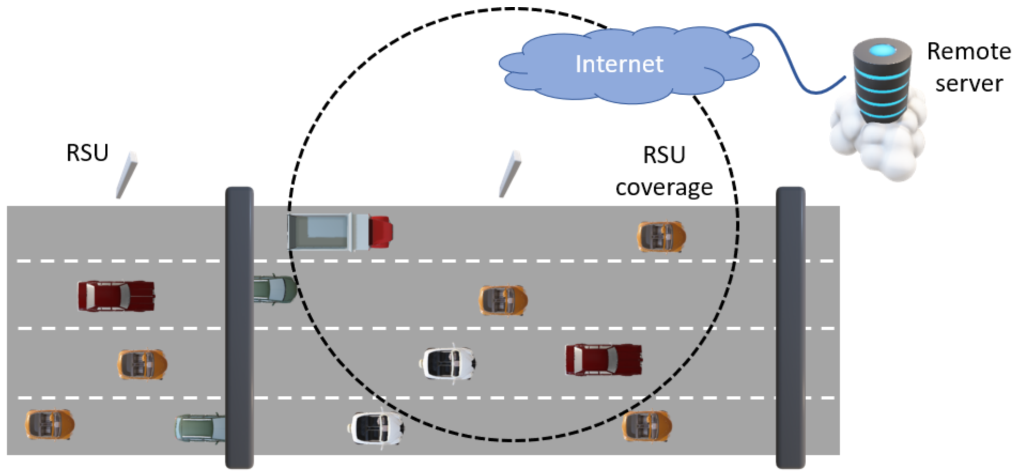


Figure 3.6: Vehicle to roadside communication.

As shown in Figure 3.3, in the event of an incident directly impacting the highway, vehicles implicated in the incident (indicated by the left red "x") initiate a signal transmission to both Roadside Units (RSUs) and inform like this, other vehicles on the highway. This signal serves as an informative alert, notifying surrounding entities of the incident ahead. Vehicles in the area are equipped to quickly adjust their speed and change lanes in response to incidents reported to them. Similarly, if a vehicle is stationary due to a mechanical issue, it will send a signal triggering a coordinated response from the

Roadside Units (RSUs) and other vehicles. This helps to ensure that the stopped vehicle is acknowledged, and that timely speed reduction and lane changes take place around it. The stopped vehicle is represented by a red "x" on the right side of the road.

The informational message is transmitted in just a few seconds through two possible pathways. The first pathway involves the message passing through the Roadside Unit (RSU), before being sent to other vehicles and VMS. The second, and the one tested, pathway directly transmits the message to other vehicles using V2V technology. Both pathways are required, first of all because the RSU pathway ensures centralised control and broader coverage, allowing this way messages to reach vehicles and VMS beyond the nearest range of V2V communication. Meanwhile, the V2V pathway enables direct, localized information sharing direct between vehicles, ensuring timely responses in critical, real-time scenarios. This fast transmission process ensures that critical information is quickly relayed, allowing relevant entities within the communication network to be aware of the situation and respond on time. The message concerning the incident transformed via vehicles or infrastructure as showned in Figure 3.7.

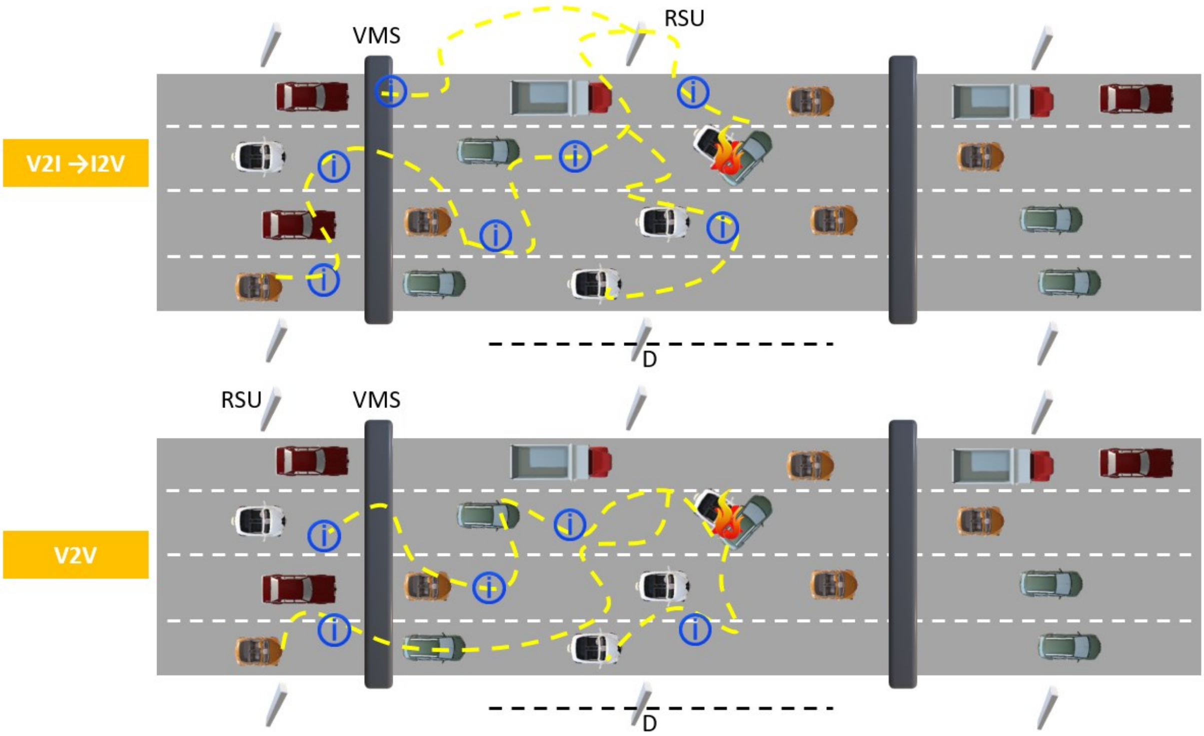


Figure 3.7: Vehicle Signal Mechanism.

This method ensures that incidents are detected in seconds, which leads to faster and more accurate dissemination of information to subsequent vehicles. The Regional Operational Centre (ROC) then confirms and forwards this information to the VMS. The manifestation of a red "X" on the VMS serves as an immediate visual indicator of the incident, providing clear and accurate details. Simultaneously, the following vehicles get timely awareness of the incident and specific lane change instructions, contributing to a swift and informed response in navigating the affected section of the roadway. (Figure 3.8).

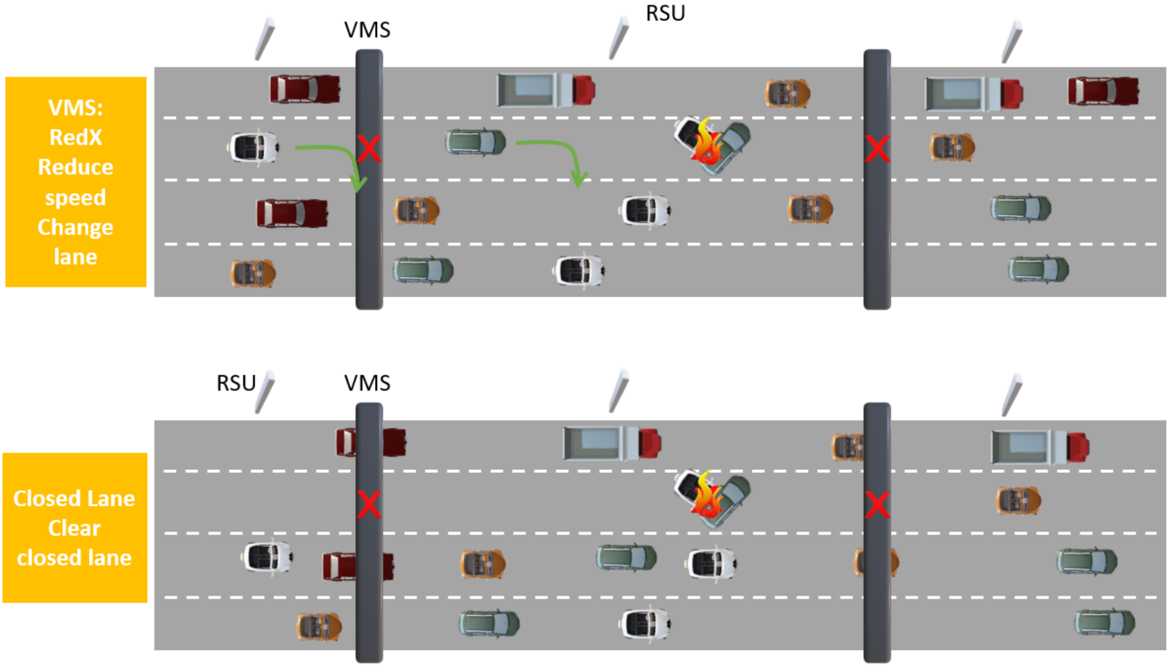


Figure 3.8: Movement of vehicle in the forward direction.

If the vehicles involved in an incident cannot send messages to other vehicles, nearby CVs will take over the responsibility using an emergency button, which the driver will react by pressing this button. It should be noted that this scenario is subject to implementation under various conditions, reflecting the dynamic nature of accident scenarios across different contextual circumstances.

3.4.3 Illustrative Methodology Overview of Incident Management

In the context of addressing the impact of incident detection on various Key Performance Indicators (KPIs) through the integration of CVs on the Strategic Road Network (SRN), Figure 3.9 illustrates the comprehensive simulation methodology comprising five modules, which explained as follows:

1. Understanding traffic incidents and their characteristics
2. Developing a simulation model in VISSIM
3. Modifying V2V communication protocol, CV driving behaviour, and simulating incidents
4. Creating representative scenarios for incident occurrences
5. Measuring effectiveness of V2V relative to the base-case scenario (i.e., no connectivity between the vehicles)

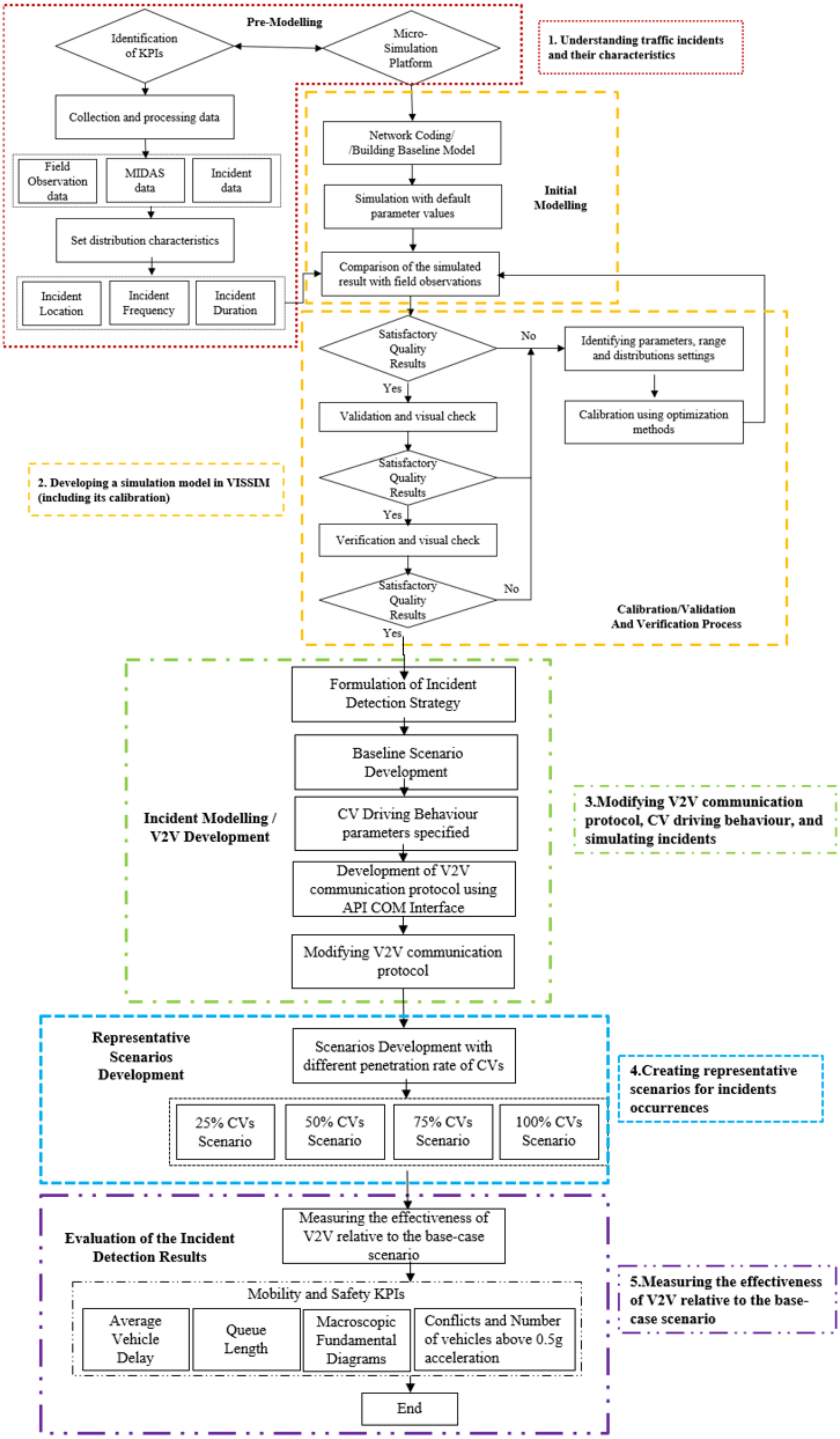


Figure 3.9: Simulation Methodological Framework

To fully understand traffic incidents and their characteristics, it's crucial to have a deep knowledge of the procedures involved in managing them on highways. This applies to situations where there are no CVs in the network, as well as when they are integrated into the system.

3.4.4 Incident management

In networked transport systems, a structured response protocol is required by other users in the event of incidents involving vehicles. This is crucial to ensure the safety of all road users and to minimise traffic disruptions. To achieve this, vehicles in close proximity to an incident should follow certain steps such as avoiding closed lanes, reducing speed, and changing available lanes. Adhering to these protocols contributes to the efficient management of traffic incidents and enhances overall road safety. Therefore, the management of incidents within networked transport systems is imperative for ensuring road safety and maintaining the flow of traffic. These protocols aim to guide vehicle behaviour, promoting the swift and safe resolution of incidents within the networked transport system.

- Avoidance of Closed Lanes: One of the most important steps for vehicles encountering an incident in the networked transport system is to avoid closed lanes. Closed lanes are usually designated by authorities to isolate the incident scene, protect emergency responders, and facilitate debris clearing. When approaching an incident, vehicles must quickly and safely merge into open lanes, avoiding any attempt to traverse closed lanes. This action is critical to prevent secondary incident, protect personnel on the scene, and ensure the unrestrained flow of traffic in adjacent lanes.
- Reduction of Speed: Reducing speed is another crucial element of incident response for vehicles. As vehicles approach an incident scene, it is imperative that they decrease their speed to adapt to the altered traffic conditions. Reduced speed not only enhances driver reaction time but also minimizes the risk of collisions with other vehicles and objects in the vicinity. Additionally, reduced speed is integral to the overall safety of the incident response zone, as it allows for better coordination and manoeuvre ability.
- Lane Change Manoeuvres: Vehicles must be prepared to execute lane change manoeuvres judiciously in response to an incident. Changing available lanes should be undertaken with due caution and adherence to traffic regulations. Drivers should assess the traffic situation, signal their intentions, and only make lane changes when it is safe to do so. This step contributes to the efficient redistribution of traffic flow around the incident site and supports the continued movement of vehicles in the networked transport system.

In summary, effectively managing incidents within a networked transport system demands a disciplined adherence to protocols. Vehicles encountering such incidents should prioritise avoiding closed lanes, reducing speed, and reasonable execution of lane change manoeuvres. When followed rigorously, these protocols contribute to the safety of all road users and the efficient resolution of incidents, minimising disruptions in the networked transport system. Implementing these measures underscores the significance of a well-coordinated response to incidents in promoting road safety and maintaining traffic flow. But still, more is needed to ensure the 100% safety of road users. For this reason, the real-time detection is crucial.

Managing incidents on motorways in a mixed network, which includes connected vehicles, requires a well-structured procedure. Connected vehicles can quickly determine the exact location of an incident and its lane through real-time awareness, allowing them to make informed decisions. When responding to an incident, connected vehicles must assess if changing lanes is necessary based on the incident's characteristics and its impact on traffic flow. Additionally, connected vehicles must evaluate if exiting the motorway is a feasible alternative. In such cases, dynamic assignment algorithms can be used to make optimal routing decisions. Connected vehicles can work together to facilitate the exit manoeuvre and ensure a smoother transition from the motorway to the exit slip road, reducing congestion and potential safety hazards.

During an incident and its resolution, CVs can adjust their speed based on the speed distribution and driving behaviours of other vehicles in their vicinity. This adaptive behaviour promotes safer lane changes and ensures that CVs integrate harmoniously into the traffic flow. Once the incident is over, the driving behaviour, assigned in VISSIM, of category 80 vehicles returns to category 70, aligning with the behaviour of human-driven vehicles. During transition phases, new driving behaviours can be assigned to CVs when they receive relevant messages, reinforcing their role in managing incidents and optimising traffic. These steps highlight the potential of in-network-connected vehicles to enhance road safety and traffic efficiency in a dynamic and adaptive manner.

Finally, it is necessary to establish different distance thresholds for V2V message distribution. This modification, in this research tested has three options to choose from, each evaluated for its effectiveness. The options cover maximum distance coverage scenarios at 500 meters, 2000 meters, and 2500 meters, respectively. Choosing the best distance threshold is important for the timely and effective dissemination of incident messages among connected vehicles. This, in turn, affects their coordinated response to road incidents. These refinements highlight the evolving landscape of CV technologies, particularly enhancing safety, and operational efficiency in response to real-time incidents.

3.5 Part B: Simulation Network Model

3.5.1 Simulation Network Model Method

For the purpose of this research, the simulation software VISSIM from PTV Group was employed to achieve the study objectives. PTV VISSIM is a microscopic, multi-modal traffic flow simulation software developed by PTV Group. It is widely used for simulating and analysing the dynamic traffic behaviour of road networks. Here are some key features and information about PTV VISSIM:

1. Microscopic Simulation: PTV VISSIM is a microscopic traffic simulation tool, meaning it models individual vehicles and their interactions in a detailed manner. This allows for a realistic representation of traffic dynamics, including lane-changing, overtaking, and interactions at intersections.
2. Multi-Modal Simulation: The software supports the simulation of various modes of transport, including cars, buses, HGVs, bicycles, and pedestrians. This makes it suitable for modelling mixed traffic scenarios.
3. Traffic Signal Control: PTV VISSIM enables users to model and analyse different traffic signal control strategies. It helps in optimising signal timings and assessing the impact of signal control on traffic flow.
4. Scenario Building: Users can create complex traffic scenarios by defining road networks, intersections, traffic demand, and other relevant parameters. This makes it a valuable tool for urban and transport planning.
5. Visualisation: The software provides detailed visualisations of the simulated traffic scenarios. This includes graphical representations of vehicle movements, traffic density, and other performance indicators.
6. Calibration and Validation: The software allows users to calibrate and validate the simulation model based on real-world data, ensuring that the simulated scenarios closely match observed traffic behaviour.

7. Dynamic Traffic Assignment: PTV VISSIM supports dynamic traffic assignment, helping modelers understand how changes in the transport network affect traffic patterns and travel times.

The absence of a self-sufficient simulation tool and CV real-world data necessitates the adoption of an integrated approach in this research. To conduct the research, we needed to combine two tools: PTV VISSIM traffic microsimulation software and its External Driver Model in Visual Studio (C++), through a Component Object Model Application Programming Interface (COM API). This integration allowed us to create a V2V connectivity environment, which helped to develop and execute reflective incident detection scenarios. The integration between PTV VISSIM traffic microsimulation software and its External Driver Model is achieved by using a Component Object (COM API in Visual Studio (C++). This integration allows for the creation of a V2V communication environment, which enables the development and execution of reflective incident detection.

PTV VISSIM has been selected as the simulation tool due to its extensive features, widespread usage, and recognition in the literature. It is an excellent tool for simulating individual vehicle behaviours, which can be customised based on the research project's objectives. It can also accommodate various network types such as highways, urban roads, intersections, and replicate diverse traffic situations incorporating factors such as traffic signals, traffic compositions, and geographical configurations. Furthermore, VISSIM supports external agents, such as its extension of the External Driver Model, providing a connected environment through a developed algorithm. The data exchange between VISSIM and its external platform takes place at every time step of the simulation, mitigating delays in controlling vehicular movements and behaviours. The framework of the integrated platform is illustrated in Figure 3.10.

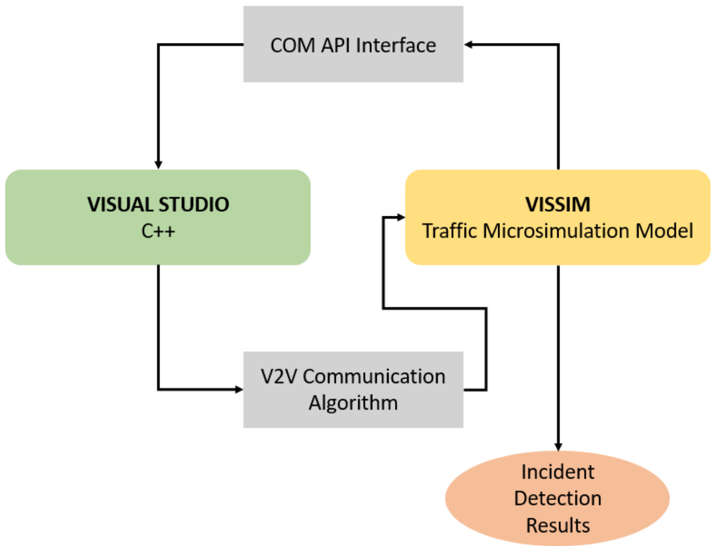


Figure 3.10: The integrated simulation platform.

The first step involves using the microscopic traffic simulator, VISSIM, to create a detailed model of the traffic network. VISSIM provides important information such as vehicle acceleration, speed, position, traffic volume, traffic routes, and incident locations. This information is then used as inputs for the External Driver Model (EDM) module of VISSIM through an COM API. Next, a V2V connectivity algorithm is used using Visual Studio C++. The algorithm is integrated into the External Driver Model and encapsulated within a dynamic-link library which is invoked by C++. This DLL is then sent back to VISSIM to control vehicle behaviour during simulation runs. The desired incident detection results are generated throughout the simulation runs, completing the iterative process.

Microsimulation plays a vital role in analysing network attributes and transport studies, particularly before implementing proposed management applications or intelligent transport system operations (Guo et al., 2021; Ištoka Otković et al., 2013; Kummetha et al., 2022; Shahdah et al., 2015). VISSIM is a preferred choice because of its ability to consider a wide range of modelling parameters, including speed, headway, and time intervals. This enables the creation of high-quality traffic control models with a detailed and prominent level of functionality.

VISSIM offers users the ability to intelligently control not only overall model attributes but also specific intersection-related modelling parameters. This includes the incorporation of traffic signals and their timing plans. The tool is recognised for its enhanced approach to simulating traffic at intersections, providing users with a diverse range of parameters for intersection modelling to better represent real-world characteristics. Moreover, VISSIM's underlying assumptions, such as car-following models, contribute to consistent assessments and estimates of performance measures, including delay, queue lengths and even evaluate safety (Saidallah et al., 2016) by identifying conflicts using the through a post processing software developed by Federal Highway Administration of the United States, the Surrogate Safety Assessment Model (SSAM).

3.5.*2 Traffic Microsimulation*

As previously stated, the main goal of this thesis is to create an integrated simulation platform that can simulate CVs and how they function alongside traditional human-driven traffic on a motorway traffic microsimulation framework. This simulation platform consists of three primary elements: the motorway infrastructure, human-driven vehicles, and Connected Vehicles. Thus, this section of the thesis is divided into three sub-sections, each focusing on one of these elements.

The developed algorithms undergo comprehensive testing within a calibrated and validated motorway network, utilising real-world data as a pivotal factor to enhance the reliability of the outcomes (Katrakazas et al., 2019a). It is important to note that, due to the lack of real-world CV data, only human driving behaviour was subjected to calibration. The driving behaviour of CVs was subjected to testing through the calibration of the Wiedemann 99 parameters. This calibration process was undertaken to accurately simulate the behaviour of CVs, aiming to minimise average vehicle delays in the event of an incident, method that will be described below.

3.5.3 Wiedemann model

As explained earlier, it is extremely important to calibrate and validate VISSIM. The success of these processes is dependent on the manipulation of various parameters, including the utilisation of Wiedemann models. There are two Wiedemann models - the 74 and 99 models. The difference between these models is that certain thresholds in the 99 model are defined differently to better capture freeway traffic dynamics. Therefore, in VISSIM, the Driving Behaviour parameter is set to 99 for freeway driving scenarios, while it is configured as 74 for urban driving contexts.

The difference between the Wiedemann 74 and Wiedemann 99 models lies in how they define specific thresholds to represent driver behaviour under different traffic conditions. The Wiedemann 99 model adjusts parameters like **following distance**, **acceleration**, and **lane-changing thresholds** to calculate the unique dynamics of freeway traffic, such as higher speeds, smoother lane changes, and greater variability in driver behaviour. These adjustments allow the 99 models to simulate freeway scenarios more accurately, where vehicles tend to maintain longer headways at high speeds and exhibit different gap-acceptance behaviours compared to urban driving, which is better captured by the Wiedemann 74 model.

PTV VISSIM employs the Wiedemann model in its car-following model, introduced by Rainer Wiedemann in 1974 (Wiedemann 74) and subsequently updated in 1999 (Wiedemann 99). These models account for both the physical and psychological aspects of driver behaviour (Durrani et al., 2016; Raju et al., 2020). Wiedemann's model is predicated on the assumption that a vehicle within a simulation environment can exist in one of several distinct driving states:

- Free Flow Driving: During this state, the vehicle operates independently of preceding vehicles. The driver's objective is to attain and sustain their desired speed. In reality, the speed in this mode may fluctuate around the desired speed due to imperfections in throttle control.
- Approaching: This phase signifies the driver adjusting their speed to match the lower speed of the preceding vehicle.
- Following: In this state, the driver tails the preceding vehicle without consciously accelerating or decelerating. The aim is to maintain a consistent safety distance. However, owing to imperfections, the speed difference oscillates around zero.
- Braking: The driver initiates moderate to high deceleration rates when the distance to the preceding vehicle falls below the desired safety distance. This situation may arise if the preceding vehicle abruptly brakes or alters its speed, or if a third vehicle changes lanes to insert itself between two vehicles.

For each of the enumerated driving states, the acceleration is computed based on the current speed, speed difference, distance to the preceding vehicle, and individual driver and vehicle characteristics. In VISSIM, these driving parameters are specified in the Car Following Model tab within the Driving Behaviour settings. Figure 3.11 illustrates the different phases of the Wiedemann following model (Aghabayk et al., 2013).

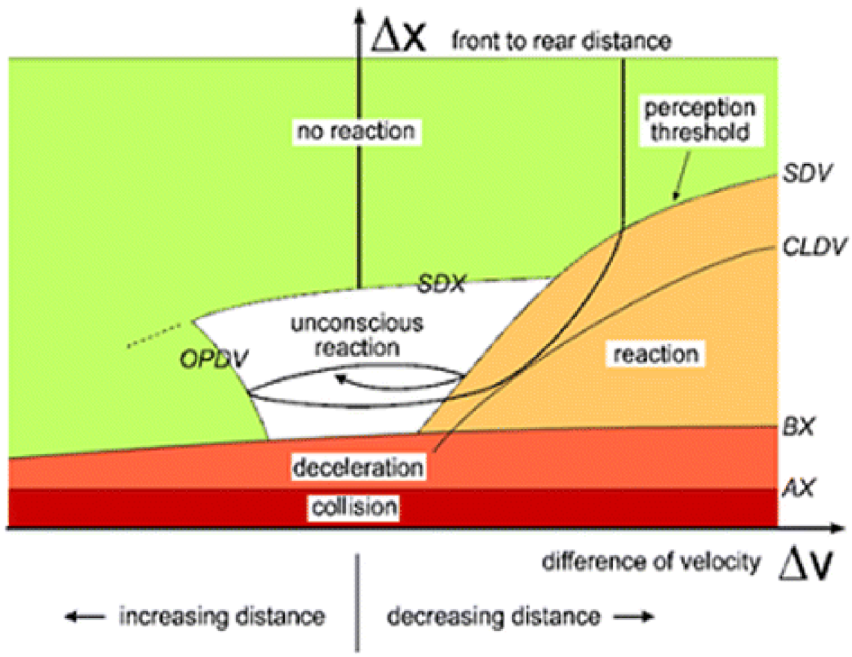


Figure 3.11:Wiedemann Thresholds and One-vehicle Trajectory (Aghabayk et al., 2013)

In essence, in other words, the primary objective of the following vehicle is to prevent a collision with the leading vehicle while endeavouring to sustain the desired speed, conditions permitting. The driving process is delineated into four principal phases. The initial phase is **Acceleration/Free Flow driving**, characterised by the vehicle moving at the desired speed without constraints from nearby vehicles. As the following vehicle approaches a leading vehicle and the distance (Δx) decreases, the driver transitions into the **Reaction phase** (observe and then react). In this phase, the driver recognizes that their speed exceeds that of the leading vehicle, either in a far distance (SDV) or a near distance (CLDV).

Upon reaching the perception threshold, the following vehicle initiates a reduction in speed. Upon attaining the Critical Lead Vehicle (CLDV) threshold, the vehicle decelerates to ensure a minimum safe distance from the leading vehicle, which encounters the **Following phase**. If the leading vehicle continues to decelerate, the following vehicle further reduces its speed, entering the **deceleration phase**. This phase aims to bring the following vehicle to a stationary state, thereby preventing a collision and sustaining the minimum gap or headway. The delineation of these phases is presented in Figure 3.12.

The aforementioned thresholds are subject to calibration as necessary, with driving behaviour exerting a notable influence. It is essential to note that the follower vehicle consistently endeavours to remain within the unconscious domain, defined by the OPDV, SDX, and SDV thresholds.

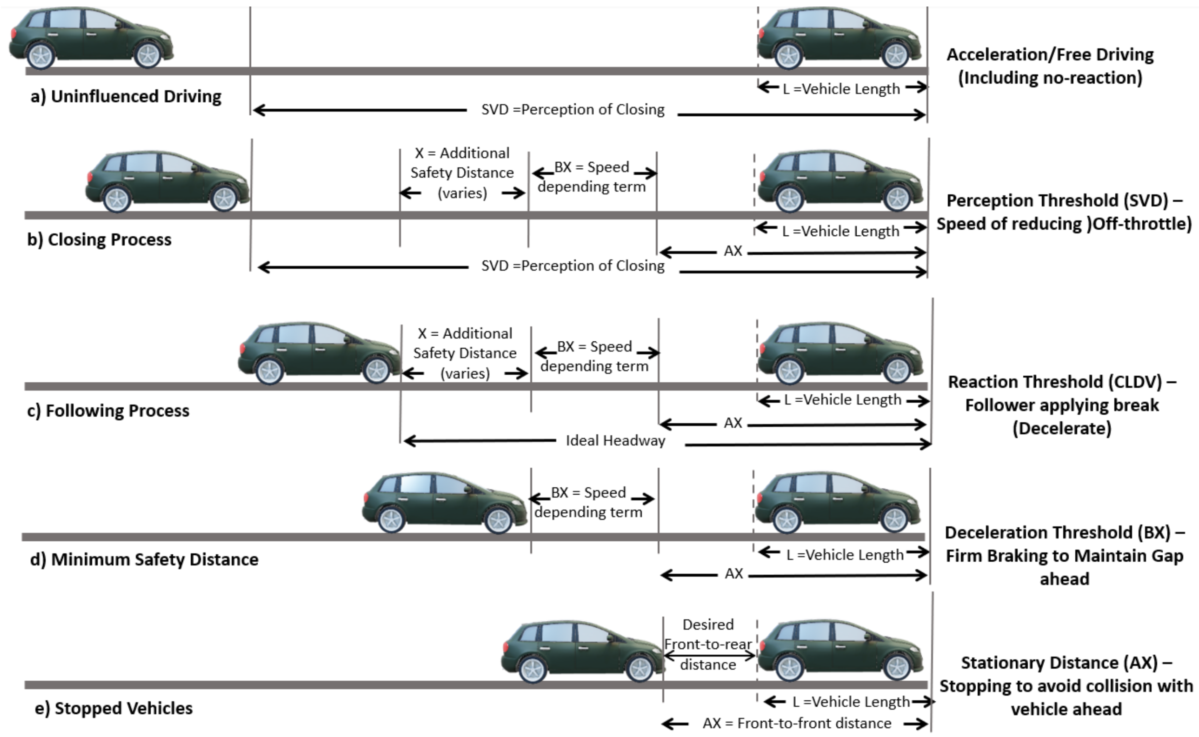


Figure 3.12:Wiedemann's Approach to Leader Distances (Vehicle Following Phases)

In the Figure 3.12, the terms are explained as follows:

- AX: desired stationary distance between two vehicles,
- BX: min following distance, named as safe distance
- CLDV: perception threshold (near): drivers perceive that their speed higher than leader,
- SDV: perception threshold (far): drivers perceive that their speed differences when approaching slower leader,
- OPDV: perception threshold (near): drivers perceive that their speed lower than leader and
- SDX: perception threshold: free acceleration, upper limit of car-following process.

It is worth mentioning that Wiedemann 74 (Wiedemann, 1974) and Wiedemann 99 (VISSIM, 2012) are two well-known psycho-physical models used in microscopic traffic simulation tool, VISSIM. These models are based on the psychological and physical aspects of driving behaviour and are significant in defining four driving states. Within each of these states, different acceleration functions (a(s, v, Δv)) are applied. The boundaries between these states are determined by nonlinear equations of the form f(s, v, Δv) = 0, which define curved areas in three-dimensional space (s, v, Δv) spanned by the exogenous variables (Fellendorf and Vortisch, 2010). This study has used the Wiedemann 99 model, which is more appropriate for modeling expressway car-following behaviour than the 74-model version. VISSIM users cannot program these thresholds directly. However, they can calibrate them using a set of parameters. These parameters make it possible to adjust driving behaviour and align it with real-world traffic patterns based on available empirical data. The following Table 3.1 enumerates the list of these parameters:

Table 3.1: Parameters of the Wiedemann 99 car following model.

Parameter	Unit	Description
CC0	m	Standstill distance: the average desired standstill distance between two vehicles. It has no variation.
CC1	s	Time headway: the time (in seconds) that a driver wants to keep.
CC2	m	'Following' variation restricts the longitudinal oscillation or how much more distance than the desired safety distance a driver allows before intentionally moving closer to the car in front.
CC3	s	Threshold for entering car following mode in VISSIM: controls the start of the deceleration process, i.e., when a driver recognizes a preceding slower vehicle.
CC4	m/s	'Following' thresholds: control the speed differences during the 'Following' state. Smaller values result in a more sensitive reaction of drivers to accelerations or decelerations of the preceding car.
CC5		
CC6	1/(m*s)	Speed dependency of oscillation: influence of distance on speed oscillation while in the following process.
CC7	m/s^2	Oscillation acceleration: actual acceleration during the oscillation process.
CC8	m/s^2	Standstill acceleration: desired acceleration when starting from standstill.

CC9	m/s^2	Acceleration at 80 km/h: desired acceleration at 80 km/h.

The thresholds of the Wiedemann car-following model are intricately tied to the associated parameters through a set of equations as shown and described below:

$AX = L + CC0$ (3.1)

where L represents the length of the preceding vehicle.

$BX = AX + CC1 * v$ (3.2)

The variable v is defined as equal to the speed of the ego-vehicle if it is slower than the preceding vehicle; otherwise, it is equivalent to the speed of the preceding vehicle. The introduction of a stochastic element is incorporated through the inclusion of random errors. These errors are determined by multiplying the speed difference between the two vehicles by a randomly generated number falling within the range of -0.5 and 0.5. This stochastic component introduces variability into the car-following model, reflecting the inherent unpredictability and randomness observed in real-world traffic dynamics.

$SDX = BX + CC2$ (3.3)

$SD_iV = -\frac{\Delta x - SDX_i}{CCC3} - CC4$ (3.4)

In the context of the Wiedemann car-following model, Δx represents the space headway, measured in meters, between the ego-vehicle and the preceding vehicle. This parameter quantifies the spatial gap or distance between the two vehicles, providing a crucial metric in understanding their relative positions on the road. The Δx value plays a significant role in determining the dynamics of vehicle interactions, influencing acceleration, deceleration, and overall traffic flow within the car-following model framework.

$CLDV = \frac{CC6}{17000} * (\Delta x - L)^2 - CC4$ (3.5)

$OPDV = -\frac{CC6}{17000} * (\Delta x - L)^2 - \delta CCC5$ (3.6)

Where the variable δ serves as a dummy variable. It takes on a value of 1 when the speed of the ego-vehicle surpasses a certain threshold denoted as CC5, and it assumes a value of 0 otherwise. This binary variable is employed to delineate two distinct states based on the speed of the ego-vehicle in relation to the specified threshold. The inclusion of δ allows for the incorporation of conditional logic within the model, distinguishing between situations where the ego-vehicle exceeds CC5 and those where it does not.

The formulation of the equation influencing the speed and acceleration of a vehicle within the Wiedemann car-following model has been a subject of ongoing debate among researchers. This debate arises primarily from the closed-source nature of the software, where the developer company has declared that the equations are embedded in the closed-source code and vary based on the longitudinal behaviour states mentioned earlier. Despite efforts by researchers to derive these equations using Wiedemann's PhD thesis (as seen in works by Gao and Rakha, 2008; Zhu et al., 2018), there is currently no conclusive evidence that these derived equations accurately represent the underlying equations utilised in the model. The specific formulation of the equation is provided below:

$$u_n(t+\Delta t) = min\{ \begin{matrix} u_n(t) + 3.6 * \left(CC8 + \frac{CC8-CC9}{8} * u_n(t)\right)\Delta t, \\ 3.6 * \frac{s_n(t)-CC0-L_{n-1}}{u_n(t)} \end{matrix}, u_f \} \quad (3.7)$$

Where the equation describes the speed (u_{next}=u_n) of the ego-vehicle in the next time step (t+Δt) within the Wiedemann car-following model. The components of the equation are defined as follows:

- U_{next} (δ, υ, Δx, u_{free}=u_f, L): Speed of the ego-vehicle in the next time step.
- Δx(t): Space headway between the ego vehicle and the preceding vehicle at time t.
- u(t): Speed of the ego-vehicle in the current simulation time step
- u_f: Space-mean traffic stream free-flow speed in km/hour.
- L_{n-1}: Length of the preceding vehicle.
- δ: Dummy variable, equal to 1 if u>CC8, and 0 otherwise.
- CC8, CC9, CC0: Defined parameter following the descriptions in Table 3.1

Equation (3.7) exhibits a dual nature, indicating that the vehicle speed in VISSIM is determined as the minimum of two distinct speeds. The upper segment within the bracket's accounts for the constraints on vehicle acceleration, grounded in the kinematic characteristics of the vehicle itself. Notably, parameters such as CC8 embody a linear relationship between speed and acceleration within a vehicle kinematics model. For instance, CC8 denotes the maximum vehicle acceleration at a speed of 0 km/h, while CC9 signifies the maximum vehicle acceleration at a speed of 80 km/h, both expressed in m/s^2.

Conversely, the lower portion of the bracket in Equation (3.5) corresponds to a steady-state car-following model. This dual formulation encompasses both the inherent acceleration limitations of the vehicle and the effects of steady-state car-following dynamics, offering a comprehensive depiction of the factors influencing vehicle speed within the VISSIM simulation framework.

VISSIM operates as a time-step-based simulation software, wherein the state of simulation vehicles undergoes updates at predefined time intervals. The simulation frequency, denoting the rate at which these updates occur, significantly influences the level of detail and accuracy achieved in the simulation. In alignment with prevailing literature practices, a simulation frequency of 10 Hz is adopted for this thesis. The software utilises the provided thresholds and equations to compute the speed and subsequent acceleration for each vehicle within the simulated network.

Vehicle lateral behaviour, specifically lane changing, within a motorway environment in VISSIM is categorised into two primary types: necessary (mandatory) lane changes and free lane changes. Necessary lane changes occur to facilitate progression to the next link (segment) of a pre-defined route. The associated driving behaviour parameters for this category encompass the maximum acceptable deceleration for the lane-changing vehicle and its follower in the target lane. The target lane is defined as the lane into which the vehicle intends to move.

Conversely, free lane changes are undertaken to gain speed advantages or additional space. The occurrence of this type of lane change is contingent upon maintaining the desired safety distance in the target lane. The desired safety distance is determined by considering the speed of the lane-changing vehicle and the preceding vehicle in the target lane. The user lacks influence over the aggressiveness of free lane changes, i.e., the frequency with which a driver opts to perform them. However, the user can impact free lane changes by adjusting the safety distance.

In both types of lane changes, the vehicle must identify a suitable gap in the direction of travel. The size of the gap is influenced by the speeds of both the lane-changing vehicle and the vehicle approaching from behind in the target lane. VISSIM provides several user-adjustable parameters governing lane-changing behaviour, with the most pertinent parameters for this study presented in the Table 3.2 below.

Table 3.2: Lane changing parameters in PTV VISSIM (adjusted from PTV VISSIM Manual Handbook (PTV Vission, 2011).

Element	Description
Diffusion Time	The maximum duration a vehicle can wait at the emergency stop distance for a necessary lane change. An emergency stop occurs when a suitable gap for a necessary lane change is not detected. When this time limit is reached, the vehicle is removed from the network, and a warning is logged (for this reason the simulation run more than it is needed).
Min. Headway	The minimum distance required between two vehicles after a lane change, ensuring the change can take place (default value 0.5 m). This parameter might demand a greater minimum distance during normal traffic flow to maintain speed-dependent safety distances.
To Slower Lane If Collision Time Is Above	Applicable only for Slow Lane rule or Fast Lane rule. Defines the minimum distance to a vehicle in front (in seconds) on the slower lane, prompting an overtaking vehicle to switch to the slower lane (the phrase "above" refers to the collision time exceeding a defined threshold).
Safety Distance Reduction Factor	A factor considered for each lane change, impacting parameters such as the safety distance of the trailing vehicle on the new lane, the safety distance of the lane changer, and the distance to the preceding, slower lane changer. VISSIM reduces the safety distance during a lane change by the specified factor (default value 0.6, reducing the safety distance by 40%). After completing the lane change, the original safety distance is reinstated.
Cooperative Lane Change	If a vehicle observes that a leading vehicle on the adjacent lane intends to change lanes, it may attempt a lane change itself to facilitate the lane change for the leading vehicle. For example, a vehicle might switch lanes to allow a merging vehicle to change lanes.
Maximum Deceleration for Cooperative Braking	Specifies the extent to which a trailing vehicle brakes cooperatively to allow a preceding vehicle to change lanes into its own lane.
Overtake Reduced	If selected, vehicles immediately upstream of a reduced speed area may perform a free lane change. If not selected, vehicles never initiate a free lane change directly upstream of a reduced speed area.
Advanced Merging	If selected, vehicles can perform lane changes earlier, increasing capacity and reducing the likelihood of vehicles coming to a stop to wait for a gap.

The calibration of lateral and lane-changing behaviour in a vehicle within a traffic microsimulation software is a challenging task. This challenge arises from the fact that certain parameters derived from high-level observations of driver behaviour in a network may not reflect the behaviour of all drivers in the network. Moreover, parameters such as the safety distance reduction factor, commonly used in existing literature for calibrating lane-changing behaviour, present difficulties in obtaining sufficient real-world data for calibration. Ideally, this data should consist of naturalistic driving data coupled with radar data, encompassing a large and representative sample of drivers in various lane change scenarios. As a result, a significant portion of the existing literature mainly focuses on calibrating car-following parameters (Habtemichael & Santos, 2013), which were also followed for this research.

3.5.4 Microsimulation Model Calibration

Calibrating a microscopic traffic model is an essential step to accurately represent a network's traffic characteristics and driver behaviour. This process is crucial to providing reliable experimental results. To achieve the desired real-world representation, a wide range of simulation parameters can be adapted. Calibration and validation are interconnected concepts that are often performed concurrently. Both endeavours focus on aligning simulated outputs with actual real-life field data. After these two stages, the verification concept is included, using an instrumented vehicle to acquire authentic ground truth data.

Validation assesses whether the model assumptions effectively replicate vehicle behaviours, ensuring an accurate representation of real-world driving patterns (Alterawi, 2014). Calibration involves the review and adjustment of parameters in the traffic microsimulation model to accurately reproduce real-world network dynamics, road traffic conditions, and constraints (Dowling et al., 2004; B. Park & Schneeberger, 2003). The primary objective of calibration is to refine the model's realistic depiction by modifying simulation parameters if necessary. This process aims to minimise discrepancies between measured real-life field data and simulated data, mitigating the risk of misleading assessment results. Consequently, calibration and validation procedures are typically conducted for traffic flow counts and travel times.

As part of the microsimulation development process outlined in this PhD study, various parameters were taken into consideration while constructing the baseline traffic model in VISSIM. These parameters included speed distributions, car following attributes, and areas with reduced speed. It is important to note that precise and dependable results can be obtained by calibrating the model based on real-world data. The calibration process in this PhD research was divided into two distinct stages: geometric calibration and traffic characteristics calibration of the traffic microsimulation model.

The simulation model must accurately replicate the field topology, taking into account the aerial photograph of the road network and the precision of intersections during development. The attributes of the pilot network, such as the number of lanes and approaches, segment length and width, curvatures, and designated turns at intersections, should match the real-world road segment and intersection characteristics. To ensure accuracy, the simulated model is overlaid on an aerial photograph of the selected road network. Moreover, on-site inspections are carried out to confirm the actual configuration of the road segment, implementations of available signalised intersections, and the locations of signal heads.

3.5.5 Calibration Methodology

A comprehensive framework outlining the calibration methodology for traffic characteristics is depicted in the flowchart presented in the Figure 3.13 below. This iterative process can be conceptualised as an optimisation problem, aiming to minimise the disparity between observed and corresponding simulated measurements. Following the completion of simulation network coding and geographical calibration, an empirical analysis is conducted to assess the adequacy of the currently employed default parameters in VISSIM. The assessment utilises the GEH (Geoffrey H. Havers) statistic, formulated by Geoffrey E. Havers in the 1970s (Shankar, Prasad, and Reddy, 2013). The GEH statistic, a non-linear empirical method, is commonly employed in traffic evaluations to compare two sets of traffic volume.

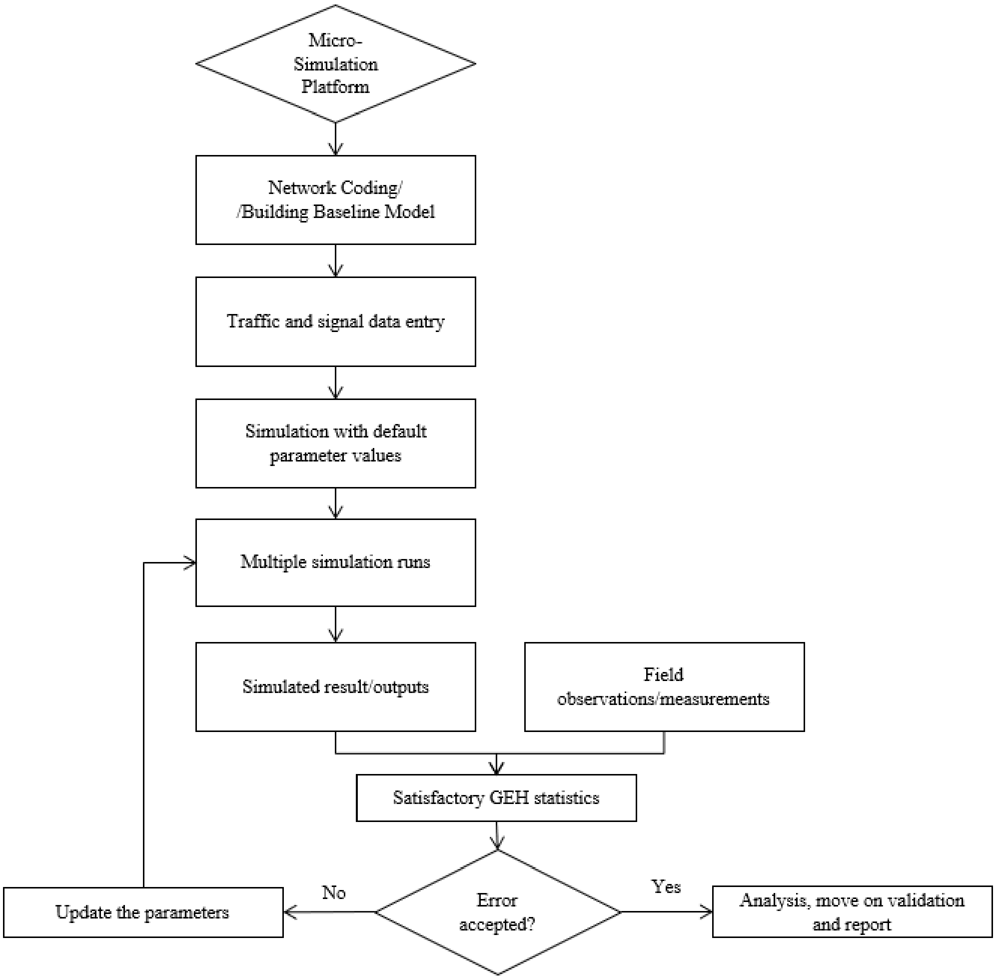


Figure 3.13: The calibration process of traffic microsimulation model

As illustrated in Figure 3.13, the calibration process starts with the default settings established by the microsimulation software. Subsequently, predetermined traffic counts and signalisation data are input into the simulation model in appropriate formats. Multiple simulation runs are then executed to acquire the corresponding simulated dataset of outputs, which is later compared with real-world measurements. If the GEH (Geoffrey H. Havers) statistic falls within an acceptable range, it indicates successful calibration, and the process of calibration is finishing to continue into validation part (Dowling et al., 2004). Validation of the model can be further conducted using another dataset derived from the initial field data. However, if the GEH statistic is unsatisfactory, the calibration procedure must be iterated. This involves modifying the desired distributions of key variables in the microsimulation model, such as adjusting the number of inputted vehicles or updating speed distributions or even changing some parameters in the driving behaviour model. The GEH statistic, used to quantify the traffic characteristics of the traffic model, is defined by Equation 3.8 (Washington State Department of Transportation, 2014) .

$$GEH = \sqrt{\frac{2(O-E)^2}{O+E}} \quad (3.8)$$

where:

- GEH is the calculated GEH statistic.
- O is the observed value or measurement from the real-world data.
- E is the expected or simulated value from the microsimulation model.

In accordance with the guidelines established by the Federal Highway Administration (FHWA) (Dowling et al., 2004) the GEH values are considered acceptable if they are consistently below 5 for over 85% of the analysed pairs of traffic flow, indicating that the traffic flow inputs do not necessitate further parameter adjustment. Conversely, for travel time calibration, the simulated values are deemed satisfactory if they fall within a range of ±15% of the measured values for over 85% of the analysed pairs, signifying a good fit (Dowling et al., 2004). All other measurements that deviate from these criteria suggest a lack of a good fit, indicating that the calibration process needs to be repeated.

To implement an effective calibration approach, it is advised to evaluate at least two types of Mobility Performance Measures (MOEs), such as traffic volume, travel speed, or travel time. These MOEs are crucial as they significantly influence the operational characteristics of the road network, including traffic density and delay. In the study all three are calculated for a concrete result. Moreover, the ground-truth data for these MOEs can be readily obtained. In this research, the GEH Statistic is employed to calibrate and validate both traffic flow and travel time. Ensuring alignment between the input values of these MOEs and the simulation outputs of the microsimulation model is essential for achieving a well-calibrated traffic model.

In consideration of the stochastic nature of the model, random seed values were employed during the collection of simulation model outputs. Initially, a default seed number is assigned by the microsimulation software to the generated model, started from 42. Various random seed numbers are then systematically utilised to observe potential random occurrences resulting from multiple simulation runs. Consequently, the simulation model is executed multiple times, each with a different seed number, as this variation yields diverse results. The performance of these runs is averaged to elucidate the randomised vehicle and driver characteristics. A greater number of simulations runs lead to a diminished impact and variation of any atypical run. Therefore, the determination of the runs needed to achieve a 95% confidence interval level for the simulated outputs can be estimated using Equation 3.9. This equation provides a prediction of the mean with a confidence interval and an acceptable error range.

$$N = \left(\frac{t_{\frac{a}{2}} * \sigma}{E}\right)^2 \quad (3.9)$$

Where:

- N is the number of runs.
- $t_{\frac{a}{2}}$ is the value from the t-distribution for a 95% level of confidence a
- σ is the standard deviation .
- E is the acceptable error range

The developed models are calibrated based on 24-hour data between 00:00 a.m. and 23:59 p.m. next day. The determination of the required number of simulation iterations (runs) to achieve a 95% confidence interval level for the simulation output is calculated using Equation (3.21). Through an iterative simulation run, the output's standard deviation is computed, and the critical t-value is determined based on the desired 95% confidence interval. The critical value for a two-sided error at a 5% significance level with N−1 degrees of freedom is identified from the t-test table. Consequently, the degrees of freedom are established as nine, leading to the determination of N as ten for the number of required simulations runs. The 9 degrees of freedom result from using N=10 simulation runs, where degrees of freedom are calculated as N−1, accounting for the loss of one degree due to estimating the sample mean. In accordance with these considerations, a minimum of ten simulation runs should be sufficient for calibration and validation purposes. The details of the calibration calculations involving GEH statistics and their outcomes are expounded in the subsequent chapter.

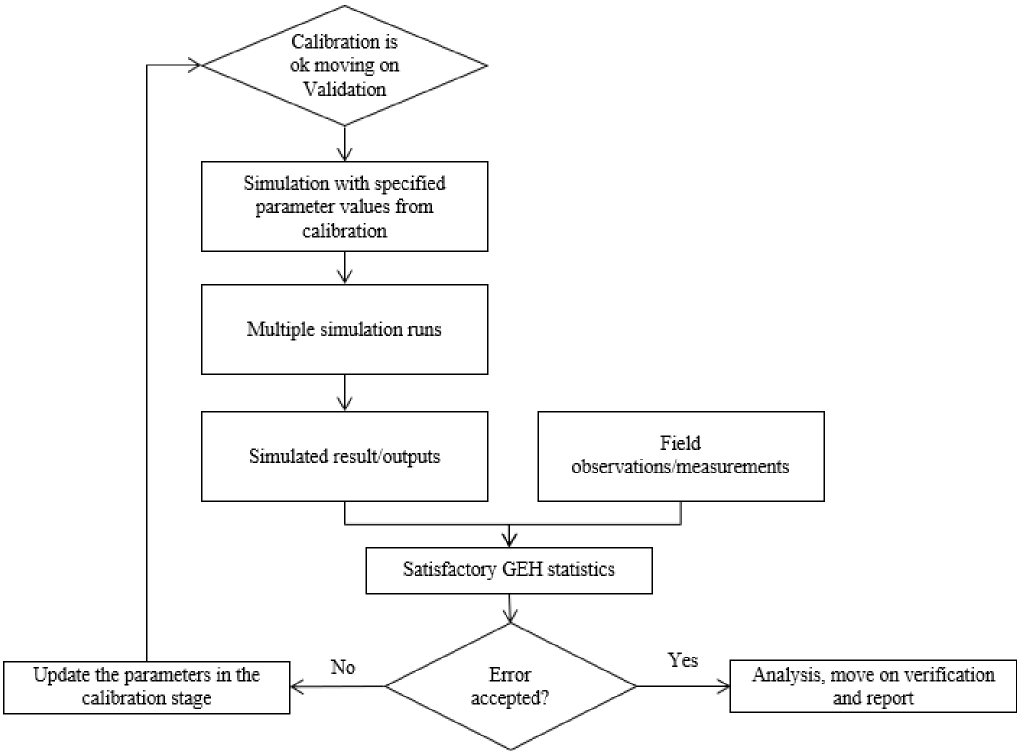


Figure 3.14:The validation process of traffic microsimulation model

The validation process, the second stage, adhered to a similar methodology for the remaining 20% of the dataset, involving the recalculation of GEH statistics, as shown in Figure 3.14. Subsequently, the third stage encompassed the verification phase, utilising data from the instrumental vehicle to compare travel times through the application of the non-parametric Mann-Whitney U test, as shown in Figure 3.15.

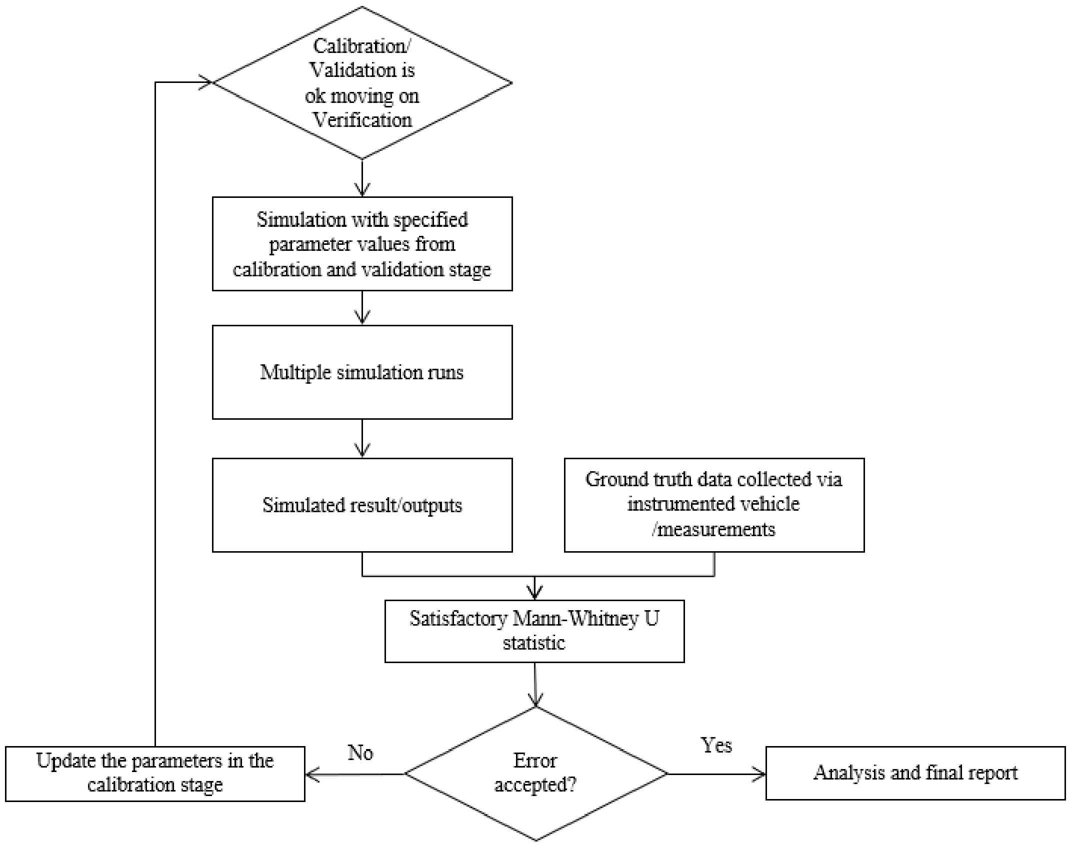


Figure 3.15: The verification process of traffic microsimulation model

In equation (3.10) U is the Mann-Whitney U statistic, n1 the sample size of the first sample, n2 the size of the second sample and Ri the rank of the sample size. The smaller value of U_1 and U_2 is the one used when consulting significance tables. Same as above, the data collection procedure and the result of the third stage of the calibration are presented in Chapter 5.

$$U = n_1 * n_2 + \frac{n_{2*}(n_2+1)}{1} - \sum_{i=n_1}^{n_2} R_i \quad (3.10)$$

The chosen safety metric for this study is the distribution of travel times for vehicles across all possible Origin-Destination (O-D) trips. The simulation platform was utilised to calculate all feasible trips for both directions, incorporating real-time traffic data to determine O-D pairs, travel speeds, and subsequently, travel times between O-D points. These simulated results were then compared with the travel data collected from the instrumented vehicle provided by Loughborough University for the research. The statistical assessment utilised the non-parametric Mann-Whitney U test, selected for its appropriateness when normal distribution assumptions cannot be assumed for the two distributions being compared. The null hypothesis for this test is articulated as follows:

- h_0: The distributions of both populations are equal.
- h_a: The distributions are not equal.

The test involves the computation of the U statistic, whose distribution under the null hypothesis is known. Depending on the value of the U statistic, conclusions can be drawn to either reject or fail to reject the null hypothesis.

In Equation 3.10, U represents the Mann-Whitney U statistic, n_1 is the sample size of the first sample, n_2 is the size of the second sample, and R_i denotes the rank of the sample size. The data collection procedure and the outcomes of the third stage of the calibration are detailed in Chapter 5.

3.6 Part C: CV Driving Behaviour and Incident Detection

In Section 3.5.1, a study was conducted to analyse the driving behaviour of humans in VISSIM. The analysis categorised human driving behaviour based on the type of movement - either longitudinal or lateral. However, CVs are complex entities that are governed by multiple subsystems that affect their movements (N. Lu et al., 2014; Rahman & Abdel-Aty, 2018c, 2018a). Despite being operated by humans, CVs rely on advanced subsystems, which makes it necessary to use driver models that differ from those used for conventional human-driven vehicles (Abdelkader et al., 2021). Therefore, it is crucial to program the behaviour of CVs in a way that aligns closely with the intricate operations of these subsystems.

As there is no to real-world data for calibrating the Wiedemann '99 car-following model parameters in the traffic simulation, the default or common values that are often applied in traffic simulation studies can be used. For better results though concerning the driving behaviour of CVs and several testing have been conducting and presenting in Chapter 6 to manage less average vehicle delays for CVs.

It is important to note that the values of CV parameters are dependent on the specific CV technology being used, its capabilities, and the desired simulated behaviour. During the calibration and validation process, these values can be fine-tuned to ensure that the behaviour of CVs in the simulation aligns accurately with the intended real-world behaviour. Thoughtful and iterative adjustment of these parameters is essential to achieve a simulation model that accurately reflects the intricacies of CV dynamics.

3.6.1 Calibrating and Validating Connected Vehicle Behaviour

Calibrating and validating the behaviour of CVs in a traffic simulation can be challenging, especially when real-world data is not available. However, a systematic approach can be used to overcome this challenge. The methodological framework involves leveraging expert insights, best practices, and hypothetical scenarios to ensure that the simulation accurately reflects the intended real-world behaviour of the CVs.

A set of hypothetical traffic scenarios is designed to calibrate simulations that replicate various conditions, including highway traffic and lane changes. The calibration process involves adjusting parameters to ensure that the simulated behaviour of CVs matches the intended real-world behaviour. Additionally, sensitivity analyses are systematically conducted to understand the individual effects of parameters on connected vehicle behaviour. To assess the accuracy of the simulation, validation metrics and criteria are defined, covering factors such as following distances, traffic flow, lane change frequency, and safety-related measures. Different validation scenarios, distinct from those used during calibration, are developed to evaluate the model's accuracy under new conditions. The model and parameter values are continuously refined based on results from validation scenarios and insights derived from sensitivity analyses. Throughout the calibration and validation processes, comprehensive documentation is maintained to ensure transparency and reproducibility.

To summarise, while real-world data is extremely helpful for calibration and validation purposes, following these systematic steps can refine the connected vehicle behaviour model to closely match real-world behaviour even when real-world data is not available. It is important to recognise that the model is still an approximation, and the quality of results depends on the thoroughness of calibration and validation efforts. Chapter 5 will provide a detailed explanation and presentation of all the results from the creation and adaptation of CVs in the simulation model.

3.6.2 Incident Detection Algorithm

Once all the necessary steps for creating CV driving behaviour are specified, it is essential to develop an Incident Detection (ID) Algorithm. This algorithm will help examine the impact of CVs on motorways in the event of an incident. Facilitating the development of the CV control algorithm, API of PTV VISSIM is used in the context of Incident Detection. This API is known as the External Driver Model Dynamic Link Library (DLL) interface, which enables users to entirely replace the internal behaviour of vehicles, even in the event of an interruption. The replacement can be customized to match user-defined behaviours for specific vehicle types or across all simulated vehicles. The API is a robust framework that is scripted in C/C++ and typically compiled using Microsoft Visual Studio. It provides users with specific functions, which are detailed in the documentation provided by PTV AG, 2010(ref). The incorporation of this API offers users a versatile platform to customize CV driving behaviour and Incident detection control algorithms within the VISSIM simulation environment.

During each simulation step, VISSIM interacts with the API code for every vehicle assigned to the API code. VISSIM sends the current state of the vehicle and its surroundings to the API code, which computes the acceleration/deceleration and lateral behaviour (lane changes) of the vehicle. The API code then sends back these calculations to VISSIM to be immediately applied in the ongoing time step. The developed API can be linked to a specific vehicle type in the simulation software by selecting the corresponding option in VISSIM's graphical user interface. This means that the incident detection algorithm can be assigned to be used by CV. The developed algorithm was linked to a specific CV type that shares geometric similarities with a conventional vehicle. Calibration was carried out by examining the CV driving behaviour while the incident detection algorithm was in use to capture their behaviour accurately using the average vehicle delay. This was crucial as there is a lack of available real-world values in existing literature. The results of this methodology will be presented in Chapter 5.

The API comprises three primary functions, with the initial one being DriverModelSetValue. This function is tasked with reading the current value of data items from VISSIM, as denoted by the type, and indexed by operators index1 and index2. The value, conveyed to the API as a long (integer), double (decimal), or string (text), is stored for potential future calculations. The function is required to return 1 if the API utilises the value; otherwise, it should return 0. Through this function, several variables can be extracted from VISSIM for the vehicle controlled by the API, as showed in Table 3.3:

Table 3.3: Variables extracted from VISSIM for the CV driving behaviour (description from (PTV Vissim, 2011; Vision, 2009b; Washington State Department of Transportation, 2014)*).*

Parameter	**Description**
Vehicle Path	Path followed by the vehicle
Simulation Frequency	Rate at which the simulation is updated
Current Simulation Time	Current time within the simulation
Vehicle ID	Unique identifier for the vehicle
Current Lane	Lane in which the vehicle is currently positioned
Odometer Reading	Total distance travelled by the vehicle
Lane Angle	Angle of the lane with respect to a reference axis
Lateral Position	Horizontal position of the vehicle within its lane
Speed	Current speed of the vehicle

Acceleration	Rate of change of velocity
Vehicle Geometric Characteristics	Dimensions and shape of the vehicle
Max Allowed Acceleration	Maximum allowable rate of acceleration
Desired Speed	Target speed for the vehicle
Vehicle Colour	Colour of the vehicle
Nearby Vehicles ID	Identifiers of vehicles in proximity
Nearby Vehicles Geometric Characteristics	Dimensions and shape of nearby vehicles
Active Lane Change	Indicator if the vehicle is currently changing lanes
Nearby Vehicles Distance	Distance between the vehicle and nearby vehicles
Nearby Vehicles Velocity	Speed of nearby vehicles
Number of Lanes in Current Link	Total number of lanes in the current road or link
Desired Acceleration	Target acceleration for the vehicle

The function named "DriverModelGetValue" is used by VISSIM to extract values of data items that are identified by type and indexed by index1 and index2. This function should return 1 when the value is intended to be sent to VISSIM. The important variables sent back to VISSIM from the API include the desired acceleration, which is responsible for controlling the vehicle's longitudinal movement, and the active lane integer variable, which governs the lane-changing dynamics of the vehicle. When the vehicles assigned to follow the Incident Detection algorithm pass the location of the incident, they stop receiving information from the algorithm, and their route and behaviour return to normal as if no incident has occurred.

The DriverModelExecuteCommand function is responsible for all computations carried out by the API. It consists of three primary commands: V2V_HasCurrentMessage, Vehicle_Type_C2X_no_message, and V2V_SendingMessage. Vehicle_Type_C2X_no_message is executed at the beginning of a VISSIM simulation run to initialize the driver model API. At the same time, the DriverModelSetValue and DriverModelGetValue functions are used to obtain the initial readings from the simulation software. After that, the V2V_SendingMessage command is executed whenever there is an incident in the VISSIM network, and V2V_SendingMessage is activated. Like the Vehicle_Type_C2X_no_message command, the other two functions are used to get measurements for any new driving behaviour introduced in case of an incident. The V2V_SendingMessage command is called from VISSIM when a vehicle with V2V capabilities reaches the incident location, activating the V2V_HasCurrentMessage command for all CVs. Finally, the most critical function among the aforementioned is the V2V_HasCurrentMessage function, which takes care of all the calculations for the vehicles controlled by the API. This command is triggered by the API at each simulation step, systematically computing the kinematic characteristics of the vehicles equipped with V2V technologies, specifically acceleration/deceleration and active lane changes.

Enabling the model to have V2V connectivity capabilities, the External Driver Model Application Programming Interface (API COM) is used to enhance the incident detection process by incorporating different CV MPRs. The pseudo-code of the V2V connectivity algorithm used to simulate an incident and utilise V2V technology in the CV environment is presented in Algorithm (1). You can find **Algorithm (1)** in full at the end of the thesis, and more information about Incident Detection will be presented in Chapter 6.

```
Algorithm (1)
Input:
Global parameters:  distDistr=distance distribution, Vehicle_Type_C2X_no_message=vehicles
with no active C2X,Vehicle_Type_C2X_HasCurrentMessage=vehicles with active C2X,
Vehicle Attributes = 'Pos'  'VehTyp' 'C2X_HasCurrentMessage'
 'C2X_MessageOrigin'  'C2X_Messag'  'DesSpeed'  'C2X_DesSpeed01'  'Lane' )
Vissim.Net.Vehicles = all vehicles in VISSIM
Output:
Veh_Rec_Message
DEFINE Initialization():
    SET global Parameters
DEFINE FUNCTION Main():
    SET Veh_attributes TO Vissim.Net.Vehicles.GetMultipleAttributes
    IF Veh_attributes:
       SET Veh_C2X_attributes TO Vehicle_Type_C2X_no_message or
              Vehicle_Type_C2X_HasCurrentMessage
          FOR all C2X vehicles
            IF Veh_C2X_attributes = 'PARKING' + Veh_C2X_attributes = to parking routing
            decision
                SET Veh_sending_Msg
                SET Coord_Veh, Position
                SET Pos_Veh_SM TO Veh_sending_Msg
                SET Attribute Values to Veh_sending_Msg
SET Veh_Rec_Message TO Vissim.Net.Vehicles
     SET Attributes TO all Vehicles who are receiving the C2X message
FOR all C2X vehicles
     SET new Veh.attributes
              IF vehicle has C2X + is in correct communication range
                   SET speed = speed_incident
              SET correct Attributes
                   IF C2X_msg_active and position current > C2X Position
                       SET Veh_attributes to old ones
                   ELSE:
                       SET Veh_attributes to current one
                 END IF
```

3.6.3 Safety Impact of the developed CV algorithm

Following the definition of participating simulation vehicles, algorithms, and proposed experiment, the subsequent step involves discussing the conflict identification process for assessing the safety impact of the developed Connected Vehicle (CV) algorithms, except of the mobility impact.

As outlined in Section 2.3 of the literature, a widely adopted approach for safety evaluation entails the identification of conflicts using traffic microsimulation data. This is typically achieved through a post-processing software developed by the Federal Highway Administration of the United States, known as the Surrogate Safety Assessment Model (SSAM) (Gettman et al., 2008; Katrakazas et al., 2019b; Z. Wu et al., 2013). VISSIM has the capability to generate binary trajectory files, encapsulating information about the trajectory followed by each vehicle during a single simulation run. To utilise this feature, users must select the corresponding Surrogate Safety Assessment Model (SSAM) option within the graphical user interface of SSAM.

The data embedded in the trajectory file are in raw, unprocessed form and encompass details about the geographical location of all vehicles at each simulation step, along with vehicle kinematics data such as speed, acceleration, and heading (direction of movement). Given its binary form, this trajectory file cannot be interpreted by a standard text editor. SSAM can interpret the trajectory files produced by VISSIM, calculating surrogate safety measures for each vehicle-to-vehicle interaction. It then determines whether the interaction satisfies the criteria to be officially categorised as a conflict. The software relies on two key threshold values for surrogate safety measures: Time to Collision (TTC) and Post-encroachment Time (PET). The default threshold values within SSAM are 1.5 seconds for TTC, and 5 seconds for PET, originally suggested by Hydén in 1987. This research thesis used the same threshold values, as current researches do as well. SSAM thoroughly examines each simulation step to identify vehicle interactions where predefined thresholds are breached. In addition to these thresholds, the software employs various algorithms to validate the occurrence and count of a conflict. The flowchart depicting the formulation process of the traffic conflict dataset is presented in Figure 3.16.

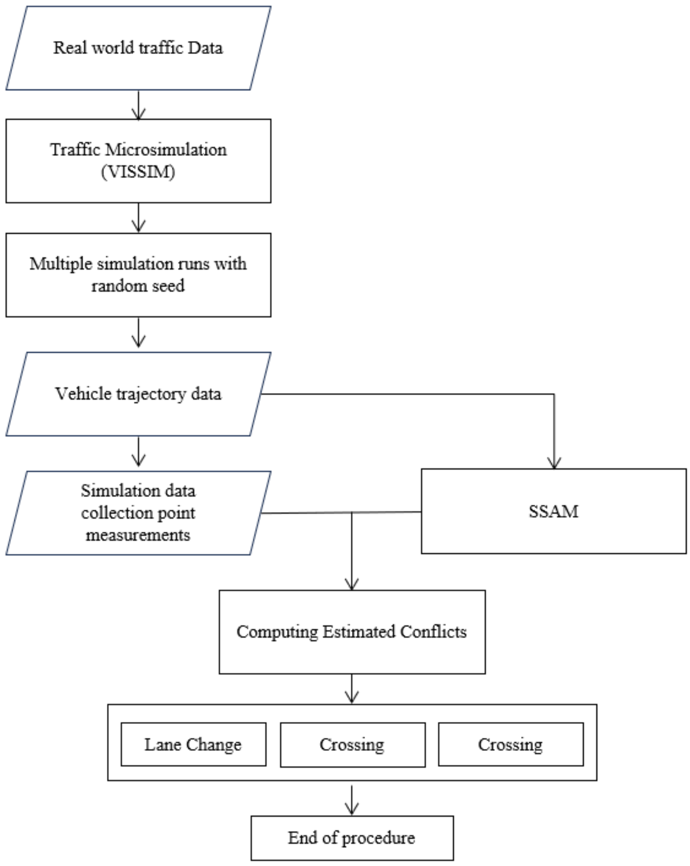


Figure 3.16: Process followed for conflicts calculations.

3.7 Summary

The proposed experiment aims to detect incidents early and safely to prevent dangerous situations and reduce traffic congestion by using innovative alternatives such as the V2V connectivity application. The experiment aims to make real-time detection of stopped vehicles more reliable than ever, thus enhancing the mobility and safety of the motorway. For the simulation, real road map data of an area around the M1 motorway will be used as the baseline scenario. Several optimal scenarios will be created, analysed, and examined in the following chapters.

This section concluded information about the methodology followed for this research. The research design, concept and challenges discussed and analysed. The main and crucial methodology followed was structured into 4 main sections named as:

1. Part A: Analysing and Modelling Incidents
2. Part B: Simulation Network Model
3. Part C: CV Driving Behaviour and Incident Detection

The following sections provide a detailed explanation of the procedural steps, along with corresponding results that will be disseminated across Chapters 4, 5, and 6. The foundational component of this research involves the definition of appropriate scenarios for examination. Chapter 4 will explain the data integration and analysis tools used to calculate incident data, such as duration, location, frequency, and traffic data. This will ensure the methodological precision of the research, along with field data collected via an instrumented vehicle. The next phase will involve the establishment of a data analysis framework and the development of a traffic microsimulation case study model. Chapter 5 will provide comprehensive details concerning the study area, calibration results, the methodology governing incident simulation, and the processes involved in incident generation. The forthcoming chapter will expound upon this exhaustive examination. Within Chapter 6, prominence will be given to the calibration results pertinent to the driving behaviour of Connected Vehicles. Furthermore, intricate insights into the relevant and utilised driving behaviours will be expounded upon later in the same chapter. Building upon the insights derived from this information, the incident detection algorithm and the formulation/analysis of representative scenarios will transpire in Chapter 6 as well. This chapter will also include the inclusion of incident detection results. Finally, Chapters 7 and 8 will include the Conclusion and Discussion, respectively, while the References and Appendix will follow.

Chapter 4. Data Collection and Integration Architecture

4.1 Introduction

As outlined in the Methodology section of Chapter 3, the successful development and execution of a traffic microsimulation experiment depends on the availability of necessary data and key performance indicators (KPIs). For this reason, the development and analysis of a traffic microsimulation model necessitate well-organised steps. Firstly, the need to collect and process data, from all fields needed is a critical step in this. It is widely known that, utilising real-world field data is a fundamental component for constructing a calibrated model, able to replicate reliable and accurate traffic conditions. To this end, the chapter provides a detailed explanation for the data acquisition and analysis, outlining the traffic and incident characteristics. This chapter mainly aims to explain the actual traffic and incident data used to create and fine-tune the traffic simulation model for the road network. The collected data include information related to the geographical configuration of the network, traffic flow and speed, and traffic signal settings as well as incident data, crucial inputs for the subsequent stages of traffic microsimulation, calibration stage and incident detection.

Highway traffic incidents are often characterised as outliers or anomalies within the traffic stream. Anomaly Intrusion Detection (AID) algorithms aim to recognise such deviations by leveraging real-time traffic data, supplemented by historical data when available. AID algorithms can be primarily classified into two categories based on the adopted methodology:

1. Real-time traffic data is correlated with the traffic data observed in the immediate past to identify abnormalities that can be classified as incidents.
2. Historical traffic data is utilised to establish "normal" traffic patterns, with significant deviations from these standard patterns being classified as incidents.

This chapter begins with an introduction to understanding traffic data and incidents, emphasising their characteristics within the motorway study area. This lays the foundation for the development of the incident detection scenario within the traffic microsimulation platform. Subsequently, the chapter provides in-depth details on the real-world motorway and naturalistic driving data utilised in this PhD study, encompassing Inductive Loop Detector (ILDs) data (referred to as Traffic Data) and Incident data. Additionally, it offers insights into the analysis of these datasets, crucial for the accurate development of the Traffic Microsimulation Model in VISSIM. Furthermore, it provides a critical understanding of the study area's limitations.

The focus then transitions to the acquisition of datasets, thoroughly exploring Traffic Data, Incident Data, and Field Observation Data. The gathered data includes key elements such as the geographical configuration of the network, traffic flow, traffic speed, and traffic signal settings. These components serve as imperative inputs for subsequent phases of traffic microsimulation, including calibration and validation processes. The chapter not only addresses dataset acquisition but also extends its exploration to the Simulation Network Model where more information will be given in chapter 6. The goal is to design a model that authentically mirrors real-world traffic conditions and driver behaviours with a discernible degree of accuracy, incorporating detailed calibration and validation methodologies to ensure precision in the simulation results. Throughout, this chapter offers a comprehensive overview of data architecture and its acquisition within the specific context of incident modelling and detection.

4.2 Methodology for understanding traffic incidents and their characteristics

This chapter introduces a methodological framework including the understanding of traffic incidents and their characteristics. It begins by establishing a comprehensive understanding of the nature and attributes of traffic incidents, identifying key performance indicators (KPIs) crucial for subsequent analysis. The subsequent methodology involves the systematic collection and processing of diverse datasets, including Field Observation data, MIDAS data, and incident data. Through statistical analysis, the distribution characteristics of the collected data are defined, providing valuable insights into patterns and trends. Moreover, specific attention is given to incident details such as location, frequency, and duration. The main goal is to use this valuable information to create a microsimulation model, ensuring an accurate and data-driven representation of traffic incidents within the simulation environment. For this reason, the steps followed for this achievement can be seen in Figure 4.1.

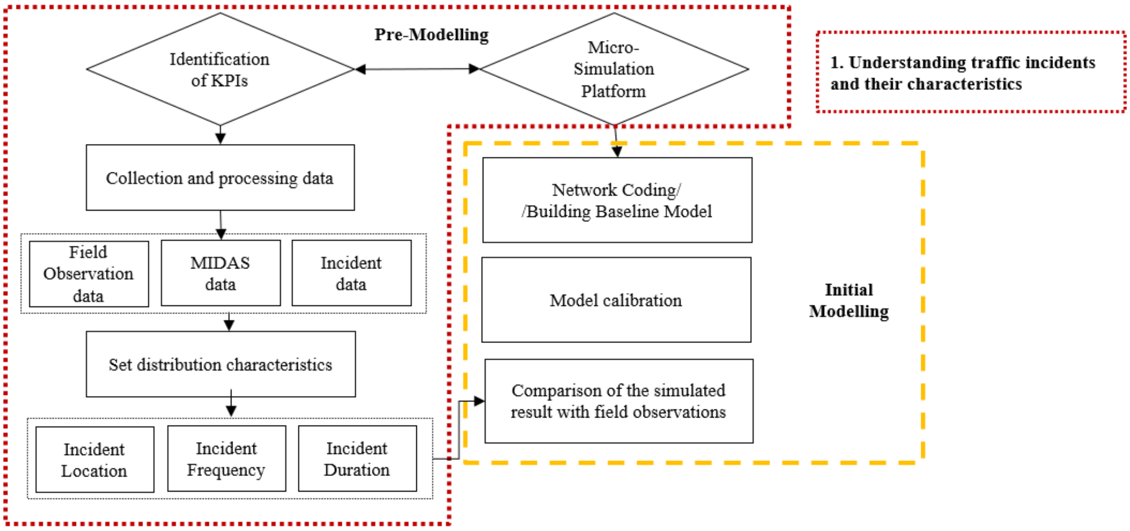


Figure 4.1: Data collection and integration methodology

As analysed in Chapter 3 the simulation process starts with pre-modelling, defining aims and objectives. To this end, this stage establishes the baseline traffic model and identifies scenarios for examination (Daamen et al., 2014). Decisions regarding location, time, frequency of incidents and network performance, are crucial and require careful planning. The second stage involves identifying necessary field data and making model assumptions based on chosen measures of effectiveness (MOEs). MOEs, such as travel time and speed, quantify traffic operation performance (Washington State Department of Transportation, 2014).

4.3 Datasets Acquisition

As mentioned above, the microsimulation platform of VISSIM needs field data to be able to replicate the baseline model accurately. The gained knowledge through data analysis depends not only on the chosen methodology but are also significantly influenced by the data's quality. This is particularly critical in applications involving safety and conflict risk assessment, where the accuracy of data from sensing systems is vital for developing classifiers and evaluating their predictive capabilities. Various factors, such as missing values, data inconsistencies, and redundancy, can adversely affect data quality. As a result, collecting and pre-processing data are crucial stages in the research process. This chapter provides an overview of the data collection, its characteristics, and the limitations of the datasets used in achieving the third objective.

In this section, the data sources used in this research are presented. Two primary datasets, Motorway Incident Detection and Automatic Signalling (MIDAS) for traffic-related information and ControlWorks for incident data, were analysed. Motorway MIDAS encompasses traffic flow, speed, headway, and occupation, while ControlWorks provides incident details, like incident types, duration, location, and number of events. Additionally, traffic data collected via an instrumental vehicle are also including as they have been used in the verification of the simulation model. In the reminder of this section, it is being analytically discussed each dataset and their characteristics.

In general, MIDAS data refers to a system detector used for real-time monitoring and managing traffic on motorways in the United Kingdom, where inductive loop detectors collect traffic speed, volume, and occupancy data. ControlWorks is referring to incidents data collected by National Highways in England which provides detailed information on road traffic incident, including their type, location, date, time, and duration, and contributing factors. A descriptive analysis is performed to examine the frequency of incidents occurring on the M1 for both northbound and southbound directions. Field observation data collected in the period of September to November of 2021, with the help of a university instrumental vehicle equipped with all necessary sensors that will be analysed below.

4.3.1 Traffic Data

As mentioned, Traffic data includes data from Inductive Loop Detectors (ILDs). These detectors are strategically positioned along the motorways of the United Kingdom, particularly in densely populated areas, to capture data on traffic flow. An inductive loop detector functions as an electromagnetic detection system, employing a magnet to induce an electric current in an adjacent wire (*Inductive Loop Detectors*, 2019) . MIDAS, overseen by Mott MacDonald, one of National Highways' suppliers, is responsible for collecting this information. The loop detectors, installed beneath the motorway surface, identify the passage of vehicles. This system allows the collection, processing, and transmission of both dynamic and static traffic data, providing precise details on various parameters such as traffic flow, average speeds, and eventually the extent of traffic congestion. Each instance of vehicle detection results in a recorded measurement.

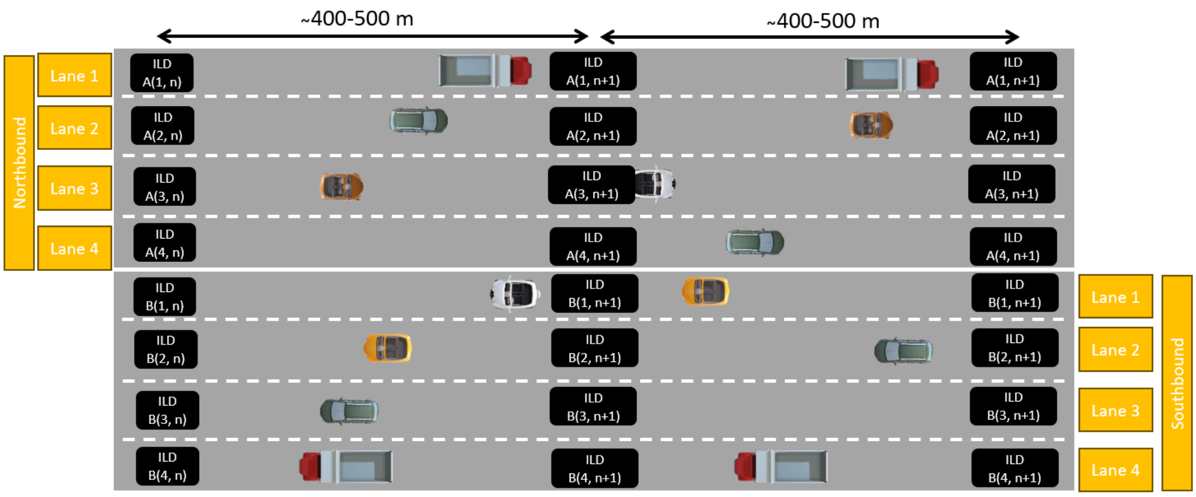


Figure 4.2:Inductive Loop Detectors along the motorway

Finally, the raw gathered data are aggregated to a minute-level detail. These loop detectors are typically positioned at the entries and exits of each junction and are evenly spaced along the motorway at intervals of approximately 400m-500m. Moreover, loop detectors are commonly situated at both entrance and exit points of each junction. Figure 4.2 provides a visual representation of the data collection process. Each loop detector captures traffic-related variables, including speed and flow measurements, every minute throughout the entire year. This information proves to be instrumental in monitoring traffic conditions, as the recorded data can be efficiently archived on hard drives. The data can be acquired in two formats: either on a lane-specific basis, denoted as ILD (2, n+1), or as an aggregate over a specific road segment, represented by ILD (1, n+1) and ILD (2, n+1), see Figure 4.2 . For the purposes of this research, data has been sourced from a total of approximately 170 loop detectors strategically positioned within the study area.

Additionally, this data can be further processed to extract information about traffic conditions on specific days, facilitating a deeper understanding and quantitative analysis of congestion patterns within the motorway network. In the context of this research, leveraging such data proves valuable as it offers parameters that can be compared and utilised in refining simulation parameters. Table 4.1 and Figure 4.3 below provide a comprehensive list and visual representation of the variables encompassed in the raw dataset, contributing to the attainment of the overall research objectives.

Table 4.1: Data from the inductive loop detector data

Variable Name	Description
Geographic Address	Name of the inductive loop detector
Date	Date of the observation
Time	Time of the observation (minute level)
Number of Lanes	Number of lanes at the position of the loop detector
Flow category per Lane	Traffic flow in each lane per vehicle category (veh)
Speed per Lane	Average speed of the vehicles that passed by the inductive loop detector during the time period (km/hour)
Flow per Lane	Traffic flow per lane (veh)
Occupancy per Lane	Average occupancy of the inductive loop detector per lane (%)
Headway per Lane	Average headway of the vehicles within the time period (m)

The vehicles are categorised in four categories according to the following's lengths:

- Category 1: Vehicle Length < 5.2 m
- Category 2: 5.2m < Vehicle Length < 6.6 m
- Category 3: 6.6 m < Vehicle Length < 11.6 m
- Category 4: Vehicle Length > 11.6 m

Alongside the main study motorway, there are 170 Loops Detectors, approximately 85 detectors in each direction. Additionally, 2018 and 2019 detector loop data have been analysed for M1, junctions 23-26, while the one from 2019 was used for the calibration and validation of the simulation model. The ILDs datasets have been analysed (refer to Figure 4.3) and the results will be shown in this chapter below.

Geographic Addre	CO Address	LCC Address	Transponder Addr	Device Address	Date	Time	Number of Lanes
3763A	62	7	17	225	01/01/2019	00:00	3
3763A	62	7	17	225	01/01/2019	00:01	3
3763A	62	7	17	225	01/01/2019	00:02	3
3763A	62	7	17	225	01/01/2019	00:03	3
3763A	62	7	17	225	01/01/2019	00:04	3
3763A	62	7	17	225	01/01/2019	00:05	3

Flow(Category 1)	Flow(Category 2)	Flow(Category 3)	Flow(Category 4)	Speed(Lane 1)	Speed(Lane 2)	Speed(Lane 3)
1	0	0	0	114	0	0
1	1	0	0	0	136	0
2	0	0	0	117	0	0
0	1	0	0	117	0	0
2	1	0	0	94	150	0
2	1	0	0	113	129	0
3	1	0	0	115	121	0
1	0	0	0	109	0	0
2	0	0	0	113	0	0
0	0	1	0	111	0	0
0	0	0	0	0	0	0

ancy(Lane 2	Occupancy(Lane 3	Occupancy(Lane 4	Occupancy(Lane 5	Occupancy(Lane 6	Occupancy(Lane 7	Headway(Lane 1)	Headway(Lane 2)	Headway(Lane 3)	Headway(Lane 4)
0	0	-1	-1	-1	-1	0	222	0	-1
0	0	-1	-1	-1	-1	245	0	0	-1
0	0	-1	-1	-1	-1	-1	0	0	-1
0	0	-1	-1	-1	-1	192	-1	0	-1
0	0	-1	-1	-1	-1	-1	-1	0	-1
0	0	-1	-1	-1	-1	187	-1	0	-1
0	0	-1	-1	-1	-1	198	0	0	-1
0	0	-1	-1	-1	-1	233	0	0	-1
0	0	-1	-1	-1	-1	-1	0	0	-1
0	0	-1	-1	-1	-1	0	0	0	-1
0	0	-1	-1	-1	-1	0	0	0	-1
0	0	-1	-1	-1	-1	151	-1	0	-1
0	0	-1	-1	-1	-1	0	0	0	-1
0	0	-1	-1	-1	-1	-1	0	0	-1
0	0	-1	-1	-1	-1	0	-1	0	-1
0	0	-1	-1	-1	-1	237	-1	0	-1
0	0	-1	-1	-1	-1	208	0	0	-1
0	0	-1	-1	-1	-1	123	175	0	-1
0	0	-1	-1	-1	-1	114	-1	0	-1
0	0	-1	-1	-1	-1	153	-1	0	-1

Figure 4.3: Example of Inductive Loop Detector data

Limitation of inductive loop detector data

Numerous challenges are associated with the process of data collection, encompassing issues such as missing data, communication disruptions, and the occurrence of spurious data resulting from hardware or software anomalies. In the context of loop detector data, a notable concern involves instances of "no-flow" data, wherein no vehicles are detected during the current minute, as noted by O'Reilly et al. (2004). Additionally, errors may manifest in the form of unrealistic values, as exemplified by:

1. speed values < 0 km/hr.
2. occupancy < 0%, or > 100%.
3. flow = 0 veh/min, and speed > 0 km/hr.
4. flow = 0 veh/min, speed = 0 km/hr, and occupancy > 0%.
5. flow > 0 veh/min, and speed = 0 km/hr.
6. flow > 0 veh/min, speed > 0 km/hr, and occupancy = 0%.

4.3.2 Incident Data

Incident data used in this study is sourced from ControlWorks, provided by National Highways. The availability of accurate and detailed incident data through ControlWorks is crucial for the precise evaluation of road incidents. The analysis of these datasets involves examining the distribution of incidents based on factors such as year and junction, exploring the maximum and minimum occurrences of each incident type, and comprehensively studying the distribution of incidents across all types. ControlWorks data provides essential values for analysis, including incident duration, incident frequency, and incident location. These values play a pivotal role in informing the VISSIM simulation model, particularly in the parameterisation process. A comprehensive list of variables contained in the ControlWorks dataset is presented in Table 4.2.

Table 4.2: Data explanation from the ControlWorks data

Variable Name	**Description**
Incident Number and ID	Name of the inductive loop detector
RocCreateDateTime	Date and Time that the incident occurred
Hour of the day	Hour of the day that the incident occurred
Day of the month	Day of the month that the incident occurred
Month of the year	Month of the year that the incident occurred
Year	Year that the incident occurred
Day of the week	Day of the week that the incident occurred
IncidentCreatedDateTime	Date and Time that the incident created
FirstAssignedDateTime	Date and Time that the incident assigned
FirstDeployedDateTime	Date and Time that the incident deployed
FirstArrivedDateTime	Date and Time that the incident arrived
IncidentClearedDateTime	Date and Time that the incident cleared
ResponseDurationFromRocCreation	First Arrived time – Incident Created time
TimeUntilClearedFromRocCreation	Incident Cleared time - Incident Creation time
Desk Time	First Deployed time - Incident Created time
Travel Time	First Arrived time - Incident Created time
Coordinates	Easting and Northing coordinates of the incident location
Area	Incident Location codes
Road Name	Name of the road that the incident occurred
Junction	Junction location that the incident occurred
Location description	Full description of the location that the incident occurred
Markerpost	Markerpost where the incident occurred
CallSourceName	Police, CCTV, Traffic Officer, Road services providers, HE contractor, Admin, Ambulance etc.
IncidentGradeName	Routine, Non-attendance, Immediate, Prompt
ResourceTypeName	Name of the resource
RCC_Region_Combine	RCC region name
TotalLaneClosureManual	Number of lanes closure
FinalCodes1	Codes for describing the type of incident
IncidentTypeDescription	Abandoned vehicle, Fire, Breakdown, Traffic collision, Network monitoring, infrastructure defect, Obstruction, Pedestrian on the network, Suicide/Attempting suicide, Animal on Network etc.
QualifierCodes	Further codes describing the incident
Details	Further details as concerns the incident.

The incidents within the ControlWorks dataset are classified into various types, each providing specific insights into different scenarios on the road. Any personal information, of the people involved, were not included in the data for data security purposes. The categorised incident types are as follows:

1. Abandoned Vehicle, as Abandoned Vehicle (unspecified), Abandoned Vehicle Not Suspicious, Abandoned Vehicle – Suspicious
2. Animal on Network, as a live animal located on any part of the verge or motorway. Includes any wild or domestic creature, tethered or otherwise.
3. **Breakdown,** as Breakdown – in live lane, Breakdown - Hard shoulder, Breakdown – offside tyre change, Breakdown – vulnerable person present
4. Cancel/Fast exit during log creation.

5. Fire, as Fire (unspecified), Vehicle Fire, Off-road Fire (e.g., verge fire)
6. Infrastructure Defect, as Infrastructure Defect - Pothole, Infrastructure Defect - Rutting, Infrastructure Defect - Other, Infrastructure Damage
7. Network Monitoring, as Congestion, Observation, Abnormal Load, Critical Asset Monitoring, Strong Winds, Snow / Ice / Freezing Rain, Flooding, Weather Condition - Other
8. Non-incident, as Incident Other (unspecified), Insecure Load, Serious Abnormal Congestion, Abortive ERT Call, Sudden Death / Suicide, Anti-Social Behaviour with Vehicle, Alarm from HA Equipment, Special Operation, Assistance to Other Agencies, Near Miss
9. **Obstruction,** as Obstruction (unspecified), Debris, Hazardous Spillage, Non-Hazardous Spillage, Shed Load, Overturned Vehicle, Other Obstruction (excluding breakdown)
10. Oncoming vehicle, as any type of vehicle driving in the wrong direction
11. Organised Event, as Event Off Network (unspecified), Event (Off Network) Planned, Event (Off Network) - Unplanned
12. Pedestrian on network, as Person(s) found in isolation of a corresponding vehicle on the network, either in a live lane or alongside the carriageway.
13. PNC transaction (Police National Computer), as PNC Enquiry or Update has been requested, this code will be the primary classification code
14. Roadworks, as Roadworks (unspecified), Roadworks Planned Notification (from contractor), Roadworks Unplanned
15. Spillage, as Spillage - Fuel, Spillage - Other
16. Suicide/Attempted suicide, as Suicide or attempted suicide on the network
17. Use of Hard Shoulder (Not Breakdown), as Hard Shoulder (unspecified), Hard Shoulder - Medical Emergency, Hard Shoulder - Tacho Break HGV, Hard Shoulder - Drive Away, Hard Shoulder - Other Non-Legal use
18. **Traffic collision,** as Traffic Collision (unspecified), Road Traffic Collision - Damage Only, Road Traffic Collision - Minor Injury, Road Traffic Collision – Serious Injury, Road Traffic Collision - Fatal, Road Traffic Collision - Other
19. Weather condition, as Weather Condition (unspecified),High Wind, Heavy rain, Snow Frost Ice, Flooding, Poor Visibility - Verge Fire or Smoke, Poor Visibility -Fog, Poor Visibility -Low Sun, Poor Visibility - Other
20. Other, as Medical Emergency, Tacho Break (HGV), Other Non-Legal Use of Hard shoulder or ERA, Thrown Object, Assistance to Other Agencies

The incident types highlighted in bold—Breakdown, Obstruction, and Traffic collision—hold particular significance in incident management due to their higher frequency and substantial occurrence percentages. These specific incidents play a pivotal role in shaping incident response strategies and understanding their patterns is crucial for effective road safety and traffic management. Regarding the incident data analysis, various aspects were considered, encompassing:

- Date, Time, and Location of incidents
- Response duration Time, Time until Cleared, Desk Time, Travel Time
- Incident type per junction

This comprehensive analysis provides insights into the temporal and spatial distribution of incidents, the efficiency of response and clearance processes, and the specific incident types associated with each junction. Understanding these dimensions is essential for formulating effective incident management strategies and optimising responses to ensure the safety and functionality of the road network.

The analysis has identified the primary categories in which most motorway segment traffic incidents occur. It is crucial to recognise that different types of traffic incidents have varying impacts on the smoothness of traffic flows. A critical aspect is the time required to manage an incident and the time taken to detect the incident, information taken from the controlworks data using the variables collected. Therefore, an overview of the average time taken to handle different types of incidents has been examined as part of this analysis.

Comprehensive analysis of all incident types has been conducted over the past months, examining incident distributions based on various factors such as month, junction, and incident type for the years 2016-2019. Special attention, however, has been directed towards Breakdowns, Traffic collisions, and Obstruction incidents. In-depth analysis of their distribution, incident duration, frequency, and location has been recorded, as mentioned earlier. These values hold significant importance for the simulation model, where they will be utilised in the parameter section. The detailed analysis of the data will be presented in the subsequent chapter.

Limitation of ControlWorks data

Challenges related to ControlWorks data have been identified, including the occurrence of false alarms in cases of stopped vehicles, leading to a potentially misleading count of recorded incidents, the conclusion of which is from the use of CCTV cameras or authorities checks. Another issue could pertain to inaccuracies in recording the duration of incidents. It is noted that there are incidents where the duration has not been accurately recorded, although such instances are relatively infrequent.

4.3.3 Field Observation Data

The vehicular data essential to this research was procured through the implementation of a dedicated test vehicle equipped with a sensing subsystem. This vehicle, facilitated by the School of Architecture, Building, and Civil Engineering at Loughborough University, is equipped with a comprehensive array of sensors, encompassing radar, camera, localisation, weather, gyroscope, accelerometer, and MobilEye sensors. Notably, these sensors are precisely aligned along the longitudinal axis, specifically at the center of the vehicle. The spatial configuration of these sensors is visually depicted in Figure 4.4 for reference.

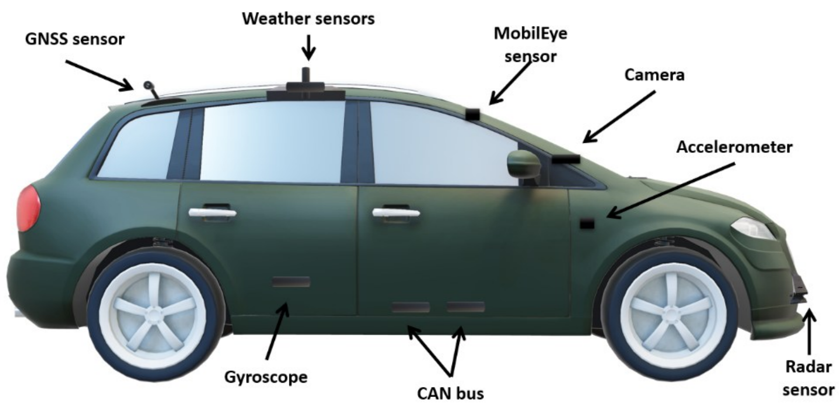


Figure 4.4: Equipment of the instrumented vehicle.

For the collection of the traffic data needed for the verification of the simulation model, 13 roundtrips were conducted on five distinct days spanning late September to early November 2021. The data collection process exclusively utilised the MobilEye sensor, radar sensor, and accelerometer from the vehicle data collection suite. GPS data, crucial for this endeavour, were acquired through a mobile phone, as the GNSS sensor in the vehicle was rendered inoperable due to a malfunction. Additionally, video data were collected for the project using a second mobile phone to capture videos and photos of the trips, though not through the instrumented vehicle. This occurred for checking the network visually for any critical event that may exist and to check whether the flow with the rest of the vehicles on the network was consistent. Notably, the radar sensor data were employed in this research to verify the simulation model and facilitate the development of the incident detection algorithm and the characterisation of connected vehicle driving behaviour.

The test vehicle is equipped with the MobilEye 560 system, specifically designed to emit an auditory alert in the face of an impending collision. The primary function of this system is to enhance driving behaviours, reduce collision incidents, and minimise near-miss occurrences by issuing relevant cautionary notifications.

The data from the remaining sensors, apart from the MobilEye sensor, were not utilised in the verification of the simulation model and thus are not expounded upon in the dataset derived from the instrumented vehicle. The vehicle's relative speed was captured independently by the instrumented vehicle and the mobile phone's GPS capability. Subsequently, these data sources were amalgamated to enhance the accuracy of the ground truth data deployment.

Limitations of instrumented vehicle data

The data acquired through the instrumented vehicle at Loughborough University offers frequent and robust measurements. Nevertheless, several limitations that may affected the accuracy of sensors used for this research should be acknowledged:

- Limited Data Size: The dataset's size is constrained, highlighting the potential benefits of incorporating a more extensive collection of real-world trips. Encompassing multiple users and diverse scenarios can significantly enhance the dataset's efficacy, ensuring it captures a broader range of encountered challenges.
- Diverse Driver Representation: Expanding data collection to include a more extensive pool of drivers would be useful. A more diverse user base ensures the dataset faithfully represents various driver behaviours, reducing dependence on any specific driving style or habits.

Given that the remaining sensors have not been utilised in this specific data collection, the limitations associated with those sensors are not applicable to this study.

4.4 Exploratory Data analysis for the Incident detection – Results

In this section, the data sources employed in the study are presented. The methodology approach for the exploratory analysis centers on traffic and incidents data, encompassing parameters such as traffic volume, traffic speed, congestion index, incident types, and counts. The ensuing discussion provides a brief overview of each dataset and its inherent characteristics.

For traffic data, as mentioned the dataset named as MIDAS were used. This system relies on inductive loop detectors (ILDs) to collect data on traffic speed, volume, and occupancy. From the other side, incident data, named as ControlWorks pertains to incident data collected by National Highways in England, offering comprehensive details on road traffic incidents, including type, location, date, time, duration, and contributing factors. A descriptive analysis is executed to examine incident occurrences on the M1 in both directions.

4.4.1 Data processing

The MIDAS data, sourced from the database, pertains to the year of 2019. After extraction, the data underwent reformatting into CSV files, consolidating them into individual files for each loop detector, following a daily organisational structure. A comprehensive cleaning process ensued, targeting anomalies, such as instances where flow registered as zero while other variables-maintained values above zero.

Post-extraction, clearance of imbalanced data, and a 5-minute and 1 -hour aggregation (from 1-min level data) was executed, involving the averaging of variables across all counting lanes, using Python scripts. The precise locations of road junctions and ILDs facilitated the grouping of detectors into road segments, spanning from one junction to another with the help of the QGIS and RStudio to conduct mapping where appropriate. The values attributed to each road segment represent the averages derived from all counting loop detectors within the segment, a measure taken to mitigate the impact of potential inaccuracies stemming from the presence of a malfunctioning detector.

Further refinement involved the averaging of data across all days, culminating in a monthly daily average. This approach serves to establish a proxy for recurrent congestion, given the inherent dismissal of outliers during the aggregation process. Incidents relevant to the designated region and time-period were extracted and subsequently categorised by type, bound, day, month, and junction segments. The dataset encompasses various incident types, including breakdowns, fires, obstructions, oncoming vehicles, animals/pedestrians on the network, roadworks, and traffic collisions as will be described in depth below in the results.

4.4.1.1 Descriptive statistics

For the exploratory analysis of the two datasets, descriptive statistics were used, aiming to explain overall patterns, trends, and data characteristics. This approach facilitated the identification and prioritisation of temporal and spatial variability in high congestion, or incidents, level. The descriptive statistics encompassed the plotting and comparison of congestion levels during peak times across various significant road segments.

Concerning the incident data, an analogous descriptive analysis involved the comparison and visualisation of the frequency of different incident types. This comparison was conducted both temporally and spatially, considering various road segments, the results of which will be analysed below.

4.4.2 Traffic Data (MIDAS) results

As delineated in section 5.4.1, traffic data used for the simulation study is provided by the Mott MacDonald, spanning a one-year period from January 2019 to December 2019. Every time a vehicle is detected a measurement is recorded. Subsequently, the raw gathered data are aggregated to a minute-level detail. Raw 1-min traffic demand data, aggregated at a 15-minute and 1-hour resolution, is collected through 170 ILDs strategically placed across the examined main motorway network, as shown in Figure 4.5. The available data encompasses 24-hour counts for all days of the year throughout the specified duration. For the calibration process a 24-hour average count for all the year were used. This happened for providing the capability to calibrate the whole network for a 24hour duration, providing the ability to use any possible hour for the next step, the one for the incident detection through V2V communication. In this way no limitation is existing for using the calibrating model for any time, either morning, evening peak or no peak time.

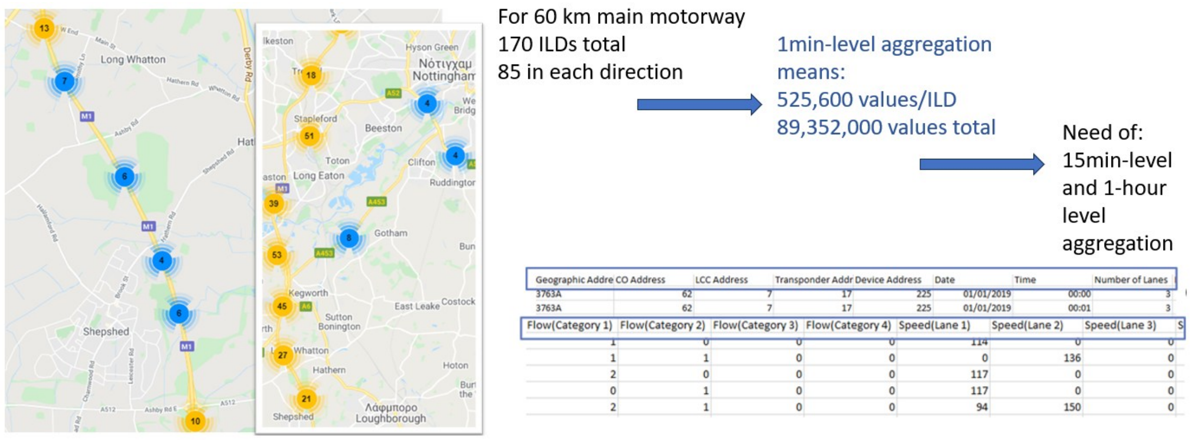


Figure 4.5:ILDs location as shown via WebTRIS, National Highways

For a 30 km main motorway in each direction, there are a total of 170 Inductive Loop Detectors (ILDs), with 85 in each direction. This results in 525,600 values per ILD, amounting to a total of 89,352,000 values, all aggregated at a 1-minute level. To manage this extensive dataset more effectively, there is a requirement to aggregate the data at different time intervals, specifically at 5, 15, and 60-minute levels. This aggregation process aims to summarize a large amount of information into more manageable and insightful summaries for analysis.

The aforementioned traffic data utilised in this study are sourced from the National Highways WebTRIS (**Web**site for **Tr**affic **I**nformation **S**ystem), the primary database for traffic data in the UK. Originally designed for detecting disturbances in motorway traffic flow to improve signalling, this dataset is identified by the name MIDAS, signifying its role in motorway incident detection and signalling. An overeview of the cariables included in the raw datasets can be seen in the aforementioned Table 4.1.

In this PhD thesis, the crucial objective of this dataset is to facilitate the initial stages of the calibration and validation processes for the baseline traffic microsimulation models under development. Henceforth, the term "baseline" will be employed to denote the scenario with 0% Connected Vehicle (CV) market penetration rate (MPR). In this context, "baseline" refers to the condition wherein the motorway is exclusively occupied by human-driven vehicles. For the calibration of first phase the 80% of the total year were used while the rest 20% were used for the second stage, the one of the validations. As mentioned above both of them conducted for a 24-hour simulation model.

Initially, as the data is downloaded in separate files, each representing a single day's worth of data, a consolidation process is undertaken to merge all these individual files. The compiled dataset incorporates traffic data spanning January 2019 to December 2019. Following this, the raw Inductive Loop Detector (ILD) data undergoes processing to achieve the following objective. Formation of a simulation input dataset for the traffic microsimulation model, encompassing simulation speed distribution, simulation time headway distribution, traffic flow per hour, route choice percentages, and fleet composition characteristics. A separate formation followed for the calibration and validation dataset containing traffic flow values which will be described in the next section.

The dataset containing traffic flow values, to be detailed in the following section, draws information from Inductive Loop Detectors (ILDs) situated along the main road, as well as entries and exits, accessible via WebTRIS. WebTRIS provides coordinates and recording duration details for these ILDs. In Figure 4.6, an illustration exemplifies the coding and naming conventions for these locations.

Specifically, ILDs on the main road are denoted with the symbol A for Northbound and B for Southbound, preceded by a four-digit number indicating their specific location. Entries are designated with the symbols K and M for Northbound and Southbound, respectively, while exits use the symbols J and L for the same bounds as previously mentioned.

Junction 23

23→26: Northbound, A

26→23: Southbound, B

Exits: J and L

Entries: M and K

Figure 4.6:Explanation of main road, exits and entries abbreviations.

Furthermore, for the analysis of slip roads, a check of the number of lanes, for each slip road (entry or exit) took place and whether or not do they have an emergency lane (see Table 4.3). It is important to mention that the numbers of lanes in each exit or entry are important as it concerns the number of incidents that occurred in these lanes, a result that will be shown below.

Table 4.3: ILDs Data Abbreviations

Main Road	Entries/Exits	(Extra Information on slip roads lanes)
J23	J23J	2lanes/emergency lane
J23/23A	J23K	2lanes/emergency lane
J23A	J23L	2lanes/emergency lane
J23A/23	J23M	2lanes/emergency lane
J23A/24	J24J	2lanes
J24	J24K	2lanes
J24/23A	J24L	2lanes
J24/24A	J24M	1lane (two entries)
J24A	J25J	2lanes/emergency lane
J24A/24	J25K	1lane/emergency lane
J24A/25	J25L	2lanes/emergency lane
J25	J25M	2lanes
J25/24A	J26J	2lanes/emergency lane
J25/26	J26K	2lanes/emergency lane
J26	J26L	2lanes/emergency lane
J26/25	J26M	2lanes/emergency lane

First of all, for each desired detector loop a sanity check had been required to verify whether or not there is equivalent in the following qualities:

1. Number of vehicles in Flow(category) columns = Number of vehicles in Flow (lanes)
2. Number of vehicles before a junction ≈ Number of vehicles after a junction
3. The number of vehicles in a segment be the same in loops consecutively
4. Number of vehicles after an exit = Number of vehicles before the exit - Number of vehicles taking the exit

Furthermore, in an initial check that took place in excel about the capacity of flow for each category for both 2018 and 2019, the results of which will be viewed below (see Figure 4.7 and Figure 4.8) to analyse the periodicity of the datasets. This check took places for all the vehicle input points which are mentioned in Table 4.5 below.

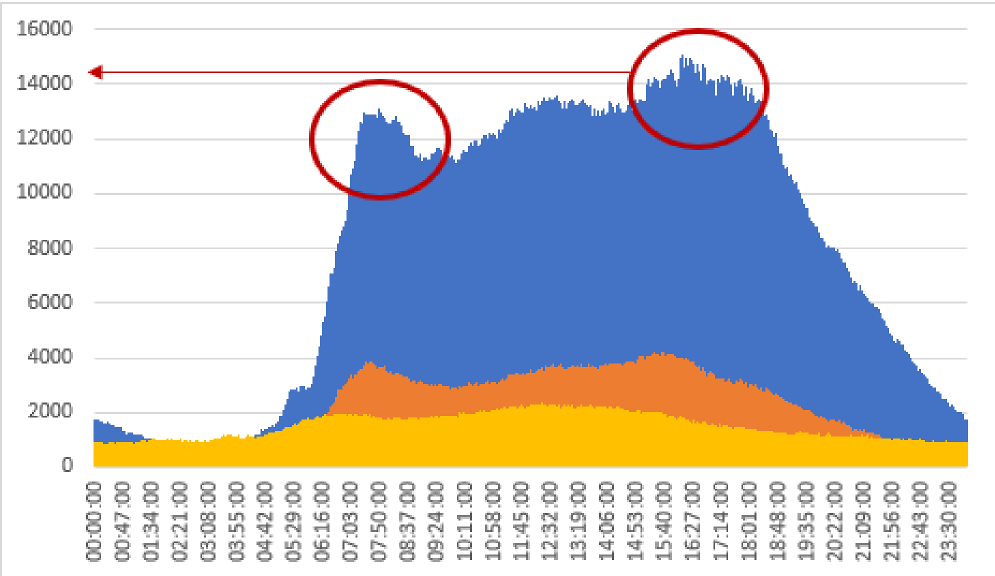


Figure 4.7: Loop Detector-3763A, Northbound, right after J23, 2018

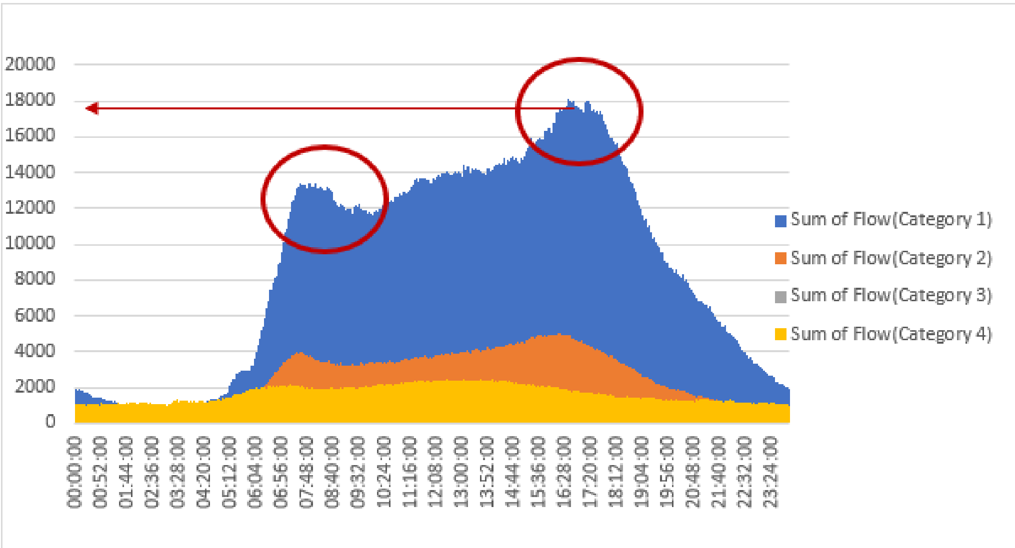


Figure 4.8: Loop Detector-3763A, Northbound, right after J23, 2019

The vehicles are being categorised according to the following lengths in four categories as shown in Table 4.4:

Table 4.4: Categories of vehicles in MIDAS data, according to their length

Type of category	**Category 1**	**Category 2**	**Category 3**	**Category 4**
Vehicle's Length	<5.2 m	5.2 m-6.6 m	6.6m - 11.6m	>11.6 m

The above figures are an example of 3763A detector loop, located right after Junction23, Northbound at the M1 motorway. In the figures, the summary of flow for each category, the maximum number of flows occurred, and its time are depicted. Many detector loops have been checked alongside the network, not only before and after each junction but also between two junctions and in the centre of them too. The analysis of them showed that the maximum summary of flow is happening around 7:30-8:30 in the morning and 16:00-18:00 in the evening. As it can be easily depicted, the maximum morning and evening time period is almost the same for both years. Finally, in the majority of loops checked the capacity of flow for category 1 (Vehicle Length < 5.2 m) had an annual increase of around 2000 vehicles from 2018 to 2019, in contrast with the other categories in which their flows remain almost stable.

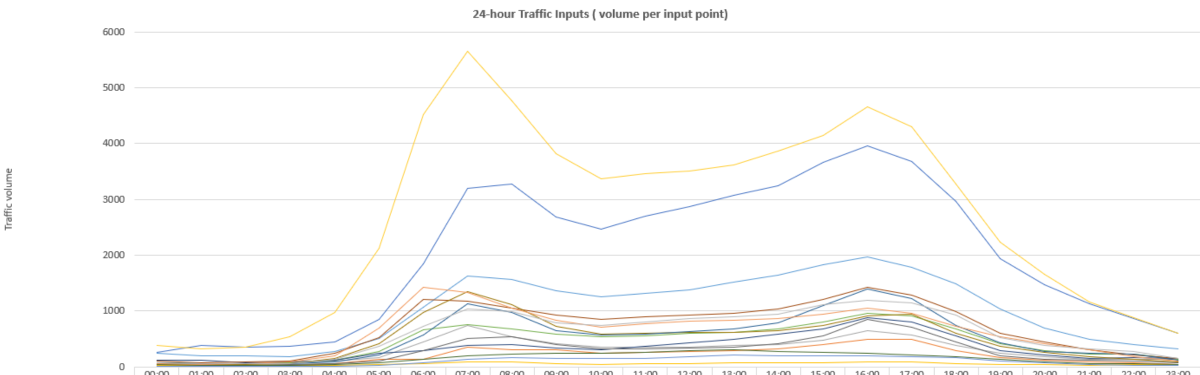
Inductive Loop Detector data will be used, as mentioned, in the calibration and validation of the traffic microsimulation model in VISSIM. In the model, there are approximately 40 input points (entries and exits of the vehicles in the main motorways, using the slip roads that are connecting them). These datasets from MIDAS contains aggregated data per minute, for a whole day, for a whole month and for a whole year. Using Python, these aggregated data have been transforming from 1-minute to 1-hr aggregated data. VISSIM vehicle input is always veh/hr, so there is no need to transform them to 15 minutes of aggregated data or so. Furthermore, for the accuracy level of the simulation, a typical day of the week has been used (Wednesday). Forty files of Midas datasets, each file consisting of 525.600 values, will be used for calibration and validation of the model. For calibration 2019 Midas data will be used, and for the validation and testing will be used 2020 Midas data.

In order to achieve these objectives, as mentioned above, data are collapsed by using the collapse command in the statistical software Python, which creates an average value by using a grouping variable. Hence the data are averaged by a minute of observation to create a dataset which consists of 525.600 observations per minute. With the help of the software, they have been converted in 1-hr traffic flow values. It should be mentioned that the traffic flow values were calculated for the Inductive Loop Detectors, corresponding to the simulation vehicle input points. The traffic flow values will be used in the baseline models, but this stage of the study will be explained in the chapters below. The observations of all Wednesdays for a whole year will be first tested as a baseline scenario. The values that will be used as input will be annual mean values of traffic flow, time headway and speed per minute of the simulation time, as a consequence sometimes not to represent some potential special conditions, arising to motorway due to an incident. On the other hand, for the VISSIM model accuracy incident data have been analysed too, the importance of which will be presented in the following section.

To fulfil the first objective, the data is aggregated using the appropriate commands in the Python software. These commands generated average values based on a grouping variable, resulting in the creation of a dataset with one observation per minute. To simulate traffic within the network, sixteen vehicle input points are designated at the entry locations of each link, determining the number of vehicles in the microsimulation model. Each vehicle input point is labelled with the traffic flow associated with the respective Inductive Loop Detector (ILD) IDs linked to those points. The per-minute traffic flow values were transformed per-hour traffic flow values as the VISSIM software is using hourly traffic input ability and they are depicted in Figure 4.9. It is crucial to note that these traffic flow values are calculated specifically for the Inductive Loop Detectors (ILDs) corresponding to the simulation vehicle input points (refer to Table 4.5), each one combined each time with the appropriate location in VISSIM software.

Table 4.5: Vehicle input point traffic flow in the model

No of input points	Name	VISSIM input point codename
1	3748A	10: J23A-23 Northbound
2	3751M	12: J23M
3	3758K	13: J23K
4	3818M	15: J23A_M
5	3823K	17: J23A_K
6	3850M	10218: J24M
7	3857K	21: J24K
8	3858M	22: J24M entry from 24A
9	3869K	24: J24A_K
10	3932M	26: J25M
11	3938K	64: J25K
12	3986M	35: entry from P
13	3996K	36: entry from P 2
14	4029M	10248: J26M
15	4034K	32: J26K
16	4041B	1: M1 J26-25 Southbound



	00:00	01:00	02:00	03:00	04:00	05:00	06:00	07:00	08:00	09:00	10:00	11:00
10: J23A-23 Northbound	260	382	347	366	450	846	1836	3192	3281	2685	2461	2702
12: J23M	20	14	14	20	54	131	131	358	297	297	235	256
13: J23K	72	63	59	79	102	169	441	738	538	418	347	346
15: J23A_M	27	23	19	24	28	45	49	83	82	57	45	53
17: J23A_K	240	197	190	184	267	503	1071	1622	1559	1363	1254	1320
10218: J24M	78	61	55	78	115	272	660	750	683	584	535	548
21: J24K	115	113	75	91	115	249	282	387	398	332	312	373
22: J24M entry from 24A	101	79	81	108	242	525	1204	1181	1054	934	850	902
24: J24A_K	49	36	30	37	53	105	287	501	539	391	316	323
26: J25M	40	35	38	63	145	414	971	1342	1113	725	585	599
64: J25K	78	60	54	62	89	218	572	1122	977	648	569	588
35: entry from P	35	29	28	31	44	75	136	193	232	241	237	255
36: entry from P 2	17	15	13	12	17	31	70	135	160	156	143	155
10248: J26M	55	43	53	81	195	695	1420	1338	1052	827	705	769
32: J26K	73	56	50	60	126	360	721	1035	982	781	735	800
1: M1 J26-25 Southbound	387	325	347	534	976	2130	4518	5648	4773	3823	3365	3459

	12:00	13:00	14:00	15:00	16:00	17:00	18:00	19:00	20:00	21:00	22:00	23:00
10: J23A-23 Northbound	2864	3075	3250	3655	3962	3680	2955	1943	1468	1128	870	606
12: J23M	280	288	321	392	496	496	293	166	125	91	69	33
13: J23K	355	377	404	478	653	563	379	235	176	134	134	134
15: J23A_M	59	64	71	78	94	89	63	36	33	32	35	33
17: J23A_K	1376	1510	1646	1835	1975	1781	1482	1042	688	489	392	323
10218: J24M	599	622	677	809	954	910	671	411	287	232	228	130
21: J24K	429	485	577	675	887	807	549	291	214	151	162	153
22: J24M entry from 24A	925	951	1028	1213	1420	1285	985	607	440	307	214	152
24: J24A_K	334	347	415	560	844	708	445	197	133	120	109	72
26: J25M	618	622	644	738	910	941	597	369	260	179	137	82
64: J25K	637	679	786	1093	1398	1221	745	423	273	241	224	120
35: entry from P	291	299	278	254	242	217	180	134	91	62	49	47
36: entry from P 2	179	205	195	200	193	185	163	110	66	44	32	21
10248: J26M	815	834	869	944	1046	959	722	533	418	300	173	97
32: J26K	857	902	947	1113	1198	1146	927	529	378	313	274	152
1: M1 J26-25 Southbound	3502	3612	3862	4139	4655	4307	3280	2230	1650	1160	884	604

Figure 4.9:Temporal distribution of traffic flow in the simulation vehicle input points

Moreover, an example of the locations of these vehicle input points are shown in Figure 4.10. This information was used as simulation input and later was used for the calibration and validation of the base simulation model. The traffic data includes two types of vehicles, passenger vehicles and **H**uman **G**oods **V**ehicles (HGVs), where each time the corresponding relative flow were used to accurate display their route in the motorway examined.

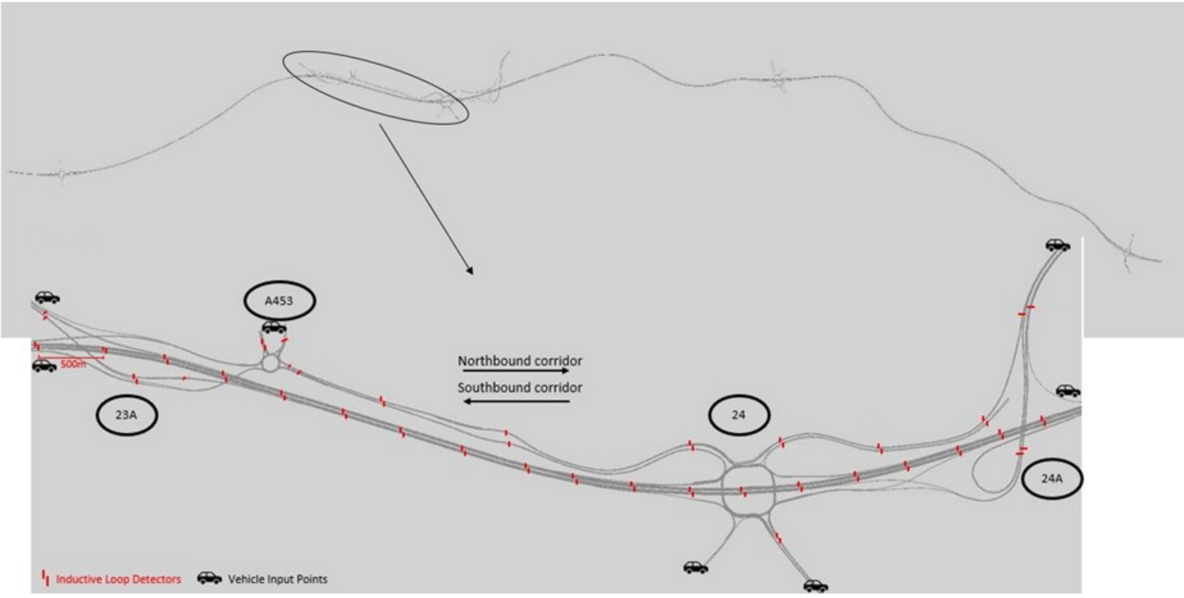


Figure 4.10: Illustration of the ILDs and the vehicle input point in VISSI.

4.4.2.2 Speed distribution

To establish the cumulative distribution function of speed, the average over time and space speed was utilised. Rather than relying on per interval values, a statistical distribution of speed was generated. This involved in putting a specific desired speed distribution into the model for each of the determined vehicle input points. To maintain model simplicity, six different distributions were considered, as illustrated in Figure 4.11. These distributions were assigned to the main motorway corridor for each bound divided in segments between all junctions, for each direction, as necessary values calculated using the ILDs data. The speed distribution ranges were set between 80 and 120 km/h with different cumulative speed distribution each time, depending on the traffic data analysis. In the base scenario, vehicles in the simulation randomly selected their speeds from the entered distributions.

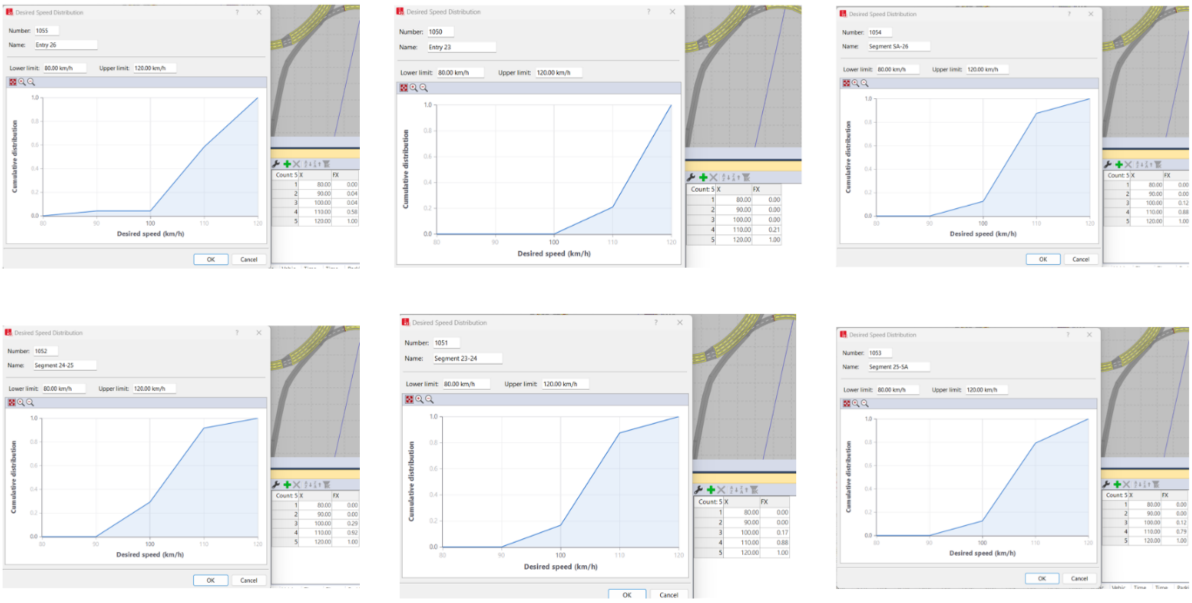


Figure 4.11: Speed distribution according to the segment/direction

The primary objective of traffic demand data is to facilitate the calibration of the base microsimulation model. This calibration focuses on refining the representation of traffic characteristics, enhancing the microsimulation model's capacity to accurately mirror real-world traffic conditions and driving patterns.

4.4.3 Incident Data (Control Works Data 2016-2019) Results

As mentioned in chapter 3, the objective of incident data analysis is to identify the root cause of a problem and propose corrective actions to minimise the risk of future occurrences. These analyses also serve as safety documents, highlighting potential safety hazards. Furthermore, incident data analysis encompasses the examination of three critical factors: incident duration, incident frequency, and incident location. These three values are pivotal reasons why incident datasets require thorough analysis for the accurate replication of real-life scenarios. Regarding incident data analysis for the simulation modelling, the following aspects were considered:

- Date, time, and location of incidents
- Response duration time, time until cleared, desk time, travel time
- Incident type per junction

While analysing the data and incident locations, a challenge emerged regarding the coordinates of some incidents in the network. Figure 4.12 and Figure 4.13, illustrate the coordinates issue for the entire motorway network and the specific study network assisted by National Highways. These figures depict the spatial distribution of incidents for the year 2019. Despite the data being related to England's motorways, the coordinates sometimes lack a meaningful association with the motorway locations. The absence of incident data due to inadvertent recording errors can occasionally be unavoidable.

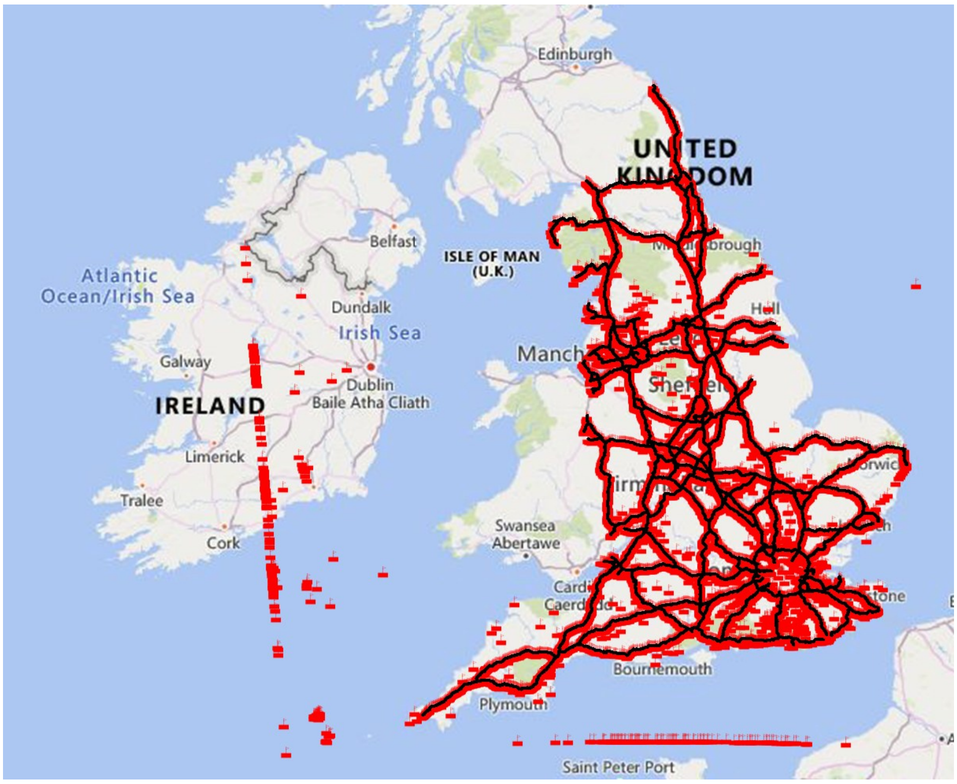


Figure 4.12: Spatial distribution of incidents for all motorways, assisting by Highways England for 2019.

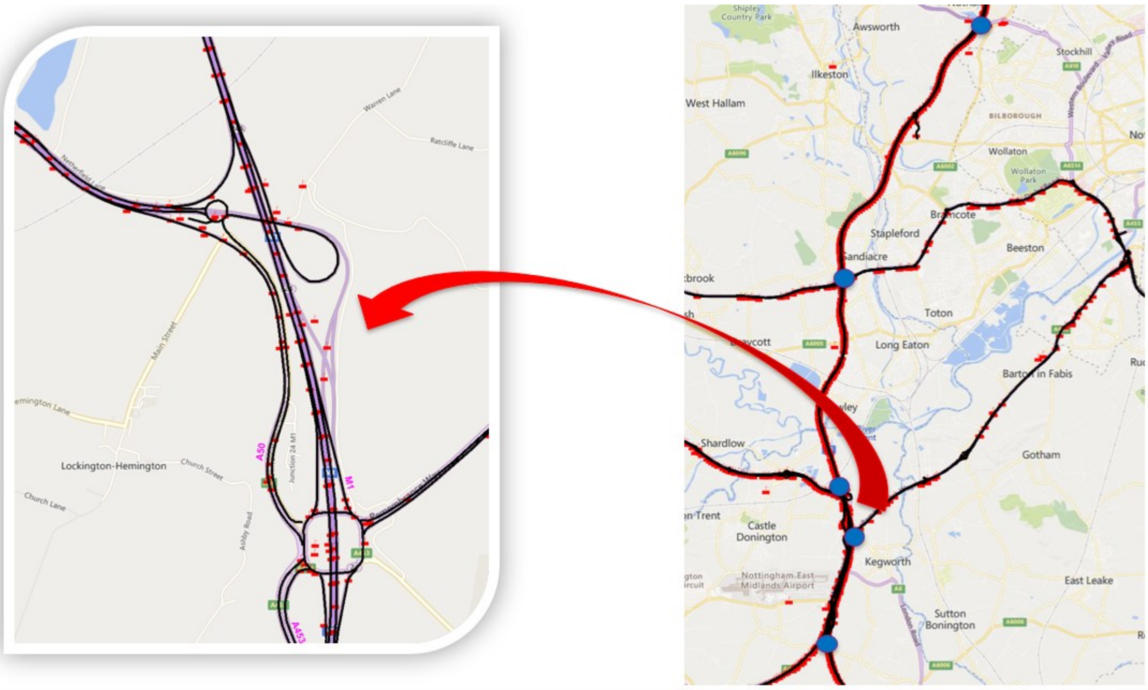


Figure 4.13: Spatial distribution of incidents for the study network, for 2019

In the section 4.3 above, all types of incidents have been referred. However, for the incident detection framework, a comprehensive analysis focused on breakdowns, traffic collisions, and obstructions. Summaries were provided for each of these three incident types, as well as an overall summary encompassing all incident types. The specific focus on breakdowns, traffic collisions, and obstructions in the incident detection framework was driven by their significance in impacting traffic flow, safety, and overall transport system performance. These incident types often have distinct characteristics, response requirements, and implications for traffic management. By using these specific incident categories, the analysis can provide more targeted insights and recommendations to improve incident detection, response strategies, and overall system resilience.

4.4.3.1 Distribution of Annual Incidents Duration

Significant attention was devoted to analysing the response duration time of incidents, with a particular focus on breakdowns. This emphasis on breakdowns stems from their substantial impact on incident duration, a crucial parameter for the traffic microsimulation model. In chapter 4 as well the importance of breakdowns was pointed out, when comparing them with the total incident in M1 motorway. The response duration time is calculated using the following equation (4.1):

$$Response\ Duration\ Time = first\ arrived\ time - incident\ created\ time \quad (4.1)$$

Utilising data from ControlWorks spanning three years (2017-2019), the distribution of breakdowns is presented in the tables below (Table 4.6-Table 4.8). Using the distributions (frequency and patterns), of the breakdowns, their contribution to total incidents and their efficiency over the three years can be seen. These insights are important for calibrating traffic microsimulation models, allowing more accurate simulations of incident impacts and reporting strategies for improved traffic management and safety.

Table 4.6: Distribution of Breakdowns, 2017

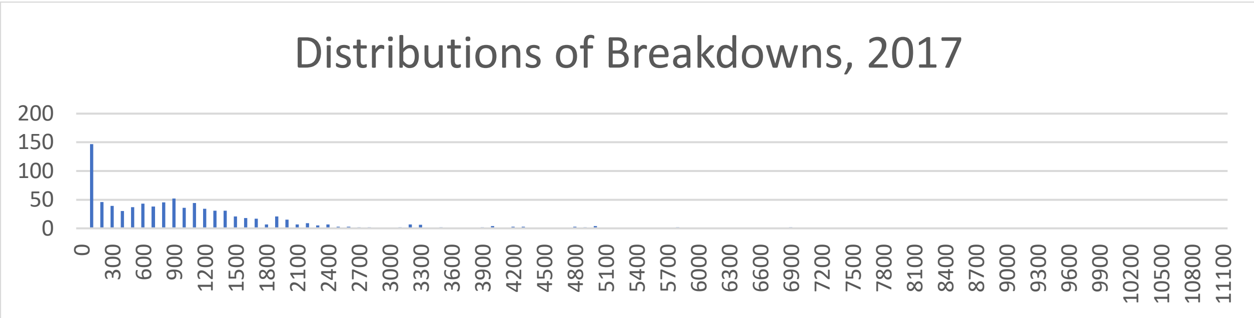


Table 4.7: Distribution of Breakdowns, 2018

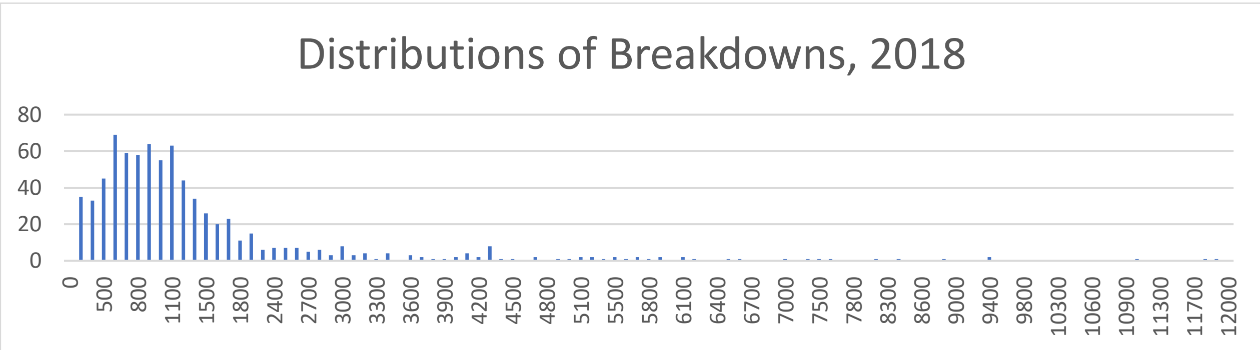
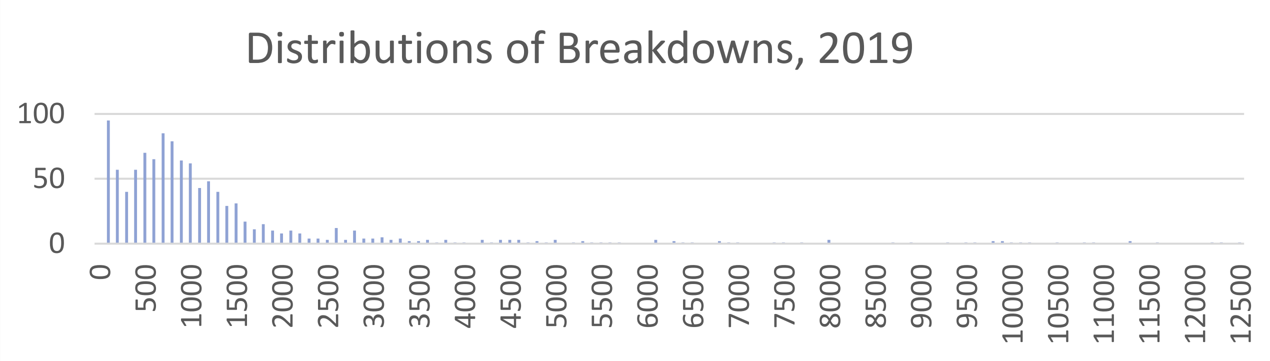


Table 4.8: Distribution of Breakdowns, 2019



Bins with a width of 100 were established to evaluate the frequency of each value within each bin. For instance, in the year 2019, the response duration time falling within the range of 0-100 (bin 100) occurred 95 times (see Table 4.8). Table 4.9 presents the mean and standard deviation for each year. Notably, 2019 exhibited a slight increase in both of these values. It's worth mentioning that 2019 marked the introduction of the ALR framework to the study network, which likely contributed to this increase. **Incident duration** is identified as one of the three crucial factors underscoring the necessity of analysing incident datasets. Incident duration calculated using the variables IncidentCreatedDateTime and IncidentClearedDateTime via the Table 4.2.

Table 4.9: Mean and Standard Deviation of each year

	2017	2018	2019
Mean	14 min	15min	17min
Standard Deviation	22min	21min	29min

Subsequent to the analysis of response duration time, an examination of the following distributions was conducted:

A. Distribution of incidents per:

- Year
- Road
- Junction
- Type of incident

B. Distribution of incidents/types per:

- Hour of the day
- Day of the month
- Month of the year

C. Distribution of incidents/types per:

- Main carriageway
- Slip roads

Before delving into the results of the aforementioned distributions, it is essential to highlight the temporal transformation of the study network. Figure 4.14 illustrates this transformation from 2016, approximately one and a half years before the construction of the ALR (All Lane Running), to the fully completed ALR network in January 2019. The ALR system is a traffic management approach that converts the hard shoulder of a motorway into a permanent running lane to increase capacity and improve traffic flow. Notably, in March 2017, the study motorway underwent construction, transitioning from three lanes plus the hard shoulder to the ALR configuration. By December 2018, the study motorway was fully operational, and from January 2019 onwards, the ALR system became a live operational feature.

Figure 4.14: ALR scheme time-transformation of the study network

4.4.3.2 Annual Distribution of Incidents per Year

While addressing incident types from 2016 to 2019, as outlined previously in section 4.3.2, a comprehensive analysis was conducted utilising ControlWorks datasets, given from National Highways for the ALR theme. The following Table 4.10 provides detailed information about incidents occurring across the entire motorway network of England, the entire M1 motorway, the specific study network of M1 (J23-J26), and the count of certain incident types, namely breakdowns, fire event, obstructions, and traffic collisions.

Table 4.10:Annual distribution of incidents

		Year		
	2016	**2017**	**2018**	**2019**
All roads	527494	508235	571208	578499
M1	58128	59429	67781	65462
J23-J26	3202	5499	7351	5829
Breakdown	1316	1977	3449	2902
Fire event	17	8	19	14
Obstruction	470	435	583	520
Traffic Collision	232	310	468	263

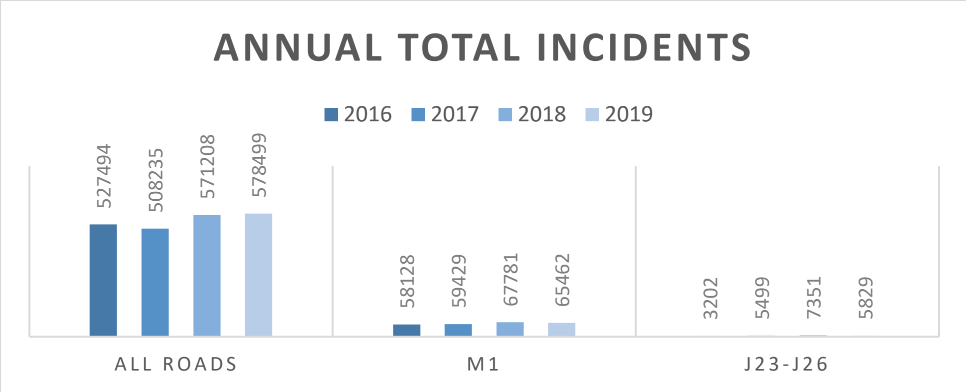


Figure 4.15: Annual distribution of total incidents per segment of motorways

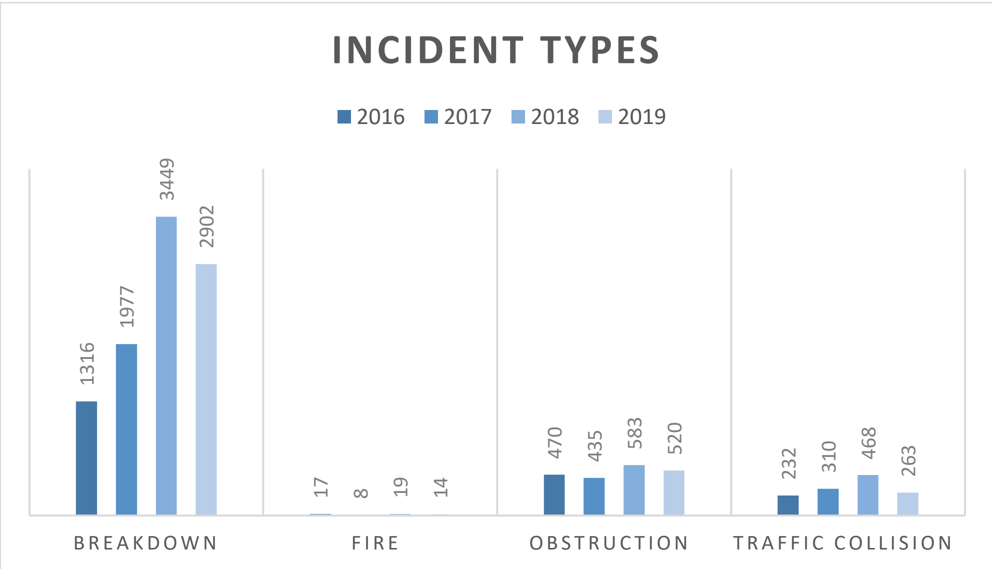


Figure 4.16: Annual distribution of different types of incidents per examined study network

Explaining the results of incidents for the four in a row year, it can be easily recognised that in the year 2018, when the motorway was under construction ALR, it is noticed the maximum number of incidents, comparing to other years (see Figure 4.15 and Figure 4.16). Additionally, however it is important to add that through years, from 2016 until today, the recording system has not been changed. It is essential then to check also the VMT calculations for these segments to have a clearer view of the vehicle's miles travelled. For example, this increase in breakdowns could be possible be affected, if the traffic flow was a lot higher that year, rather than the previous years, and the reason that the motorway was under construction should not be too important in the end.

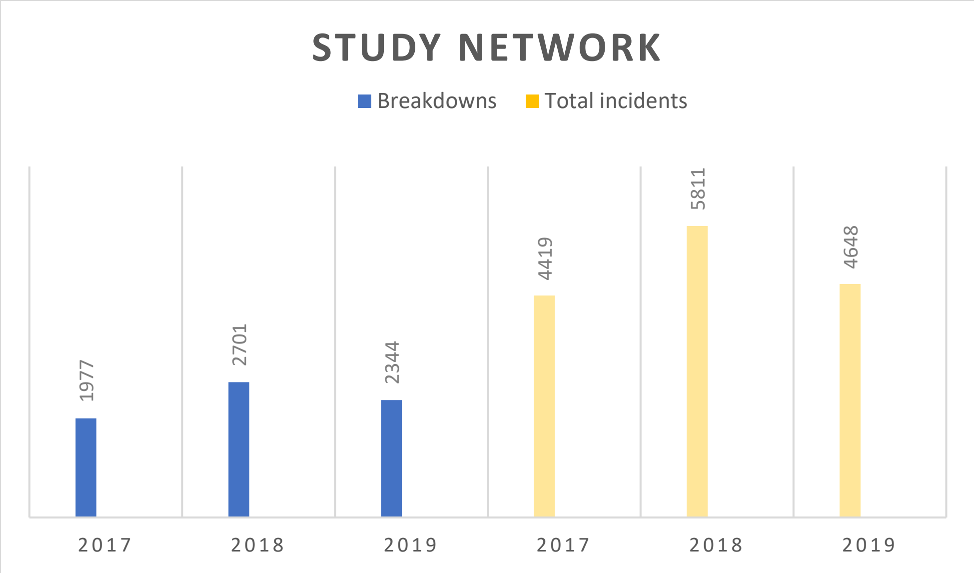


Figure 4.17: Breakdown - Total Incidents differences

Upon comparing the annual total incidents on the study network (M1, J23-J26) with the annual breakdowns on the network, it becomes evident that breakdowns constitute the majority of incident types occurring on the motorway (refer to Figure 4.17). Consequently, a more detailed analysis of breakdowns will be discussed in the subsequent section.

4.4.3.2.1 Annual Distribution of Breakdowns per Year

Breakdowns have emerged as the most frequent incident type on contemporary motorways, as evidenced by the aforementioned data analysis. Recognizing the significance of these incidents, National Highways provided to this study some extra datasets specifically focused on breakdowns. This dataset pertains to breakdown types concerning the ALR motorway, spanning from 2018 to 2020. The breakdown dataset encompasses various breakdown types, for easier explanation to the ROC/RCC, including:

- Breakdown – Chevrons
- Breakdown – ERA Bay
- Breakdown – Hard shoulder
- Breakdown – Live Lane
- Breakdown – not in Live Lane
- Breakdown – type not specified
- Breakdown – Verge

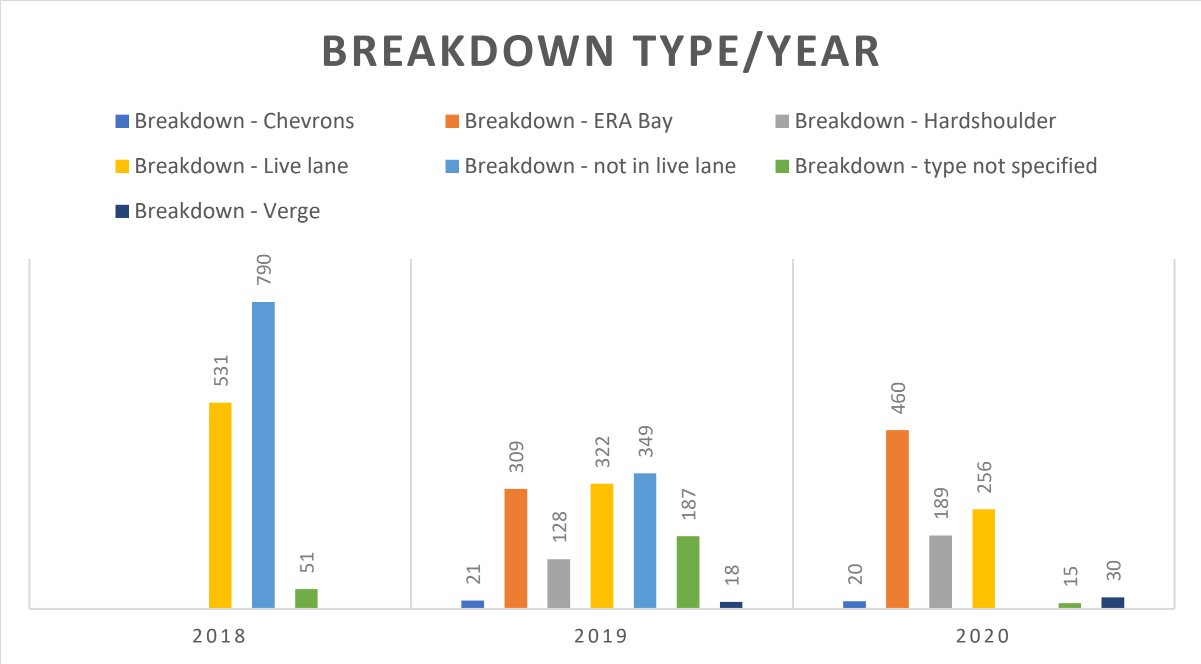


Figure 4.18: Number of different types of Breakdowns through years

The breakdown dataset for ALR incidents indicates that the majority of incidents occur in a Not Live Lane (refers to a lane on a motorway that is not currently open for active traffic), followed by incidents in the Live Lane (refers to a lane on a motorway that is currently open for active traffic) and the ERA Bay (refer to Figure 4.18). Moreover, the data have allowed to identify the specific sections of the motorway where the majority of breakdowns have been happened. Figure 4.19 illustrates the junctions with the highest number of breakdowns. Notably, Junctions 24A-25 and Junctions 25-26 stand out as locations with the highest incidence of breakdowns. It is essential to highlight that Junction 24-25 is also identified as the segment with the most incidents in the subsequent sections, emphasising its significance in terms of incident occurrences.

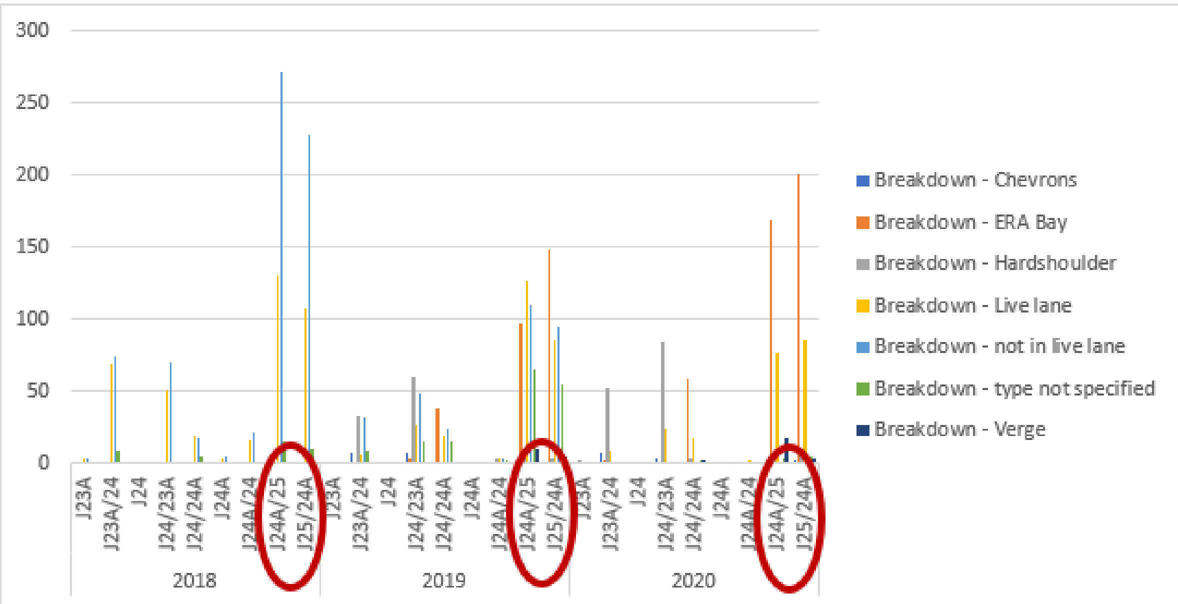


Figure 4.19: Number of different types of Breakdowns through years per segments of the selected motorway

4.4.3.3 Distribution of Incidents/Types per Date and Time

Following the analysis of the annual distribution of incidents and different types of incidents, it is crucial to understand where and when incidents occur for the simulation parameters. The tables below provide information about the distribution of incidents/types for the year 2019 based on:

1. Hour of the day
2. Day of the week
3. Day of the month

Similar results were also observed for the year 2018 when analysing the data for that year. The tables presented below specifically detail the results for the year 2019 (refer to Figure 4.20-Figure 4.22).

Hour/day	Breakdown	Obstruction	Roadworks	Traffic coll.	Grand Total
0	47	2		5	87
1	30	5	1	2	62
2	15	3		4	40
3	18	3	1		31
4	28	5		3	50
5	54	8		3	88
6	141	28		17	245
7	154	35	9	16	276
8	139	43	12	24	295
9	149	29	7	8	297
10	152	39	6	10	282
11	169	50	4	12	329
12	189	36	1	12	318
13	182	46	1	9	302
14	299	51	122	26	617
15	237	40	105	12	488
16	204	27	41	31	390
17	230	27	31	29	425
18	204	20	13	25	339
19	200	13	38	8	314
20	123	16	252	6	456
21	103	6	98	8	279
22	94	12	14	8	178
23	70	8	3	13	141
Grand Total	3231	552	759	291	6329

Figure 4.20: Distribution of incident types per hour of the day

Day of the week	Breakdown	Obstruction	Roadworks	Traffic coll.	Grand Total
Monday	460	78	123	55	915
Tuesday	497	97	141	42	1019
Wednesday	423	83	139	56	920
Thursday	473	86	146	39	971
Friday	526	105	129	53	1047
Saturday	418	54	43	18	746
Sunday	434	49	38	28	711
Grand Total	3231	552	759	291	6329

Figure 4.21: Distribution of incident types per day of the week

Day of the month	Breakdown	Obstruction	Roadworks	Traffic coll.	Grand Total
1	95	15	21	14	198
2	108	6	21	11	204
...	...	.	...	...	...
7	127	19	25	9	229
8	105	25	28	8	210
9	108	24	30	10	220
10	109	10	21	16	205
11	101	25	31	9	220
12	101	22	26	8	206
13	109	32	22	7	216
..	...	...		...	
17	113	17	38	3	239
18	119	15	37	7	234
19	99	19	26	8	218
...	...	...	...	...	...
24	119	11	26	10	217
25	110	18	29	14	229
...	...	...	...	...	...
29	125	15	20	12	210
30	108	15	13	10	192
31	48	19	14	5	113
Grand Total	3231	552	759	291	6329

Figure 4.22: Distribution of incident types per day of the month

The presented tables highlight that the majority of incidents occurred after 11:00 a.m., with peak hours observed between 14:00 and 18:00 in the evening. Additionally, the majority of incidents were concentrated in the middle of the week, particularly on Fridays, and within the first half of the month. This information is pivotal for the traffic microsimulation model, as it helps identify peak incident days and times, enabling the formulation of scenarios representing the most "dangerous" periods (days and times) in the model.

4.4.3.4 Distribution of Incidents/Types per Junction

Incident Location is one of the three essential values for the traffic microsimulation parameter section. This section provides information about the location of different types of incidents on the study network, highlighting areas considered the most dangerous—more prone to incidents. These areas have been identified not only for the main motorway carriageway but also for the slip roads, entries, and exits of vehicle inputs.

Main Road	Breakdown	Fire	Obstruction	Other	Traffic collision	Grand Total
J23	5		4	3		26
J23/23A	232	3	52	39	23	555
J23A	4	1	2	1	1	26
J23A/23	242	1	57	51	23	552
J23A/24	86	1	17	8	20	217
J24	16		6	2	8	55
J24/23A	160	1	26	7	20	264
J24/24A	96		5	15	7	142
J24A	1		3		1	20
J24A/24	11	1	7	1	4	43
J24A/25	411		62	45	20	656
J25	20	1	1	1	7	65
J25/24A	391	1	53	31	18	683
J25/26	379		76	29	29	696
J26	11	1	4	2	7	73
J26/25	279	1	79	21	25	648
Grand Total	2344	12	454	256	213	4721

Figure 4.23: Distribution of incidents/type per location for the main motorway-2019

Entries/Exits	Breakdown	Fire	Obstruction	Other	Traffic collision	Grand Total
J23J	35		4	3	6	71
J23K	10		1	16	1	38
J23L	38		1	11	1	70
J23M	6		1	5	1	28
J24J	39		1	4	9	58
J24K	7		2	7	1	61
J24L	52		3	3	6	79
J24M	20		4	2		60
J25J	130	1	2	5	7	152
J25K	17		7	11	2	57
J25L	38		5	2	6	73
J25M	30		7	3	3	96
J26J	30	1	4		4	70
J26K	30		10	7		58
J26L	59		8	4	3	92
J26M	17		6	3		45
Grand Total	558	2	66	86	50	1108

Figure 4.24: Distribution of incidents/type per location for the slip roads-2019

The figures above depict the distribution of incidents per type per junction. Figure 4.23 illustrates the main road area, while Figure 4.24 showcases the slip roads in the exits and entries areas. It is evident that the segment between J24A-J25 (Northbound) has the majority of breakdowns, and the grand total of all types of incidents is highest in the segment between J25-J26 (Southbound). Analysing incident data in this manner allows for a clear identification of locations where the majority of breakdowns or total incidents occur. This information is crucial for creating incidents in these locations within the traffic microsimulation model in VISSIM.

Furthermore, concerning the slip roads analysis, it is notable that the majority of breakdowns occurred, especially in exits. As indicated in Figure 4.24 and from earlier explanation in Figure 4.6, the descriptors J and L are used for exits from the motorway, while K and M are used for entries. To illustrate, exit 25J (Northbound) had 130 breakdowns in 2019. This could possibly be explained by the fact that if an incident occurs on the main motorway carriageway, drivers may immediately seek the closest exit to stop. Therefore, it is crucial to examine whether there is an emergency lane in this specific part of the road (refer to Table 4.3). Similar results were observed when analysing the data for 2018, and although the tables for that year are not included in this report, the findings align closely with those for 2019.

4.4.3.5 Distribution of Incidents/Types per Junction and Segments on the Main Motorway

The third but highly essential value for the traffic microsimulation model parameter section in VISSIM is **Incident Frequency**. The upcoming tables and figures will provide information about the distribution of breakdowns and total incidents per junction and segments on the main motorway. For each segment, the tables display a summary of breakdowns and total incidents, along with the length of the road where these incidents occurred. Similar results were obtained for the years 2016, 2017, and 2018 when analysing ControlWorks data, and while those specific tables are not included in this report, they yielded comparable findings. The focus here is solely on the results from ControlWorks data for the year 2019.

Table 4.11: Distribution of Total Breakdowns-2019

2019	Segment	Junctions	Breakdown	Sum of Breakdowns	% of Total Breakdowns	Length of Main Road (Km)	% of Total Length
	J23-J23A	**J23**	5	483	20.5%	6.44	24%
		J23/23A	232				
		J23A/23	242				
		J23A	4				
	J23A-J24	**J23A**		262	11%	2.9	10.5%
		J23A/24	86				
		J24/23A	160				
		J24	16				
	J24-J24A	**J24**		108	5%	1.29	4.5%
		J24/24A	96				
		J24A/24	11				
		J24A	1				
	J24A-J25	**J24A**		822	35%	7.08	26%
		J24A/25	411				
		J25/24A	391				
		J25	20				
	J25-J26	**J25**		669	28.5%	9.66	35%
		J25/26	379				
		J26/25	279				
		J26	11				
		Grand Total	2344	2344	100%	27.37	100%

Table 4.12: Distribution of Total Incidents-2019

2019	Segment	Junctions	Total Incidents	Sum of Total Incidents	% of Total Incidents	Length of Main Road (Km)	% of Total Length
	J23-J23A	**J23**	26	1133	24.2%	6.44	24%
		J23/23A	555				
		J23A/23	552				
		J23A	26				
	J23A-J24	**J23A**		507	11%	2.9	10.5%
		J23A/24	217				
		J24/23A	264				
		J24	55				
	J24-J24A	**J24**		240	5%	1.29	4.5%
		J24/24A	142				
		J24A/24	43				
		J24A	20				
	J24A-J25	**J24A**		1359	29.5%	7.08	26%
		J24A/25	656				
		J25/24A	683				
		J25	65				
	J25-J26	**J25**		1409	30.3%	9.66	35%
		J25/26	696				
		J26/25	648				
		J26	73				
		Grand Total	5221	4648	100%	27.37	100%

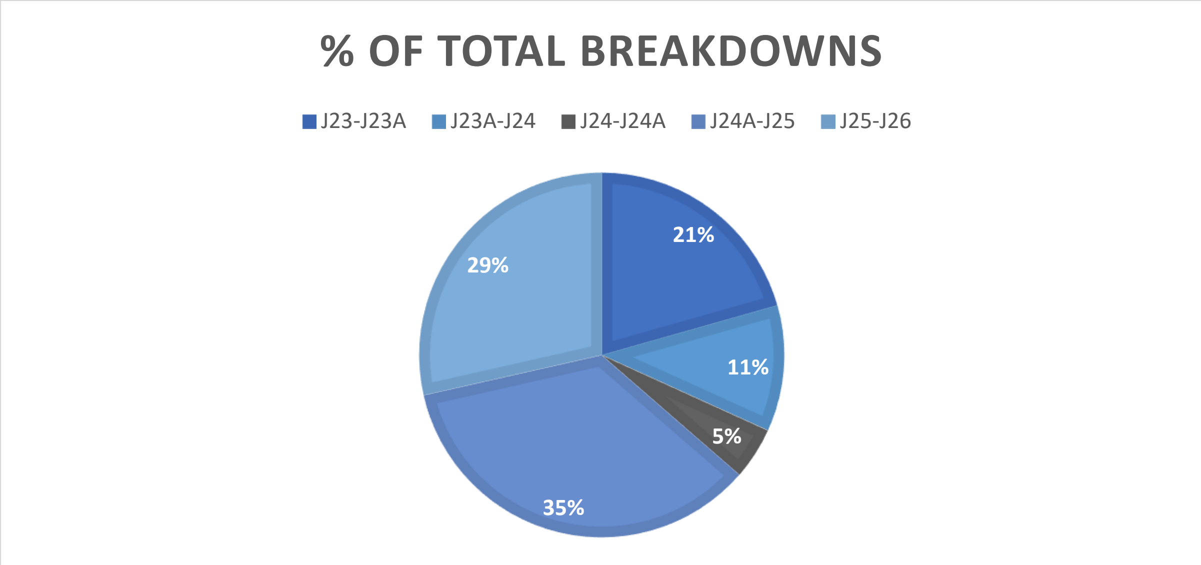


Figure 4.25: Distribution of Total Breakdowns-2019

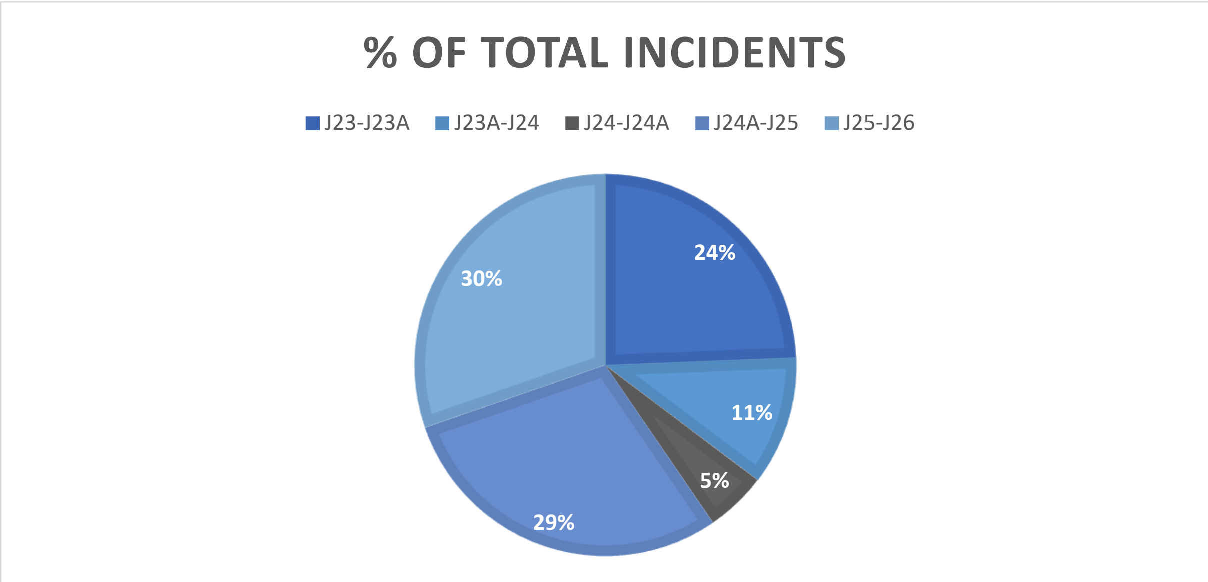


Figure 4.26: Distribution of Total Incidents-2019

Upon examining the provided tables and figures (refer to Table 4.11-Table 4.12, Figure 4.25, and Figure 4.26), a noteworthy observation is the concentration of breakdowns in the segment from 24A until 25, where the majority of breakdowns occur. Additionally, the distribution of breakdowns across segments is evidently uneven.

Furthermore, examining the breakdown frequency reveals that in the segment 24A-25, there are 822 breakdowns, meaning that nearly every ten hours, a breakdown occurs—equivalent to 2 breakdowns per day. This uneven distribution is also evident in Table 4.11, which displays almost identical results for total incidents. The issue persists in the segment from 24A until 25 (Table 4.12), where the majority of total incidents are concentrated. Specifically, there are 1359 total incidents in 24A-25, signifying that almost every six hours, an incident occurs—equivalent to 3 incidents per day (meaning that 3 incidents of summary from all types).

Considering the comprehensive analysis of ControlWorks data, all essential values—**Incident Duration, Incident Frequency, and Incident Location**—have been thoroughly examined and have been utilised in the parameter section of the traffic microsimulation model for both calibration and validation but more important for the incident detection part in VISSIM.

4.4.3.6 Comparison of Incident Types 2016-2019 Before ALR, Under-Construction ALR, and ALR

The All-Lane Running (ALR) Smart Motorways project is a National Highways initiative, representing a significant undertaking in the highways sector. Smart Motorways employ real-time traffic management techniques to alleviate congestion and facilitate the smooth flow of traffic. These techniques include variable speed limits and 'all lane running' schemes. The M1 motorway, the second-longest in England at 193.5 miles, was undergoing the Smart Motorway project, but currently is frozen.

The studied network of the M1 until February 2017 comprised three live lanes and an emergency lane. Subsequently, from March 2017 until almost one and a half years later, the examined section underwent construction for ALR implementation. National Highways officially declared the project's completion in December 2018. As of January 2019, the examined section had been operational as an ALR (refer to **Error! Reference source not found.**Table 4.13).

Certainly, keeping in mind the operational rules of the study network is crucial when analysing incident data from the ControlWorks datasets. The data under analysis spans from 2016 to 2019, providing a comprehensive dataset covering four years.

In the next diagrams, the fluctuation of incidents in J23-26 will be analysed for the periods:

1. Before ALR: Period January 2016-February 2017
2. Under Construction ALR: Period March 2017-December 2018
3. ALR: Period January 2019 – December 2019

The types of incidents that were analysed more are:

- Breakdowns
- Traffic Collisions
- Obstruction
- Total of Breakdowns, Traffic Collisions and Obstructions
- Grand Total of all types of incidents mentioned in section 5.3.

Following the exploration and analysis of incident data, it has been established that the number of incidents occurring in the selected road segments did not remain relatively constant during the examined period from 2016 to 2019 (refer to Table 4.13, Figure 4.27 and Figure 4.28). Hightlights shows the most dangerous months per type of incident.

Table 4.13: Count of incidents/type in the selected M1 segment

		Breakdown	Traffic Collision	Obstruction	Total	Grand Total
Before ALR	1	93	17	22	132	132
	2	78	19	37	134	135
	3	96	16	37	149	150
	4	100	25	32	157	158
	5	112	15	36	163	167
	6	128	26	56	210	210
	7	124	19	51	194	196
	8	137	14	48	199	202
	9	102	17	50	169	171
	10	134	13	36	183	183
	11	96	30	44	170	171
	12	116	21	21	158	160
	13	108	21	38	167	254
	14	118	14	40	172	260
Under construction ALR	15	119	22	53	194	386
	16	215	29	33	277	492
	17	249	30	49	328	528
	18	277	31	48	356	553
	19	256	39	46	341	499
	20	237	33	40	310	452
	21	267	39	32	338	472
	22	235	39	44	318	521
	23	269	52	35	356	571
	24	264	37	33	334	511
	25	238	47	48	333	587
	26	232	28	38	298	516
	27	308	23	49	380	629
	28	310	38	41	389	618
	29	293	30	41	364	603
	30	337	42	60	439	656
	31	335	66	67	468	681
	32	362	33	54	449	656
	33	269	38	52	359	584
	34	268	41	51	360	611
	35	255	38	43	336	602
	36	242	44	39	325	608
ALR	37	208	22	27	257	512
	38	209	30	31	270	496
	39	216	14	57	287	529
	40	226	15	41	282	448

	41	247	18	48	313	484
	42	273	16	55	344	526
	43	298	24	60	382	560
	44	286	12	49	347	502
	45	247	20	34	301	445
	46	248	28	36	312	461
	47	216	36	41	293	450
	48	228	28	41	297	416

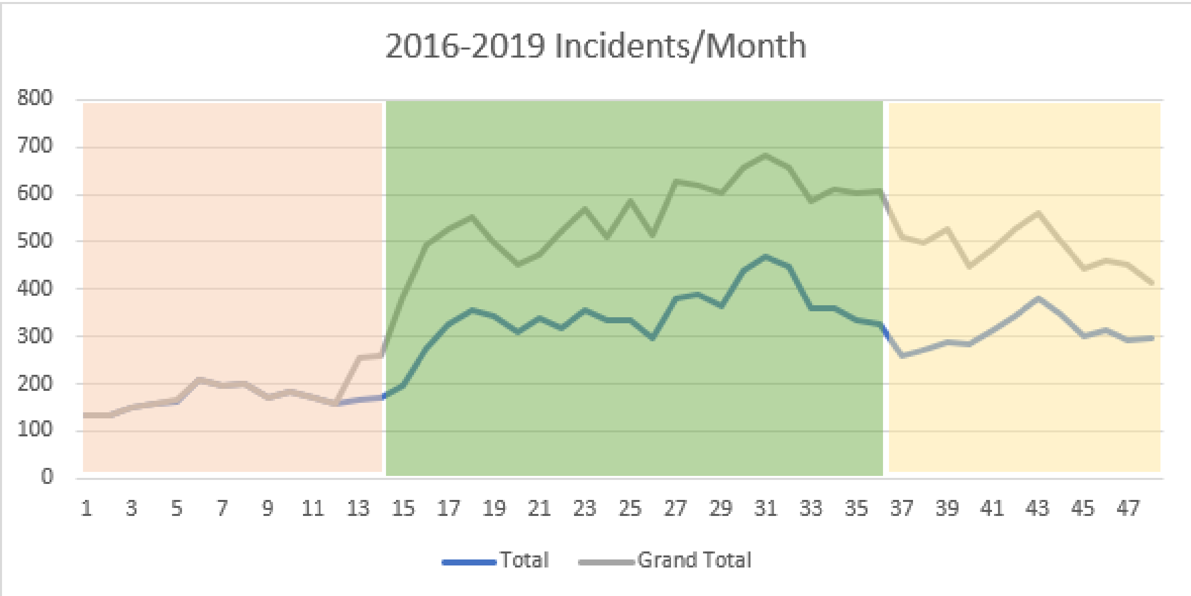


Figure 4.27: Number of Total and Grand Total per month in the selected M1 segment

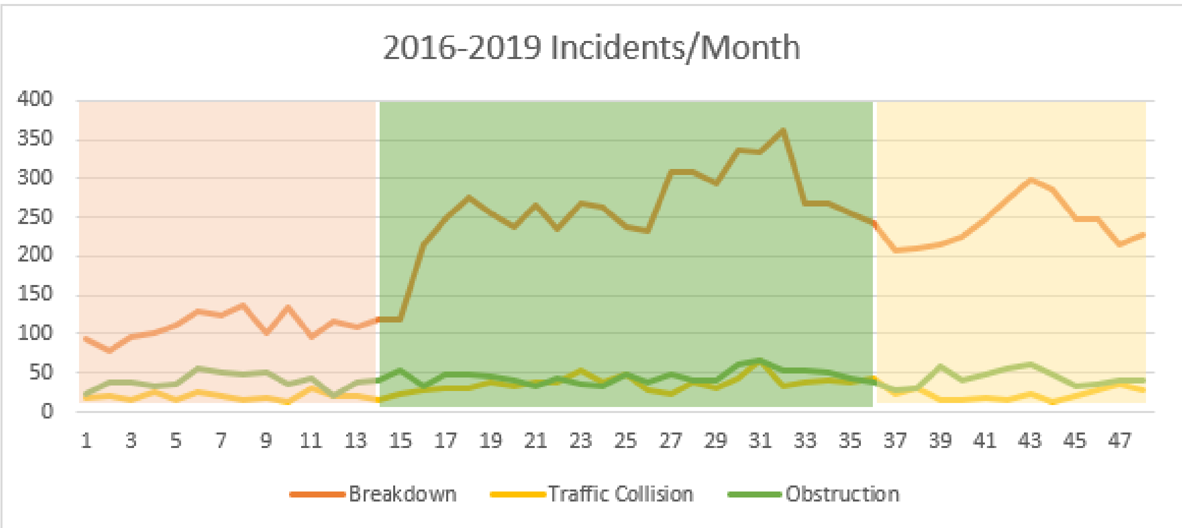


Figure 4.28: Number of Breakdowns, Traffic Collision and Obstruction per month in the selected M1 segment

A better look in Figure 4.27 and Figure 4.28 reveals that during the summer periods, especially in 2018 when the motorway was under construction, the number of breakdowns significantly increased. In 2018, the number was nearly three times higher during the summer period compared to 2016. After the construction phase, a decrease in the number of breakdowns is observed, although it did not reach the level of 2016. Conversely, traffic collision and obstruction followed a similar pattern each year, experiencing an increase during the summer period. The grand total incidents also exhibit a similar pattern to breakdowns, as depicted in Figure 4.27.

While the increase in traffic flow over the years has been noted, it is not sufficient for an accurate comparison of incidents. To assess them correctly, both the incident rate and exposure need to be considered. Therefore, the monthly Average Annual Daily Traffic (AADT) and Vehicle Miles Travelled (VMT) were calculated for both directions—Southbound and Northbound.

4.4.4 VMT and Incident Rate

4.4.4.1 Vehicle Miles of Travel (VMT)

As previously mentioned, for an accurate comparison of incidents per segment and month, both rate and exposure are crucial. Consequently, the incident data were divided for each direction—Southbound and Northbound—for each examined section of the study network for the years 2018 and 2019. The results for 2019 will be presented below.

Using incident data from ControlWorks in 2019, the directions were separated into Northbound and Southbound via analysis as the initial data is not being separated. Subsequently, the incidents were roughly categorised into junctions and segments, and the number of incidents was calculated (see Table 4.14, Table 4.15, Figure 4.29, and Figure 4.30).

Table 4.14: Number of incidents for 2019 for the Northbound examined section of M1 motorway

		Segments	BREAKDOWN	OBSTRUCTION	TRAFFIC COLLISION	Grand Total
2019	Northbound	**23-23A**	235	54	23	574
		23A-24	91	19	22	238
		24-24A	100	7	10	160
		24A-25	416	64	22	678
		25-26	390	79	35	748
		All motorway	1232	223	112	2398

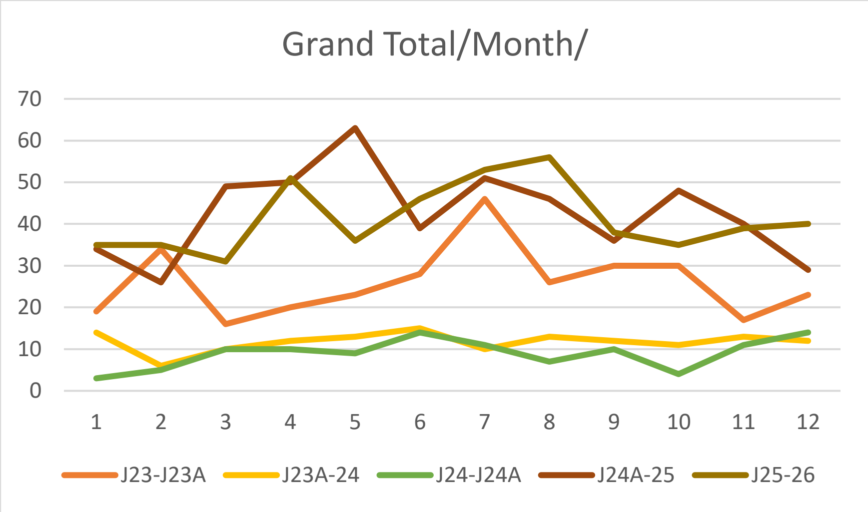


Figure 4.29: Monthly number of incidents per segment for 2019 for the Northbound examined section of M1 motorway

Table 4.15: Number of incidents for 2019 for the Southbound examined section of M1 motorway

		Segments	BREAKDOWN	OBSTRUCTION	TRAFFIC COLLISION	Grand Total
2019	Southbound	**23-23A**	246	58	24	571
		23A-24	165	27	22	285
		24-24A	16	10	6	62
		24A-25	396	53	20	706
		25-26	289	81	29	699
		All motorway	1112	229	101	2323

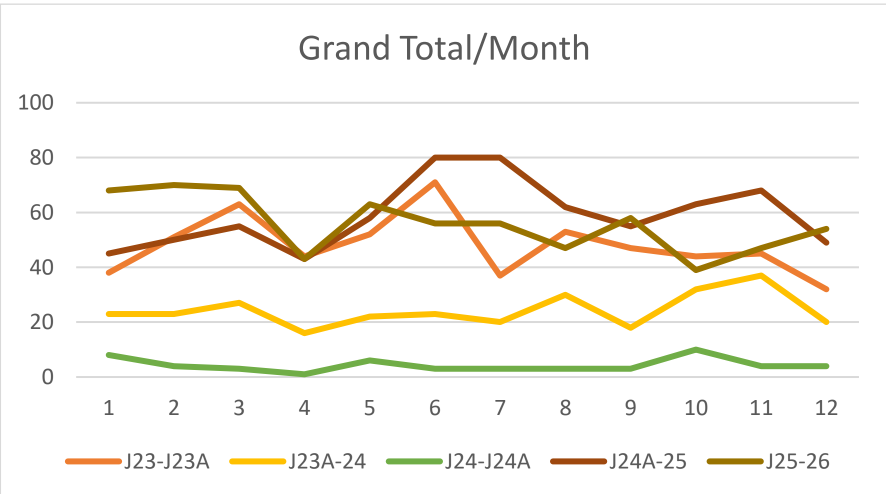


Figure 4.30: Monthly number of incidents per segment for 2019 for the Southbound examined section of M1 motorway

Vehicle miles travelled (VMT) is a widely used measure in transport planning for various purposes. It quantifies the total travel distance covered by all vehicles in a specific geographic region over a given period, typically measured monthly or annually. VMT is calculated by summing the mileage of each vehicle.

For the calculation of VMT, data from ILDs in 2018 and 2019 were utilised. Detector loops for each segment of the study network were considered—loops before, in the center, and after each junction—to calculate the monthly and Average Annual Daily Traffic (AADT), calculated as the total volume of vehicle traffic on a roadway over a year, divided by the number of days in the year. Using programming software, Python, the monthly and annual average AADT for each segment of the study network was determined. Additionally, the distance of each motorway segment was calculated with the assistance of Google Maps (see Table 4.16).

Table 4.16: Length of each segment on the study network

Junction		**23-23A**	**23A-24A**		**24A-25**	**25-26**
			23A-24	**24-24A**		
Google maps	Km	6.44	2.90	1.29	7.08	9.66

Moreover, subsequent to the calculation of the monthly and annual VMT for each segment and incident type, the outcomes are presented in the following tables. The tables include the VMT for each segment of the study network (M1, J23A-J26) both on a monthly and annual basis for the following incident types:

- Breakdowns
- Traffic Collision
- Obstruction
- Total: Summary of Breakdowns, Traffic Collision and Obstruction
- Grand Total: Summary of all types of incidents as mentioned in section 4.3

The VMT have been calculating as mentioned above both for Northbound and Southbound. The Table 4.17 is for Southbound for the year 2019 and Table 4.18 is for Northbound 2019.

Table 4.17: Monthly and Annual VMT for Southbound, examined network, 2019

Incident Rate		Months												Total
Segment		1	2	3	4	5	6	7	8	9	10	11	12	
J23-J23A	BREAKDOWN	0.0485536	0.0596739	0.0900805	0.0219293	0.0850543	0.0935056	0.0681912	0.1012977	0.0572236	0.0595619	0.0661318	0.0618013	0.8051017
J23A-24		0.1809803	0.1178324	0.1869855	0.1194159	0.1874794	0.2449429	0.17873	0.2371518	0.1537259	0.1332506	0.1762977	0.0879614	1.9238916
J24-J24A		0.0268999	0.0256432	0.0525398	0	0.0735025	0.0970542	0.0245127	0.0489344	0.0248522	0.0371653	0.0334539	0.0184813	0.4568884
J24A-25		0.0652306	0.0572811	0.0717136	0.0694495	0.0838004	0.1123028	0.110828	0.0856313	0.0818841	0.0811605	0.0901256	0.0825962	0.9967979
J25-26		0.053085	0.0527086	0.0459168	0.0389064	0.0532086	0.0351211	0.0654912	0.058064	0.0426769	0.030721	0.0214516	0.0413614	0.5384929
Total		0.0694365	0.0651162	0.0803978	0.0524756	0.0838702	0.0907442	0.0928653	0.0925784	0.0697682	0.0627249	0.0663815	0.0627549	0.8860082

Incident Rate		Months												Total
Segment		1	2	3	4	5	6	7	8	9	10	11	12	
J23-J23A	OBSTRUCTION	0.0097107	0.0094222	0.0310623	0.012531	0.014792	0.0323673	0.010767	0.0139721	0.0063582	0.018809	0.0220439	0.0137336	0.1954774
J23A-24		0	0.0471329	0.0467464	0.0119416	0.0170436	0.0163295	0.0487445	0.1264809	0.0128105	0.0177667	0.0160271	0	0.3206486
J24-J24A		0.0268999	0	0.0262699	0	0.0490016	0.0242636	0	0.0489344	0	0.0185827	0.016727	0.0184813	0.2284442
J24A-25		0.0108718	0.0052074	0.0159364	0.0102888	0.0123236	0.0122068	0.0197028	0.0097864	0.0099253	0.0050725	0.010014	0.0192725	0.1402145
J25-26		0.0098306	0.0094122	0.0153056	0.0037054	0.014189	0.0158045	0.0177003	0.003519	0.0160038	0.0090356	0.0125134	0.0216655	0.1483603
Total		0.0110082	0.0113953	0.0237912	0.0088805	0.016608	0.0204379	0.0197236	0.0162418	0.0126851	0.011807	0.0149894	0.018042	0.1851837

Incident Rate		Months												Total
Segment		1	2	3	4	5	6	7	8	9	10	11	12	
J23-J23A	TRAFFIC COLLISION	0.0097107	0.0157036	0.0062125	0.0031328	0.007396	0.0071927	0.003589	0	0.0063582	0.0094045	0.0031491	0.0034334	0.076203
J23A-24		0.0361961	0.0353497	0.0116866	0	0.0170436	0.0163295	0.0324964	0	0.0384315	0.0088834	0.0320541	0.0087961	0.2375175
J24-J24A		0	0.0256432	0	0.0255606	0	0	0.0245127	0.0244672	0	0.0371653	0.016727	0.0184813	0.1827554
J24A-25		0	0.0078111	0.0053121	0	0.0049294	0	0.0073885	0.0048932	0.0049627	0.0025363	0.005007	0.0027532	0.0458884
J25-26		0.0019661	0.0094122	0.0038264	0.0018527	0.0035472	0.0052682	0.0088502	0	0.0071128	0.0072285	0.0071505	0.0019696	0.0586115

Total		0.0059275	0.0138372	0.0057427	0.002422	0.0058128	0.0049051	0.0098618	0.0024363	0.008721	0.0081173	0.0085654	0.0039222	0.0806188

Incident Rate		Months												Total
Segment		1	2	3	4	5	6	7	8	9	10	11	12	
J23-J23A	Total	0.0679751	0.0847997	0.1273552	0.0375931	0.1072423	0.1330657	0.0825472	0.1152697	0.0699399	0.0877755	0.0913248	0.0789683	1.0767821
J23A-24		0.2171763	0.200315	0.2454184	0.1313575	0.2215665	0.2776019	0.2599709	0.3636327	0.2049679	0.1599007	0.2243789	0.0967575	2.4820577
J24-J24A		0.0537999	0.0512863	0.0788097	0.0255606	0.1225041	0.1213178	0.0490254	0.1223361	0.0248522	0.0929133	0.0669079	0.055444	0.868088
J24A-25		0.0761024	0.0702996	0.0929621	0.0797383	0.1010534	0.1245096	0.1379193	0.100311	0.0967721	0.0887693	0.1051465	0.1046219	1.1829009
J25-26		0.0648816	0.071533	0.0650488	0.0444645	0.0709448	0.0561937	0.0920417	0.061583	0.0657935	0.0469851	0.0411156	0.0649965	0.7454646
Total		0.0863722	0.0903488	0.1099317	0.0637781	0.1062909	0.1160872	0.1224507	0.1112565	0.0911743	0.0826493	0.0899363	0.0847191	1.1518107

Incident Rate		Months												Total
Segment		1	2	3	4	5	6	7	8	9	10	11	12	
J23-J23A	Grand Total	0.1230025	0.1601772	0.1956922	0.1378415	0.1922966	0.2553423	0.1327934	0.1851302	0.1494171	0.1379329	0.1417109	0.1098689	1.9117024
J23A-24		0.2775031	0.2710144	0.315538	0.1910655	0.3749587	0.3755791	0.3249637	0.4743035	0.2305889	0.2842679	0.2965007	0.1759228	3.4558793
J24-J24A		0.2151995	0.1025726	0.0788097	0.0255606	0.1470049	0.0727907	0.0735381	0.0734017	0.0745567	0.1858266	0.0669079	0.0739254	1.1879099
J24A-25		0.1223074	0.1301844	0.1460833	0.1106048	0.1429537	0.1953091	0.1970276	0.1516898	0.1364734	0.1597848	0.1702372	0.1349072	1.8049436
J25-26		0.1336955	0.1317714	0.1320108	0.0796655	0.111738	0.098339	0.0991219	0.0826972	0.1031358	0.0704776	0.0840187	0.1063579	1.2271777
Total		0.1541151	0.1611626	0.1780237	0.1186757	0.16691	0.1904811	0.1610761	0.1583578	0.1435005	0.1387327	0.1434698	0.1247253	1.8342765

Table 4.18: Monthly and Annual VMT for Northbound, examined network, 2019

Incident Rate		Months												Total
Segment		1	2	3	4	5	6	7	8	9	10	11	12	
J23-J23A	BREAKDOWN	0.0507736	0.0754339	0.0417682	0.0572718	0.0573599	0.0760777	0.1545047	0.0672712	0.0870205	0.0752635	0.0331142	0.049305	0.8153036
J23A-24		0.0661993	0.0325751	0.0444404	0.0622863	0.0679448	0.0879495	0.0599735	0.0664102	0.0617719	0.0624479	0.0626954	0.0594703	0.7202003
J24-J24A		0.0431754	0.0420203	0.1230236	0.1270299	0.1423178	0.1737587	0.161118	0.0937465	0.1362282	0.0419357	0.1549501	0.1818713	1.4067154
J24A-25		0.078847	0.0595155	0.0870843	0.1115711	0.1317858	0.0889445	0.1055379	0.0985153	0.0752891	0.098651	0.0792394	0.0665272	1.0867906

J25-26		0.0582648	0.0538991	0.0522548	0.0667286	0.0530556	0.0633909	0.068221	0.092051	0.0553417	0.0482234	0.0504471	0.0648694	0.7279554
Total		0.0615923	0.0567385	0.0615359	0.0797485	0.0847112	0.0827367	0.1024324	0.0900389	0.0725932	0.0690574	0.0613086	0.0674263	0.886746

Incident Rate		Months												Total
Segment		1	2	3	4	5	6	7	8	9	10	11	12	
J23-J23A	OBSTRUCTION	0.0067698	0.0262379	0.0064259	0.0101068	0.026768	0.0266272	0.0231757	0.026161	0.0096689	0.0065447	0.0132457	0.0105654	0.1873464
J23A-24		0.0066199	0	0.0190459	0.0138414	0.0291192	0.0390887	0.0099956	0.0379487	0	0.0069387	0.0069662	0.0074338	0.1592022
J24-J24A		0	0.0140068	0	0.0141144	0	0.0315925	0	0	0	0	0	0.0151559	0.0732664
J24A-25		0.0056319	0.0054105	0.0395838	0.0129734	0.0174057	0.0049414	0.0226153	0.0098515	0.007286	0.0177066	0.0102244	0.0110879	0.1648213
J25-26		0.0083235	0.007985	0.0077414	0.0209719	0.0091475	0.0163005	0.0221257	0.0090246	0.0107113	0.0129832	0.0130789	0.0081087	0.1474819
Total		0.0065992	0.0106385	0.016594	0.0155263	0.0164924	0.017889	0.0212452	0.0147605	0.0080659	0.0117398	0.011147	0.0097394	0.1596574

Incident Rate		Months												Total
Segment		1	2	3	4	5	6	7	8	9	10	11	12	
J23-J23A	TRAFFIC COLLISION	0.0067698	0.0098392	0.0032129	0	0.003824	0.0038039	0	0.0037373	0	0.0163616	0.0099343	0.0211307	0.0797957
J23A-24		0.0198598	0.006515	0	0.0069207	0.0291192	0.0195443	0.0299868	0.0189743	0.0205906	0.0069387	0.0208985	0.0223014	0.1895264
J24-J24A		0	0.0140068	0.0136693	0	0	0.0157962	0.0161118	0.0156244	0	0.0139786	0	0.0151559	0.102573
J24A-25		0.0112639	0.0054105	0.0026389	0.0051894	0.0074596	0.0024707	0	0.0049258	0.0048574	0.005059	0.0127806	0.002772	0.0643833
J25-26		0.0062427	0.007985	0	0.0095327	0.003659	0.0036223	0.0073752	0	0.0017852	0.0037095	0.0093421	0.0081087	0.0605054
Total		0.0087989	0.0078015	0.0020742	0.0056459	0.0067469	0.0052176	0.0060701	0.0044281	0.004033	0.0075963	0.011147	0.0112377	0.0805479

Incident Rate		Months												Total
Segment		1	2	3	4	5	6	7	8	9	10	11	12	
J23-J23A	Total	0.0643133	0.111511	0.051407	0.0673785	0.0879519	0.1065088	0.1776804	0.0971695	0.0966895	0.0981698	0.0562942	0.0810011	1.0824457
J23A-24		0.092679	0.0390901	0.0634863	0.0830485	0.1261833	0.1465825	0.0999559	0.1233333	0.0823626	0.0763252	0.09056	0.0892055	1.0689289
J24-J24A		0.0431754	0.0700338	0.1366929	0.1411443	0.1423178	0.2211475	0.1772298	0.1093709	0.1362282	0.0559142	0.1549501	0.2121832	1.5825548
J24A-25		0.0957427	0.0703365	0.129307	0.1297339	0.156651	0.0963566	0.1281532	0.1132926	0.0874325	0.1214166	0.1022444	0.080387	1.3159953
J25-26		0.072831	0.0698692	0.0599962	0.0972332	0.0658621	0.0833138	0.097722	0.1010757	0.0678382	0.0649161	0.0728681	0.0810867	0.9359427
Total		0.0769904	0.0751786	0.0802041	0.1009206	0.1079505	0.1058434	0.1297477	0.1092275	0.0846921	0.0883935	0.0836026	0.0884034	1.1269513

Incident Rate		Months												Total
Segment		1	2	3	4	5	6	7	8	9	10	11	12	
J23-J23A	Grand Total	0.1794001	0.2066233	0.1349434	0.1313881	0.0573599	0.1939983	0.2858338	0.1831272	0.1482572	0.1570717	0.1357684	0.1338279	1.9393818
J23A-24		0.1985979	0.1368154	0.222202	0.1799383	0.0679448	0.175899	0.1799206	0.1517948	0.1029532	0.0971412	0.1184247	0.1263744	1.7739672
J24-J24A		0.1007425	0.0980473	0.1503621	0.2117164	0.1423178	0.315925	0.2094534	0.1718686	0.2043423	0.1537641	0.1972092	0.2273392	2.1686862
J24A-25		0.1745897	0.1379678	0.1794465	0.2023848	0.1317858	0.1358875	0.1633325	0.1453101	0.0995759	0.1517708	0.1201372	0.1025628	1.7409253
J25-26		0.1040443	0.0978168	0.1064449	0.1220181	0.0530556	0.1141037	0.1493486	0.140784	0.1053277	0.0853183	0.1139732	0.1114943	1.3046474
Total		0.1481148	0.1354633	0.1458886	0.156674	0.0847112	0.1542928	0.1904484	0.157199	0.1183	0.1236127	0.1254039	0.1213674	1.6591427

4.4.4.2 Risk Level

Finally, the last step in this procedure involved the calculation of the Incident Rate for each segment, both on a monthly and annual basis, following the equation (4.2):

$$Incident\ Rate = \frac{total\ incidents}{appropriateVMT} \quad (4.2)$$

The following tables include the incident rate for each segment of the study network (M1, J23A-J26) on a monthly basis for the following types of incidents:

- Breakdowns
- Traffic Collision
- Obstruction
- Total: Summary of Breakdowns, Traffic Collision and Obstruction
- Grand Total: Summary of all types of incidents as mentioned in section 4.3

For the calculation of the risk band of each segment of the motorway, the monthly incident rate of each segment was used. The examined segments have been coded as depicted in the tables below (refers to Table 4.19-Table 4.21) for easier specification in the coding used:

Table 4.19: Location codes for the examined network

Segment	Code for Location
J23-J23A	S1
J23A-24	S2
J24-J24A	S3
J24A-25	S4
J25-26	S5

Table 4.20: Incidents codes for the examined network

Name	Definition
rate_BR	breakdown
rate_OB	obstruction
rate_TC	traffic collision
rate_Tot	total of the three above
rate_GrTot	grand total of all incidents

The distribution of risk rate was divided in five levels as below:

Table 4.21: Risk bands

Band rate	Risk level	Risk Code
<10	owl	1
10.1-15	medium	2
15.1-20	High 1	3
20.1-25	High 2	4
>25	Highest	5

Additionally, based on the incident rate and the risk code as mentioned above, the monthly risk level of each segment, both for Southbound and Northbound, for all the mentioned categories of incidents were calculated. The results are presented in the tables below (see Table 4.22 - Table 4.31):

Table 4.22: Monthly risk band for Breakdowns, Southbound, in the selected M1segment

	Location	rate_BR_1	rate_BR_2	rate_BR_3	rate_BR_4	rate_BR_5	rate_BR_6	rate_BR_7	rate_BR_8	rate_BR_9	rate_BR_10	rate_BR_11	rate_BR_12
Southbound	S1	1	1	1	1	1	1	1	1	1	1	1	1
	S2	3	2	3	2	3	4	3	4	2	2	3	1
	S3	1	1	1	1	2	1	1	1	1	1	1	1
	S4	1	1	1	1	2	2	2	1	1	1	2	1
	S5	1	1	1	1	1	1	1	1	1	1	1	1

Table 4.23: Monthly risk band for Breakdowns, Northbound, in the selected M1 segment

	Location	rate_BR_1	rate_BR_2	rate_BR_3	rate_BR_4	rate_BR_5	rate_BR_6	rate_BR_7	rate_BR_8	rate_BR_9	rate_BR_10	rate_BR_11	rate_BR_12
Northbound	S1	1	1	1	1	1	1	2	1	1	1	1	1
	S2	1	1	1	1	1	1	1	1	1	1	1	1
	S3	1	1	2	2	2	3	3	1	2	1	1	3
	S4	1	1	1	2	2	1	2	1	1	1	1	1
	S5	1	1	1	1	1	1	1	1	1	1	1	1

Table 4.24: Monthly risk band for Obstructions, Southbound, in the selected M1 segment

	Location	rate_OB_1	rate_OB_2	rate_OB_3	rate_OB_4	rate_OB_5	rate_OB_6	rate_OB_7	rate_OB_8	rate_OB_9	rate_OB_10	rate_OB_11	rate_OB_12
Southbound	S1	1	1	1	1	1	1	1	1	1	1	1	1
	S2	1	1	1	1	1	1	1	2	1	1	1	1
	S3	1	1	1	1	1	1	1	1	1	1	1	1
	S4	1	1	1	1	1	1	1	1	1	1	1	1
	S5	1	1	1	1	1	1	1	1	1	1	1	1

Table 4.25: Monthly risk band for Obstructions, Northbound, in the selected M1 segment

	Location	rate_OB_1	rate_OB_2	rate_OB_3	rate_OB_4	rate_OB_5	rate_OB_6	rate_OB_7	rate_OB_8	rate_OB_9	rate_OB_10	rate_OB_11	rate_OB_12
Northbound	S1	1	1	1	1	1	1	1	1	1	1	1	1
	S2	1	1	1	1	1	1	1	2	1	1	1	1
	S3	1	1	1	1	1	1	1	1	1	1	1	1
	S4	1	1	1	1	1	1	1	1	1	1	1	1
	S5	1	1	1	1	1	1	1	1	1	1	1	1

Table 4.26: Monthly risk band for Traffic collision, Southbound, in the selected M1 segment

	Location	rate_TC_1	rate_TC_2	rate_TC_3	rate_TC_4	rate_TC_5	rate_TC_6	rate_TC_7	rate_TC_8	rate_TC_9	rate_TC_10	rate_TC_11	rate_TC_12
Southbound	S1	1	1	1	1	1	1	1	1	1	1	1	1
	S2	1	1	1	1	1	1	1	1	1	1	1	1
	S3	1	1	1	1	1	1	1	1	1	1	1	1
	S4	1	1	1	1	1	1	1	1	1	1	1	1
	S5	1	1	1	1	1	1	1	1	1	1	1	1

Table 4.27: Monthly risk band for Traffic collision, Northbound, in the selected M1 segment

	Location	rate_TC_1	rate_TC_2	rate_TC_3	rate_TC_4	rate_TC_5	rate_TC_6	rate_TC_7	rate_TC_8	rate_TC_9	rate_TC_10	rate_TC_11	rate_TC_12
Northbound	S1	1	1	1	1	1	1	1	1	1	1	1	1
	S2	1	1	1	1	1	1	1	1	1	1	1	1
	S3	1	1	1	1	1	1	1	1	1	1	1	1
	S4	1	1	1	1	1	1	1	1	1	1	1	1
	S5	1	1	1	1	1	1	1	1	1	1	1	1

Table 4.28: Monthly risk band for Total incidents, Southbound, in the selected M1 segment

	Location	rate_Tot_1	rate_Tot_2	rate_Tot_3	rate_Tot_4	rate_Tot_5	rate_Tot_6	rate_Tot_7	rate_Tot_8	rate_Tot_9	rate_Tot_10	rate_Tot_11	rate_Tot_12
Southbound	S1	1	1	2	1	2	2	1	2	1	1	1	1
	S2	4	3	4	2	4	5	5	5	3	3	3	1
	S3	1	1	1	1	2	2	1	2	1	1	1	1
	S4	1	1	1	1	1	2	2	1	1	1	2	1
	S5	1	1	1	1	1	1	1	1	1	1	1	1

Table 4.29: Monthly risk band for Total incidents, Northbound, in the selected M1 segment

	Location	rate_Tot_1	rate_Tot_2	rate_Tot_3	rate_Tot_4	rate_Tot_5	rate_Tot_6	rate_Tot_7	rate_Tot_8	rate_Tot_9	rate_Tot_10	rate_Tot_11	rate_Tot_12
Northbound	S1	1	2	1	1	1	2	3	1	1	1	1	1
	S2	1	1	1	1	2	2	1	2	1	1	1	1
	S3	1	1	2	2	2	4	3	2	2	1	2	4
	S4	1	1	2	2	3	1	2	2	1	2	1	1
	S5	1	1	1	1	1	1	1	1	1	1	1	1

Table 4.30: Monthly risk band for Grand Total, Southbound, in the selected M1 segment

	Location	rate_GranTot_1	rate_GranTot_2	rate_GranTot_3	rate_GranTot_4	rate_GranTot_5	rate_GranTot_6	rate_GranTot_7	rate_GranTot_8	rate_GranTot_9	rate_GranTot_10	rate_GranTot_11	rate_GranTot_12
South bound	S1	2	3	3	2	2	5	2	3	2	2	2	2
	S2	5	5	5	3	5	5	5	5	4	5	5	3
	S3	4	1	1	1	2	1	1	1	1	3	1	1
	S4	2	2	2	2	2	3	3	2	2	3	3	2
	S5	2	2	2	1	2	1	1	1	1	1	1	2

Table 4.31: Monthly risk band for Grand Total, Northbound, in the selected M1 segment

	Location	rate_GranTot_1	rate_GranTot_2	rate_GranTot_3	rate_GranTot_4	rate_GranTot_5	rate_GranTot_6	rate_GranTot_7	rate_GranTot_8	rate_GranTot_9	rate_GranTot_10	rate_GranTot_11	rate_GranTot_12
Northbound	S1	3	4	2	2	1	3	5	5	2	2	2	2
	S2	3	2	4	3	1	3	3	2	1	1	2	3
	S3	1	1	2	4	2	5	4	3	3	2	3	4
	S4	3	2	3	3	2	2	3	2	1	2	2	1
	S5	1	4	2	2	1	2	2	2	2	1	2	2

Analysing the tables above, the location with the highest monthly incident risk rate is identified with the darker orange, as stated in Table 4.21, for every section between junctions (23-26).

4.5 Summary

A significant amount of work has been conducted for the development and display of the examined section of the motorway in the traffic microsimulation model. The solid and detailed foundation of the model had, as a consequence the better results while testing it. Chapter 4 includes all the data analysis results and discussion needed for the simulation model to be developed and accurate representative the real-world data. Four-year detailed Incident datasets used for the best decoding of the examined area. Additionally, exploring the reason why an incident occurred, analysing the location, the frequency and the duration, much information for the driving behaviour, and much more can be reported. All of the above are more than essential for the detection of an incident in motorways. Incident Location, Incident Duration and Incident Frequency are the vital parameters that Incident Data analysis provided to the project as all of them will be imported to the parameter section of the traffic microsimulation model that has been built in VISSIM.

After analysing ILDs data of the examined segment of the M1 motorway (J23-J26), a summary of the flow for each category, the maximum capacity occurred, and the time of the maximum capacity have been recognised. All of them will be used for the baseline scenario development in the traffic microsimulation model in the parameter section. Their analysis showed that the maximum capacity occurs around 7:30-8:30 in the morning and 16:00-18:00 in the evening, where the number of vehicles passing by, is being known and will be inserted in the VISSIM model with all the real speeds and time headways as ILDs datasets are being shown. Finally, the real percentage of passenger vehicles and HGVs has been considered too.

For the calibration and the validation of the Incident Detection scenario, MIDAS data for 2019 have been used. Forty files of MIDAS datasets, each file consisting of 525.600 values, have been used for calibration and validation of the model and will be used in Chapter 5 below. For this step, the vehicle inputs have been already recognised and evaluated, transforming the one-minute aggregated data to one-hour aggregated data to be ready to be used in the calibration and validation procedure. These datasets will be inductive loop detector data, as it has already explained in chapter 3 and 4. The highly disaggregated inductive loop detector data used in this PhD is one of the most detailed datasets that can be found in the existing literature. The calibration and the validation of the traffic microsimulation models have been based on these data, as they will be used as direct input to the baseline scenarios, providing this way with a solid foundation for the results. Python algorithms needed for MIDAS data have been used, and calibration/validation phases have been taken part and analysed in Chapter 5 below.

In the subsequent phase of this Ph.D. research, an in-depth analysis of both traffic and incident data has been conducted, extending beyond the initial focus on the segment between Leicester and Nottingham to encompass a broader network, specifically the M1. The outcomes of this comprehensive analysis will be detailed in the forthcoming Chapter 5: Incident Modelling and Findings. This chapter not only involves descriptive analysis but also delves into statistical modelling to unveil the intricate connections between traffic data, particularly congestion, and incident occurrences.

Chapter 5. Simulation modelling and its calibration - Scenario Development

5.1 Introduction

This chapter outlines the framework for developing an effective traffic microsimulation experiment. As mentioned in the previous chapter, calibration, validation, and verification processes are necessary for accurate results. To calibrate and validate a traffic microsimulation model, real-world data is first used and then compared to simulated data. Based on this comparison, adjustments are made to the simulation model parameters to minimise discrepancies between the simulated and actual real-world data. This chapter will comprehensively analyse the details and outcomes of these three processes.

The chapter starts with an introduction to the motorway study area, which lays the foundation for developing the incident detection scenario in the traffic microsimulation platform. It then provides insights into the development of the Traffic Microsimulation Model in VISSIM, including the signalisation of roundabouts and slip roads. Additionally, it offers a detailed understanding of the study area's limitations.

The data collected includes crucial elements like the network's geographical configuration, traffic flow, traffic speed, and traffic signal settings. These components are essential inputs for the next phases of traffic microsimulation, such as the calibration and validation processes. Additionally, the chapter elaborates on the datasets presented in Chapter 4 and how they relate to the Simulation Network Model. The discussion covers aspects like the Simulation platform, the Wiedemann 99 - Car Following model, the traffic microsimulation CV framework approach, a review of existing simulation tools, and the traffic microsimulation methodology. The goal is to create a model that accurately reflects real-world traffic conditions and driver behaviours with a high degree of accuracy by using precise calibration and validation methodologies. The chapter then focuses on the incident detection methodology, its implementation in the simulation platform, and the creation of representative scenarios for incident detection. It also explains the metrics used to measure the effectiveness of the developed methodology.

The concluding section examines key aspects of the V2V technology, exploring incident detection time with and without V2V implementation on the motorway. It explores real-time incident detection with severity assessment and rapid information transfer, highlighting the challenges linked with V2V implementation. Further analysis of these challenges will be covered in Chapter 6.

5.2 Methodology for the Development of a Microscopic Traffic Simulation Model

The concept of traffic microsimulation involves the mathematical modelling of real-world transport systems within the dimensions of time and space facilitated by computer software. This methodology offers distinct advantages, as it enables the analysis of intricate dynamic models and accommodates various levels of detail. Established simulation platforms exhibit efficacy in assessing the performance of both extant traffic operations and proposed systems. Prior to establishing the simulation model, it is imperative to adhere to a series of essential steps to ensure the execution of a reliable and comprehensive computational experiment as described in Chapter 3. The preparatory measures contribute significantly to the simulation process, the details of which are briefly summarised in Figure 5.1. The analytical methodology of each step (calibration, validation, and verification) analysed in Chapter 3. This visual representation serves as a guide, outlining the fundamental sequential stages to traffic microsimulation, thus aiming to the creation of a robust model.

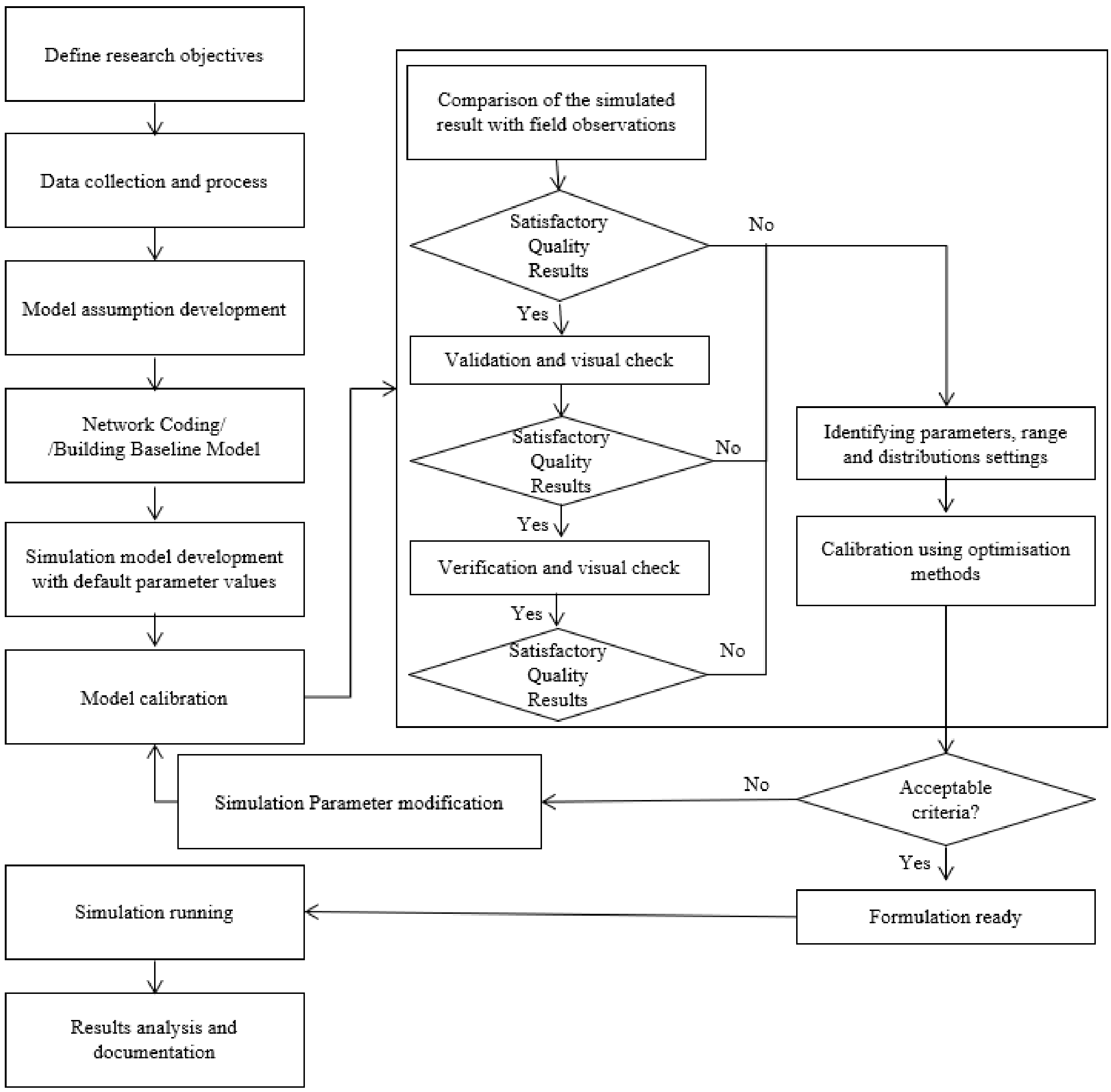


Figure 5.1:The traffic microscopic simulation development process

During calibration, the model is validated by comparing simulated measurements with real traffic data. This validation process ensures that the microsimulation platform reflects real-world driver behaviours. To gather simulated outputs, data collection points are strategically positioned based on real-world network coding. The calibration criteria requires that the difference between simulated and real-world outputs must be within a specified threshold. If the threshold is not met, adjustments are made to key variables such as speed distribution, traffic flow, and other driving behaviour parameters until calibration is achieved. After the calibration stage is completed, the verification stage adds extra accuracy to the model calibration. Once the calibration phase is finished, results are recorded through simulation runs for analysis. Finally, these outcomes are used to evaluate the simulation model's performance under various conditions, including signal-controlled intersections and slip roads, testing the desired scenarios. The results of the three stages of calibration will be presented in section 6.4 of this chapter.

5.3 Study Area

This PhD research aims to evaluate how incident detection using V2V communication technologies affects the performance of highway traffic. The study will establish connections between incident detection algorithms and the human driver model while developing and selecting a CV driving model. The research will be conducted on a segment of the M1 motorway, including slip roads and roundabouts, stretching approximately 100 km. The M1 motorway is a vital component of the government-operated Strategic Road Network (SRN) overseen by National Highways, connecting Leeds to London in the United Kingdom. The selected study area for the incident detection scenario is a segment of the M1 motorway between junctions 23 and 26, west of Loughborough and northwest of Nottingham, with GPS coordinates for these junctions being (52°45'20.86"N 1°16'25.70" W) and (52°59'38.13"N 1°13'53.86"W) respectively. The microsimulation platform of VISSIM was used to design the main motorway, slip roads, roundabouts, and their signalisation (traffic lights) for the subsequent analysis. Figure 5.2 illustrates the delineated study area. The microsimulation platform of VISSIM was employed to design the main motorway, slip roads, and roundabouts including their signalisation (traffic lights) for the subsequent analysis.

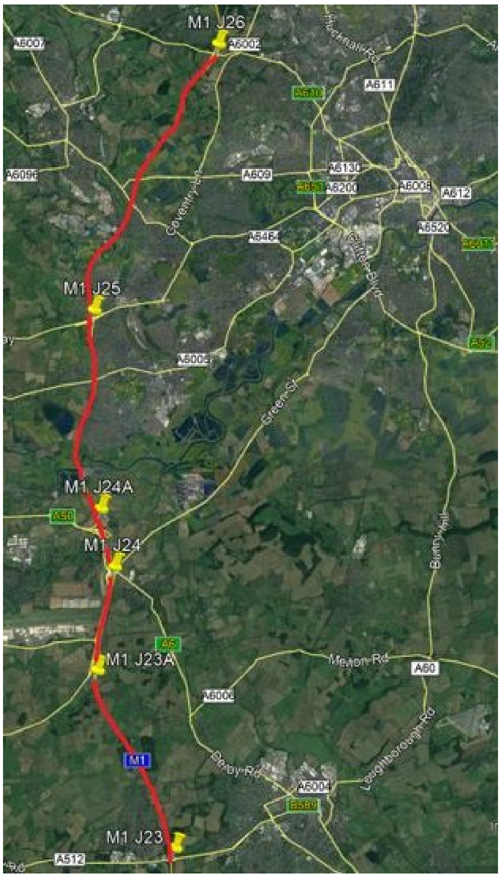


Figure 5.2: Motorway network study area.

The study area comprises approximately 30 km of the main motorway in each direction, encompassing six significant roundabouts (Roundabouts: 23, 23A, 24, 24A, 25, and 26), along with a parking/rest area where drivers can have a rest during their trips. It is important to note that the design of the slip roads connecting the main motorway and the roundabouts ensures a precise representation of real-world conditions. Notably, the entrances and exits to the main motorway, along with the signalisation within the roundabouts, have been designed with high accuracy and have been modelled to reflect the actual infrastructure. The rationale behind selecting this specific segment is multifaceted:

1. **Technological Transition:** This section of the road presents a wide range of opportunities and highlights the evolution of technology. Until March 2017, the road was contained three live lanes and one lane for hard shoulder throughout its entire length. Spanning the period from March 2017 to December 2018, this segment underwent construction for All Lane Running (ALR) and subsequently transitioned into a smart motorway with ALR from January 2019. This development of the smart motorway allows for an in-depth examination of the transformative changes over the years, particularly focusing on the most critical areas where the data will show us the emergency safety gap. The in-depth examination is conducted by analysing historical and real-time traffic data, comparing key performance indicators before and after smart motorway implementation, and using traffic simulation models to evaluate safety measures and identify critical gaps in emergency response and operational efficiency.
2. **Consistent Lane Configuration:** In order to avoid any potential issues with the simulation software, such as bugs and problems related to varying lane numbers, the segment used keep the number of lanes constant in the selected segment. The selected portion between junctions 23A and 26 consistently featured four live lanes with ALR, ensuring model accuracy during simulation. Segments 23-23A and 25-26 were specifically generated and modelled to enhance simulation precision.
3. **Proximity to Loughborough University:** The selected section was close to Loughborough University, where this research started from. There was a necessity for the required traffic and safety surrogate measure data to be gathered frequently in specified time. As a result, this specific segment of M1 was a convenient location due to the proximity to the Loughborough University.
4. **Availability of Historical Data:** This segment offers a big availability of historical, minute-level traffic data encompassing headway, average speed, traffic flow, and occupancy. Notably, the presence of few identified faulty inductive loop detectors distinguishes it, from other UK motorways.
5. **Favourable Traffic Conditions:** The chosen M1 segment exhibited stable Annual Average Daily Traffic flow throughout peak and non-peak hours, a characteristic evident in the traffic flow data analysis.
6. **Consistent Safety Performance**: After the examination of ControlWorks incident data and ControlWorks data from the NH UK (covering the period 2016-2019) a nearly constant number of incidents revealed in the selected road segments. Consistent safety performance ensures reliable comparisons and validates conclusions about the effectiveness of safety measures and interventions. Detailed results of this data analysis will be shown later in this chapter.

5.3.1 Traffic Microsimulation Model Development in VISSIM

By utilising an aerial photograph provided by VISSIM, both the Southbound and Northbound directions of the motorway network were mapped, ensuring the inclusion of all slip roads and roundabouts connecting to the main motorway. Lane width was accurately configured to reflect real-world measurements (3.5 meters), and the lengths of links, merging, and diverging areas were drawn based on the aerial photograph details (see Figure 5.3). For a better depiction, Figure 5.4 -Figure 5.6, provide detailed representations of the merging/diverging area at Junction 24 in comparison to its real-world counterpart. Like the Junction 24, rest of the junctions were created with high accuracy.

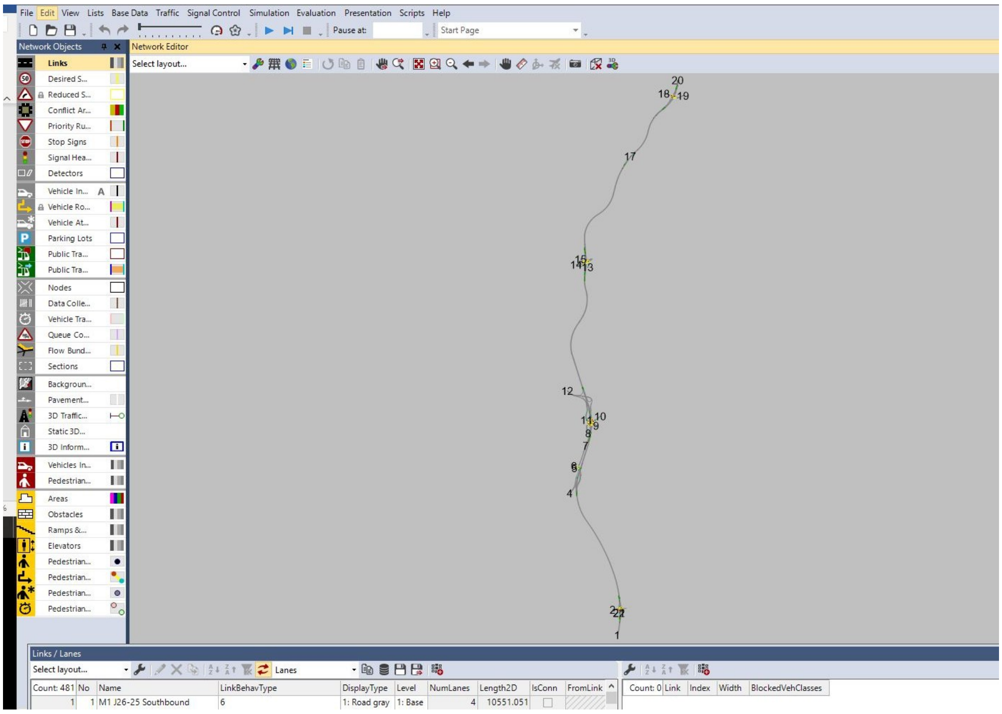


Figure 5.3: The motorway study area as it appeared in the simulation software VISSIM.

Figure 5.4: A detail of a merging/diverging area of the simulated network, VISSIM view

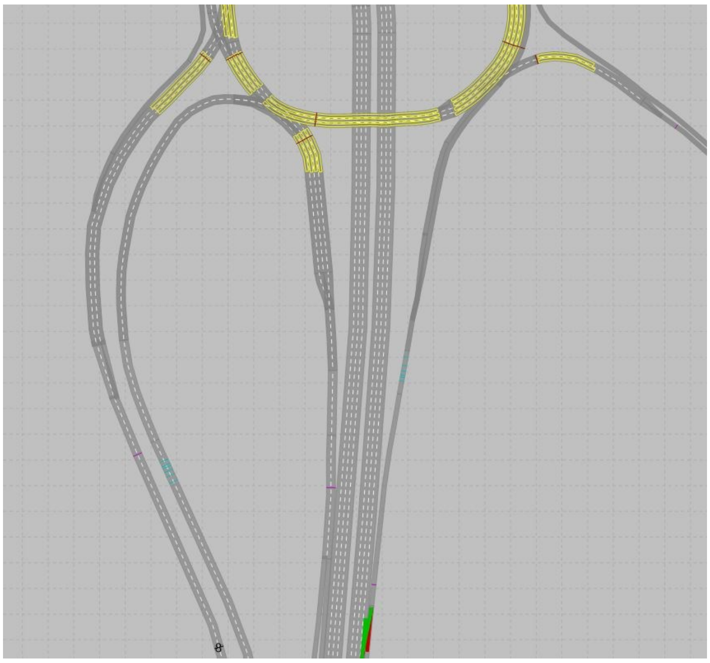


Figure 5.5: A detail of a merging/diverging area of the simulated network, VISSIM view

Figure 5.6: A detail of a merging/diverging area of the simulated network, Google map's view

The mainline corridor's total length in the designed model was approximately 30 km, encompassing a total of 30 entries and exits, along with corresponding vehicle input points. The VISSIM model comprehensively includes all roundabouts, as visually depicted in the Figure 5.7 - Figure 5.12. The signalisation within each roundabout was considered, accounting for real-time signalisation data. Further details on this aspect will be given in the next section.

Figure 5.7: Roundabout 23, VISSIM view

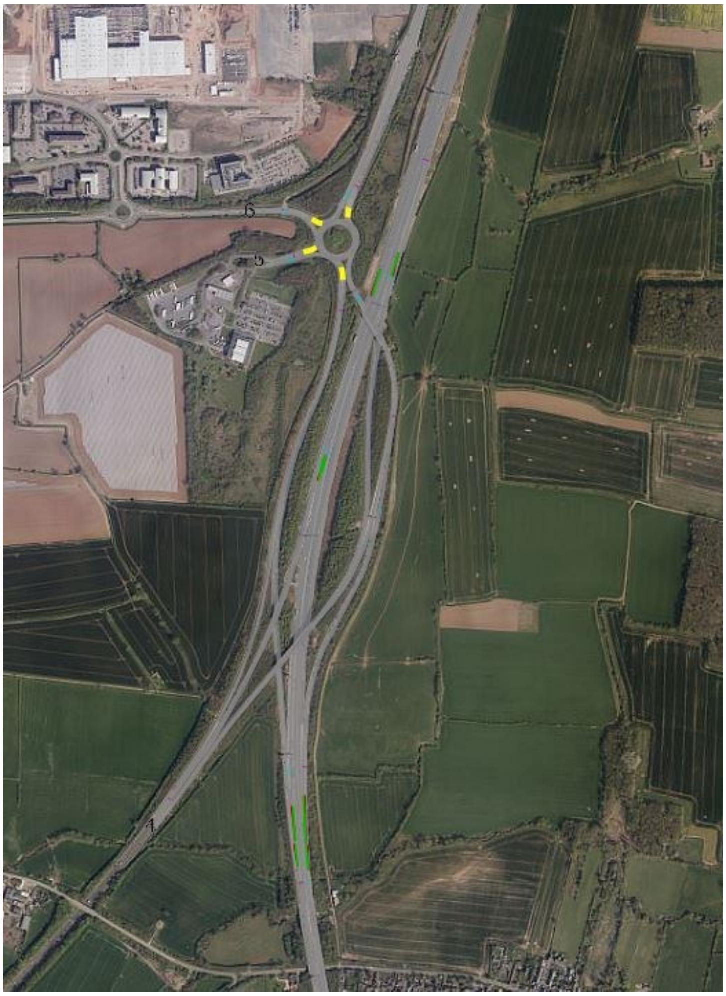


Figure 5.8: Intersection 23A, VISSIM view

Figure 5.9: Roundabout 24, VISSIM view

Figure 5.10: Intersection 24A, VISSIM view

Figure 5.11: Roundabout 25, VISSIM view

Figure 5.12: Roundabout 26, VISSIM view

The company managing the M1 motorway operation has deployed numerous inductive loop detectors (IDL) along the roadway. Positioned at consistent intervals of around 400 to 500 meters, these inductive loop detectors are designed to capture traffic data. The recorded data is accessible for download through WebTRIS, as illustrated in Figure 5.13.

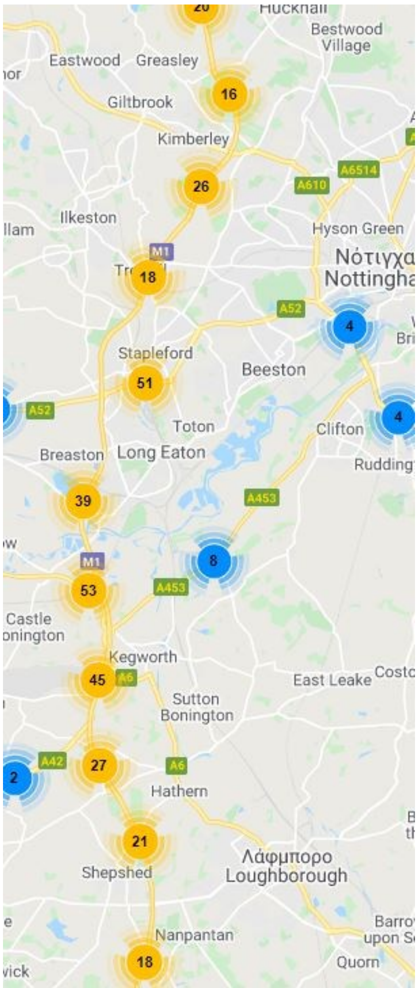


Figure 5.13: Location of inductive loop detectors (IDL) along the motorway (cc.: webtris.highwaysengland.co.uk)

Moving on, Figure 5.14 provides an overview of the entire network while Figure 5.15 is an informative model illustrating the network's structure and key components within VISSIM. This example focuses on the segment from 23A to 24A, highlighting the recognition of inductive loop detectors and specific vehicle inputs.

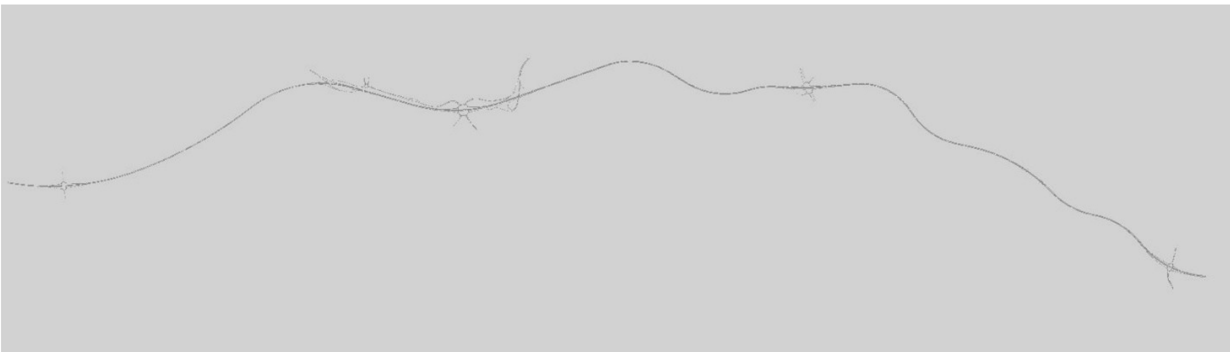


Figure 5.14: Whole simulated motorway network as depicted in VISSIM.

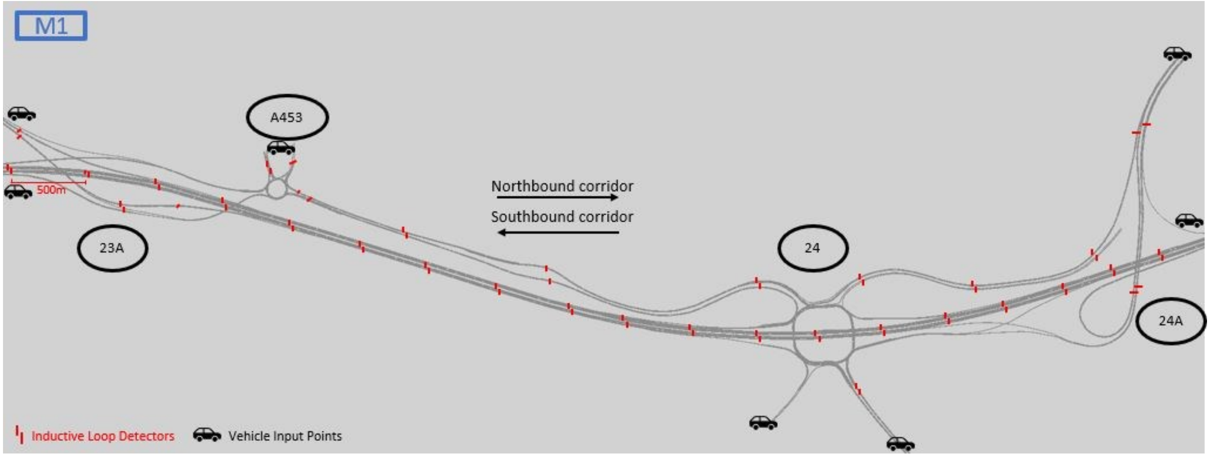


Figure 5.15: Outline of the simulated motorway, segment 23A-24A.

5.3.2 Signalisation of Roundabouts and Slip Roads in VISSIM

The signal control section in the traffic microsimulation model is essential for the valuable and correct illustration. The VISSIM simulation software has the ability to simulate the real-time road condition reduction simulation of roundabouts and intersections. As concerns the study's network area, it encompasses six major roundabouts and two minor roundabouts that link the slip roads with the main motorway, as illustrated in the previous section. All the signalised roundabouts and intersection were designed according to real-time signalisation data from MOVA diagrams and information given by the company that is responsible for the operation of the M1 motorway. More specific, using PTV VISSIM simulation software, the current signal control plan of all intersections and roundabouts has been depicted in the model. Additionally, the current optimisation plan of the traffic light duration of the roundabouts, which is making the interlaced area smooth, fastest, and is maximizing the travel efficiency, was not neglected in any of the signalised roundabouts in the model. Figure 5.16, depicts the signal control diagram of Junction 24 and 25 as it was given through MOVA diagrams and the operating company of the examined section of the M1 motorway.

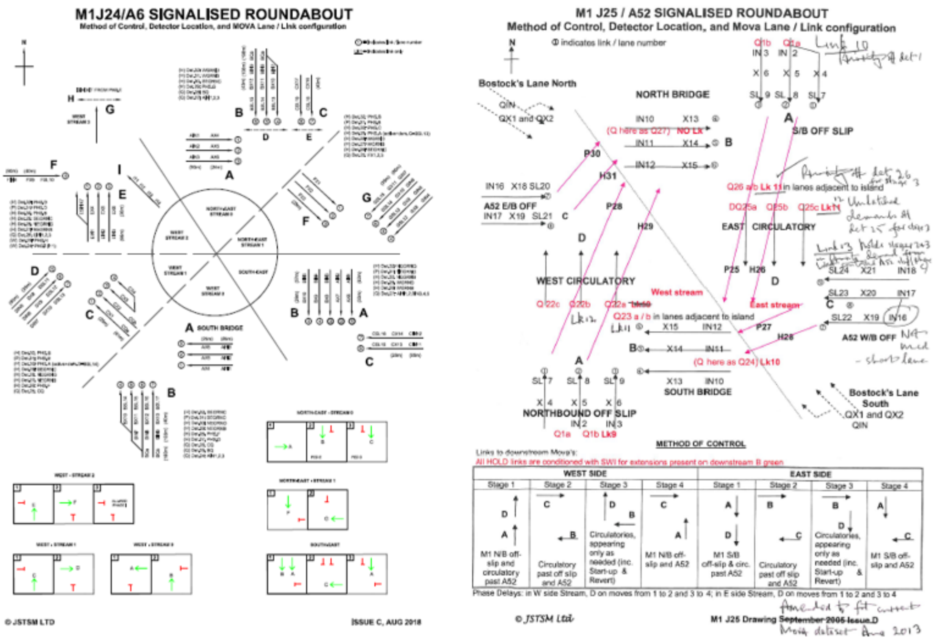


Figure 5.16: Example of a signalised roundabout information

Utilising the above information of the signalised roundabouts, the signal control panel of the traffic microsimulation model was designed, an example of which can be shown in the following Figure 5.17 and Figure 5.18. The phases and the duration time of traffic light (red, amber, and green) have been designed as in real life, a view of which can be found in Figure 5.19.

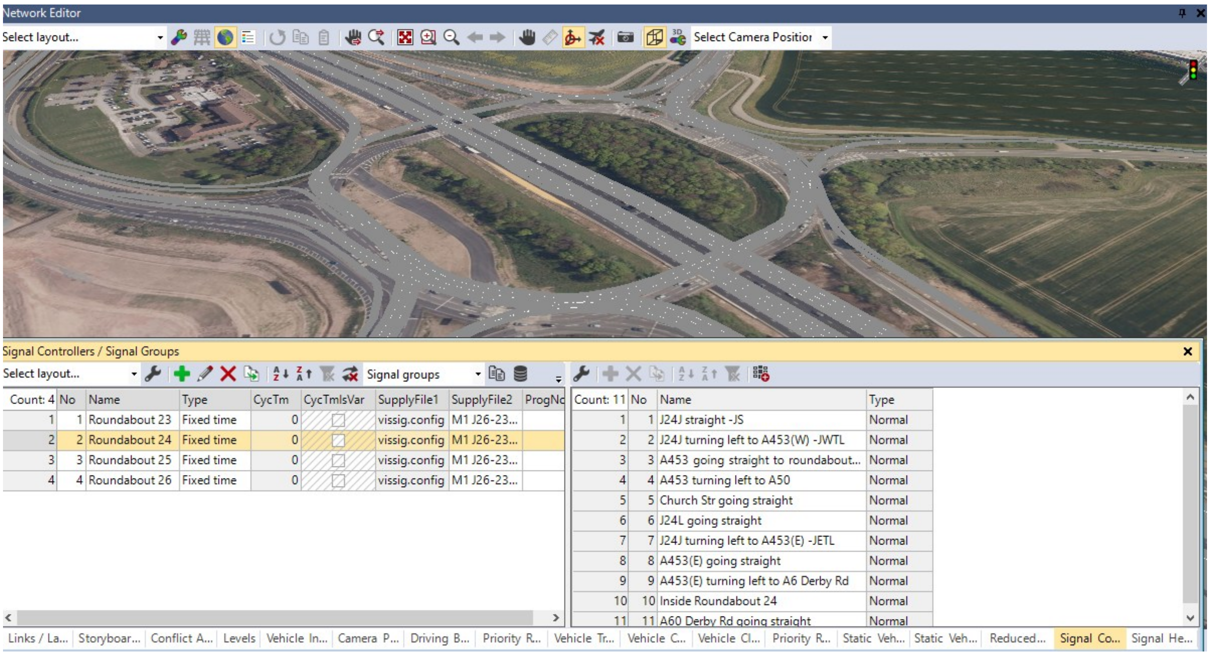


Figure 5.17: Roundabout 24 - Signal Controller, VISSIM view

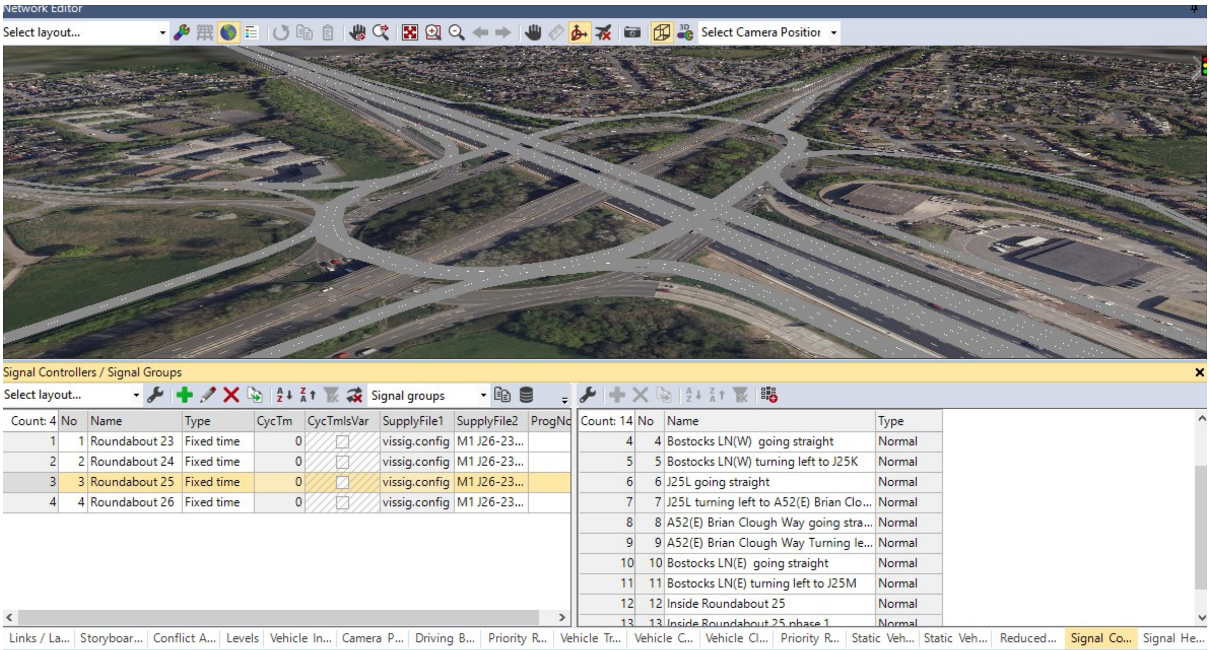


Figure 5.18: Roundabout 25 - Signal Controller, VISSIM view

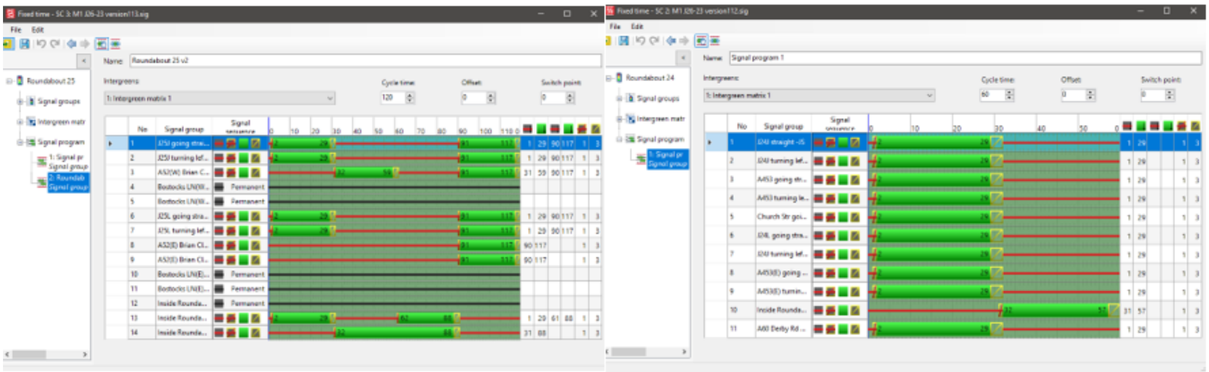


Figure 5.19: Example of signal control panel-green light durations

The microscopic simulation modelling of signalised roundabouts involves five fundamental components, encompassing both driver behaviour representations and signal control objects. These components, developed in sequential order due to their interconnected nature and collective impact on the simulation model, include:

1. Signal Controller
2. Signal Timing Plan
3. Signal Head
4. Priority Control for Permissive Movements
5. Detector

The figures presented above clearly illustrate that these procedures have been systematically executed, ensuring the coherent integration of all five components into the simulation model.

5.3.3 Limitations of the study area

The simulated network in the traffic microsimulation adheres to established guidelines from specialised literature on simulation network design. While drawing with the aid of an aerial map, it remains a simulated representation that cannot replicate the real network entirely. Despite this, the simulation model incorporates all relevant criteria to optimise the portrayal of the motorway network.

The study area, featuring six intricate roundabouts connecting slip roads to the main motorway, includes comprehensive modelling of signalisation, merging, and diverging processes. However, further analysis is deemed necessary to ensure the thorough examination of the motorway weaving section.

Moreover, the study area encompasses a segment of the M1 motorway with a consistent number of lanes along the main examined stretch. Notwithstanding, variations occur in slip roads, roundabouts, and a small portion of the A roads. Potential impacts arising from sudden changes in the number of live lanes warrant careful consideration in forthcoming assessments.

Finally, due to the constraints posed by the absence of data in roundabout routes and flows, the model does not intricately replicate intersection flows, for those leading to other slip roads and A roads, excluding the motorway. However, this deviation in detail regarding roundabout routes is inconsequential for the primary focus of this Ph.D. study, which centres on incident detection through V2V in the main motorway. The accuracy of traffic volume entering or exiting the main motorway remains a priority and is faithfully reproduced in the simulation.

5.4 Model Calibration

This chapter section outlines the step-by-step process of developing the base simulation model for the chosen UK motorway network, incorporating the collected field data. A comprehensive description of the baseline scenario for incident detection is provided, covering all relevant aspects. The finalisation of the baseline model involves crucial steps such as calibration, validation, and verification to ensure the accurate representation of real-world vehicle behaviours and traffic conditions within the simulation environment.

Once the model is well-calibrated, additional scenarios can be introduced to analyse the performance of the developed incident detection algorithm under various assumptions. Using VISSIM, the V2V communication of Connected Vehicle (CV) systems is integrated into the model to create different scenarios with varying market penetration rates (MPRs). Multiple scenarios, involving different durations and the number of lanes occupied, are implemented to simulate diverse environments.

The chapter also details how the driving behaviour of CVs in response to incidents is incorporated into the VISSIM model. Two types of vehicles, conventional and V2V-equipped, are defined, and various fleet compositions are characterised accordingly. Finally, the selected key performance indicators (KPIs) for analysing both mobility and safety traffic performance are highlighted.

5.4.1 Calibration of the Baseline Scenario in VISSIM

Developing the microscopic simulation model necessitates an extensive dataset from the study network, encompassing details on geometric configuration, traffic data, and signal data (for roundabouts), particularly when examining a high speed and volume traffic corridor. The intricacies of the collected data for the examined network have been discussed upon in Section 5.3.

The baseline model of the examined motorway, connecting Loughborough with Nottingham and the associated slip roads, has been developed using the VISSIM microsimulation package. The temporal scope of the model for both simulation and calibration corresponds to an average Wednesday throughout the entirety of 2019, covering a full day (a 24-hour period). This choice facilitates the flexibility to simulate scenarios at any desired time. The analysis discussed in Section 5.4 of Chapter 5 identified the most prevalent period for incidents, occurring mostly between 14:00 and 20:00. Consequently, the incident detection scenarios examined in the subsequent chapter are constrained to a five-hour window, initiating at 15:00 and concluding at 20:00. Hence, the simulation duration is set to five hours. Many tests had been conducted to determine the timeslot of the incident based on the analyses made from the ILDs and ControlWorks data, showing the most “dangerous” time for an incident to occur. Simulating an incident scenario in a 24-hour would be impossible due to the time needed for a simulation to run and execute 10 runs with a different simulation random seed. The primary objective of the simulation model is to faithfully replicate the traffic system along the M1 motorway from Loughborough to Nottingham, ensuring accurate alignment with observed data within the simulation framework. Figure 5.20 presents a schematic depiction of the motorway, featuring the locations of vehicle input detectors, the routes and the ILDs used for the calibration process needed to be taken into consideration while Table 5.1 include the information for the Inductive Loop Detectors (ILDs) used per stage. For the ILDs used in calibration and validation, ILDs recording all year long were used to avoid under-sampling of the real world.

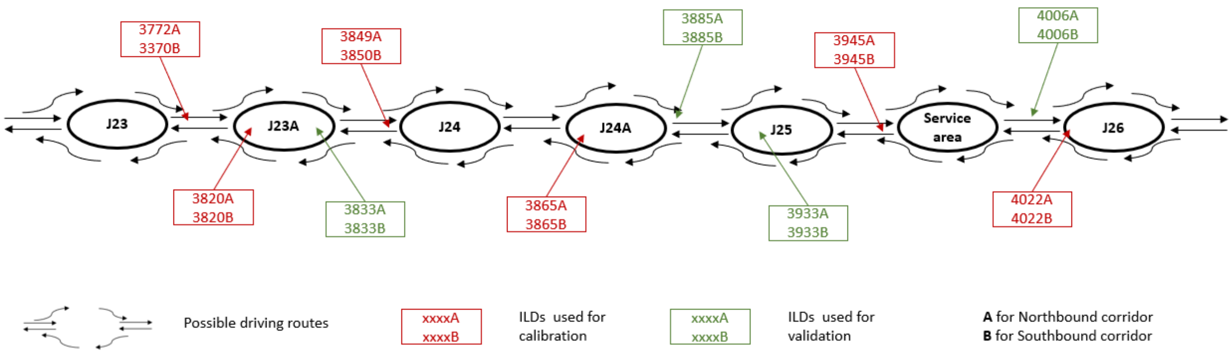


Figure 5.20: Schematic depiction of the examined motorway network

Table 5.1: ILDs used per calibration/validation stage

Stage used	No	ILDs Name	VISSIM Collection code names	Number of lanes	Direction
Calibration stage	1	3772A	108,109,110	3	Northbound
	2	3770B	105,106,107	3	Southbound
	3	3820A	15,16,17,18	4	Northbound
	4	3820B	11,12,13,14	4	Southbound
	5	3849A	33,34,35,36	4	Northbound
	6	3850B	37,38,39,40	4	Southbound
	7	3865A	41,42,43,44	4	Northbound
	8	3865B	45,46,47,48	4	Southbound
	9	3945A	65,66,67,68	4	Northbound
	10	3945B	69,70,71,72	4	Southbound
	11	4022A	89,90,91,92	4	Northbound
	12	4022B	93,94,95,96	4	Southbound
Validation stage	1	3833A	25,26,27,28	4	Northbound
	2	3833B	29,30,31,32	4	Southbound
	3	3885A	49,50,51,52	4	Northbound
	4	3885B	53,54,55,56	4	Southbound
	5	3933A	57,58,59,60	4	Northbound
	6	3933B	61,62,63,64	4	Southbound
	7	4006A	81,82,83,84	4	Northbound
	8	4006B	85,86,87,88	4	Southbound

5.4.2 Calibration Results

The developed baseline microsimulation model requires calibration, as detailed in Chapter 3, to ensure the accuracy of the traffic microsimulation model and, consequently, achieve a trustworthy assessment. The calibration focuses on traffic parameters such as flow and travel time, which are selected as the calibration parameters. The simulated values for these parameters are compared to the observed measures, aiming to minimise the disparity between the two by adjusting the simulation parameters. The calibration results indicate that the model accurately represents real-world traffic conditions and vehicle behaviours.

The calibration process involved simulating a duration of 5 hours, specifically from 15:00 to 20:00, with three simulation runs, and the average of the results was considered. Twelve data collection points (refer to Figure 5.20), covering all lanes and direction, were observed, and the simulated data were compared with ILDS 2019 data, utilising metrics such as GEH statistics . If significant differences were identified, VISSIM parameters were adjusted iteratively until satisfactory alignment with the ILDS 2019 data was achieved. Once the calibration results were deemed acceptable, the validation phase commenced.

During validation, a similar approach was taken, simulating a 5-hour duration with three runs, and averaging the results as in the calibration stage. Eight different data collection points were observed (refer to Figure 5.20), covering all lanes and direction, and comparisons were made between simulated data and ILDS 2019 data using metrics like GEH statistics and Traffic Flow. In cases where notable differences persisted, further adjustments to VISSIM parameters were made, repeating the process until satisfactory results were obtained.

In both two stages, calibration and validation, the inputted values were compared with the microsimulation outputs by calculating the GEH statistic for each entry point. The resulting GEH statistics for each vehicle input entry were computed for every 15-minute interval. The average GEH for each vehicle input point is presented in Table 5.2.

Table 5.2: Average GEH statistics of traffic flow

ILDs Name	**Direction**	**Stage of:**	**GEH (average of all pairs)**		**% Count of pairs**
			Random Wednesday (03/04/19)	**Average Wednesday of 2019)**	
3772A	Northbound	Calibration	1.547	1.519	100%
3820A			0.820	2.130	100%
3849A			1.995	2.244	100%
3865A			2.944	2.945	100%
3945A			3.184	4.658	100%
4022A			3.903	4.007	100%
3770B	Southbound		2.457	3.134	100%
3820B			2.758	2.785	100%
3850B			2.773	3.762	100%
3865B			3.120	2.888	100%
3945B			2.710	2.393	100%
4022B			3.618	3.673	100%
3833A	Northbound	Validation	1.570	2.264	100%
3885A			3.594	2.876	100%
3933A			3.023	3.650	100%
4006A			3.079	3.437	100%
3833B	Southbound		2.476	3.105	100%
3885B			3.830	3.131	100%
3933B			3.923	3.007	100%
4006B			3.832	3.697	100%

It is noteworthy that the GEH statistics consistently remain below 5 for every entry point, indicating that the number of vehicles within the microsimulation model accurately reflects the throughput of the study network. Below in Figure 5.21 and Figure 5.22 the results for both a random

Wednesday and the average Wednesday of the year are being presented for every 15-minute interval both for calibration and validation stage.

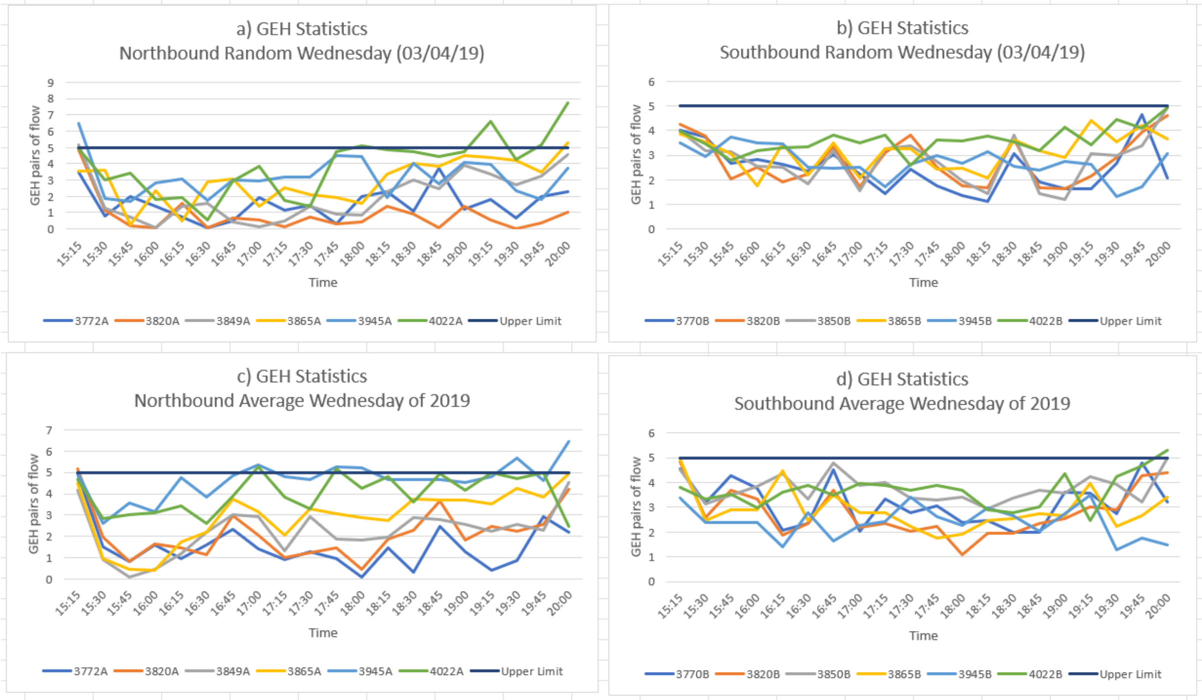


Figure 5.21: Calibration of traffic flow per time interval

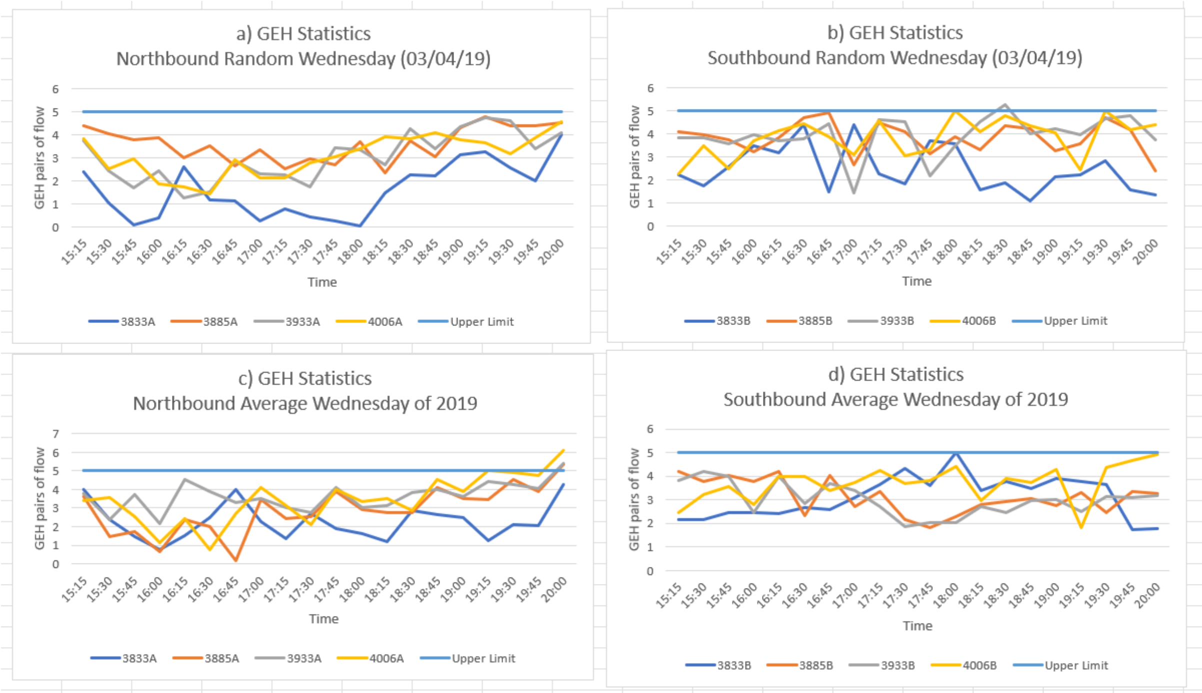


Figure 5.22: Validation of traffic flow per time interval

After completing the calibration and validation process, it becomes important to replicate driver behaviour in different traffic conditions to accurately predict travel time. This is why the verification phase is initiated. Model verification is a crucial step to ensure that the microsimulation model matches the observed traffic patterns and behaviours. The verification process for travel time data assesses the model's success in replicating real-world vehicle behaviours and traffic conditions, ensuring that simulated outputs do not exhibit unexpected tendencies when compared to observed behaviours (Nadezda & Merkutyev, 2019). This process aims to establish a good fit between simulated and observed travel time data.

Ground Truth Data, as described in section 4.3.3 of Chapter 4, consisting of 13 round trips with instrumental vehicles, was used to establish O-D pairs and speed distributions. These were then compared with the corresponding simulated data. Illustrations and comparisons, including Mann Whitney U Tests (Vierra et al., 2023), were conducted. If the results were found to be acceptable, indicating a close alignment between simulated and actual data, the model was deemed ready for replication and further analysis.

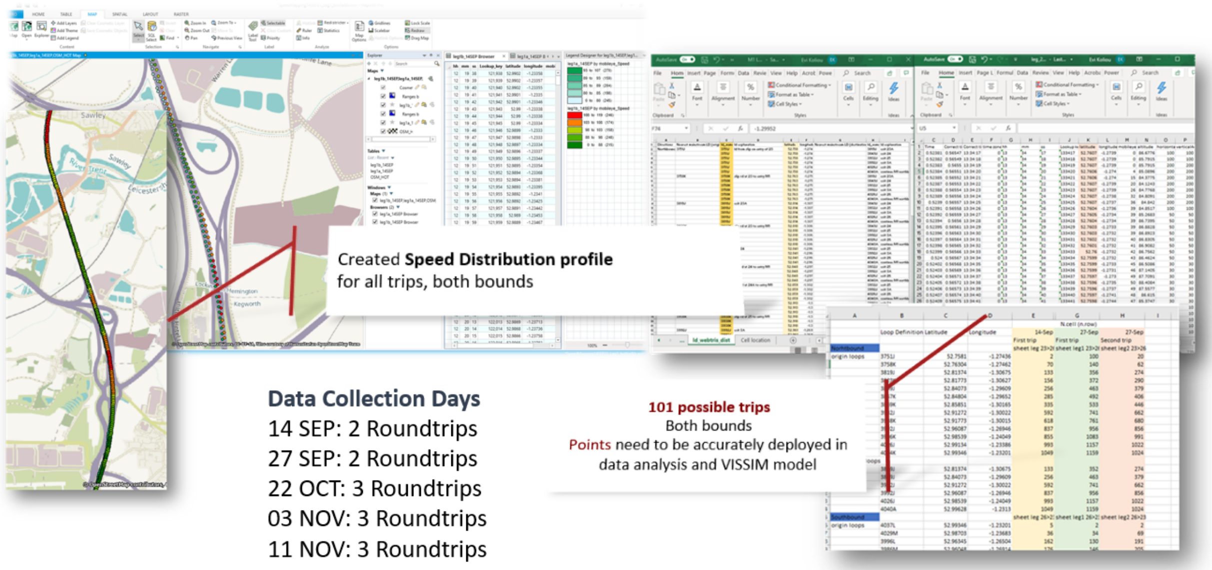


Figure 5.23: Verification process

For the verification process, data from instrumental vehicles were utilised to create origin-destination (O-D) pairs. These O-D pairs were carefully matched with GPS locations closest to inductive loop detector (ILD) locations, ensuring accuracy in the verification procedure. The time duration was then created for every possible trip, capturing the temporal aspect of travel patterns. In parallel, a similar procedure unfolded within VISSIM to assess whether the time distribution for trips was comparable (refer to Figure 5.23). The aim was to ensure consistency in points, emphasising factors such as identical locations and equivalent distances for the trips. An analytical approach was adopted, aligning 101 possible trips in both directions (refer to Figure 5.24 and Figure 5.25), demanding precise deployment of points.

Number of trips	Origin	Destination	Explanation
1	3751J	3819J	exit 23A
2		3849J	exit 24
3		3932J	exit 25
4		3992J	exit SA
5		4026J	exit 26
6		4040A	continue M1
7	3758K	3819J	exit 23A
8		3849J	exit 24
9		3932J	exit 25
10		3992J	exit SA
11		4026J	exit 26
12		4040A	continue M1
13	3819J	3849J	exit 24
14		3932J	exit 25
15		3992J	exit SA
16		4026J	exit 26
17		4040A	continue M1
18	3823K	3849J	exit 24
19		3932J	exit 25
20		3992J	exit SA
21		4026J	exit 26
22		4040A	continue M1
23	3849J	3932J	exit 25
24		3992J	exit SA
25		4026J	exit 26
26		4040A	continue M1
27	3857K	3932J	exit 25
28		3992J	exit SA
29		4026J	exit 26
30		4040A	continue M1
31	3869K	3932J	exit 25
32		3992J	exit SA
33		4026J	exit 26
34		4040A	continue M1
35	3932J	3992J	exit SA
36		4026J	exit 26
37		4040A	continue M1
38	3938K	3992J	exit SA
39		4026J	exit 26
40		4040A	continue M1
41	3992J	4026J	exit 26
42		4040A	continue M1
43	3996K	4026J	exit 26
44		4040A	continue M1
45	4026J	4040A	continue M1
46	4034K	4040A	continue M1

Figure 5.24: O-D pairs for Northbound

Number of trips	Origin	Destination	Explanation
1	4037L	3996L	exit SA
2		3939L	exit 25
3		3869L	exit 24A first one
4		3857L	exit from 24A but actually exit to 24
5		3828L	the actual exit for 23A
6		3757L	exit 23
7		3747B	continue M1
8	4029M	3996L	exit SA
9		3939L	exit 25
10		3869L	exit 24A first one
11		3857L	exit from 24A but actually exit to 24
12		3828L	the actual exit for 23A
13		3757L	exit 23
14		3747B	continue M1
15	3996L	3939L	exit 25
16		3869L	exit 24A first one
17		3857L	exit from 24A but actually exit to 24
18		3828L	the actual exit for 23A
19		3757L	exit 23
20		3747B	continue M1
21	3986M	3939L	exit 25
22		3869L	exit 24A first one
23		3857L	exit from 24A but actually exit to 24
24		3828L	the actual exit for 23A
25		3757L	exit 23
26		3747B	continue M1
27	3939L	3869L	exit 24A first one
28		3857L	exit from 24A but actually exit to 24
29		3828L	the actual exit for 23A
30		3757L	exit 23
31		3747B	continue M1
32	3932M	3869L	exit 24A first one
33		3857L	exit from 24A but actually exit to 24
34		3828L	the actual exit for 23A
35		3757L	exit 23
36		3747B	continue M1
37	3869L	3857L	exit from 24A but actually exit to 24
38		3828L	the actual exit for 23A
39		3757L	exit 23
40		3747B	continue M1
41	3857L	3828L	the actual exit for 23A
42		3757L	exit 23
43		3747B	continue M1
44	3858M	3828L	the actual exit for 23A
45		3757L	exit 23
46		3747B	continue M1
47	3850M	3828L	the actual exit for 23A
48		3757L	exit 23
49		3747B	continue M1
50	3828L	3757L	exit 23
51		3747B	continue M1
52	3818M	3757L	exit 23
53		3747B	continue M1
54	3757L	3747B	continue M1
55	3751M	3747B	continue M1

Figure 5.25: O-D pairs for Southbound

To ensure accuracy in both data analysis and the VISSIM model, synchronisation was needed to combine the locations, distances, and overall trip characteristics. This was important to make a meaningful comparison between the field data we collected, and the data simulated by the model. The analysis involved calculating the O-D pairs and the speed distribution to get a comprehensive evaluation of how well the model replicates real-world travel patterns.

Real-world travel time counts are estimated based on real-world data where 13 roundtrips took place for the verification of the model, calculation distances, average vehicle speed, and GPS location data (refer to Figure 5.26). Simulated travel times are directly obtained from VISSIM. A comparison between simulated and observed travel times along the determined routes indicates that the deviation between the two observations falls within an acceptable range.

All possible trips for Northbound		Date	03-Nov	03-Nov	03-Nov	11-Nov	11-Nov	11-Nov	22-Oct	22-Oct	22-Oct	14-Sep	14-Sep	27-Sep	27-Sep
		Trip number	First trip	Second trip	Third trip	First trip	Second trip	Third trip	First trip	Second trip	Third trip	First trip	Second trip	First trip	Second trip
		Loop Definition	Time												
Norhtbound	origin loops	3751J	11:25:40	12:02:00	12:37:46	11:33:07	12:09:00	12:46:33	11:25:22	12:00:00	12:36:00	12:01:06	12:37:32	12:59:57	13:34:35
		3758K	11:26:55	12:03:26	12:38:40	11:34:13	12:09:44	12:47:05	11:25:44	12:01:22	12:36:59	12:02:13	12:37:56	13:00:37	13:35:17
		3819J	11:30:37	12:06:59	12:42:36	11:37:47	12:13:54	12:50:36	11:29:15	12:05:02	12:40:28	12:03:16	12:41:16	13:04:12	13:38:48
		3823K	11:30:53	12:07:16	12:42:54	11:38:03	12:14:11	12:50:54	11:29:34	12:05:20	12:40:45	12:03:39	12:41:34	13:04:28	13:39:04
		3849J	11:32:21	12:08:50	12:44:23	11:39:34	12:15:49	12:52:32	11:31:01	12:07:04	12:42:15	12:05:19	12:43:01	13:06:00	13:40:33
		3857K	11:32:50	12:09:17	12:44:49	11:40:01	12:16:17	12:53:00	11:31:28	12:07:31	12:42:46	12:05:48	12:43:29	13:06:29	13:41:00
		3869K	11:33:30	12:09:56	12:45:31	11:40:40	12:16:57	12:53:44	11:32:05	12:08:13	12:43:24	12:06:38	12:44:11	13:07:10	13:41:41
		3932J	11:37:08	12:13:36	12:49:07	11:44:25	12:20:38	12:57:28	11:35:45	12:11:49	12:47:29	12:10:55	12:47:40	13:10:37	13:45:16
		3938K	11:37:27	12:13:55	12:49:26	11:44:48	12:20:57	12:57:48	11:36:04	12:12:08	12:47:52	12:11:21	12:47:58	13:10:57	13:45:34
		3992J	11:40:36	12:17:17	12:52:33	11:48:07	12:24:25	13:01:03	11:39:15	12:15:22	12:51:16	12:15:17	12:51:02	13:14:12	13:48:39
		3996K	11:43:04	12:19:31	12:54:38	11:50:30	12:26:55	13:03:25	11:41:26	12:17:31	12:53:37	12:15:36	12:53:19	13:16:33	13:50:54
		4026J	11:43:37	12:19:50	12:56:24	11:51:44	12:27:51	13:05:00	11:42:13	12:18:36	12:53:51	12:17:53	12:53:56	13:17:57	13:51:28
		4034K	11:43:52	12:20:00	12:56:58	11:51:59	12:28:25	13:05:18	11:42:22	12:18:55	12:55:07	12:18:49	12:54:00	13:17:59	13:51:30
	destination loops	3819J	11:30:37	12:06:59	12:42:36	11:37:47	12:13:54	12:50:36	11:29:15	12:05:02	12:40:28	12:03:16	12:41:16	13:04:12	13:38:48
		3849J	11:32:21	12:08:50	12:44:23	11:39:34	12:15:49	12:52:32	11:31:01	12:07:04	12:42:15	12:05:19	12:43:01	13:06:00	13:40:33
		3932J	11:37:08	12:13:36	12:49:07	11:44:25	12:20:38	12:57:28	11:35:45	12:11:49	12:47:29	12:10:55	12:47:40	13:10:37	13:45:16
		3992J	11:40:36	12:17:17	12:52:33	11:48:07	12:24:25	13:01:03	11:39:15	12:15:22	12:51:16	12:15:17	12:51:02	13:14:12	13:48:39
		4026J	11:43:37	12:19:50	12:56:24	11:51:44	12:27:51	13:05:00	11:42:13	12:18:36	12:53:51	12:17:53	12:53:56	13:17:57	13:51:28
		4040A	11:43:52	12:20:00	12:56:58	11:51:59	12:28:25	13:05:18	11:42:22	12:18:59	12:55:07	12:18:49	12:54:00	13:17:59	13:51:30

All possible trips for Southbound		Date	03-Nov	03-Nov	03-Nov	11-Nov	11-Nov	11-Nov	22-Oct	22-Oct	22-Oct	14-Sep	14-Sep	27-Sep	27-Sep
		Trip number	First trip	Second trip	Third trip	First trip	Second trip	Third trip	First trip	Second trip	Third trip	First trip	Second trip	First trip	Second trip
		Loop Definition	Time												
Southbound	origin loops	4037L	11:44:00	12:20:53	15:26:14	11:51:13	12:28:48	14:48:07	11:43:00	12:19:00	14:33:00	12:19:41	12:54:11	13:18:00	13:51:31
		4029M	11:44:18	12:21:38	15:28:28	11:51:49	12:28:50	14:48:24	11:43:11	12:19:21	14:34:12	12:20:12	12:54:50	13:18:32	13:52:42
		3996L	11:46:30	12:23:52	15:30:30	11:53:49	12:30:49	14:50:29	11:44:42	12:21:12	14:36:15	12:22:18	12:56:47	13:20:25	13:54:44
		3986M	11:46:45	12:24:06	15:30:44	11:54:05	12:31:02	14:51:12	11:44:57	12:21:26	14:36:33	12:22:32	12:57:01	13:20:41	13:54:58
		3939L	11:50:05	12:27:03	15:33:54	11:57:13	12:34:25	14:54:13	11:48:02	12:24:23	14:39:39	12:25:36	13:00:00	13:23:37	13:57:53
		3932M	11:50:32	12:27:24	15:34:17	11:57:34	12:34:42	14:54:33	11:48:23	12:24:43	14:40:00	12:25:56	13:00:20	13:23:59	13:58:13
		3869L	11:54:40	12:31:10	15:38:03	12:01:19	12:39:02	14:58:15	11:52:15	12:28:27	14:43:46	12:29:47	13:04:01	13:27:31	14:01:38
		3857L	11:55:13	12:31:48	15:38:42	12:01:59	12:39:46	14:58:53	11:52:54	12:29:05	14:44:29	12:30:29	13:05:07	13:28:10	14:02:15
		3858M	11:55:21	12:31:42	15:38:34	12:01:52	12:39:38	14:58:46	11:52:47	12:28:58	14:44:21	12:30:22	13:04:47	13:28:03	14:02:09
		3850M	11:55:47	12:32:11	15:39:06	12:02:24	12:40:17	14:59:15	11:53:18	12:29:30	14:44:53	12:30:53	13:08:20	13:28:33	14:02:38
		3828L	11:57:20	12:33:31	15:40:24	12:03:48	12:41:37	15:00:30	11:54:40	12:30:58	14:46:14	12:32:19	13:08:20	13:29:50	14:03:50
		3818M	11:57:53	12:34:09	15:40:56	12:04:22	12:42:11	15:01:03	11:55:17	12:31:30	14:46:45	12:32:59	13:17:26	13:30:21	14:04:21
		3757L	12:01:48	12:37:35	15:44:56	12:08:14	12:45:57	15:04:41	11:58:62	12:35:05	14:50:25	12:36:48	13:21:16	13:33:58	14:07:51
		3751M	12:01:53	12:37:45	15:45:00	12:08:37	12:47:03	15:06:50	11:59:02	12:35:59	14:51:42	12:37:06	13:24:26	13:34:16	14:10:49
	destination loops	3996L	11:46:30	12:23:52	15:30:30	11:53:49	12:30:49	14:50:29	11:44:42	12:21:12	14:36:15	12:22:18	12:56:47	13:20:25	13:54:44
		3939L	11:50:05	12:27:03	15:33:54	11:57:13	12:34:25	14:54:13	11:48:02	12:24:23	14:39:39	12:25:36	13:00:00	13:23:37	13:57:53
		3869L	11:54:40	12:31:10	15:38:03	12:01:19	12:39:02	14:58:15	11:52:15	12:28:27	14:43:46	12:29:47	13:04:01	13:27:31	14:01:38
		3857L	11:55:13	12:31:48	15:38:42	12:01:59	12:39:46	14:58:53	11:52:54	12:29:05	14:44:29	12:30:29	13:05:07	13:28:10	14:02:15
		3828L	11:57:20	12:33:31	15:40:24	12:03:48	12:41:37	15:00:30	11:54:40	12:30:58	14:46:14	12:32:19	13:08:20	13:29:50	14:03:50
		3757L	12:01:48	12:37:35	15:44:56	12:08:14	12:45:57	15:04:41	11:43:62	12:35:05	14:50:25	12:36:48	13:21:16	13:33:58	14:07:51
		3747B	12:01:53	12:37:45	15:45:00	12:08:37	12:47:03	15:06:50	11:43:100	12:35:59	14:51:42	12:37:06	13:24:26	13:34:16	14:10:51

Figure 5.26: Real-world roundtrips collected data

Consequently, the default parameters governing driving behaviours in VISSIM accurately capture expected vehicle behaviours without necessitating additional modifications to microsimulation model parameters. The model was extensively tested and verified for all possible trips originating from Junction 23 (J23) and concluding at Junction 26 (J26). These included trips such as 23-23A, 23-24, 23-25, 23-SA, 23-26, 23A-24, 23A-24A, and so forth, covering both directions of travel, where 23-23A are the segments between the numbered Junctions. This verification process involved a thorough evaluation of each trip scenario, guaranteeing the accuracy and reliability of the model for different routes and directions in the study network.

In Figure 5.27 (Northbound) and Figure 5.28 (Southbound), a visual depiction of the Origin-Destination (OD) pairs is presented, and simulated travel times are compared with observed travel times for validation purposes. The graphical representation illustrates that both series exhibit similar patterns, indicating that the simulated model accurately reflects the network travel time. This unity between the simulated and observed travel times further validates the model's ability to capture and reproduce real-world travel patterns within the studied network.

Travel time (estimated vs simulated)					
Start - End Point	O-D pairs	Estimated Travel Time	Simulated Travel Time	*Difference in sec*	*Difference in min*
3758K-3819J (23-23A)	1	205.8	187.309	*18.46*	*0.31*
3758K-3849J (23-24)	2	316.2	291.753	*24.48*	*0.41*
3758K-3932J (23-25)	3	607.8	562.9815	*44.86*	*0.75*
3758K-3992J (23-SA)	4	825.6	759.972	*65.64*	*1.09*
3758K-4026J (23-26)	5	1016.1	972.241	*43.84*	*0.73*
3823K-3849J (23A-24)	6	88.1	80.0255	*8.05*	*0.13*
3823K-3932J (23A-25)	7	381.8	353.3665	*28.40*	*0.47*
3823K-3992J (23A-SA)	8	598.8	551.929	*46.92*	*0.78*
3823K-4026J (23A-26)	9	786.7	765.5295	*21.16*	*0.35*
3857K-3932J (24-25)	10	263.7	249.192	*14.50*	*0.24*
3857K-3992J (24-SA)	11	481.5	453.298	*28.16*	*0.47*
3857K-4026J (24-26)	12	671.9	621.538	*50.39*	*0.84*
3869K-3932J (24A-25)	13	222.5	207.294	*15.24*	*0.25*
3869K-3992J (24A-SA)	14	440.3	412.2245	*28.08*	*0.47*
3869K-4026J (24A-26)	15	630.8	611.111	*19.66*	*0.33*
3938K-3992J (25-SA)	16	197.6	168.7915	*28.82*	*0.48*
3938K-4026J (25-26)	17	388.1	328.233	*59.84*	*1.00*
3996K-4026J (SA-26)	18	61.6	76.166	*-14.55*	*-0.24*

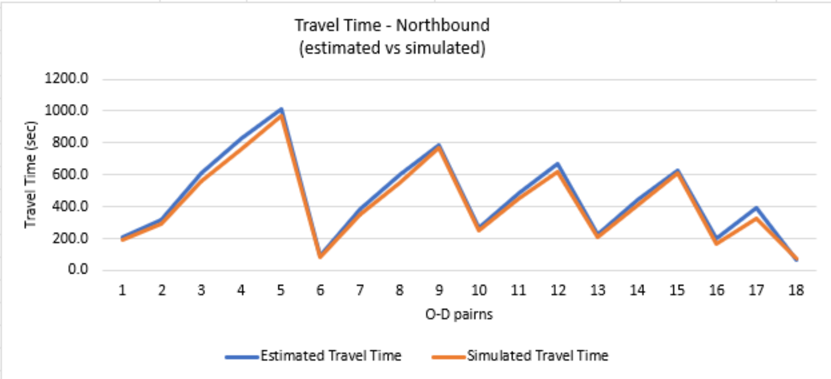


Figure 5.27: Illustration of travel time (observed vs simulated) for Northbound

Travel time (estimated vs simulated)					
Start - End Point	O-D pairs	Estimated Travel Time	Simulated Travel Time	*Difference in sec*	*Difference in min*
4029M-3996L (26-SA)	19	119.6	97.3715	*22.24*	*0.37*
4029M-3939L (26-25)	20	321.2	295.011	*26.22*	*0.44*
4029M-3869L (26-24A)	21	569.8	538.5355	*31.23*	*0.52*
4029M-3857L (26-24)	22	611.0	556.6945	*54.31*	*0.91*
4029M-3828L (26-23A)	23	724.2	690.595	*33.56*	*0.56*
4029M-3757L (26-23)	24	1020.7	1000.258421	*20.43*	*0.34*
3986M-3939L (SA-25)	25	184.7	168.146	*16.55*	*0.28*
3986M-3869L (SA-24A)	26	433.2	412.7345	*20.50*	*0.34*
3986M-3857L (SA-24)	27	474.5	430.8995	*43.56*	*0.73*
3986M-3828L (SA-23A)	28	587.6	564.726	*22.89*	*0.38*
3986M-3757L (SA-23)	29	884.2	833.6342105	*50.52*	*0.84*
3932M-3869L (25-24A)	30	227.5	211.125	*16.41*	*0.27*
3932M-3857L (25-24)	31	268.8	229.2795	*39.49*	*0.66*
3932M-3828L (25-23A)	32	381.9	363.074	*18.85*	*0.31*
3932M-3757L (25-23)	33	678.5	621.0595	*57.40*	*0.96*
3858M-3828L (24A-23A)	34	120.1	109.575	*10.50*	*0.18*
3858M-3757L(24A-23)	35	416.6	378.2685	*38.35*	*0.64*
3850M-3828L (24-23A)	36	75.1	80.236	*-5.16*	*-0.09*
3850M-3757L (24-23)	37	371.6	321.789	*49.83*	*0.83*
3818M-3757L (23A-23)	38	223.3	202.02	*21.29*	*0.35*

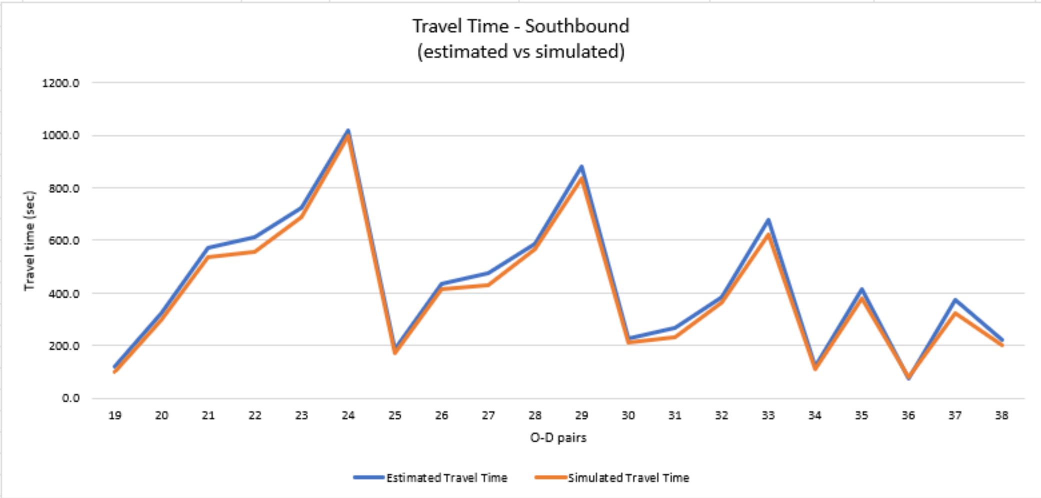


Figure 5.28: Illustration of travel time (observed vs simulated) for Southbound

In the final step of the model verification process, the focus was on evaluating the differences in speed distribution between the collected field data and the simulated data. This analysis focused on trips conducted between 10:00 and 15:00, and the representative VISSIM results were computed. For the field data, the speed distribution was derived from Inductive Loop Detectors (ILDs) and calculated for both a typical day (03/04/19) and an average Wednesday throughout the year 2019. In contrast, the simulated data involved the utilisation of the average speed from three VISSIM simulation runs. This comparative analysis aimed to ascertain the degree of alignment between the speed patterns simulated by VISSIM and the real-world speed distributions obtained from ILDs during the specified time window. The results of this analysis are presented in the figures below (refer to Figure 5.29 until Figure 5.32). In Figure 5.29 during a trip collection with the instrumented vehicle we had a minus closure of the road for some minutes, which can be depict in collection date of September the 14th of 2019.

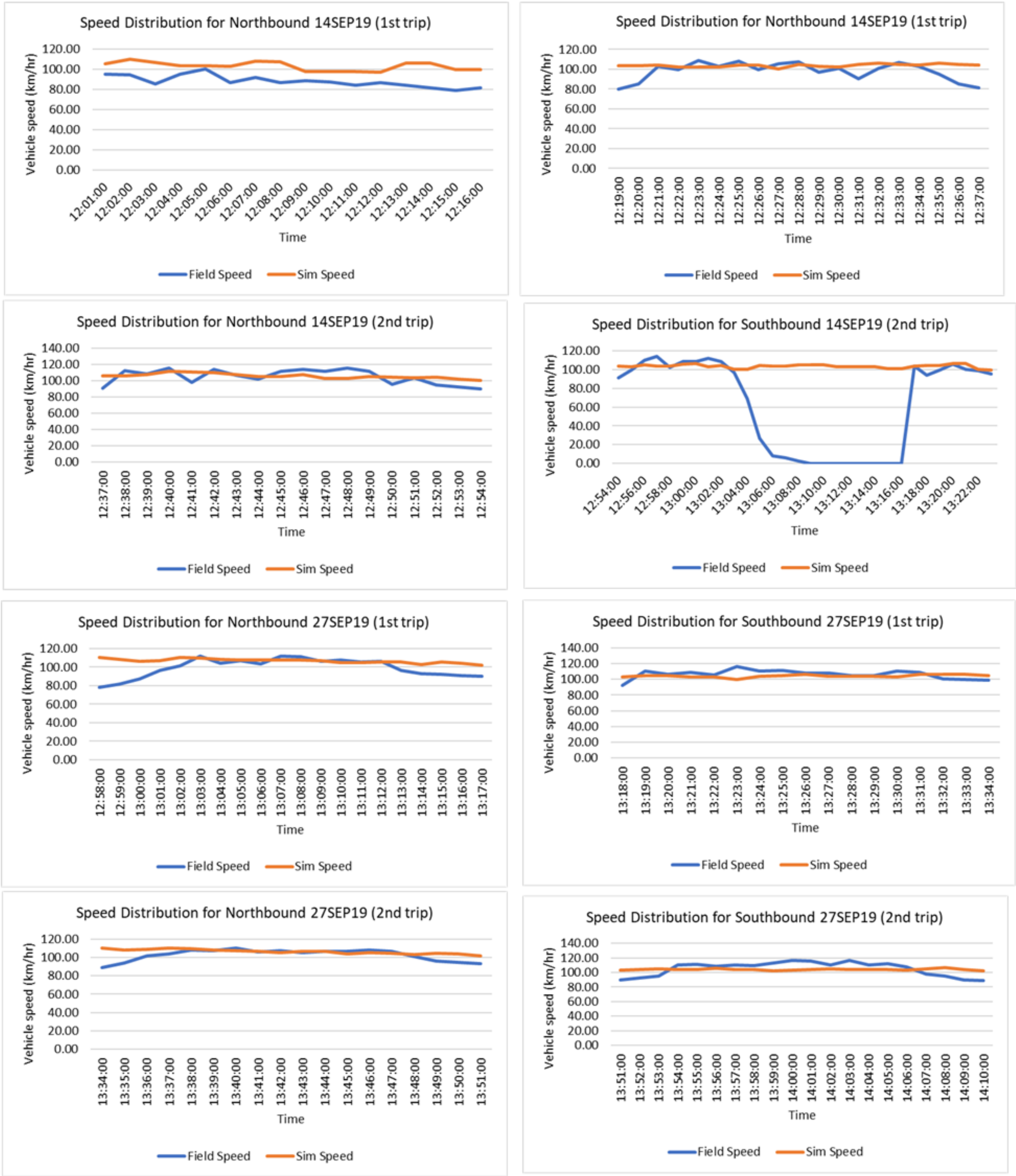


Figure 5.29: Speed distribution for September trips.

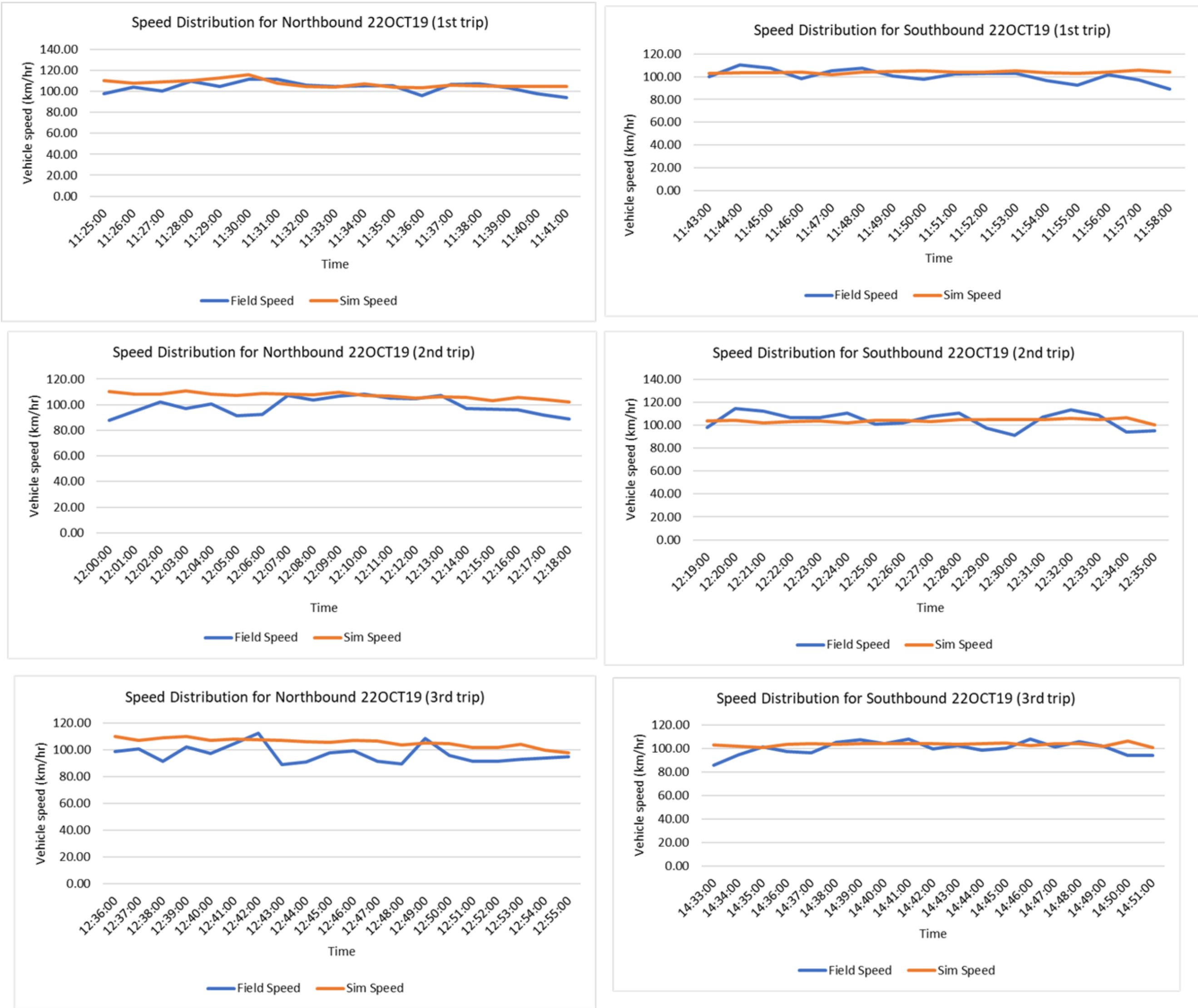


Figure 5.30: Speed distribution for October trips.

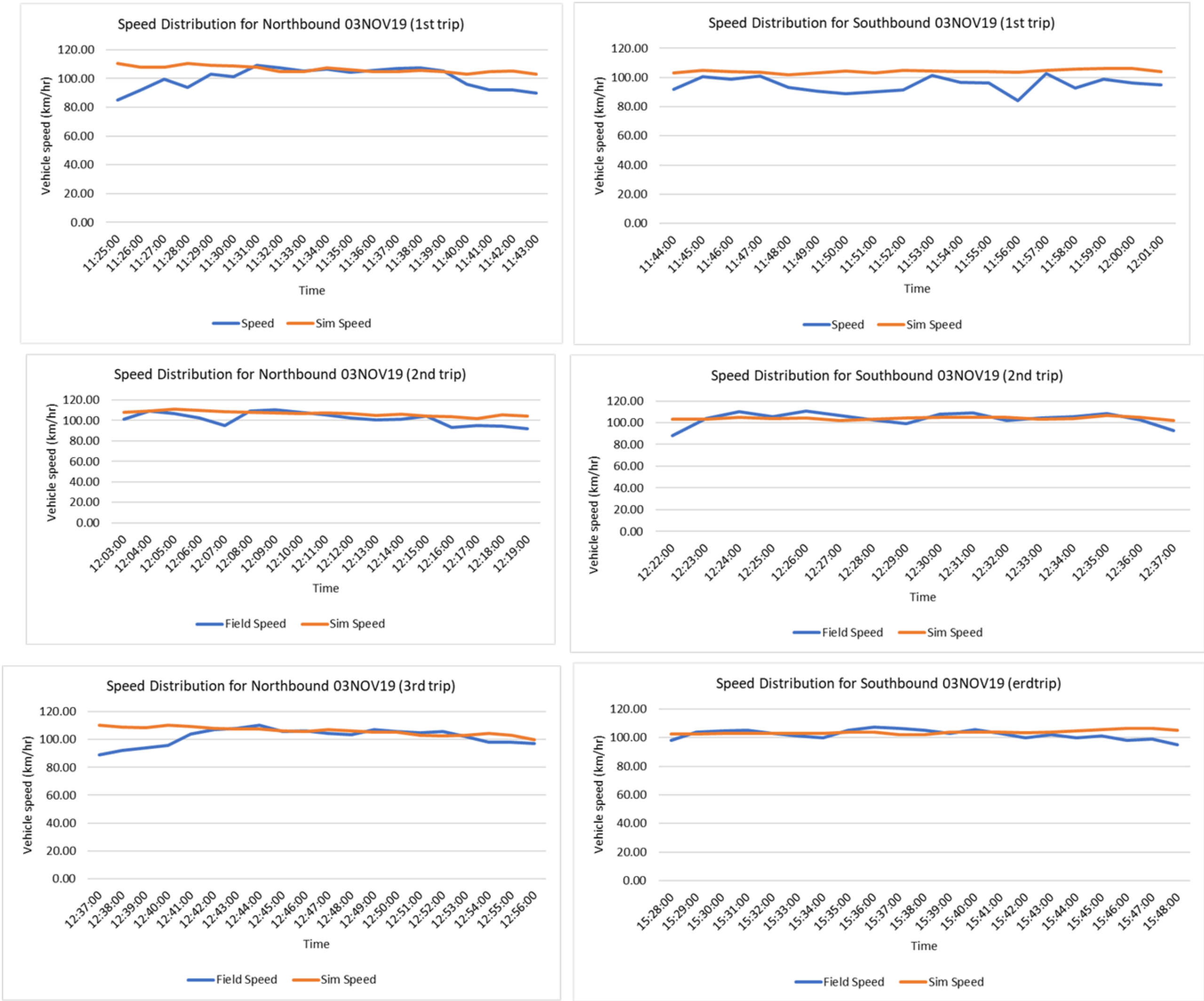


Figure 5.31: Speed distribution for November (a) trips.

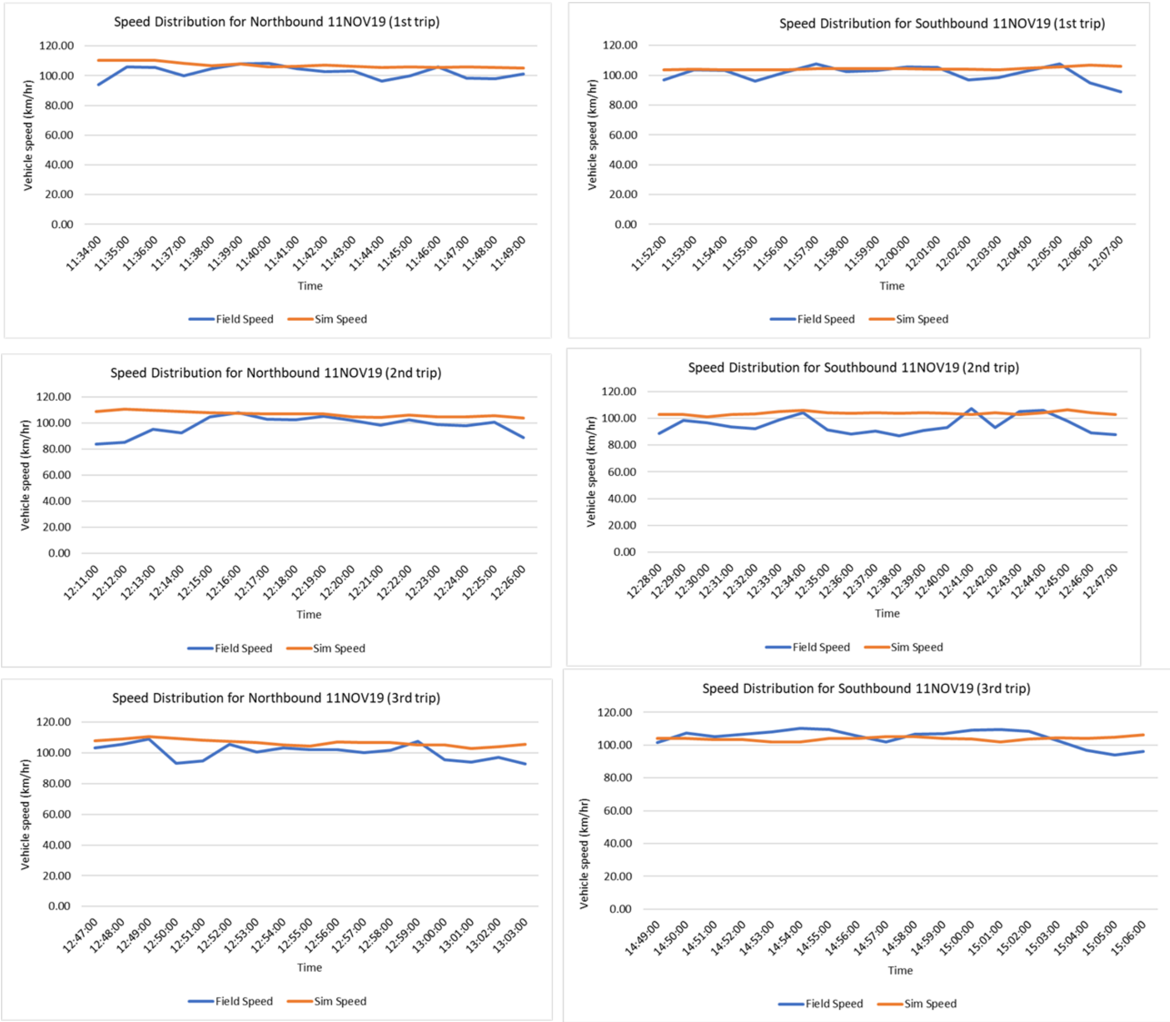


Figure 5.32: Speed distribution for November (b) trips.

The GEH statistic and Mann U-test have aligned with the evaluation assumptions of each method, indicating that the designed base model is successfully calibrated, validated, and verified. As a result, further adjustments can be made to construct the proposed scenario development of incident detection. This will allow for scenario-based comparisons with and without connected vehicle cases.

5.4.3 Summary

To evaluate the calibration and validation results, different metrics and tests were employed as presented above. The GEH statistics were used to assess the number of vehicles in the simulation, providing insights into the overall accuracy of the model, as explained in section 3.5.5 of Chapter 3. Additionally, the Mann Whitney U Test was applied to assess traffic flow, ensuring a reliable comparison between simulated and real-world data. Verification results were examined using Mann Whitney U Tests, focusing on speed distribution and travel time. These tests aimed to verify the consistency and reliability of the simulation outputs against the ground-truth data. Visual inspection was a critical component of this process, enabling a qualitative evaluation of the model's performance.

The mantra "Garbage In – Garbage Out (GIGO)" underscored the importance of the quality of input data, emphasising that the accuracy of simulation outputs depends on the accuracy of the input parameters. This principle guided the entire calibration, validation, and verification process. The overarching purpose of these assessments was to verify the success of the calibrated simulation model in replicating real-world data. The comparison with ILDS 19 data at different data points during each step facilitated a comprehensive evaluation of the model's performance. The ultimate goal was to ensure that the simulation outputs aligned closely with actual observed data, signifying the model's readiness for replication and further analysis.

The calibration process is a crucial optimisation effort for ensuring the accuracy of a microsimulation model to real-world conditions. It starts with a predefined set of parameters from the microsimulation software and integrates pertinent real-world data into the simulation environment. Preliminary simulation runs generate a dataset that serves as the basis for comparison with observed real-world measurements. This process continues until an acceptable level of agreement between simulated and observed data is achieved. After calibration, the selected parameters are validated by comparing them with a validation dataset originally collected from the initial real-world data. If the error exceeds predetermined thresholds, the calibration process is repeated with alternative parameter values. If the calibration meets predefined accuracy criteria, the verification process is initiated. Validation ensues as the calibrated parameters undergo scrutiny against a separate dataset, ensuring the model's generalisation beyond the calibration dataset. This rigorous assessment involves comparing the simulated dataset with ground truth data acquired from instrumented vehicles. Should the model perform acceptably, meeting established goodness-of-fit metrics, the verification process is further strengthened by employing statistical measures such as Geoffrey E. Havers (GEH) (Washington State Department of Transportation (WSDOT), 2014) and the Mann Whitney U test. These statistical validations ascertain the model's robustness and accuracy by comparing simulated outputs with real-world measurements, providing a comprehensive evaluation of the microsimulation model's reliability and applicability to real-world scenarios. Whitney U test to compare the simulated data with ground truth collected by instrumented vehicle. All measurements of goodness-of-fit fall within an acceptable range as specified from literature (Dowling et al., 2004; Washington State Department of Transportation (WSDOT), 2014) .

5.5 Scenarios Development

Due to the variability observed in on-road driving environments, incident detection encounters various challenges, including delayed detection and a high rate of false alarms (F. Ahmed & Hawas, 2015; Hawas et al., 2020b). By leveraging CVs and V2V technologies, nearby vehicles can receive immediate notifications in the event of an incident along their route, enabling faster detection and rapid transfer of information to road users, network providers, VMS and emergency services providing more and crucial response time.

Real-world incident data from the SRN between 2016 and 2019 were analysed for spatio-temporal distribution and characteristics as described and analysed in previous Chapters. On average, there were around 570,000 incidents per year across the 4,300 miles of the SRN. Data preparation involved examining incidents based on type, location, and duration for the three-year period. The majority of incidents were breakdowns, more common on Fridays after midday, average lasting about 1 hour. For the M1 motorway, breakdowns accounted for 66% of incidents, followed by 17% obstructions. On average, one breakdown occurred every ten hours, while an additional incident (excluding breakdowns) happened daily in each direction on the examined motorway segment (J23-J26 of M1 motorway). This information provides insights into the incident frequency required for developing the breakdown model in the simulation. Other incident types include traffic collisions, abandoned vehicles, oncoming vehicles, and animal/people crossings.

5.5.1 Base Model construction

The first step of this methodology involves creating a base model that includes various elements, such as the main motorway segment, merging and diverging sections, weaving and reduced speed areas, signal phases, and vehicle routes. This model includes important traffic data such as traffic volume at each entry point, desired speed distributions, and compositions of traffic. This information helps to determine the percentage of Heavy Goods Vehicles (HGVs) and conventional vehicles and the relative flows of vehicles opting for an exit slip road route. The configuration involves assigning over 80 different input traffic flows to both the main carriageway and the slip roads, creating over 250 static and partial vehicle routes. The VISSIM software uses this information to simulate the current road network conditions by generating routes based on the links and connectors outlined in the model.

Figure 5.33 visually represents the network as building within the VISSIM platform.

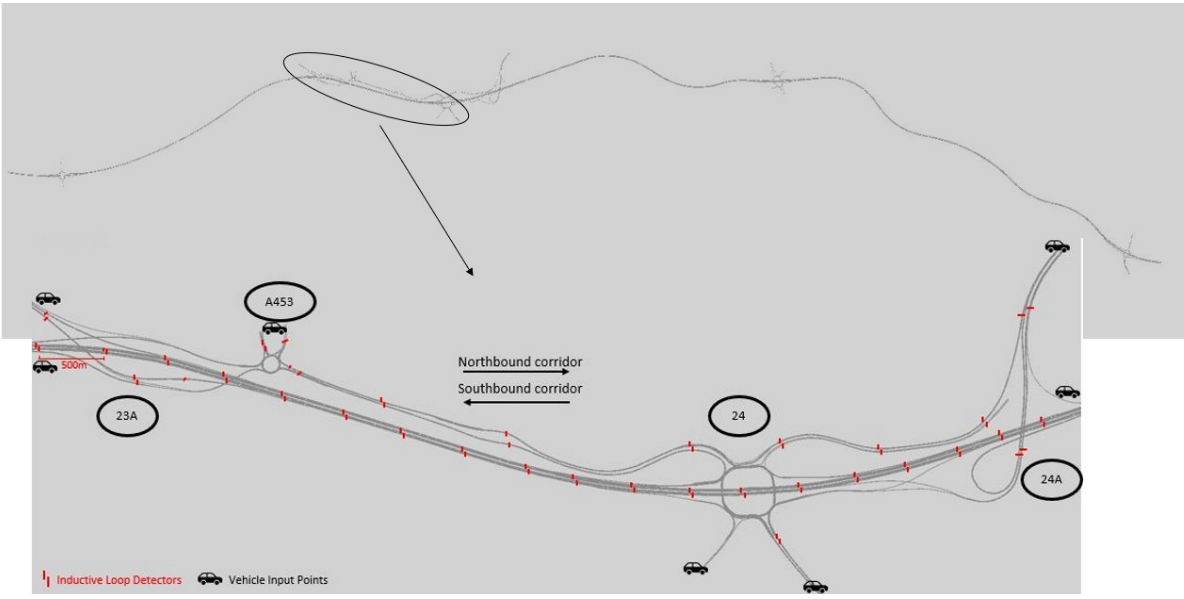


Figure 5.33:Whole simulated motorway network as depicted in VISSIM.

5.5.2 Simulating incidents

An incident is assumed to occur at 16:30 in the middle of Junction 24, Northbound, with duration of one hour to three hours, based on the case examined, during a 5-hour simulation period from 15:00 to 20:00. To simulate the incident in VISSIM, different methods have been identified, including: (1) simulating a traffic signal that blocks the affected lane due to the incident, allowing vehicles to use only the open lanes; (2) simulating a busstop where a vehicle is assigned to stop at the designated location; (3) simulating a parking lot where the vehicles involved in the incident can remain in the blocked lane while allowing following vehicles to use the available lanes. After examining all three ways, a parking lot was the best option to simulate the incident. The parking lot is placed in the middle of J24, between an exit and an entry ramp, where the incident would happen. The vehicle responsible for the incident is assigned to stop in the parking lot, as depicted in Figure 5.36 below. To ensure that only one vehicle occupies the parking lot at a time, the following regulations were implemented: (1) The route to the parking lot is active only during the incident time, which corresponds to simulation seconds 5,400 (incident start time) to 6,300 or 9,900 (incident end time); (2) The parking lot accommodate only one vehicle at a time, enabled with V2V technologies. Further explanation will be given below.

The creation of a new partial route is needed to control all traffic over created connector during the incident, as will be explained in the following subsection. This involved specifying the time interval for the partial route, which corresponds to the duration of the incident.

5.5.3 Incident Generation Processes

The replication of an incident within VISSIM is a nuanced process lacking a universally standardised method. In the course of an extensive literature review, from PTV VISSIM related work and exploration of VISSIM functionalities, three distinct approaches to simulate incidents were considered for this research. Each method represents a potential means to replicate an incident, and a detailed examination of these alternatives follows. Subsequently, the chosen approach, selected based on its appropriateness and fulfilment of specific requirements, will be expounded upon in detail. This subsection aims to provide a comprehensive understanding of the considered incident generation methods and elucidate the rationale behind the selection of the most suitable approach for the current research.

The simulation of incidents within the network necessitates a detailed approach, considering the reliability and effectiveness of the incident detection algorithm. Three distinct methodologies were explored to simulate incident events, each bearing distinct advantages and disadvantages. A notable distinction lies in the randomness of incident occurrence, particularly evident in the first method as opposed to the other two. The first approach, involving a car stop, introduces an element of unpredictability in the incident timing, a feature absents in the other two methods where incident times must be predetermined. This approach differentiates itself from **the car stop method**, which focuses on simulating the dynamics of an incident after it occurs rather than specifying its accurate timing. By specifying the vehicle where the incident will occur, the method allows for analysing its impact on traffic flow, interactions with other vehicles, and the effectiveness of incident detection systems. This flexibility reflects real-world scenarios where the timing of incidents is unpredictable, but their location (e.g., a specific vehicle or type of vehicle) can influence the outcomes and is critical for modelling purposes. Regardless of the chosen method, certain parameters such as duration, location, lane, and the type/class of the involved vehicle must be precisely defined to ensure accurate simulation outcomes. Below are detailed insights into each method, shedding light on their respective strengths and limitations, ultimately contributing to a comprehensive understanding of incident simulation considerations in the context of incident detection problems.

1. "Car" Stop: This method involves the establishment of a PT (Public Transport) lane, followed by the assignment of a car to the lane. Subsequently, the entry time of the designated car is inserted into the simulation. To introduce an element of unpredictability in the timing of the incident, the dwell time is determined. Notably, the randomness of the incident time is ensured by this approach. A PT is necessary, as is the only way to determine the time and the duration that the vehicle will stop in the predefined stop, named as Public Transport stop. In the case of an incident, a vehicle will stop in the predefined location.
2. Parking Lot: In this method, two distinct points are essential to ascertain the duration of the incident. The first point is determined through the utilisation of a parking lot, while the second point is determined via both partial routing decisions and parking routing decisions. By integrating these elements, the method establishes the duration of the incident in a controlled manner.
3. Signal/Traffic Light: For this approach, the time and duration of the incident are determined in connection with the red signal duration and the subsequent dwell time. Unlike the "Car" Stop method, this approach does not involve the stopping of cars. Instead, the breakdown occurs when no cars are utilizing the lane, effectively simulating an incident scenario at a signal or traffic light without causing car stops.

The procedural framework for creating an incident scenario in VISSIM involves a systematic series of steps, each in detail executed to ensure the accuracy and realism of the simulated incident. The comprehensive methodology is outlined as follows:

1. Link Creation: Establish the necessary links within the simulation network, strategically configuring the layout to accurately replicate the real-world scenario.
2. Conflict Area Specification: Identify and demarcate conflict areas within the network, critical for simulating interactions and potential incidents.
3. Static Vehicle Route Insertion: Integrate static vehicle routes into the simulation, verifying the correctness and completeness of each designated route to avoid any omissions.
4. Parking Lot Creation: Designate a specific location within the network to serve as the site of the breakdown incident. Create and assign a parking lot to facilitate the simulated breakdown.
5. Connector Addition: Add a connector adjacent to the parking lot insertion point. This connector is pivotal for accurately establishing partial routes and must be incorporated to proceed effectively.
6. Parking Lot Route Establishment: Develop the route for vehicles within the parking lot, incorporating the parking duration at the specific seconds corresponding to the duration of the incident. This entails navigating to Base Data > Distribution > Time and adding a new duration.
7. Partial Vehicle Route Creation:
    a. Normal Route: Define a standard route encompassing all lanes of the motorway.
    b. Incident Route via Connector (Lane 2,3 Only): Design a route specifically for the incident via the connector, covering only the lanes where vehicles can operate, excluding the lane where the breakdown transpires.
8. Assignment of Vehicle Types: Specify the vehicle types involved in the simulation by adding new vehicle types through Base Data > Vehicle Types.
9. Vehicle Compositions/Relative Flows: Define the relative flows of traffic compositions through Traffic > Vehicle Compositions.
10. Driving Behaviour Specification:
    a. Vehicle Classes: Define vehicle classes under Base Data > Vehicle Classes.
    b. Link Behavior Types/Driving Behaviors: Specify driving behaviors for different vehicle types.
11. User-Defined Attributes Specification: Define user-defined attributes to capture specific characteristics of the vehicles involved.
12. Distance Distribution Specification: Establish the distance distribution parameters to govern the spacing between vehicles.

All the above steps are briefly shown in the Figure 5.34 below. In order to accurately simulate incidents within the VISSIM environment, a script must be entered that includes the V2V incident detection connectivity algorithm. This algorithm is crucial during an incident to enable the detection and response mechanisms associated with connected vehicles. By following this procedure, the simulation will provide a dynamic and precise representation of these incidents.

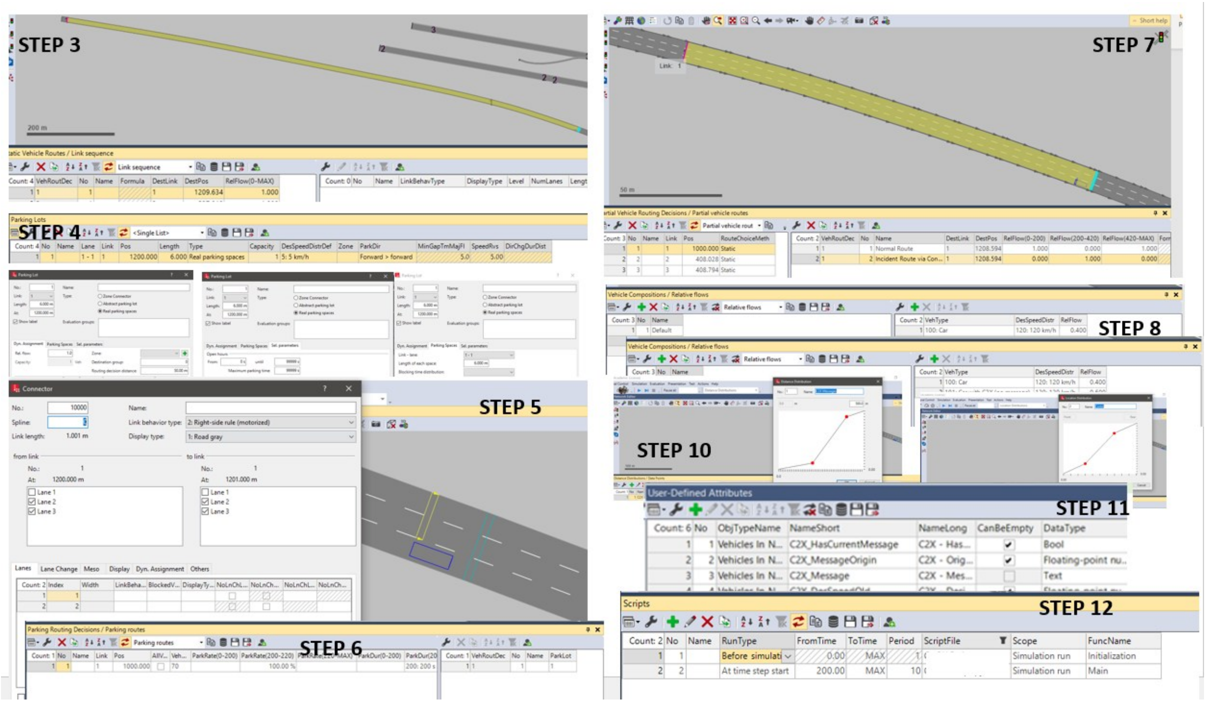


Figure 5.34: VISSIM brief representation of steps needed to be followed.

Advancing to the subsequent phase, the initiation of an incident in VISSIM needs the explicit specification of pivotal parameters. These parameters encompass delineating the incident's precise location, pinpointing the specific time of occurrence, stipulating the duration of the incident, designating the lane in which the incident unfolds, and clearly defining the vehicle type involved. It is essential to articulate whether the breakdown vehicle possesses V2V capabilities or lacks them. In this research, it is assumed that the vehicle that has an incident has this ability. In any other option, when a vehicle that stops has not this ability, the first vehicle approaching the stopped vehicle will be the one noticed down as the vehicle sending the message of a breakdown, that will be explained below.

The illustrative Figure 5.35 below provides a visual representation of some of the indispensable parameters and routes that necessitate configuration when simulating an incident through the utilization of a parking lot. This intricate set of parameters and routes is instrumental in crafting a realistic incident scenario within the VISSIM simulation environment.

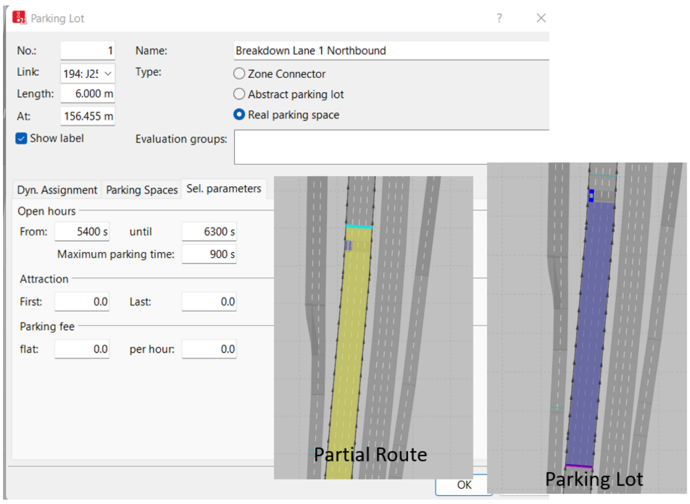


Figure 5.35:Incident simulation in VISSIM interface via a parking lot

5.5.4 V2V connectivity generation process

When the incident occurs, a vehicle equipped with V2V capability is assigned to use the parking lot for a duration equivalent to the incident duration through the VISSIM parameters. As now the incident lane is blocked, all subsequent vehicles are forced to use the three available open lanes. To facilitate this lane change, a partial vehicle route was established, directing them towards the connector on the other lanes through the created incident algorithm. This is oblligatory to happen in order to let the following vehicles know where they need to move, otherwise all of them will stop without trying to change lane until the stooped vehicle starts moving again. All vehicles must adhere to this during the incident period for the incident-purpose created partial route. This is accomplished by setting the partial route's time interval to correspond with the incident timeframe.

To differentiate between vehicles with different V2V capabilities, various colours have been employed to vehicles on the network for all classes defined in the user-defined attribute in VISSIM . Specifically, white colour indicates vehicles with none V2V equipment (status 0), yellow color signifies vehicles without an active V2V message (Status 1), and green colour represents vehicles receiving a V2V message (Status 2). Figure 5.36 illustrates the identification of vehicles based on their V2V status within the VISSIM software.

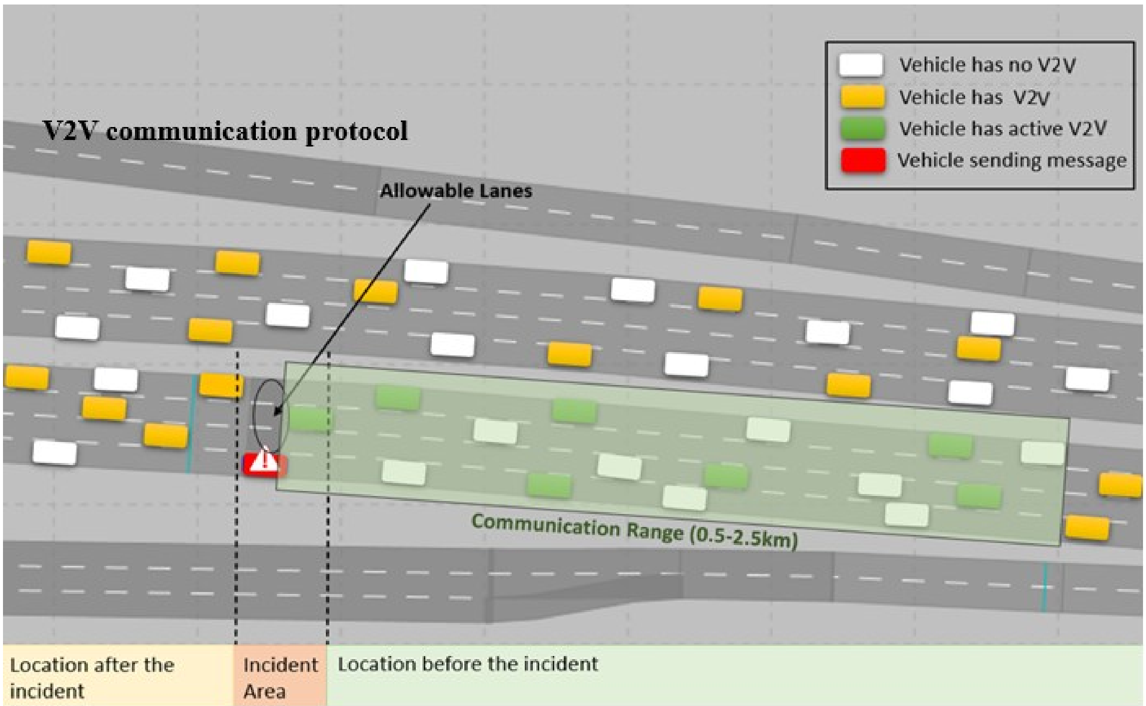


Figure 5.36:V2V connectivity protocol

The transmission range of the message has been determined to after several testing in the distance distribution area in VISSIM and is active only during incident duration via the algorithm created. The time distribution of transmitting the message corresponds to the headway of the vehicles. The vehicles when approaching the incident location, they are informed to reduce their speed, informed for the lane closure and directed to change lanes using the available open lanes. Once V2V-equipped vehicles pass the incident location, they stop receiving the message and transition from green to yellow.

The initial speeds for vehicles and heavy goods vehicles (HGVs) are set to be 120 km/h and 100 km/h, respectively, based on the observed data collected for the studied motorway. The speed distribution and relative flow are adjusted to reflect real-time conditions, and it is assumed that HGVs possess none V2V communication devices. Conversely, the conventional vehicle driving behaviour parameters are set to the validated values from calibration/validation method in VISSIM, while the CV driving behaviour was set after several testing to assign their driving behaviour to the most appropriate one. The current vehicle speed is stored as a user-defined attribute for future subsequent use once the vehicle has passed the incident location, as depicted in Figure 5.36 . CVs have their separate driving behaviour for the incident duration which is being assigned through the parameters in VISSIM and is being activated through the algorithm immediately when the incident will start. This aims to minimise the challenge of detection in real time as the CVs will be informed directly both when the incident will be occurred and when the incident will be cleared.

To enable the simulation software to incorporate vehicles with V2V capabilities, an event-based script file written in Python 3.7 is required. This script file is selected in the script attributes and specified the times at which the script would run during the simulation. It is automatically executed with two attributes: one before the simulation starts when there is no incident, and another at the time step when the incident begins. After the incident duration is over, the attribute returns to the initial one via script and the simulation is continued as normal. Various penetration rates of conventional vehicles and CVs tested to determine which one had the most significant impact on alleviating traffic congestion, minimise disruption following vehicles and improving the road user's safety.

To be more precise, in the context of incident detection within the framework of V2V connectivity, a scenario of particular interest entails the response to an incident event characterised by varying incident durations, ranging from one hour to three hours. The incidents primarily manifest as either a single lane closure (specifically, the slow lane, designated as lane 1) or the closure of two lanes, encompassing lanes 1 and 2. Within this scenario, it is hypothesised that the incident configuration will entail a one-hour duration and will transpire in the slow lane (lane 1).

In case of an incident, a response strategy is activated, which involves assigning a V2V-capable vehicle to a designated parking lot, with a parking duration equal to the specified incident duration. This is done in order to reroute subsequent vehicles, as the slow lane would become impassable due to the incident. All following vehicles are directed to transition to the remaining three available lanes. A partial vehicle route is configured to facilitate this lane change and the ensuing routing adjustments. This route leads vehicles to a connector that grants access to the open lanes. All vehicles within the network must adhere to this selected partial route during the incident. This adherence is enforced by establishing a defined time interval for utilising the partial route, ensuring that vehicles operate according to the incident management protocols and navigate safely through the affected roadway segment.

The same methodology is followed when additional lanes need to be closed. For each extra lane closure, a V2V-capable vehicle is assigned to simulate the incident within the affected lane, with the parking duration set to match the incident duration. The partial route is updated to redirect vehicles from the newly closed lane to the remaining open lanes, ensuring smooth traffic flow. This process is repeated for each additional lane closure, and the algorithm is adjusted to include new time intervals and routing parameters for the affected lanes. This ensures that vehicles follow the updated routing instructions and navigate safely through the affected road segment during multi-lane closures.

This incident detection paradigm, reliant on V2V communication and responsive routing, represents a dynamic approach to mitigate the disruptive effects of incidents on traffic flow and safety. It exemplifies the potential of connected vehicle technologies to adapt and optimize vehicular behaviours in real-time scenarios, thereby contributing to enhanced roadway management and incident response strategies.

As explained briefly above, in the context of vehicular communication categorisation, a colour-coded system has been implemented as an effective means to distinguish between various classes of Vehicle-to-Vehicle (V2V) equipped vehicles. Furthermore, to codify these vehicle classes in VISSIM, a user-defined attribute system has been employed. This attribute-based classification system augments the precision and versatility of vehicle categorisation, enabling comprehensive analysis and modeling of V2V-equipped vehicles and their communication behaviours within the simulation environment.

In the academic discourse centered on vehicular communication and categorisation, a hierarchical classification system has been devised to delineate vehicles based on their technological capabilities and associated driving behaviours. This classification encompasses three distinct categories, each denoted by specific attributes and characteristics:

- White Vehicles: These vehicles are representative of the conventional, non-connected automotive cohort. Classified under vehicle category 100, they exhibit standard driving behaviour consistent with traditional roadway norms. Specifically, they adhere to the Freeway (free lane selection) driving behaviour model.
- Yellow Vehicles: Within this category, denoted by vehicle category 70, reside connected vehicles endowed with Vehicle-to-Vehicle (V2V) communication capabilities. However, it is pertinent to note that these yellow vehicles do not engage in the active dissemination of messages. In terms of driving behaviour, they mirror their white counterparts, adhering to the Freeway (free lane selection) model.
- Green Vehicles: Distinguished by the vehicle category 80, green vehicles represent a specialized subset of connected vehicles equipped with V2V capabilities and actively engaged in message transmission and reception. Notably, these vehicles deviate from standard driving behaviour, as they are configured to operate under a distinct paradigm known as "Freeway (free lane selection) (active C2X)." This novel driving behaviour is employed exclusively when green vehicles are in receipt of pertinent messages, thereby enabling them to respond effectively to real-time communication cues and incident management protocols.

This framework provides a structured basis for analysing driving behaviours and communication modalities in diverse vehicular contexts, applicable to both connected and conventional vehicles.

6.5.5 Communicational Range of message distribution

In the context of CV connectivity, the communicational range, denoting the distance within which CVs can effectively exchange information with one another, is a parameter of paramount importance. It is noteworthy that this communicational range is not a fixed constant but rather a variable that can be subject to adjustment based on specific contextual considerations. In the course of research endeavours, a deliberate exploration of communicational range alternatives has been undertaken, spanning a spectrum from 500 meters to 2500 meters, as shown in Table 5.3.

The **Cumulative Distribution Function (CDF)** F(x) defines the cumulative probability of a message being successfully distributed within a specified communicational range. For a given range x, F(x) indicates the proportion of messages that have been successfully delivered to CVs up to that distance. For example, in the 1st range, 90% of messages (F(x)=0.90 are delivered by 400 meters, and 100% (F(x)=1.00) are delivered by 501 meters. Upon examining Figure 5.4, the 2nd and 3rd ranges are identical in terms of their F(x) values, suggesting that they represent the same distribution of message delivery probabilities over the respectively communicational distances. This indicate a calculated redundancy to confirm consistency across different scenarios.

The rationale behind this extensive range of communicational distances lies in the pursuit of optimising the deployment of connected vehicle technologies and, by extension, the selection of the most appropriate range for a given application scenario. Investigations and analyses have been conducted to evaluate various communicational ranges in terms of key performance metrics, such as information exchange reliability, latency, and system efficiency. These analyses involved simulating CVs interactions across different ranges, comparing message delivery success rates, examining latency trends, and assessing the impact on system-wide traffic performance. Consequently, the research has endeavoured to inform and guide practitioners and policymakers in making informed decisions concerning selecting the most suitable communicational range. This decision holds significant implications for the efficacy and safety of CV systems.

Table 5.3:Cumulative Distribution Function (CDF) Ranges for message distribution

Range	x	F(x)
1st	0.00	0.00
	200.50	0.10
	400.00	0.90
	501.00	1.00
2nd	0.00	0.00
	750.50	0.10
	1500.00	0.90
	2501.00	1.00
3rd	0.00	0.00
	750.50	0.10
	1500.00	0.90
	2501.00	1.00

The research selected the third range for V2V active messages, as depicted in Figure 5.37 for conclusive results.

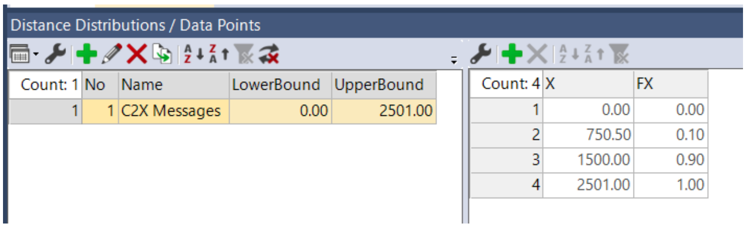


Figure 5.37: V2V Message distribution selected.

6.5.6 Incident duration

Moreover, within the domain of incident management within the context of connected vehicle systems, the temporal dimension of incident duration is a critical parameter subject to systematic scrutiny. To comprehensively evaluate the operational dynamics and efficacy of incident management strategies, a range of incident durations have been systematically investigated and analysed as shown in Table 5.4. These distinct incident durations have been systematically examined to offer valuable insights into the varying temporal dynamics of incident management strategies within the context of connected vehicle systems. Such meticulous analysis contributes to the refinement of incident response protocols, aiding in the enhancement of traffic safety and efficiency in diverse operational scenarios.

Table 5.4: Incident and Parking Lot Durations.

Incident Duration	Start Time (sec)	Finish Time (sec)	Parking Lot Start Time (sec)	Parking Lot Finish Time (sec)	Parking Lot Duration
1 hour	5400	9000	5370	9010	3600
2 hours	5400	12600	5370	12610	7200
3 hours	5400	16200	5370	16210	10800

5.7 Creating representative scenarios for incident occurrences

5.7.1 Developing Representative Scenarios

As part of this study, five different scenarios (referred to as Cases A, B, C, D, and E) were simulated. All scenarios had an incident occurring at the midpoint of Junction 24 with a shared incident point. Below the cases that took place are summarised briefly:

- **Case A:** Incident on Lane 1 (the left most lane) for a duration of 1 hour
- **Case B:** Incident on Lane 1 for a duration of 2 hours
- **Case C:** Incident on Lane 1 for a duration of 3 hours
- **Case D:** Incident on Lane 1&2 for a duration of 1 hour
- **Case E:** Incident on Lane 1&2&3 (the high-speed lane only open) for a duration of 1 hour

For all cases, multiple scenarios were developed and examined, each characterised by varying MPR of CVs. The baseline scenario, devoid of any inter-vehicle connectivity, exclusively features conventional vehicles and HGVs within the network. Subsequent scenarios introduce augmented MPRs of CVs. Specifically, the ensuing scenarios involve a 25% increase in the MPR of CVs and a corresponding 25% reduction in the number of conventional vehicles while maintaining a consistent count of HGVs. The incident in all cases created at 16:30. The subsequent scenarios are delineated as follows:

1) **Baseline Scenario:** 100% normal vehicles, 0% CVs, HGVs
2) **25% CVs Scenario:** 75% normal vehicles, 25% CVs, HGVs
3) **50% CVs Scenario:** 50% normal vehicles, 50% CVs, HGVs
4) **75% CVs Scenario:** 25% normal vehicles, 75% CVs, HGVs
5) **100% CVs Scenario:** 0% normal vehicles, 100% CVs, HGVs

These scenarios allow the examination of different combinations of normal vehicles, CVs, and HGVs, with varying degrees of MPR.

5.8 Measuring effectiveness of V2V relative to the base-case scenario (i.e., no connectivity between the vehicles)

5.8.1 Measuring effectiveness

The effectiveness of the incident detection model evaluated through various metrics as concerns mobility and safety Key Performance Indicators KPIs. This analysis encompassed the examination of Macroscopic Fundamental Diagrams (MFDs), the average total delay per vehicle (measured in seconds), the average queue length formed at the incident location, and the aggregate traffic conflicts using the Surrogate Safety Assessment Model (SSAM). The three types of conflicts, rear end, lane change, and crossing were calculated for every scenario in each incident case and the percentage reduction of each type of conflict relative to the baseline scenario were recorded. The calculation of all these measurements shows the effectiveness of the model.

For each scenario, ten simulation runs were executed with distinct random seeds, ensuring a robust assessment. Each simulation run had a duration of 10,800 simulation seconds, with a warm-up period of 1,800 simulation seconds to allow the motorway segment to reach a stable state.

The vehicle trajectory files generated by VISSIM were then transferred to SSAM for further analysis. SSAM utilised metrics such as Time-to-Collision (TTC) and Post Encroachment Time (PET) as surrogate safety measures to identify traffic conflicts and assess the impact of the incident detection model. Further explanation will be provided in the Chapter 7.

5.9 Summary of the proposed experiment

This chapter begun by describing the framework for developing an accurate traffic microsimulation model. The overall simulation development process encompasses the formulation of the network and the design considerations pertinent to the chosen road network. The focal point of this investigation is the M1 Motorway, Junction 23 to Junction 26, situated between Loughborough city and Nottingham City, in the UK. A comprehensive explanation of this network is provided, accompanied by the rationale underpinning its selection. Subsequently, a detailed account of the datasets utilised for the simulation model, encompassing both traffic characteristics and signalisation phasing and timing, where roundabout are, is presented, along with a discussion of potential limitations associated with these datasets. The chapter culminates in an exploration of the calibration/validation and verification process applied to the developed traffic microsimulation model, addressing both geographic configuration and traffic characteristics. Calibration serves the critical purpose of accurately portraying real-world features within the simulation environment, while verification compare the simulated data with ground truth data collected with an instrumented vehicle enhancing this way the accuracy of the model. Consequently, the methodology employed for calibrating the baseline simulation model is expounded through the presentation of a flowchart. Additionally, the selected GEH statistic and the Mann-Whitney U statistic, which will be subject to statistical analysis in Chapter 5 for evaluating the empirical results of the three-stage calibration process, is delineated.

The proposed experiment analysed after aims at early and safe incident detection to avoid dangerous situations and reduce traffic congestion with the help of other innovative alternatives, such as the V2V communication application. Via these experiments, the goal of detecting a stopped vehicle in real-time is more reliable than ever enhancing the mobility and safety of the motorway. For the simulation, real road map data of an area around the M1 (J23-26) motorway will be used as the baseline scenario and several optimal scenarios will be created and examined in the follow stages.

This section concluded information about incident detection scenario development and the proposed experiment scenarios. The scenarios that will be analysed in the next chapter took place on the smart motorway. Hence some information about the segment of the motorway has been included in this chapter. Also, in the above section, information about Individual Incident Detection have been included, including some reasons why the rates of incidents are so high on highways due to the many minutes needed for an incident to be detected. Hence, it is obligatory to have an informative view of this section. Due to the non-existence of CV data a calibration of the driving behaviour of CVs is needed and will be examined in the next chapter with the results of the incident detection scenario development.

Chapter 6: Incident Detection through V2V Technologies: Analysis and Findings

6.1 Introduction

This chapter of the thesis presents the results obtained using the methods introduced in Chapters 3 and 5, using the datasets presented in Chapter 4. The chapter focuses on traffic microsimulation and statistical modelling as the primary methodologies. It sequentially discusses the results obtained from traffic microsimulation and their methodological implications while aligning them with existing literature. Finally, the chapter presents the results obtained from statistical modelling.

Starting with an initially empty traffic network, the microsimulation model incorporates a warm-up period to ensure the network reaches a state of equilibrium with the required number of vehicles for accurate analysis. In this study, a 30-minute warm-up period has been implemented. The warm-up duration is essential to allow the network to attain a stable configuration, considering the time it takes for a trip from origin to destination, which averages around 20 minutes based on field data collection occurred for the verification process explained in Chapter 5. Additionally, an extra 10 minutes are allocated for added assurance.

As explained, the combined warm-up period of 30 minutes accounts for the time needed for the road network to become fully occupied by the inputted number of vehicles. This is helping to a rapid adaptation of vehicles to the designated driver behaviour characteristics within the microsimulation platform, ensuring a comprehensive and accurate analysis of the specified scenarios.

As concerns the results of the microsimulation traffic modelling, they are systematically presented, accompanied by illustrative figures and graphs, offering insights into each scenario at both the system and incident location levels, as applicable. It is important to note that, the initial scenario serves as the reference or baseline, wherein an incident occurs on the motorway without the activation of the V2V algorithm. Conversely, the subsequent scenarios (second through fifth) entail instances where the incident detection on the motorway involves the activation of the V2V algorithm. This algorithm follows planned procedures, explained in Chapter 3 and Chapter 5, encompassing all available vehicles capable of communicating with each other on the network across various fleet compositions. It is crucial to note that this process is iterated for all five examined cases explained above.

Subsequently implemented, the recorded numerical datasets undergo processing to extract vehicle trajectories and generate a comprehensive summary of the simulated vehicle activities in VISSIM. Moreover, managing and analysing these extensive datasets involved the use of Excel, and RStudio.

6.2 The Selected Key Performance Indicators (KPIs)

To begin with, it should be noted that the traffic volume on a motorway is a significant factor affecting its traffic and control challenges (Cappellari & Weber, 2022; Nathanail et al., 2017). Measuring traffic movements is the fundamental way to evaluate mobility efficiency. Several performance parameters specific to users contribute to assessing the KPIs. These parameters include motorway density, travel speed, delay caused by unexpected incidents or anticipated congestion during peak hours, conflict rates, and queues arising from unforeseen events. Each operational service is individually evaluated based on these parameters. Additionally, the effectiveness of movement is quantified by calculating the average daily journeys of a vehicle.

Moving on in assessing the developed incident detection V2V connectivity control algorithm, a set of key performance indicators has been selected to assess its impact on both mobility and safety indicators. The results will provide insights into how the implemented V2V control algorithm influences traffic and safety outcomes by comparing scenarios with and without V2V compositions, thereby highlighting the differences between the initial scenario and the subsequent ones.

6.2.1 Key Performance Indicators of Road Traffic Performance

In this research, KPIs are used to evaluate the traffic functionality performance of a specific motorway segment. Average vehicle delays and queue length are considered crucial measures for assessing the efficiency of traffic performance, especially when making changes to the current traffic operation or future management applications. Therefore, we have selected specific KPIs to evaluate traffic efficiency, which are highlighted below. Our research investigates the impact of the developed V2V connectivity protocol in incident detection on mobility, with a focus on changes in network capacity and traffic operation productivity. We will assess travel time, delay, number of stops, and queues, as these measures are closely interconnected.

Average Vehicle Delay is a widely used performance metric at motorway segments, offering insights into the characteristics of traffic flow conditions and serving as a key indicator for evaluating the effectiveness of the traffic systems (Sadoun, 2008) . It represents the additional travel time, or loss time, that a vehicle experiences in reaching its destination during its journey. The overall delay is calculated as the difference between the ideal travel time and the actual travel time (HCM, 2000; PTV VISSIM 11 USER MANUAL, 2019; Vision, 2009b). The ideal travel time is the time required to complete a journey without hindrances, such as when a vehicle faces no obstructions from other vehicles or traffic signals (i.e., in a free-flowing situation) (PTV Group, 2020). Conversely, the actual travel time accounts for the real-time taken by a vehicle to complete its trip, encompassing dwell times at congestion and/or unexpected event, as an incident. The delay obtained from the VISSIM microsimulation model represents the average loss time in seconds for all vehicles traveling through a specific O-D pair, which is determined in VISSIM parameters. This metric aids in assessing the performance of a particular route and identifying problematic locations characterised by higher delay events.

Lastly, the number of stops gives the number of vehicles that have to stop at traffic signals. However, the stopping at public transport stops and/or parking lots are excluded from the calculation of stopped vehicle numbers. This is one of the important indicators to identify the stop-and-go conditions at signalised intersections while analysing the network performance. Finally, the number of stops represents the count of vehicles compelled to halt at traffic unexpected condition. This indicator is significant for pinpointing stop-and-go conditions at the examined segment when scrutinising network performance during the incident occurrence.

6.2.2 Safety Key Performance Indicators

It has been noted that in addition to the mobility indicators, safety indicators also need to be examined. This includes conflicts that are calculated via SSAM. The process of identifying conflicts to assess the safety impact of the developed CV algorithms remains to be discussed. The simulation framework will provide the number of conflicts computed for each formulated scenario using SSAM, as explained in section 3.6.4 of Chapter 3. It is important to note that the computation time has seen a significant increase with the increase in CVs' MPR across various scenarios. For instance, the scenario with a 0% market penetration rate lasted an average of 2.5 hours, while a simulation run with a 100% CV market penetration rate extended to approximately 3.5 hours.

Finally, the selected key performance indicators for analysing the traffic model, covering both mobility and safety estimates, are explained to improve understanding of the expected results from the simulation model.

6.3 Connected Vehicles Driving Behaviour

Connected Vehicles (CVs) are a critical link between traditional human-driven vehicles and fully autonomous systems, combining human intuition with technological advancements. Unlike autonomous vehicles, CVs depend on human drivers for decision-making while enhancing situational awareness through V2V and V2I communication with real-time data exchange. This dual functionality highlights the need for a dedicated driving behaviour model that incorporates both human factors and the dynamic influence of connectivity. These models are fundamental for analysing traffic flow, improving safety, and optimising infrastructure. However, the shift to a fully connected system is not without challenges, as CVs must coexist with conventional and partially connected vehicles, adding complexity to traffic behaviour. Understanding these mixed-traffic scenarios and the varying levels of connectivity is essential for supporting the transition, ensuring safer and more efficient transport networks.

6.3.1 Connected Vehicle Driving Behaviour in VISSIM

In the context of traffic simulation and modelling, such as in the microsimulation VISSIM software, the integration of CVs presents a unique challenge. Unlike conventional vehicles, CVs often require specialised profiles and parameters to accurately simulate their behaviour within the system. Since there are not ready-to-use profiles for connected vehicles readily available in VISSIM or similar software, creating a custom profile becomes essential. This custom profile is typically based on a thorough understanding of the specific connected vehicle technology being simulated, including its communication protocols, sensor capabilities, and cooperative behaviours. Developing such profiles is crucial for conducting realistic simulations that can help assess the impact of connected vehicle technologies on traffic flow, safety, and overall transport efficiency.

Implementing an adaptive driving behaviour in connected vehicles can significantly enhance the driving experience, increase road safety, and contribute to more efficient and sustainable transport systems. The realisation of these advantages in CVs is achievable through the creation of an integrated VISSIM built-in driving behaviour profile, a matter that will be elaborated on in subsequent sections.

6.3.1.1 Factors affecting CVs’ Driving Behaviour in VISSIM.

As proposed above, as there is no ready to use profiles for CVs, a new driving behaviour need to be created and evaluated via a new user interface. Developing a driving behaviour profile for CVs in Vissim involves rigorous consideration of various factors. Initially, the key characteristics of the vehicle, such as size, weight, and maximum speed, had to be defined, influencing its behaviour within the simulation environment. The process included specifying the communication protocol and standards for V2V communication, ensuring compatibility with the Vissim environment and other simulated vehicles. Additionally, factors like sensor range, accuracy, and data exchange format played a crucial role in shaping the behaviour of the connected vehicle.

The configuration extended to programming the V2V communication logic, defining how the vehicle sends and receives messages about its speed, position, acceleration, and intentions during motorway incidents. These communication protocols enable vehicles to share critical information with nearby vehicles, creating a cooperative traffic ecosystem. Cooperative maneuvers, driven by V2V communication, were implemented to allow vehicles to adjust their speeds based on real-time inputs, ensuring smoother traffic flow during incidents. For instance, vehicles receive lane closure alerts and rerouting instructions through the incident detection algorithm, enabling timely and coordinated responses.

Additionally, some features, such as collision avoidance systems, are augmented by automation rather than communication alone. These systems include sensors and automation logic that enable vehicles to process incoming data and execute actions like issuing collision warnings or performing automatic braking when a potential collision is detected. Automation enhances the ability of CVs to act on V2V data autonomously, reducing driver dependency and improving reaction times in critical situations. By combining V2V communication with automation-driven safety features, the behaviour of CVs integrates both proactive and reactive strategies, significantly contributing to improved safety and efficiency during motorway incidents.

For testing the CV driving behaviour, the average total delay per vehicle has been as will be described below. The development process further has been encompassed route handling behaviours, and responses to an incident situation. Validation and testing procedures have been instituted to ensure the safe and effective operation of the CV behaviour in the event of an incident. A limitation than couldn't be considered and addressed in this thesis was the privacy and security considerations through the implementation of encryption, authentication measures, and keys management to safeguard data exchanged between vehicles. Finally, a user interface has been created within Vissim to visualise V2V communication and decision-making processes, enhancing the understanding of functionality.

Additionally, comprehensive documentation has been created within PTV Vissim software. Specifications of the connected vehicle behaviour were documented, including any assumptions made during development. Operational details and settings have been provided, ensuring clarity and transparency throughout the thesis, and will be presented below. By specifying these parameters and settings in PTV Vissim, a well-defined and customisable CV driving behaviour created for the traffic simulation and analysis needs as concerns the incident detection scenario development. These settings allowed to fine-tune the behaviour and characteristics of the connected vehicle within the simulation environment.

6.3.1.2 Connected vehicles and Wiedemann 99 parameters

In the literature, as there is no to real-world data for calibrating the Wiedemann '99 car-following model parameters in the traffic simulation, the default or common values that are often have been applied in traffic simulation studies. The Figure 6.1 below, provide the default values for the Wiedemann '99 model parameters for conventional vehicles and autonomous vehicles provided by the literature, parameters (Sonnleitner et al., 2020; Vision, 2009b):

Driving behavior		Autonomous vehicles			Car2X example	Normal cars
		AV cautious	AV normal	AV aggresive	Cars and HGVs	Cars and HGVs
Car following model-W99 Model parameters	**Range**	**Values**				
CC0 - standstill distance (m)	0.5-5	1.5	1.5	1	1.5	1.5
CC1 - gap time distribution (s)	0.5-2.5	1.5	0.9	0.6	1.3	0.9
CC2- following distance oscillation (m)	1-10	0	0	0	6	4
CC3 - threshold for entering 'following'	(-20)-(-1)	-10	-8	-6	-8	-8
CC4 - negative speed difference	(-3)-(-0.1)	-0.1	-0.1	-0.1	-0.35	-0.35
CC5- poritive speed difference	0.1-3	0.1	0.1	0.1	0.35	0.35
CC6 - distance dependency of oscillation	1-20	0	0	0	11.44	11.44
CC7 - oscillation acceleration (m/s2)	0.05-1	0.1	0.1	0.1	0.25	0.25
CC8 - acceleration from standstill (m/s2)	0.5-8	3	3.5	4	3.5	3.5
CC9 - acceleration at 80 km/h (m/s2)	0.5-8	1.2	1.5	2	1.5	1.5

Figure 6.1: Default values for Car-following models/W99 for different types of vehicles

The default parameter values above are typically intended for conventional vehicles and autonomous vehicles, not specifically for connected vehicles. However, many of these parameter values can be used as starting points for modelling the behaviour of connected vehicles in a traffic simulation. Connected vehicles can have similar driving characteristics to conventional vehicles but may also exhibit enhanced behaviours due to their connectivity.

In the context of connected vehicles, certain adjustments to the parameters of the Wiedemann '99 car-following model are deemed necessary to account for the potential enhancements afforded by V2V connectivity. It's important to note that the parameter values for connected vehicles will depend on the specific connected vehicle technology, its capabilities, and the behaviour you want to simulate. These values can be adjusted during the calibration and validation process to ensure that the connected vehicle behaviour in your simulation accurately reflects the intended real-world behaviour.

6.3.1.3 Calibrating and Validating Connected Vehicle Behaviour

The behaviour of Connected Vehicles (CVs) is expected to vary greatly from that of non-connected vehicles because of their ability to communicate and share real-time data with other vehicles and infrastructure. Unlike non-connected vehicles, which depend only on driver perception and reaction, CVs can receive information about road conditions, traffic incidents, and lane closures quickly and sufficiently before any visual or auditory detection. This ability allows CVs to predict and react to situations earlier; as a result, smoother lane changes, coordinated deceleration, and improved route optimisation.

Furthermore, CVs can be part of cooperative manoeuvres, such as platooning or even synchronised lane changes, which are not impossible for non-connected vehicles. These behaviours are driven by V2V communication, enabling CVs to make decisions based on a cooperative understanding of traffic conditions rather than isolated observations, which is a common thing for conventional vehicles. This difference enhances traffic flow stability, reduces stop-and-go, and minimises delays caused by reactive driving, making CVs more efficient and safer in managing traffic dynamics.

Calibrating and validating the behaviour of connected vehicles within a traffic simulation, in the absence of real-world data, poses a challenge that can be addressed through a systematic approach. This methodological framework involves leveraging best practices, expert insights, and hypothetical scenarios to ensure that the simulation accurately reflects the intended real-world behaviour of connected vehicles. Below, it is outlined a systematic step-by-step approach designed to ensure that the simulation faithfully mirrors the intended real-world behaviour of connected vehicles.

The process begins by clearly defining specific objectives for the simulation study, establishing a foundation for subsequent parameter selection and validation efforts. For that reason, the baseline incident detection scenario took place, and the average vehicle delay was examined. The profile that provided less delays as the MPR of CVs were increased, assumed as the most appropriate one for the selection of a CV. Via the website https://jlitraffic.appspot.com/trafficcircle.html, using the traffic circle the range of each w99 parameters were specified as showed in Figure 6.2 below.

W99 parameters	The range according to traffic circle
CC0	0.5 – 5 (m)
CC1	0.5 – 2.5 (s)
CC2	1 – 10 (m)
CC3	(-20) – (-1) (s)
CC4	-3 – -0.1 (m/s)
CC5	0.1 – 3 (m/s)
CC6	1 – 20 (1/m*s) (1 – 10)
CC7	0.05 – 1 (m/s2)
CC8	0.5 – 8 (m/s2)
CC9	0.5 – 8 (m/s2)

Figure 6.2: W99 parameters range according to traffic circle

A suite of hypothetical traffic CV scenarios took place, each time with a different range for four of the major W99 parameters, that through literature showed to be more critical and changeable according to the driving behaviour it is needed to be incorporate. The test started by changing the CC0 parameter from [0.5 to 5(m)], testing different values inside this range to fully understand how delays and performance is being affecting. Next one was the CC1 parameters which was tested individual for its own range from [0.5 to 2.5 (s)], but also tested accordingly the best fitted result with the changes of CC0 values. Following this methodology, the CC3 and CC7 W99 parameters tested according to their ranges, [(-20) – (-1) (s)] and [0.05-1 (m/s2)] respectively. The iterative calibration process involves fine-tuning parameters to align the simulated behaviour of connected vehicles with the intended real-world behaviour. Furthermore, a sensitivity analyses has systematically been conducted to understand the individual impacts of parameters on connected vehicle behaviour.

Validation metrics were used to assess the accuracy of the simulation, focusing on following distances, traffic flow, lane change frequency, and safety indicators like collision rates and time-to-collision (TTC). During calibration, metrics such as vehicle acceleration, deceleration, and reaction times were used to ensure realistic driving behaviour. Separate validation scenarios, including different traffic volumes and incident settings, were created to test the model under new conditions, ensuring it accurately represents connected vehicle behaviour. The model and parameter values undergo continuous refinement based on results from validation scenarios and insights derived from sensitivity analyses. Comprehensive documentations were maintained throughout the analysis of CV driving behaviour, ensuring transparency and reproducibility.

In conclusion, while real-world data is typically invaluable for calibration and validation, these systematic steps enable the refinement of the connected vehicle behaviour model to closely approximate real-world behaviour, even in the absence of such data. It is essential to acknowledge that the model inherently remains an approximation, and the quality of results depends on the thoroughness of calibration and validation efforts.

6.3.1.4 Driving behaviour of a connected vehicle

The W99 car-following model is a popular car-following model used for connected vehicles in PTV VISSIM software. It includes parameters such as safe time headway and desired speed that can be adjusted for connected vehicles to improve their behaviour on the road (Anil Chaudhari et al., 2019; Durrani et al., 2016). The use of these parameters can lead to improvements in traffic flow and safety. Overall, the W99 model and its parameters play a critical role in the development and testing of connected vehicle technology.

To accurately replicate and simulate the behaviour of CVs within the VISSIM framework, precise specification of driving behaviour parameters is imperative. These parameters encompass various facets of vehicular behaviour, each comprising a set of sub-parameters necessitating explicit declaration(PTV VISSIM 11 USER MANUAL, 2019). The critical dimensions of driving behaviour parameters encompass the following:

- Following Behaviour: This parameter governs how a connected vehicle follows the vehicle immediately ahead. It encompasses sub-parameters relating to following distance and response dynamics.
- Car Following Model: The choice of a car following model plays a pivotal role in determining how a connected vehicle reacts to the movements of leading vehicles. Different models exhibit varying characteristics and require specific parameterization.
- Lane Change Behaviour: The lane change behaviour of connected vehicles involves factors such as the frequency of lane changes, the criteria for initiating lane changes, and the degree of aggressiveness in executing lane changes.
- Lateral Behaviour: Lateral behaviour parameters pertain to lateral vehicle control, encompassing elements like lane-keeping, trajectory planning, and lateral position control.
- Autonomous Driving Behaviour: In cases where autonomous driving functionality is integrated into connected vehicles, parameters related to autonomous decision-making, perception, and control systems become crucial considerations.
- Meso Behaviour: Meso-level behaviour parameters refer to the interaction and coordination of connected vehicles within groups or platoons, necessitating the definition of protocols for group formation, dissolution, and coordination.

Each of these parameters comprises a range of specific values and settings, tailored to the particularities of the CVs under examination. Accurate and comprehensive parameterization is fundamental to achieving fidelity in the simulation of connected vehicle behaviour within the VISSIM platform, contributing to a deeper understanding of the dynamics and implications of vehicular communication and connectivity in real-world traffic scenarios. As connected vehicle technology continues to evolve, further research and experimentation are anticipated to refine and expand these driving behaviour parameters below, advancing the state of simulation capabilities and enhancing our ability to model and analyse connected vehicle systems effectively. All the above include multiple parameters that need to be declared, information of which will be provided below.

Below, an exhaustive presentation and analysis of parameters crucial to the W99 model can be observed, categorised into three main aspects: Following parameters, Car Following Model (W99) parameters, and Lane Change parameters. The breakdown of each parameter within these aspects facilitates a comprehensive examination of their impact on the simulation. The detailed parameters are as follows in Figure 6.3.

Driving behaviour parameters		
1.Following	**3.Lane change**	**4.Lateral**
1. Look ahead distance	1. General behavior	1. Desired position at free flow
• minimum (m)	2. Necessary lane change (route)	2. Observe adjacent lanes
• maximum (m)	• Maximum deceleration (m/s2)	3. Diamond queuing
• number of interaction objects	• (-)1 m/s2 per distance (m)	4. Consider next run
• number of interaction vehicles	• accepted deceleration (m/s2)	5. Collision time gain (s)
2. Look back distance	3. Waiting time before diffusion (s)	6. Minimum longitudinal speed (km/h)
• minimum (m)	4. min.clearance (front/rear)	7. Time between direction changes (s)
• maximum (m)	5. to slower lane if collision time is above (s)	8. Default behavior when overtaking vehicles on the same or on adjacent lanes
3. Behavior during recovering from speed breakdown - slow recovery	6. safety distance reduction factor	• Overtake on same lane
• speed	• Overtake reduce speed areas	• overtake left (default)
• acceleration	• Advanced merging	• overtake right (default)
• safety distance	• Vehicle routing decisions look ahead	○ Minimum lateral distance
• distance	7. maximum deceleration for cooperative braking (m/s2)	○ distance standing (m) at 0 km/h
4. Standstill distance for static obstacles (m)	8. Cooperative lane change	○ distance driving (m) at 50 km/h
5. Jerk limitation	• maximum speed difference (km/h)	**5.Autonomous driving**
2.Car following model	• maximum collision time (s)	1. Enforce absolute braking distance
W99- Model parameters	9. Rear correction of lateral position	2. use implicit stochastics
1. CC0 - standstill distance (m)	• maximum speed (km/h)	3. Platooning
2. CC1 - gap time distribution (s)	• active during time period from ..(s) until ..(s) after lane change start	4. Platooning possible
3. CC2- following distance oscillation (m)		• max number of vehicles
4. CC3 - threshold for entering 'following'		• max desired speed
5. CC4 - negative speed difference		• max distance for catching up to a platoon
6. CC5- positive speed difference		• gap time
7. CC6 - distance dependency of oscillation		• minimum clearance
8. CC7 - oscillation acceleration (m/s2)		**6.Meso**
9. CC8 - acceleration from standstill (m/s2)		• Meso reaction time (s)
10. CC9 - acceleration at 80 km/h (m/s2)		• Meso standstill distance (m)
		Meso maximum waiting time (s)

Figure 6.3: W99 Model Parameters: Following, Car Following, Lane Change, Lateral, Autonomous Driving, and Meso Aspects

After conducting a comprehensive analysis of these parameters, the optimal configuration was chosen, prioritising reduced delays as explained, especially with the increasing market penetration rate of CVs. This selection emerged as the most promising, demonstrating its effectiveness in addressing delays in the evolving landscape of connected mobility. The chosen presentation method ensures clarity and facilitates a nuanced understanding of the intricate interplay between the parameters within the W99 model. The insightful results derived from this optimisation will be thoroughly analysed in section 6.4 below, providing valuable information for further interpretation and application.

6.4 Connected Vehicles Driving Behaviour Results

Following a detailed examination of the various parameters within the Wiedemann '99 car-following model, a selection of optimal configurations was undertaken, with a primary focus on mitigating delays, particularly in the context of escalating market penetration rates of Connected Vehicles (CVs). This discerning selection emerged as a promising strategy, showcasing its efficacy in addressing delays within the dynamic landscape of connected mobility. The chosen presentation methodology prioritises clarity and promotes a comprehension of the intricate interactions among the W99 model parameters. This section, delves into a comprehensive analysis of the insightful results stemming from this optimisation, offering valuable insights for further interpretation and practical application.

As the examination progressed, a comprehensive testing approach was adopted, encompassing a representative selection of 12 scenarios, each one having a different driving behaviour for CVs (refer to Figure 6.4). The results shown and compiled, are incorporating the minimum, median, and maximum values for each parameter tested. More test for the values in between took place, but these 12 tests trials will be presented as they are the most suitable for the result needed to be explained in detail. The beginning point was to range first the CC0 parameter from the minimum value to the maximum one and then after checking its results started changing to its ranges the CC1 parameter. Several similar combinations made based on the importance of each parameters in the results but also in the literature. A parallel examination of the driving behaviours of both conventional and autonomous vehicles was conducted, aligning the CV behaviour assumptions with those employed in the examination of the Incident detection using V2V communication protocol. Notably, each test involved a rigorous iteration of 10 simulation runs to mitigate the potential impact of non-accurate results. The tested parameters are explicitly depicted in the Figure 6.4, providing a visual representation of the extensive testing framework.

Driving behaviour		**Connected vehicles**											
Car following model-W99	**Range**	**Test 1**	**Test 2**	**Test 3**	**Test 4**	**Test 5**	**Test 6**	**Test 7**	**Test 8**	**Test 9**	**Test 10**	**Test 11**	**Test 12**
CC0 - standstill distance (m)	0.5-5	**0.5**	**2.5**	1.5	1.5	1.5	1	1	1.5	1.5	1.5	**5**	**1**
CC1 - gap time distribution (s)	0.5-2.5	1.3	1.3	**0.5**	**2.5**	**1**	0.7	0.7	0.9	0.9	0.9	1.3	1.3
CC2- following distance oscillation (m)	1-10	6	6	6	6	6	2	2	**3**	**6**	**10**	6	6
CC3 - threshold for entering 'following'	(-20)-(-1)	-8	-8	-8	-8	-8	-8	-8	-8	-8	-8	-8	-8
CC4 - negative speed difference	(-3)-(-0.1)	-0.35	-0.35	-0.35	-0.35	-0.35	-0.35	-0.35	-0.35	-0.35	-0.35	-0.35	-0.35
CC5- poritive speed difference	0.1-3	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35
CC6 - distance dependency of oscillation	1-20	11.44	11.44	11.44	11.44	11.44	11.44	11.44	11.44	11.44	11.44	11.44	11.44
CC7 - oscillation acceleration (m/s2)	0.05-1	0.25	0.25	0.25	0.25	0.25	**0.25**	**0.1**	0.1	0.1	0.1	0.25	0.25
CC8 - acceleration from standstill (m/s2)	0.5-8	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5
CC9 - acceleration at 80 km/h (m/s2)	0.5-8	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5

Figure 6.4: Parameters' values of examined tests for W99-Car following model

The results of the average total vehicle delay will be presented for the delay measurement point n4, which include the segment started 1000 m before incident point till the incident point. As the behaviour of CVs were tested the baseline scenario with 0% MPR of CVs is not including in the results below. Figure 6.5 and Figure 6.6 represent all the MPR of each test trial, while Figure 6.7 – Figure 6.10 presents all test trial for each one MPR, from 25% till 100%, with a 25% increasement.

Figure 6.5: Average vehicle delay per test examined for all four MPR of CVs, part a

Figure 6.6: Average vehicle delay per test examined for all four MPR of CVs, part b

Scenario 25%

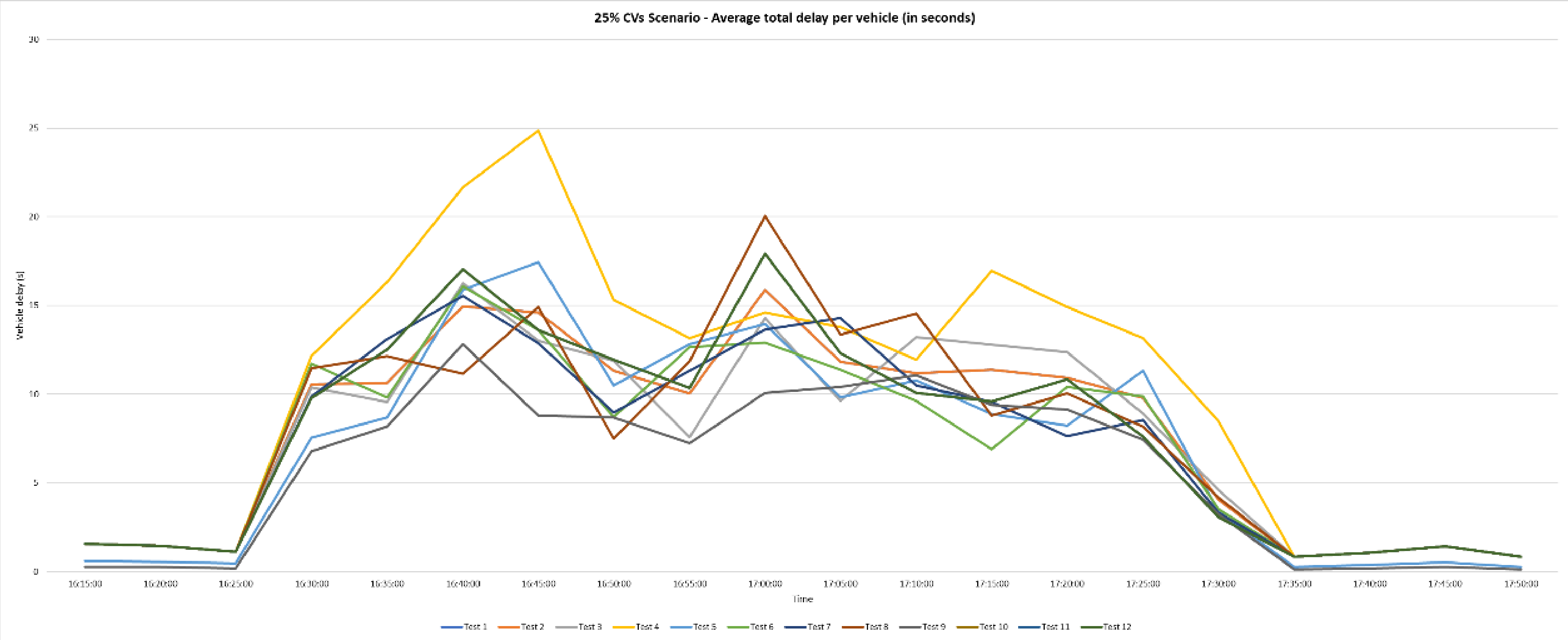


Figure 6.7: Average total delays per vehicle for 25% CVs scenario

Scenario 50%

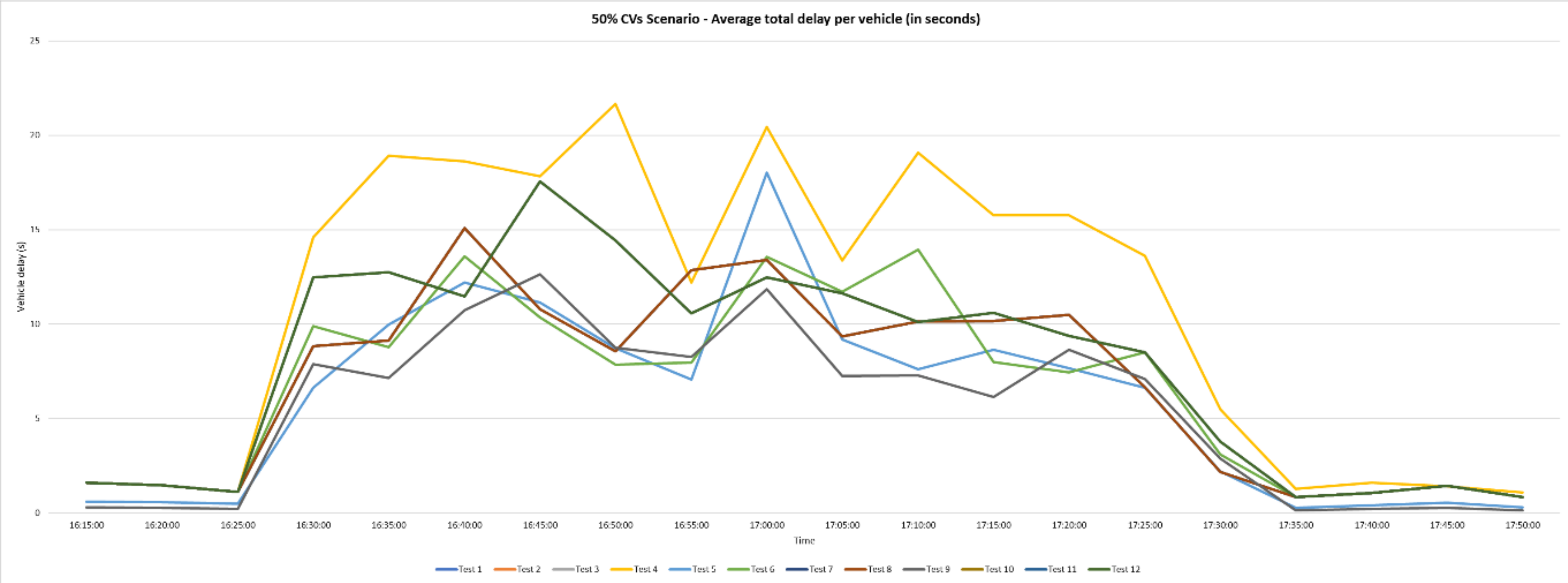


Figure 6.8:Average total delays per vehicle for 50% CVs scenario

Scenario 75%

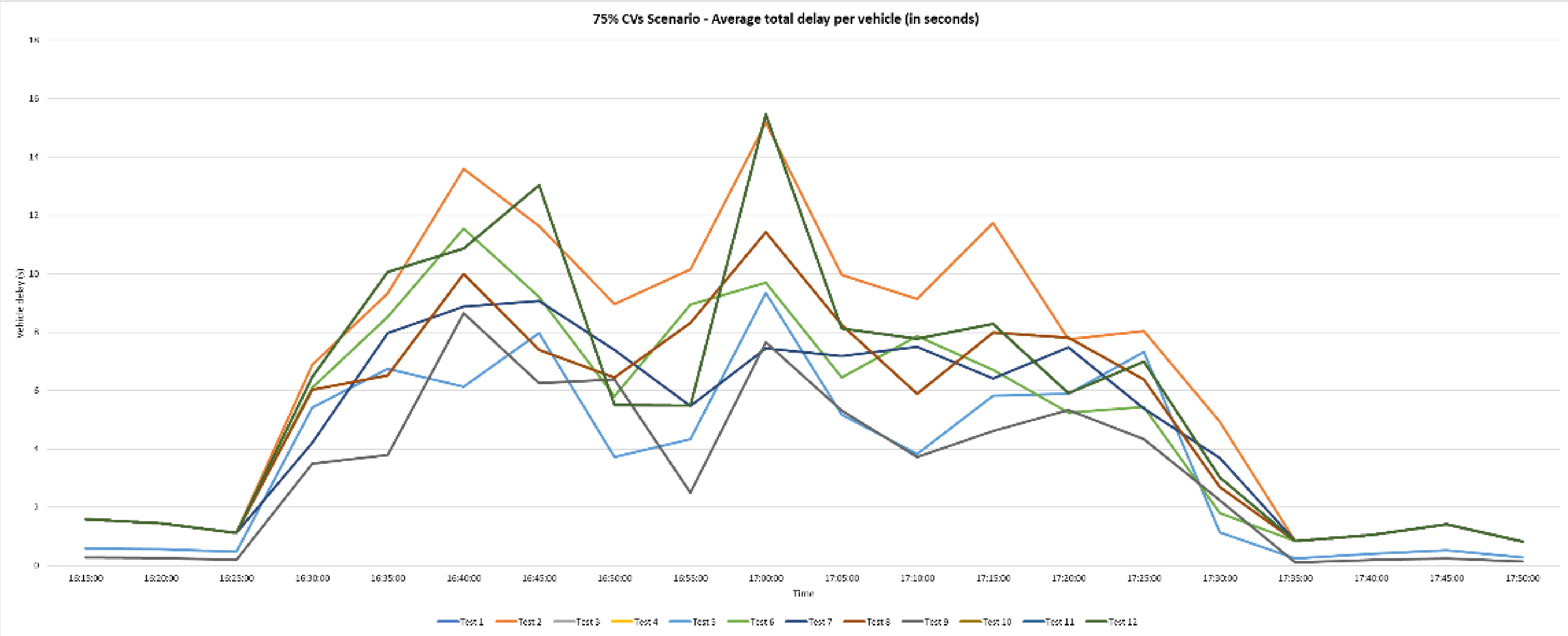


Figure 6.9:Average total delays per vehicle for 75% CVs scenario

Scenario 100%

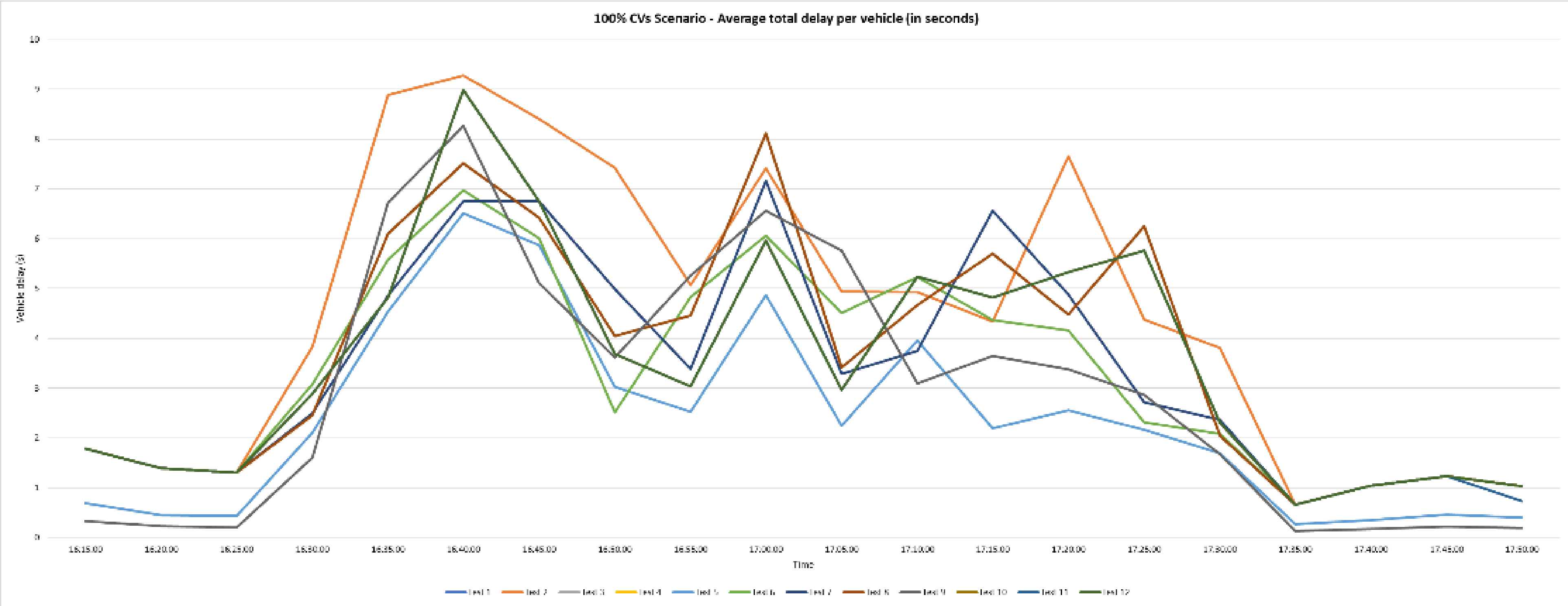


Figure 6.10: Average total delays per vehicle for 100% CVs scenario

To ascertain the test result with the least delay among Test1 through Test12, a systematic approach was employed, involving the calculation of average delays for each test, thereby facilitating a comparative evaluation. The test exhibiting the lowest average delay emerges as the most suitable option. In order to garner deeper insights and discern the optimal performance based on the dataset, a multifaceted analysis was conducted using various data analysis and visualisation techniques.

Through these rigorous analyses, a comprehensive understanding of the relative test performances and the factors influencing their outcomes was achieved. The results presented refers to the 100% MPR of CVs, where the rest of the MPR are not included as they provided same results realising trial Test 5 as the most appropriate within an average vehicle delay of 1.0209 sec as shown in Table 6.1 and in Figure 6.11.

Table 6.1: Most appropriate test concerning average delay of vehicles results.

```
> # Print the results
> cat(paste("The most appropriate test is",
most_appropriate_test, "with an average delay
of", min_delay, ".\n"))
The most appropriate test is Test5 with an
average delay of 1.02092592592593 .
```

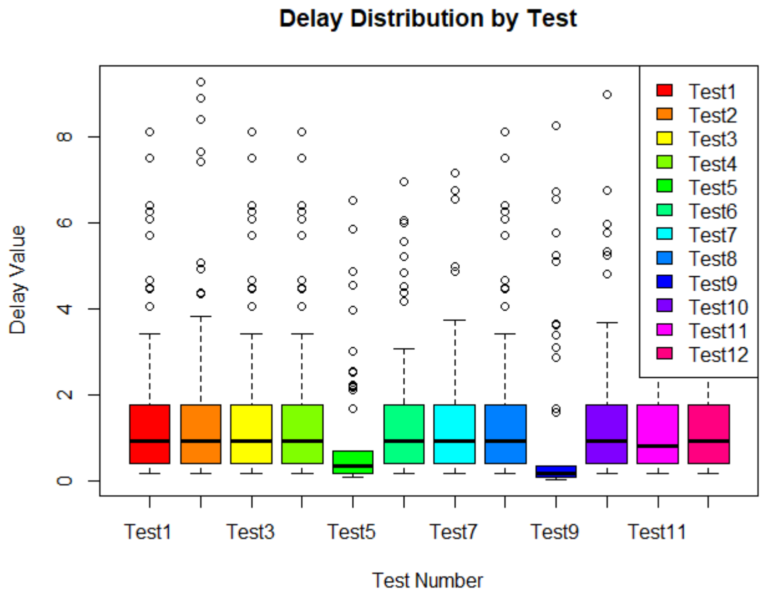


Figure 6.11: Delay value distribution by test examined

The summary of the ANOVA test (refer to Table 6.2 and Table 6.3) provides critical insights into the statistical significance of differences among the various tests examined. The Degrees of Freedom (Df) column delineates the degrees of freedom attributed to each factor, encompassing individual tests and residuals. Sum of Squares (Sum Sq) quantifies the total variation inherent in the dataset, while Mean Squares (Mean Sq) elucidates the average variation for each factor, obtained by dividing the sum of squares by its corresponding degrees of freedom.

Table 6.2: One-way ANOVA test comparing all tests examined

```
> # Perform one-way ANOVA
> result_anova <- aov(Test1 ~ Test2 + Test3 + Test4 + Test5 +
Test6 + Test7 + Test8 + Test9 + Test10 + Test11 + Test12, data =
data)
> # Print the ANOVA table
```

```
> print(summary(result_anova))
             Df Sum Sq Mean Sq   F value Pr(>F)
Test2         1 207.80  207.80 3.653e+33 <2e-16 ***
Test3         1  26.85   26.85 4.720e+32 <2e-16 ***
Test5         1   0.00    0.00 1.590e-01  0.692
Test6         1   0.00    0.00 1.215e+00  0.276
Test7         1   0.00    0.00 1.873e+00  0.178
Test9         1   0.00    0.00 3.480e-01  0.558
Test10        1   0.00    0.00 7.400e-02  0.786
Test11        1   0.00    0.00 1.700e-02  0.896
Residuals    45   0.00    0.00
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> result_ttest <- t.test(data$Test1, data$Test2)
> # Print the t-test results
> print(result_ttest)
```

The F-statistic (F value) is a pivotal metric, representing the ratio of variation between group means (Test2, Test3, etc.) to the variation within the groups (Residuals). A higher F value indicates a more significant difference among group means. The p-value (Pr(>F)) associated with the F-statistic is a key determinant of statistical significance. A smaller p-value underscores a more robust rejection of the null hypothesis, which posits no significant differences among the groups.

Table 6.3: Welch Two Sample t-test

```
        Welch Two Sample t-test

data:  data$Test1 and data$Test2
t = -0.60112, df = 101.86, p-value = 0.5491
alternative hypothesis: true difference in
means is not equal to 0
95 percent confidence interval:
 -1.1712773  0.6264625
sample estimates:
mean of x mean of y
 1.750370  2.022778
```

After analysing the results, it is evident that Test2 and Test3 exhibit extremely small p-values (typically denoted as <2e-16), indicating that there are statistically significant differences between these tests. However, for Test5, Test6, Test7, Test9, Test10, and Test11, the relatively large p-values (greater than 0.05) suggest that there is insufficient evidence to support significant differences among these tests. The "Residuals" row represents the unexplained variation within the data, acknowledging the remaining discrepancies that contribute to the overall statistical landscape.

Histograms, illustrated in Figure 6.12 and Figure 6.13, visually represent the distribution of average vehicle delay values, aiding in comprehending the shape of the data distribution.

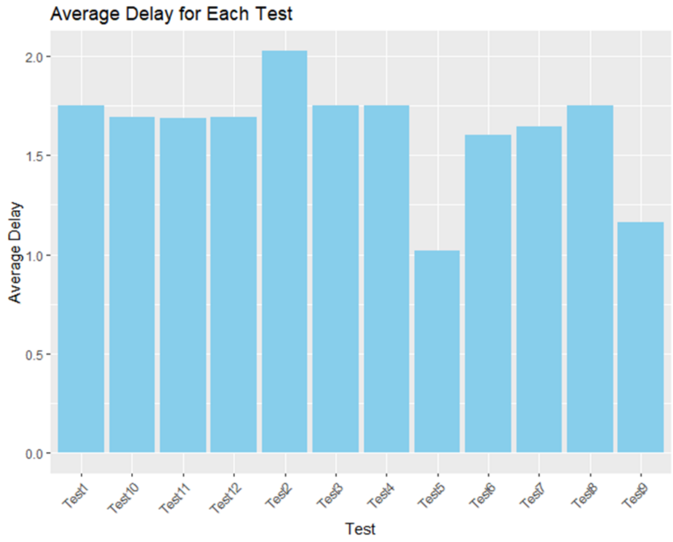


Figure 6.12: Applicability of Bar charts for average vehicle delay for each test examined

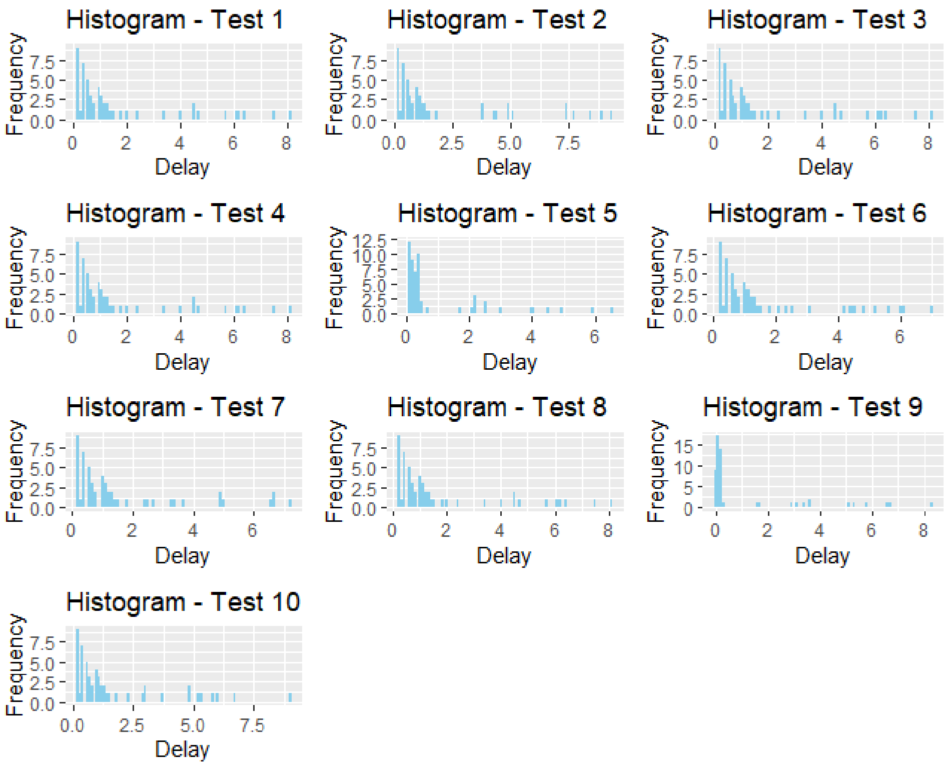


Figure 6.13: Distribution of average vehicle delay values

Test trial 5 was the best option for simulating connected vehicle (CV) driving behaviour. It showed better results in terms of reducing delays and improving visualisations. Test trial 5 was particularly effective in achieving better delay results, which aligned with the research objectives and provided valuable insights into CV driving behaviour. Therefore, the W99 Wiedemann parameters used to replicate the CV driving behaviour in VISSIM are the ones depicted in the Table 6.4 below.

Table 6.4: W99 - Car following model parameters specified for CV driving behaviour

W99 parameters	CV values used
CC0 - standstill distance (m)	1.5
CC1 - gap time distribution (s)	1
CC2- following distance oscillation (m)	6
CC3 - threshold for entering 'following'	-8
CC4 - negative speed difference	-0.35
CC5- positive speed difference	0.35
CC6 - distance dependency of oscillation	11.44
CC7 - oscillation acceleration (m/s2)	0.25
CC8 - acceleration from standstill (m/s2)	3.5
CC9 - acceleration at 80 km/h (m/s2)	1.5

6.5 Incident Detection Scenario Results

As long as the CV driving behaviour has been specified the next step followed was the implementation of all possible scenarios tested for the incident detection using V2V connectivity on motorways. The results will be provided in five sections each one for every case, as analysed in Chapter 6, where a different incident duration and location is taken place. In more detail the simulation results are organised as follows:

- Case A results:
  - Incident on Lane 1
  - Duration: 1 hour
- Case B results:
  - Incident on Lane 1
  - Duration: 2 hours
- Case C results:
  - Incident on Lane 1
  - Duration: 2 hours
- Case D results:
  - Incident on Lanes 1&2
  - Duration: 1 hour
- Case E results:
  - Incident on Lanes 1&2&3
  - Duration: 1 hour

The results that will be shown will be organised per MPR scenario for all cases, as follows:

- Macroscopic Fundamentals Diagrams (MFDs) including speed/density, and flow/density, and speed/flow respectively.
- Average Total Delay per Vehicle (in seconds) results
- Average Queue Length results
- Number and Percentage Reduction of Total Conflicts

The analysis is centered on plotting results across different penetration rates, ranging from 0 percent to 100 percent, in increments of 25 percent. The comprehensive results cover various aspects for all scenarios. These aspects encompass MFD diagrams for both the entire network and the critical link, average total delay per vehicle measurements at the incident location for several segments extending from 250 m before up until the incident location, 500m-750m-1km and up until 2.5 km before the incident up until the incident location. Additionally, the analysis includes the total queue length and number and percentage reduction of total conflicts, as previously mentioned.

The effectiveness of the incident detection model evaluated through various metrics as concerns mobility and safety KPIs. These include analysing the MFDs, the average total delay per vehicle (in seconds), the average queue length created in the location of the incident, and the total traffic conflicts using the SSAM. The three types of conflicts, rear end, lane change, and crossing were calculated for every scenario in each incident case and the percentage reduction of each type of conflict relative to the baseline scenario were recorded. In this paper the percentage of total reduction of all conflict types will be presented in the results section below. The calculation of all these measurements shows the effectiveness of the model.

The vehicle trajectory files generated by VISSIM were then transferred to SSAM for further analysis. SSAM utilised metrics such as Time-to-Collision (TTC) and Post Encroachment Time (PET) as surrogate safety measures to identify traffic conflicts and assess the impact of the incident detection model.

6.5.1 Case A results

In the first case study, named as Case A, the incident occurred on Lane 1 (the leftmost lane) for a duration of 1 hour. The simulation period is a five-hour simulation, started at 15:00 with a warm-up period of 30 minutes. In accordance with the outlined methodology, the assessment of the V2V connectivity effectiveness involved a comprehensive examination of various metrics, including Macroscopic Fundamental Diagrams (MFDs), average total delay per vehicle (in seconds), average queue length at the incident location, and total traffic conflicts. The evaluation of the V2V algorithm took place in the simulation model, specifically at 16:30 during a 5-hour simulation period, considering a one-hour incident duration in the slow lane.

6.5.1.1 Macroscopic Fundamental Diagrams (MFDs)

In order to plot the MFDs, the study utilised data from link segment evaluations. Average speed, traffic volume, and density values were calculated for each link segment in VISSIM at 5-minute intervals (300 seconds), with speed measured in kmph, volume in veh/hr, and density in veh/km. VISSIM automatically calculated these values based on the length of each link segment. MFDs were generated the critical link before the incident location till the incident location. By concentrating on the MFDs of the critical link for each penetration rate, more accurate and insightful congestion metrics can be offered. In this way, via analysing the MFDs, valuable insights offer into the mobility of the proposed models can be extracted. Finally, the critical link was identified by pinpointing the link where the incident happened and where it is expected the longest queues to be created. Figure 6.14 illustrates the MFDs for different scenarios, presenting speed/density, flow/density, and flow/speed relationships.

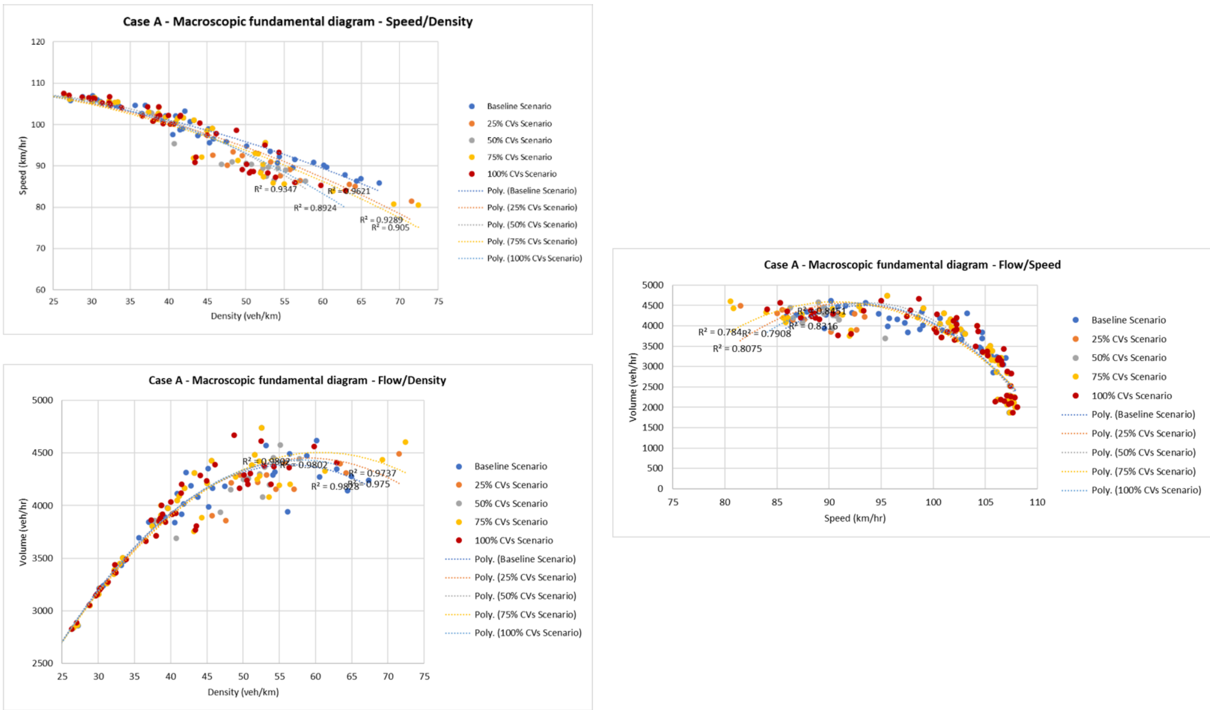


Figure 6.14: Case A - Macroscopic fundamental diagrams

As mentioned, the MFD for the volume and speed created using the link segment data from the simulation results. Figure 6.14 compares the volume and the speed obtained from the granular approximations to check the capacity of the network, approximately 1km before the incident location. Even though different spatial and temporal demand patterns simulated, including different MPR of CVs, the average volume and speed are consistent and closely predicted for all scenarios.

The MFD referring to the speed/density profile (Figure 6.14) shows that the average speed does not drop below the average speed reached at the capacity level; the traffic flow is still in the free-flow region, even at high-density levels. Each subplot represents a scenario with fixed MPR ranging from 0% to 100% of CVs. The results imply that the road network is able to handle the traffic demand without experiencing high congestion, and the traffic is still flowing smoothly. Regarding that, all vehicles (concerning all five scenarios of all cases) were moving at an appropriate speed limit in free flow at 110km/hr. As average density increases, average speed reduces until the jam density is reached, where the speed is the lowest for all cases. This is observed in the baseline scenario and 50% CVs scenario for case A. Scenarios with 75% and 100% MPR of CVs doesn't reach the capacity level and the vehicles speed appear to be higher concerning the rest scenarios.

Based on the flow/density diagram (refer to Figure 6.14) of the MFD, the maximum flow rate represents the capacity where is the highest traffic flow rate that the motorway can accommodate. Each subplot in the diagram corresponds to a specific scenario with a fixed MPR ranging from 0% to 100% of CVs. In the diagram, the positive slope suggests that the flow is in the free-flow region, where traffic moves smoothly. Conversely, the negative slope indicates that the traffic has entered the congested region due to the occurrence of incidents in all scenarios. In the baseline scenario, the capacity reached approximately 4,550 vehicles per hour. However, scenarios with 75% and 100% MPR of CVs surpassed this capacity, reaching around 4,700 vehicles per hour. On the other hand, scenarios with 25% and 50% MPR of CVs reached the same capacity but at a lower rate, even lower than the baseline, at slightly below 4,500 vehicles per hour.

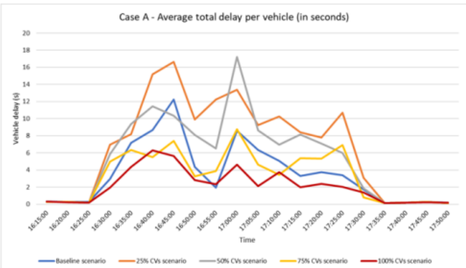
This does not mean that connectivity worsens the situation. Instead, the results highlight that the degree of connectivity (market penetration rate, MPR) is critical in traffic performance. Higher MPRs of Connected Vehicles (75% and 100%) improve the system by increasing capacity beyond the baseline scenario due to better coordination, smoother traffic flow, and reduced stop-and-go enabled by V2V communication. However, at lower MPRs (25% and 50%), the mixture of connected and non-connected vehicles creates inconsistencies in traffic behaviour, such as varied reaction times and less efficient lane changes. This mixed traffic environment can reduce overall system efficiency, causing the capacity to drop slightly below the baseline. Thus, connectivity does not inherently worsen the situation, but its benefits depend significantly on achieving a critical mass of CVs.

The baseline scenario, representing the absence of any connectivity, reached its maximum traffic flow capacity, resulting in minor traffic congestion within the corridor. Conversely, in all other examined scenarios, the network did not reach its total capacity, as evident from the consistent slopes of the trendlines on MFDs, which only reached the maximum level for the first cases.

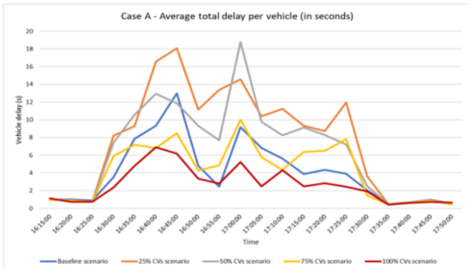
6.5.1.2 Average Total Delay per Vehicle

Vehicle delays were computed at 5-minute intervals (300 seconds) using delay data collected from VISSIM, measured in seconds per vehicle per kilometer. These measurements were gathered for predefined routes established in vehicle travel time measurements. These routes varied in length along the motorway, in the direction where the incident occurred. Specifically, average vehicle delays were calculated for four distance measurements, ranging from 250m, 500m, 750m, and eventually 1000m before the location of the incident to the exact location of the incident. In this research, average total delay per vehicle results for the incident location were analysed, obtained from the network vehicle performance results. Figure 6.15 provides the results for average total delay per vehicle (in seconds) for the four delay measurements calculated.

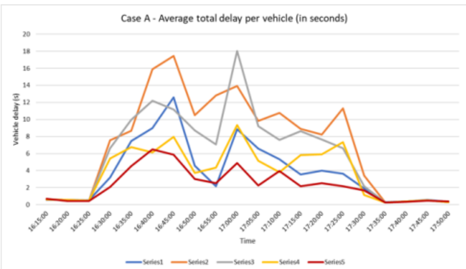
Delay Measurement 1 = 250 m before incident point



Delay Measurement 3 = 750 m before incident point



Delay Measurement 2 = 500 m before incident point



Delay Measurement 4 = 1000 m before incident point

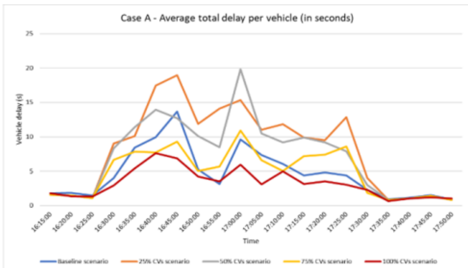


Figure 6.15: Case A - Average total delay per vehicle

Across case A, a noticeable reduction was observed in the average total delay per vehicle, especially as the MPR of CVs is increasing to the highest level. It is important to note that as the MPR is increasing from 0% to 50% the average total vehicle delays are increasing as well. However, after reaching 50% CV proportion, these delays decreased in the region of 7 seconds, becoming lower than the baseline scenario. This adjustment period aligns with the introduction of CVs, as indicated in the literature review. This has been tested as well, as an example for this research, demonstrating that delays improve notably after reaching 60% CV proportion.

6.5.1.3 Queue Length

Queues are counted from the location of the queue counter on the link or connector upstream to the last vehicle in the queue. If the queue extends onto multiple different approaches, the queue counter will record information for all of them and report the longest queue length. Queues were calculated at 5-minute intervals (300 seconds) using the queues counters from VISSIM, measured in meters. The queue counter feature in VISSIM outputs three main metrics:

- Average queue length
- Maximum queue length
- Number of vehicles stops within the queue

The average queue length is determined by measuring the current queue length upstream (in meters) at every time step and computing the arithmetic average from these values for each time interval. On the other hand, the maximum queue length is calculated by measuring the current queue length upstream (in meters) at every time step and determining the maximum value from these measurements for each time interval.

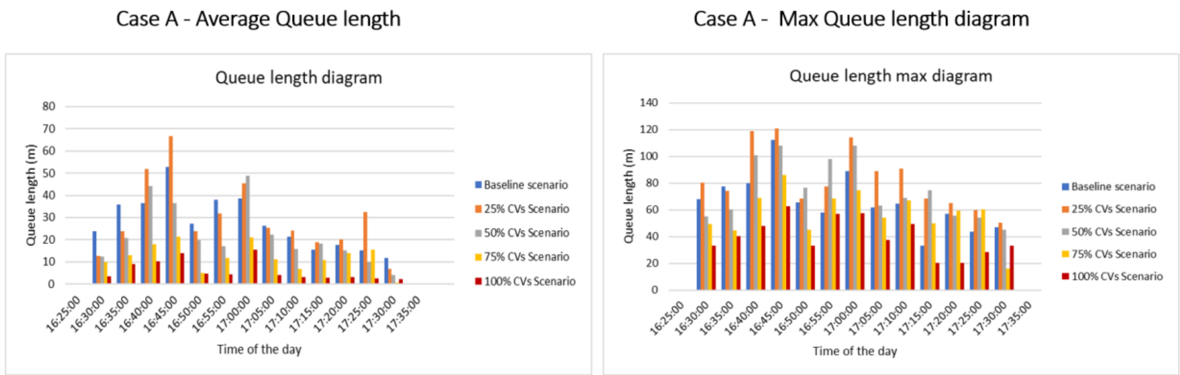


Figure 6.16: Case A - Average and Max Queue length

Similar to the average vehicle delays, a similar trend is observed in the length of queues generated by the incident, both in terms of average and maximum queue lengths, as shown in Figure 6.16. As the proportion of CVs increases, queue lengths also increase from 0% to 50% CV proportion. However, after reaching 50% CV proportion, these queues decrease significantly, falling below the levels observed in the baseline scenario. This highlights the positive impact of V2V connectivity in incident detection, as higher proportions of CVs contribute to more efficient management of queues during incidents.

6.5.1.4 Conflicts

The simulation framework results will include the number of conflicts calculated for each scenario by SSAM. The conflicts calculated via SSAM are categorised into three types: Unclassified, Crossing, Rear-end, and Lane Change. However, the focus of the research is on assessing the percentage decrease of total conflicts. For better depiction of what is happening in reality, not only the total conflicts but also the rear end and lane change will be presented and analysed, which are the majority of conflicts type. The simulation results will be discussed based on their alignment with existing literature, underlying assumptions, and practical implications.

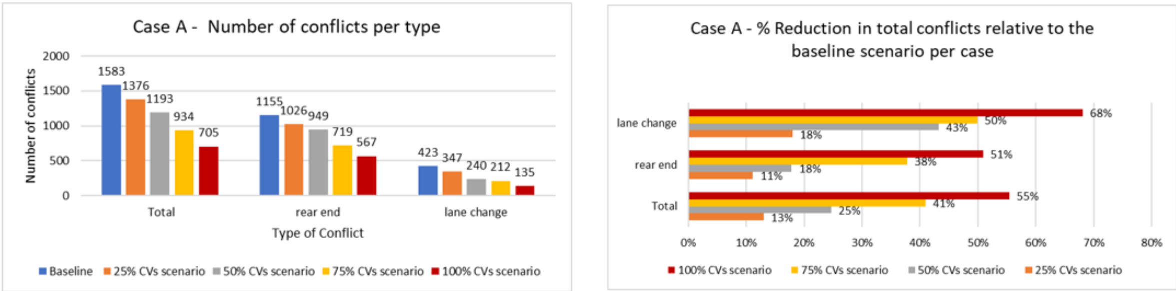


Figure 6.17: Case A - Number of conflicts per type and % reduction relative to the baseline scenario per case

As Figure 6.17 the total number of conflicts, correlating with the increase in the Market Penetration Rate (MPR) of Connected Vehicles (CVs), are decreasing, more than 50% when exists 100% MPR of CVs. As anticipated, the scenario with 100% CVs exhibited the least conflicts, indicating less congestion and showcased improved traffic flow. It is important to note that even in the 25% of MPR of CVs, there is still exists a reduction in conflicts of 13% for total conflicts, reaching the 18% for lane changing conflicts. This indicates the importance of the existence of V2V connectivity, by using CVs in the real-life, especially when it comes to an incident. More insights can be seen in the rest of the cases where the same patterns are been observed.

6.5.2 Case B results

In the second case study, denoted as Case B, an incident occurred on Lane 1 (the leftmost lane) for a duration of 2 hours. The simulation model evaluated the developed algorithm at 16:30 during a 5-hour simulation period, considering the extended incident duration, as explained in chapter 5.

6.5.2.1 Macroscopic Fundamental Diagrams (MFDs)

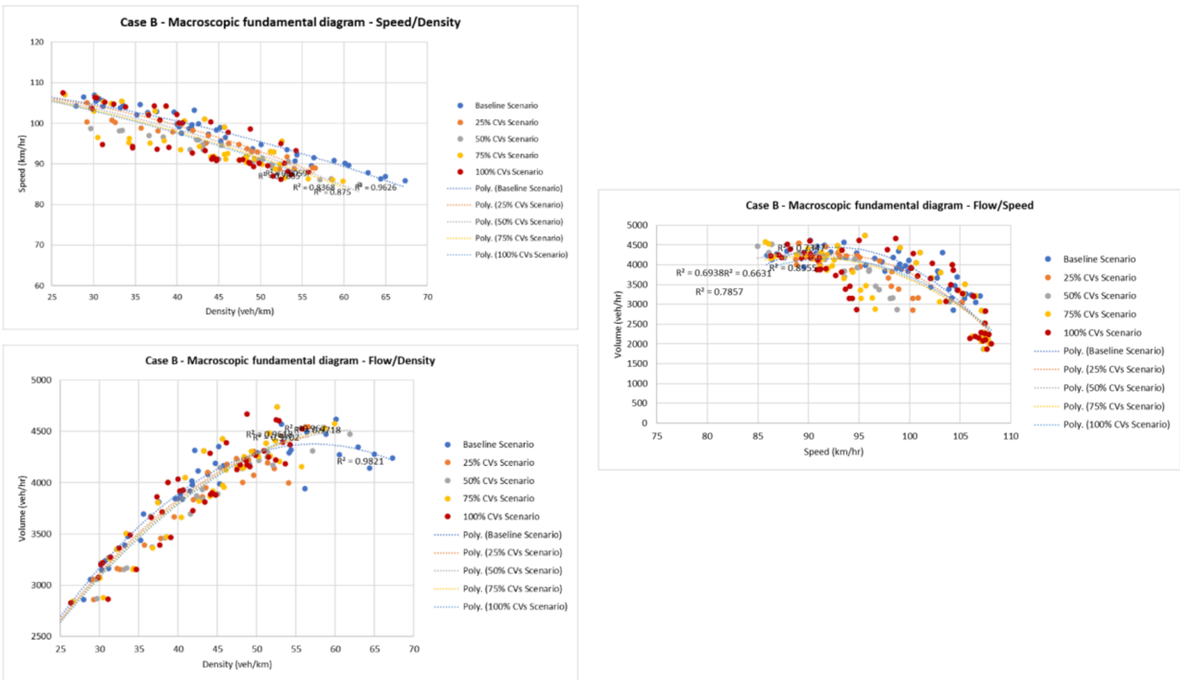


Figure 6.18: Case B - Macroscopic fundamental diagrams

The speed/density profile depicted in Figure 6.18, representing the Macroscopic Fundamental Diagram (MFD), indicates that the average speed remains consistently above the threshold observed at capacity level, suggesting that traffic flow remains within the free-flow region even under high-density conditions. Each subplot illustrates different scenarios with varying proportions of CVs. This implies that the road network effectively manages traffic demand without encountering significant congestion, maintaining smooth traffic flow. Across all scenarios, vehicles adhered to the appropriate speed limit of 110 km/hr in free-flow conditions. As average density increases, average speed decreases until reaching jam density, where speed is at its lowest. Moderate congestion is observed in certain scenarios, particularly in the baseline scenario and specific CV proportion scenarios at the highest density level. However, scenarios featuring 75% and 100% CV proportions consistently exhibit higher speeds compared to others, indicating smoother traffic flow.

As in the precious case, the flow/density diagram within the MFD (Figure 20) showcases the maximum flow rate, representing the motorway's capacity to accommodate traffic. Each subplot corresponds to a scenario with a fixed proportion of CVs. In the baseline scenario, the capacity reached approximately 4,550 vehicles per hour approximately in the same density level as case A. As in case A, scenarios with 75% and 100% CV proportions exceeded this capacity, reaching around 4,700 vehicles per hour. Conversely, scenarios with 25% and 50% CV proportions reached the same capacity but at a slower rate, even lower than the baseline, at slightly below 4,500 vehicles per hour for all cases.

6.5.2.2 Average Total Delay per Vehicle

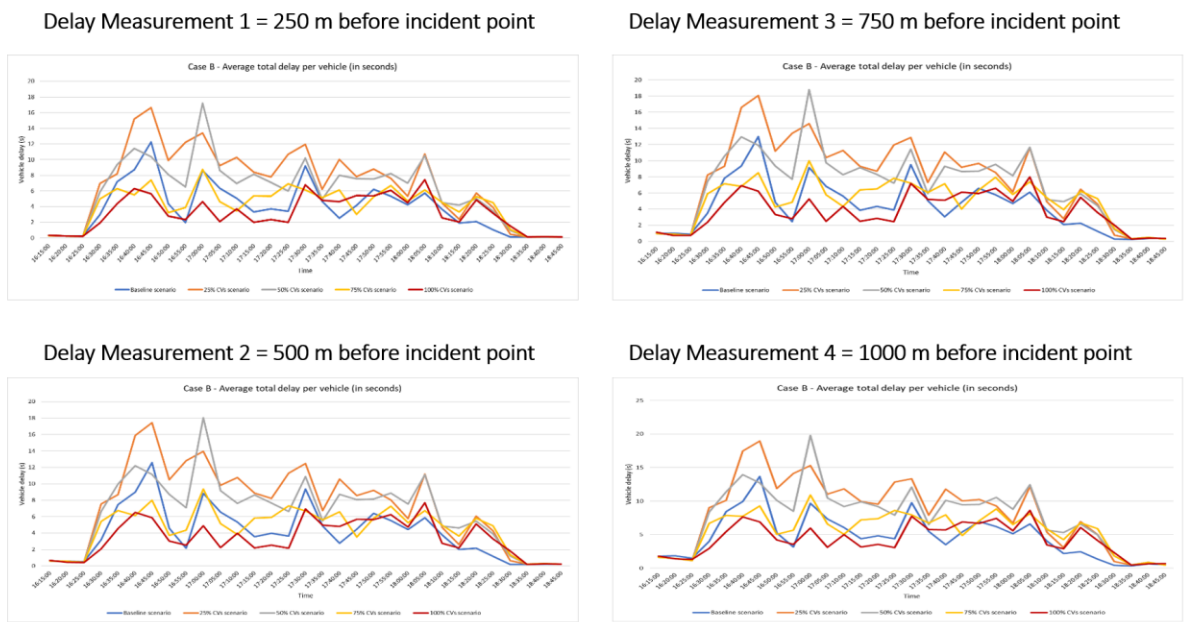
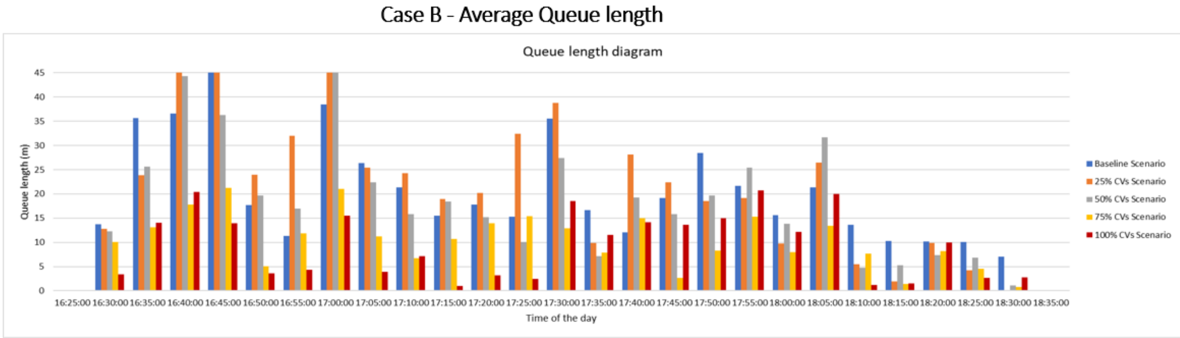


Figure 6.19: Case B - Average total delay per vehicle

In Case B, as depicted in Figure 6.19, a similar pattern to the previous case is observed. An important reduction is observed in the average total delay per vehicle, at the 75% and 100% MPR of CVs. As previously, as the proportion of CVs increases from 0% to 50%, the average total vehicle delays also increase. However, after reaching a 50% CV proportion, these delays decrease significantly, dropping below the levels observed in the baseline scenario.

6.5.2.3 Queue Length



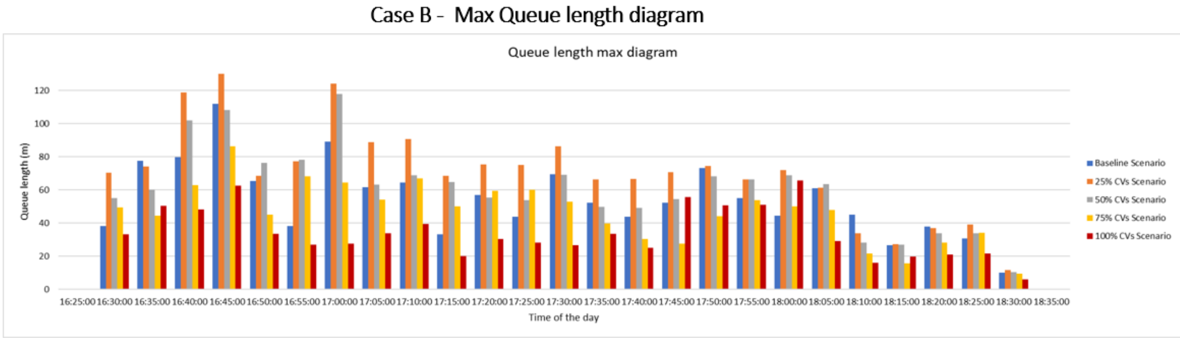
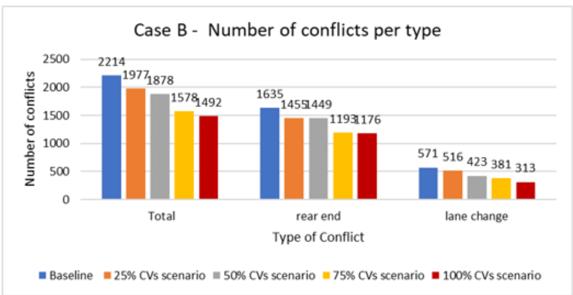


Figure 6.20: Case B - Average and Max Queue length

In Figure 6.20, Just like the average vehicle delays, a comparable pattern is noticeable in the length of queues produced by the incident, reflected in both average and maximum queue lengths as illustrated in case A too. With the rise in the proportion of CVs from 0% to 50%, queue lengths also escalate for the first hour of the incident, but started decreasing more than the baseline after the first hour of incident has been passes. However, upon reaching a 50% CV proportion, these queues markedly decrease, dropping below the levels seen in the baseline scenario. This shows the beneficial influence of V2V connectivity in incident detection, wherein higher percentages of CVs aid in more effective queue management during incidents.

6.5.2.4 Conflicts



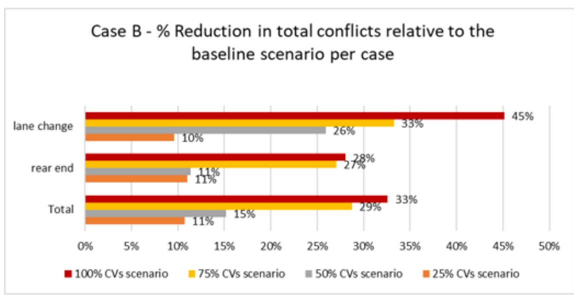


Figure 6.21: Case B - Number of conflicts per type and % reduction relative to the baseline scenario per case

In Figure 6.21 it is clear that the total number of conflicts decreases with the increase in the Market Penetration Rate (MPR) of Connected Vehicles (CVs), with a reduction of 45% observed when there is 100% MPR of CVs, when it comes to 2hour incident duration. As expected, the scenario with 100% CVs exhibited the fewest conflicts, indicating less congestion and improved traffic flow. Even with just a 25% MPR of CVs, there is still a reduction in conflicts, with a decrease of 10% observed for total conflicts, reaching 11% for lane-changing and rear end conflicts. This underscores the significance of V2V connectivity, particularly in real-life scenarios involving incidents.

6.5.3 Case C results

In the third case study, denoted as Case C, an incident occurred again on Lane 1 (the leftmost lane) for a duration of 3 hours. The simulation model evaluated the developed algorithm at 16:30 during a 5-hour simulation period, considering the extended incident duration, as explained in Chapter 5.

6.5.3.1 Macroscopic Fundamental Diagrams (MFDs)

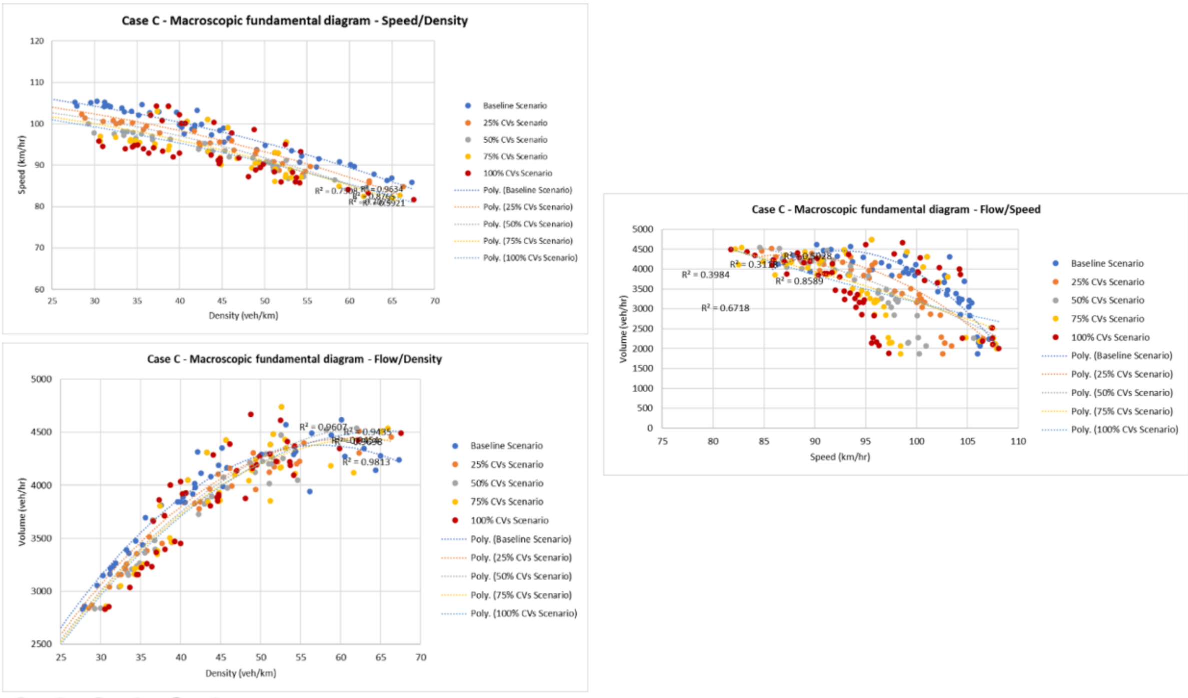


Figure 6.22: Case C - Macroscopic fundamental diagrams

In case C, the speed/density profile presented in Figure 6.22, indicates that the average speed consistently remains above the threshold observed at the capacity level. As the incident in this case has a duration of 3 hours, the speed as the MPR of CV is increasing is remaining in lower level as the baseline scenario, as the V2V algorithm inform in real time the vehicles to reduce their speed in proper time, managing not the capacity level to be reached shortly. This suggests that traffic flow stays within the free-flow region even under high-density conditions. Across baseline scenario, vehicles adhere to the appropriate speed limit of 110 km/hr in free-flow conditions and suddenly they are braking reaching speed of 90km/hr, but as concerns the rest of scenarios there is existing lower speed of 95-100 km/hr for a longer period till proceed the incident location and pass by.

Similarly, the flow/density diagram illustrates the maximum flow rate, representing the motorway's capacity to accommodate traffic. Each subplot corresponds to a scenario with a fixed proportion of CVs, same as before. In the baseline scenario, the capacity reached approximately 4,550 vehicles per hour, similar to case A. As with the rest of cases explained above, scenarios with 75% and 100% CV proportions exceeded this capacity, reaching around 4,700 vehicles per hour. Conversely, scenarios with 25% and 50% CV proportions reached the same capacity but at a slower rate, even lower than the baseline, at slightly below 4,500 vehicles per hour for all cases.

At 75% MPR, most vehicles are connected, improving coordination and traffic flow, but the remaining 25% of non-connected vehicles cause some variability. At 100% MPR, all vehicles are connected, ensuring full coordination and efficiency, but the system starts to reach its limits, which affects performance. These trends show how different levels of connectivity impact traffic behaviour.

6.5.3.2 Average Total Delay per Vehicle

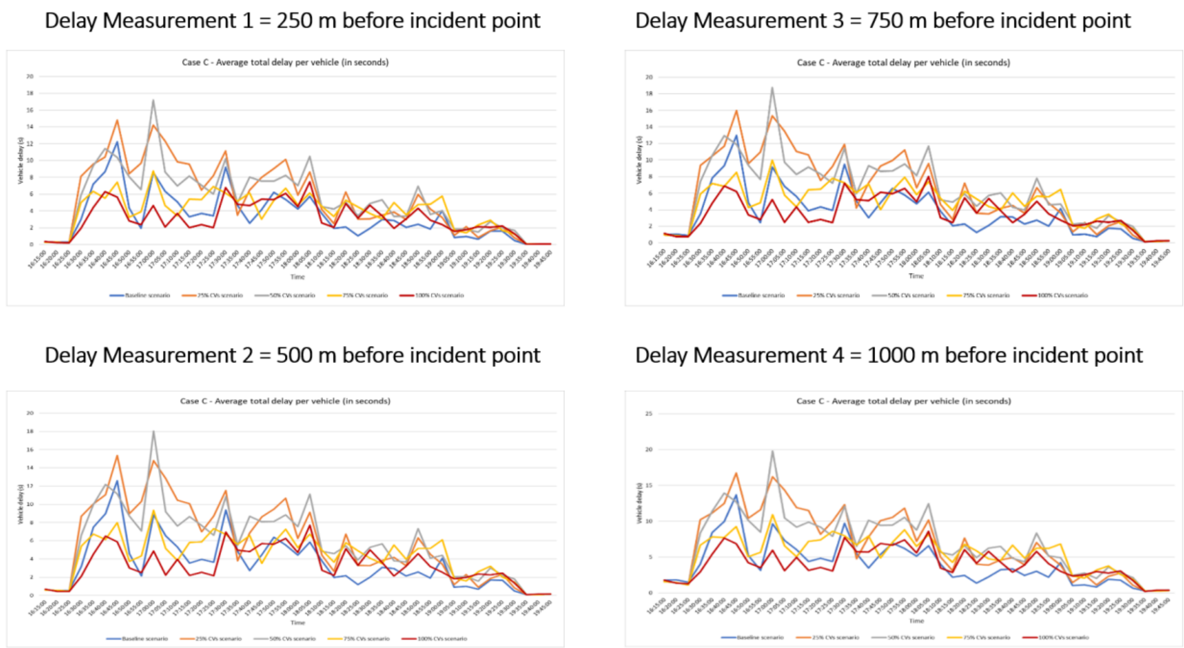


Figure 6.23: Case C - Average total delay per vehicle

In Case C, illustrated in Figure 6.23, a pattern similar to the previous case emerges. A notable reduction is evident in the average total delay per vehicle, particularly at the 75% and 100% MPR of CVs. Patterns remain almost the same as Case B, in 2-hour incident and then in the third hour of incident, where a lane is closed the delays are having almost the same values with small fluctuations.

6.5.3.3 Queue Length

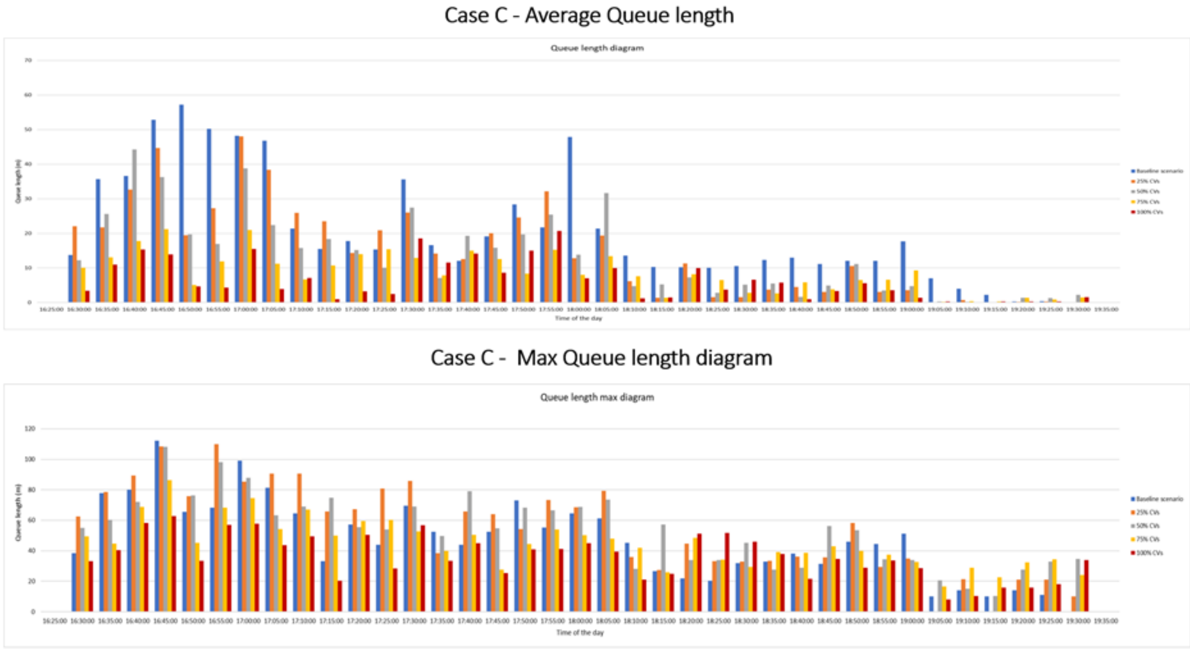


Figure 6.24: Case C - Average and Max Queue length

In Figure 6.24, it is observed a similar trend to average vehicle delays in the length of queues resulting from the incident, seen in both average and maximum queue lengths as also seen in Case B. As the proportion of CVs increases from 0% to 50%, queue lengths rise during the first hour of the incident but start decreasing, surpassing the baseline levels after the initial hour has passed. However, once the CV proportion hits 50%, these queues notably decrease, falling below the levels observed in the baseline scenario. This underscores the positive impact of V2V connectivity in incident detection, where higher percentages of CVs contribute to more efficient queue management during incidents.

6.5.3.4 Conflicts

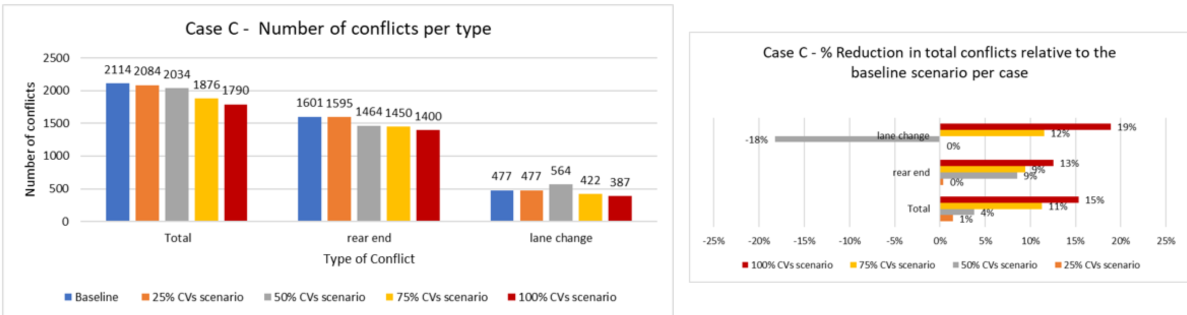


Figure 6.25: Case C - Number of conflicts per type and % reduction relative to the baseline scenario per case

Looking at Figure 6.25, it's clear once again, that the total number of conflicts decreases as the Market Penetration Rate (MPR) of Connected Vehicles (CVs) increases, with a reduction of 15% observed at 100% MPR of CVs for a 3-hour incident duration. As anticipated, the scenario featuring 100% CVs had the fewest conflicts, indicating reduced congestion and improved traffic flow. At 25% MPR of CVs, there was not a noticeable decrease in conflicts, which eventually started at 25% MPR of CVs. It is needed to be highlighted that as concern the lane change conflicts, there is an increase of 18% compared to the baseline scenario, but when compared to the total conflicts this is not happening. It is essential to point out that, when there is an incident for so long duration in the motorway, more lane changes need to be conducting for better traffic flow to be made. This highlights the importance of V2V connectivity, as even in a 3-hour incident duration the conflicts when it comes to the 100% MPR of CVs are still decreased a lot (20%) compared to the baseline scenario.

6.5.4 Case D results

In the fourth case study, denoted as Case D, the scenario involved an incident occurring on Lane 1 and Lane 2 (the two leftmost lanes) for a duration of 1 hour. The simulation model evaluated the developed algorithm at 16:30 during a 5-hour simulation period, considering the incident's duration and its impact on the network.

6.5.4.1 Macroscopic Fundamental Diagrams (MFDs)

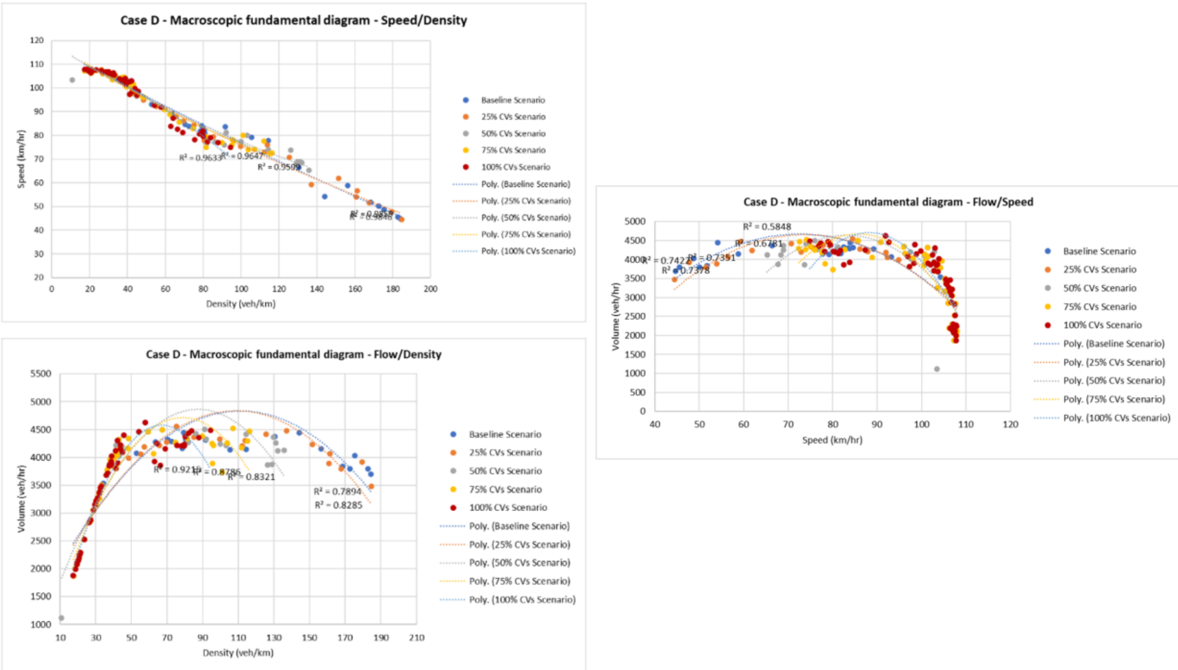


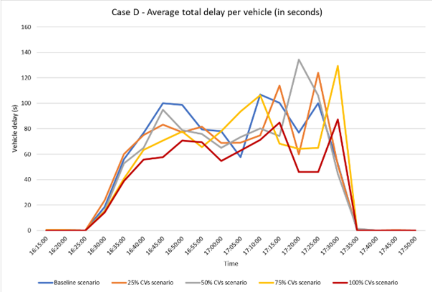
Figure 6.26: Case D - Macroscopic fundamental diagrams

Moving on case D, the MFDs depicted in Figure 6.26 illustrates that the average speed remains consistent, not dropping below the level observed at capacity, indicating free-flow traffic even under high-density conditions. In all scenarios, vehicles maintained appropriate speeds of 110 km/hr in free-flow conditions. As density increases, average speed decreases until reaching jam density, where speed is at its lowest. However, scenarios with 75% and 100% CV proportions consistently exhibit higher speeds compared to others, indicating smoother traffic flow. To be more specific, Scenario 75% and scenario 100% has lower speed around 75kmph, while scenario 50% around 65kmph and finally the 25% and baseline scenario speed below 50kmph, in the most congested times.

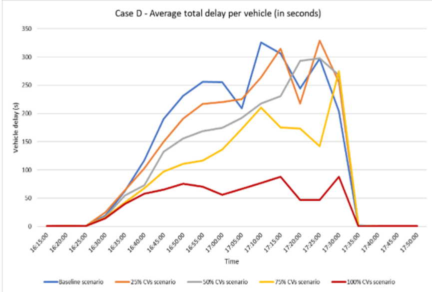
Moving on the analysis of the flow/density diagram within the MFD reveals the maximum flow rate, representing the motorway's capacity to handle traffic. In the baseline scenario, capacity reached approximately 4,550 vehicles per hour for all incidents. This time, in Case D, where the incident blocked two lanes, congestion was observed in the baseline, 25% MPR, and 50% MPR scenarios. However, scenarios with 75% and 100% MPR of CVs demonstrated better traffic conditions. The simulated network's traffic volume was sufficient to facilitate free-flow movement.

6.5.4.2 Average Total Delay per Vehicle

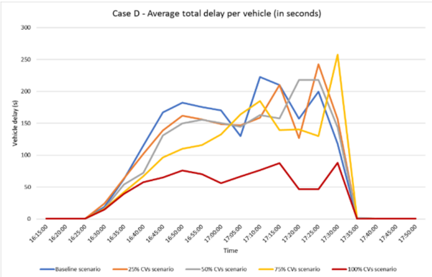
Delay Measurement 1 = 250 m before incident point



Delay Measurement 3 = 750 m before incident point



Delay Measurement 2 = 500 m before incident point



Delay Measurement 4 = 1000 m before incident point

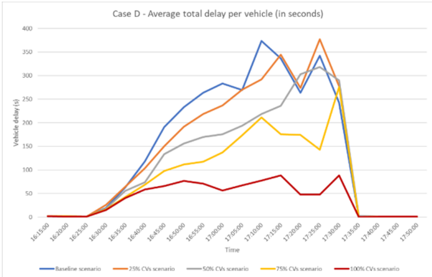
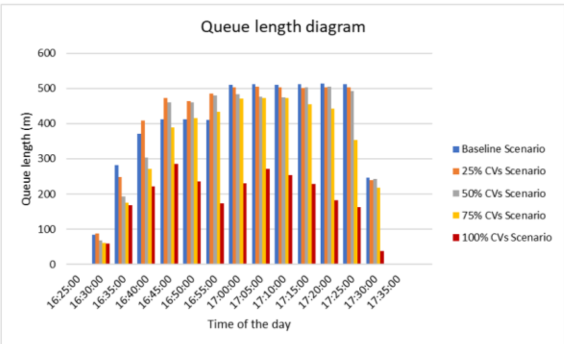


Figure 6.27: Case D - Average total delay per vehicle

In Case D (Figure 6.27), a significant decrease has been observed in the average total delay per vehicle, till the network to be congested, particularly as the MPR of CVs increased to the highest level. It's worth noting that comparing to the rest of the cases, where one lane was closed, the average vehicle delays are lower for almost all scenarios as the MPR increased from 0%. This is a important indicator of how the CV and V2V can handle incident detection, by decreasing the speed and change lanes in time to avoid not only a following incident but also to avoid delays due to higher speed and no knowledge of what to expect while driving. V2V connectivity via the CV can provide significant lower delays in these occasions and need not to be neglected from the network and manufacturer operators.

6.5.4.3 Queue Length

Case D - Average Queue length



Case D - Max Queue length diagram

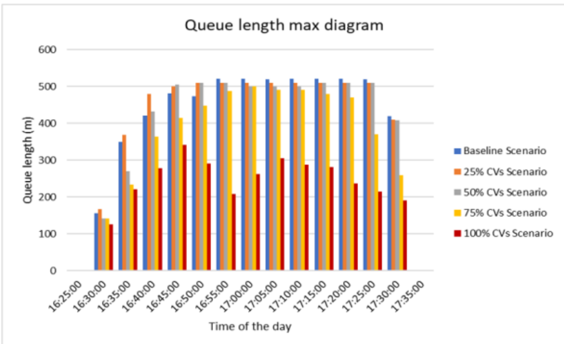


Figure 6.28: Case D - Average and Max Queue length

The trend observed in the average vehicle delays is mirrored in the length of queues resulting from the incident, highlighted in Figure 6.28. However, in the case of two lanes closure, for positive results the MPR of CVs need to be higher than 75%. Upon reaching the 100% CV proportion threshold, these queues exhibit a significant decrease, dropping below the levels observed in the baseline scenario, more than the half queues length has been created. Once more, the beneficial effect of V2V connectivity in incident detection, as higher percentages of CVs enable more effective management of queues during incidents has been observed.

6.5.4.4 Conflicts

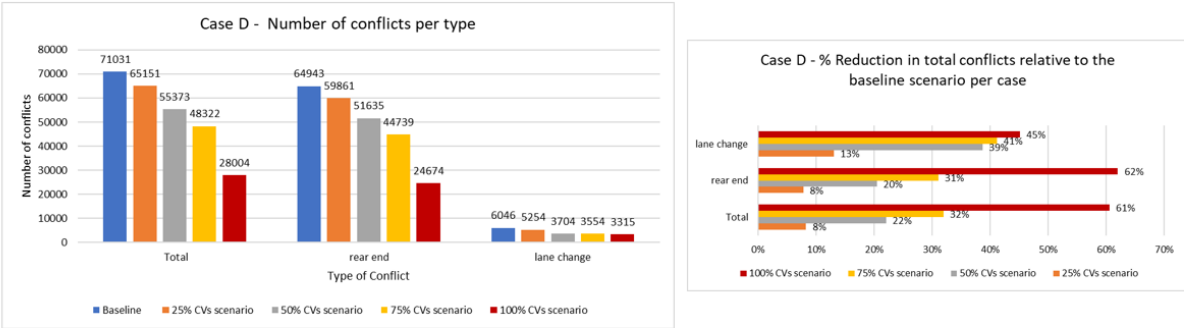


Figure 6.29: Case D - Number of conflicts per type and % reduction relative to the baseline scenario per case

As depicted in Figure 6.29, the total number of conflicts decreases with the increase in the MPR of CVs, with a reduction of more than 60% observed when there is a 100% MPR of CVs. As expected, the scenario with 100% CVs exhibited the fewest conflicts, indicating less congestion and improved traffic flow. Notably, even at a 50% MPR of CVs, there exists a reduction in conflicts of 22% for total conflicts, reaching 39% for lane-changing conflicts. Moreover, at 25% MPR of CVs, there exists a reduction in conflicts of 13% for total conflicts, something useful especially in real-life scenarios involving incidents.

6.5.4 Case E results

In the fifth and last case study, denoted as Case E, the scenario involved an incident occurring on Lane 1, Lane 2 and Lane 3 (the three leftmost lanes, high speed lane on the right will be open only) for a duration of 1 hour. The simulation model evaluated the developed algorithm at 16:30 during a 5-hour simulation period, considering the incident's duration, location, and its impact on the network.

6.5.4.1 Macroscopic Fundamental Diagrams (MFDs)

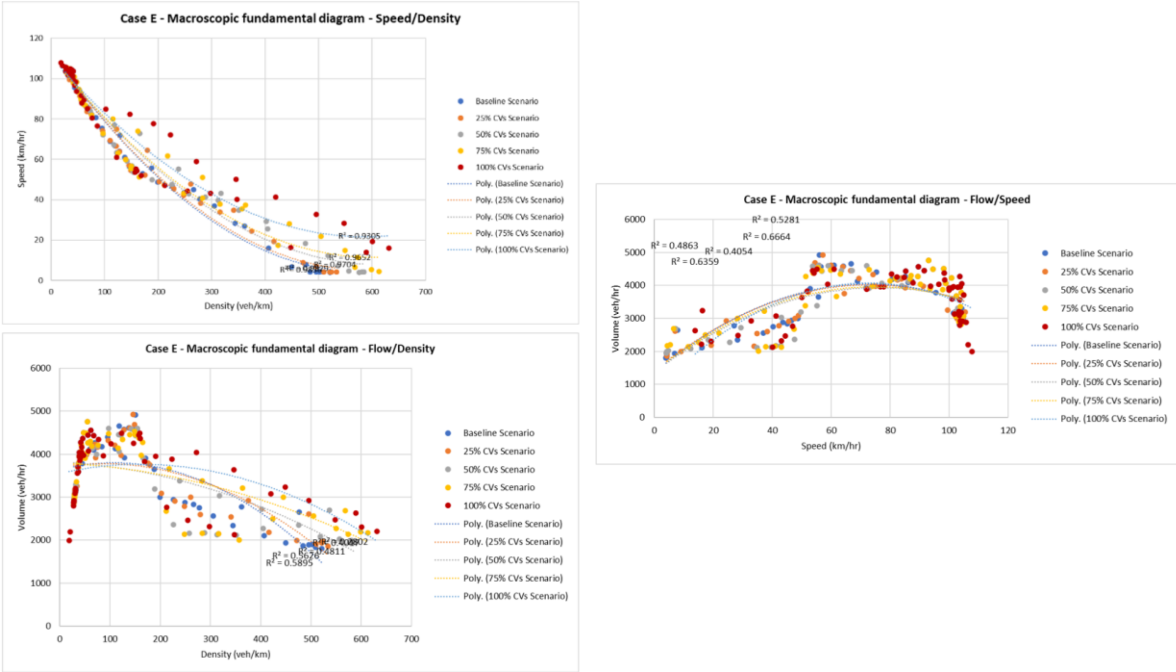


Figure 6.30: Case E - Macroscopic fundamental diagrams

In the last case, Case E, as depicted in Figure 6.30, the MFDs illustrate that the average speed remains consistently above the capacity level up until when the network became congested, as the three out of four lanes are occupied due to an incident, indicating non smooth traffic flow under high-density conditions. Across this congested period, vehicles-maintained speeds of 110 km/hr in free-flow conditions, and in congested lower than 20 km/h. However, as the MPR of CVs is increasing the speed noticed to be higher than the one of the baseline scenarios in the congested areas.

Analysing the flow/density diagram within the MFD reveals the maximum flow rate, representing the motorway's capacity to not handle traffic. In the baseline scenario, capacity reached approximately 4,700 vehicles per hour for all incidents. As in Case D, the incident blocked three lanes, congestion was observed in scenarios, up until the 100% scenarios. In this occasion it is compulsory to address dynamic assignment and redirect the vehicles from another possible route to avoid the closure because of the incident. This is a limitation of this research, as the dynamin assignment routes have been not considered.

6.5.4.2 Average Total Delay per Vehicle

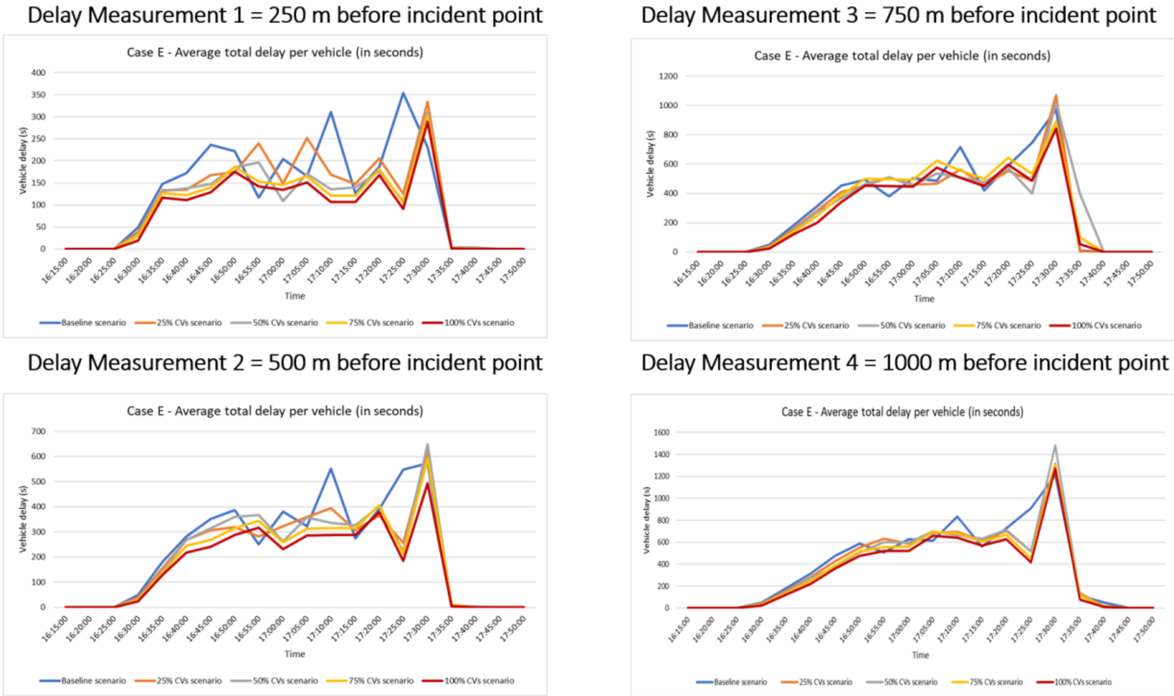


Figure 6.31: Case E - Average total delay per vehicle

Moving on, as concerns the average vehicle delays in a congested network not that many changes can V2V offer as the motorway is almost fully closed, allowing vehicles use only one live lane, the fast lane (Figure 6.31). Even with this small allowance, a reduction has been observed in the average total delay per vehicle, as the MPR of CVs increasing, contributing to ease the traffic flow. It's noteworthy that compared to other cases where only one lane was closed, average vehicle delays are consistently lower across almost all scenarios as the MPR increases from 0%, for at least the first half an hour of the total duration of the closure. This underscores the efficacy of CVs and V2V connectivity in incident detection, facilitating timely speed adjustments and lane changes to minimise delays as possible, without having the ability for the drivers to change their route.

6.5.4.3 Queue Length

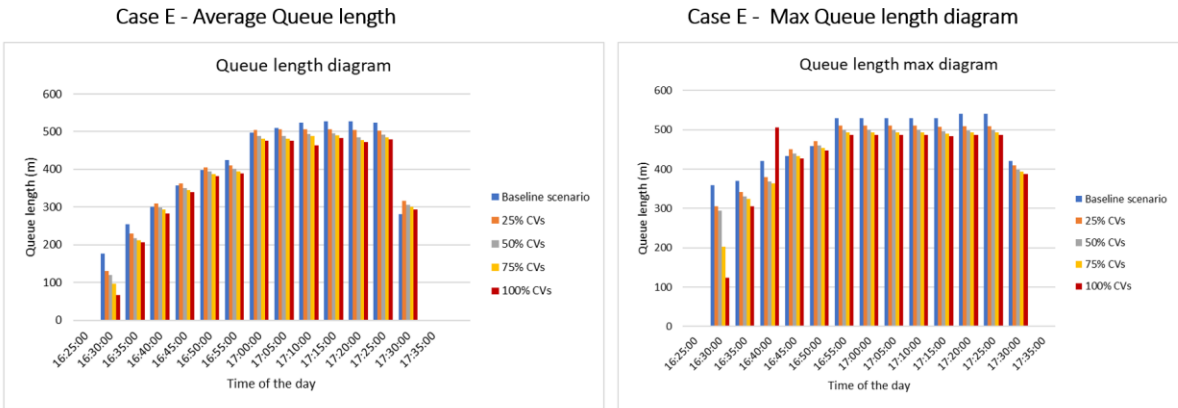


Figure 6.32: Case E - Average and Max Queue length

Similar patterns observed in average vehicle delays are also marked in queue lengths (Figure 6.32). As the Market Penetration Rate (MPR) of Connected Vehicles (CVs) increases, there is a corresponding reduction in queue lengths, as possible it could be with three lanes out of four closure, indicating improved traffic flow and queue management. These patterns are consistent across various scenarios, highlighting the effectiveness of CVs and V2V connectivity in incident detection and response.

6.5.4.4 Conflicts

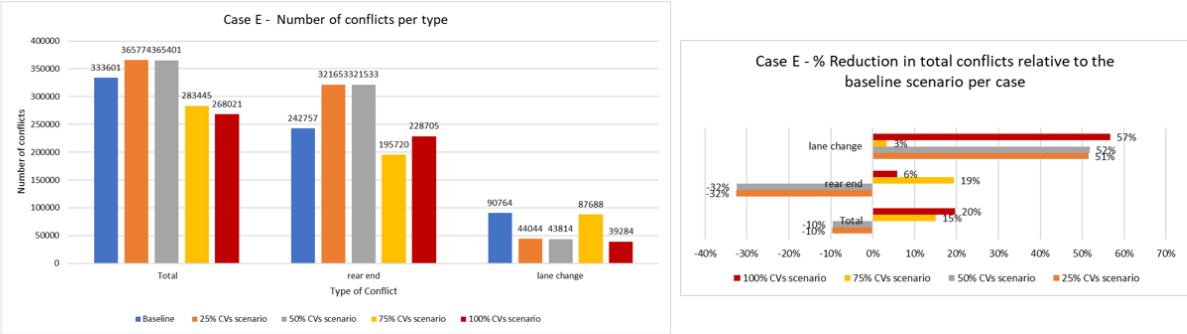


Figure 6.33: Case E- Number of conflicts per type and % reduction relative to the baseline scenario per case

As it can be imaged, the closure of three lanes out of four can cause a lot of disruption to a network. This can be obviously seen through the number of conflicts been calculated via SSAM (Figure 6.33). The existence of the big number of conflicts cannot be neglected but it's still important of the reduction measured compared with the baseline scenario. The rear-end conflicts minimised up until 19% and the lane change conflicts up to 19%. It is important to note that, the scenarios of 25% and 50% MPR of CVs in this case, provide an increase in conflicts compared to the baseline scenario, indicating the importance of the existence of re-routing in these occasions.

6.5.5 Summary

The purpose of this research was to utilise VISSIM to implement and assess different scenarios that demonstrate the effectiveness of V2V technologies in reducing the impact of traffic incidents. This involved utilising V2V communication for real-time incident detection and determining the optimal simulation approach to evaluate different MPRs of CVs in terms of capacity, average total vehicle delays, queue length, and conflicts. The study addressed the unique challenges of simulating incidents in the CV environment, given the limited availability of CV data on motorways worldwide, particularly in UK motorways.

The simulation results were promising, indicating that CV technology can help mitigate traffic and safety impacts. The observed shapes of the MFD in different scenarios confirmed the theoretical relationship between speed and density, which confirmed the accurate calibration of the simulation incident model.

The findings demonstrated that the consequences varied based on the MPR of CVs with V2V connectivity and the traffic volume on the motorway. MPRs exceeding 75% showed reductions in average total vehicle delays and queue length compared to the baseline scenario. Moreover, higher MPRs of CVs resulted in a significant decrease in total conflicts. The safest scenario was 100% MPR of CVs, followed by 75% MPR, while the scenario without any connectivity exhibited the least safety.

The study showcased that incident detection utilising V2V connectivity led to improved message reception rates and enhanced safety efficiency across different CV penetration rates. The research methodology assumed that CVs are equipped with V2V communication technologies, allowing them to interact with each other. Stopped vehicles transmit notifications to nearby vehicles, which receive the message and adapt their driving behaviour accordingly.

To evaluate the proposed analytical method for mixed traffic corridors with varying MPR of CVs, simulation tests were conducted using VISSIM due to the absence of real-world CVs on UK motorways. The simulation results aligned with the trends observed in the analytical results concerning the variation of corridor capacity with CV penetration rate. Future research should consider incorporating V2V communication technologies for HGVs and test these scenarios in areas with higher traffic congestion.

In summary, this research successfully integrated knowledge from various domains to develop a framework for evaluating incident detection using V2V technologies with VISSIM and API COM Interface. Future expansions could include integrating the incident control algorithm into a more complex re-routing environment at a network level, allowing the simulation of CVs within a mixed traffic flow and incorporating dynamic assignment for vehicle rerouting in the event of an incident.

The algorithm developed in this study offers potential benefits for network operators in enhancing motorway safety during incidents. It can aid traffic authorities in addressing motorway traffic conditions and devising traffic demand management strategies for mixed flows. The findings have the potential to enable instantaneous identification of traffic incidents, facilitating the transmission of information to drivers, road-side infrastructure, and traffic control centres, thereby reducing traffic and safety impacts and minimising disruptions.

Chapter 7: Discussion

7.1 Discussion Framework

This thesis provides insights into two critical challenges long faced by the transport sector: a) traffic incident modelling and analysis, and b) the integration of CVs via V2V connectivity in motorway incidents. It introduces an innovative approach to real-time traffic incident management using CVs' V2V connectivity technologies, leveraging highly detailed minute-level traffic data within the VISSIM microsimulation platform. Given the absence of comprehensive real-time traffic data worldwide, understanding how CVs operate in real-world scenarios, particularly during motorway incidents, remains elusive. The research aims to not only enhance incident detection but also to model incidents and their impact on traffic KPIs, particularly congestion.

This has been achieved through a range of statistical modelling using linear regression models, negative binomial, fixed effect negative binomial, random effect negative binomial and simultaneous equation models to interlink the connection between incidents and traffic KPIs, with a specific focus on congestion effects. Furthermore, traffic simulation was used to replicate real-world scenarios, facilitating incident detection using CVs' V2V connectivity integrated with Incident Management (IM) strategies. Due to the lack of not only real-world CV data but also the nonexistence of a specified driving behaviour from the literature review, this research critically examines the creation and calibration of CV driving behaviour. The evaluation of the incident detection algorithm and traffic incident management strategies in the developed scenarios included an assessment of both mobility and safety KPIs.

Even though several studies have been conducted research on V2V connectivity, only a few have integrated this technology with CVs into traffic incident management, especially in contrast to the predominant focus on Connected and Autonomous Vehicles (CAVs) or Autonomous Vehicles (AVs). Moreover, fewer studies have combined both aspects as comprehensively as demonstrated in this research, for a fully understanding of how traffic incident management can be improved, with the integration of CVs' V2V connectivity, as stated in Chapter 3. To achieve this goal, Chapter 4 details the integration of data architecture for replicating real-world scenarios. Chapter 5 presents the calibration of the traffic microsimulation model and the development of representative scenarios, and Chapter 6 showcases the results of CV driving behaviour profiles, the V2V connectivity algorithm, and the evaluation of incident scenarios.

7.2 Discussion on Incident Modelling

Traffic congestion and road incidents have been identified as significant external costs associated with vehicle travel (Shefer & Rietveld, 2017. Particularly during rush hour in densely populated areas, traffic congestion is a widespread issue Lord et al., 2005a). Addressing congestion is a critical challenge for road transport and a key focus for transport policy across different levels. Congestion often arises during periods of high travel demand which can be termed as recurrent congestion or due to unexpected events such as incidents or accidents called non-recurrent congestion (Adler et al., 2013). Non-recurrent congestion accounts for approximately one-quarter of highway congestion (Snelder et al., 2013). Apart from its impact on congestion, road accidents have severe consequences, leading to the loss of thousands of lives and injuring millions of people (Pasidis, 2019). Many researchers have investigated the relationship between traffic congestion and road accidents starting from the 1970s (Q. Li et al., 2020; Pasidis, 2019; Skabardonis et al., 2003; C. Wang et al., 2009) but not many explore this relationship with incidents, where more type can be used, and not only accidents, where an injury is included.

However, the existing literature on this topic presents varying and inconclusive findings. For example, (Dickerson et al., 2019 concluded that the impact of traffic congestion on road accidents is negligible for low to moderate traffic flows but high during high traffic flows. On the other hand, Quddus et al.(C. Wang et al., 2009) report that the severity of road crashes remains unaffected by the level of traffic congestion, while Lord et al. (Lord et al., 2005b) identify a U-shaped relationship between congestion and crash rates. Despite this heterogeneity of results in the literature, it is worth noting that road accidents predominantly occur during times of high congestion (Pasidis, 2019). Additionally, all the above studies have focused on accidents and not incidents, studying incidents is a significant contribution as they are more frequent than accidents and less understood. Moreover, studies often rely on inadequate proxies for traffic congestion. Consequently, there is a pressing need for more robust empirical evidence and accurate measurements of congestion to further our understanding in this area.

Congestion patterns on highways are characterised by high traffic volumes during peak hours, leading to reduced travel speeds and increased travel times (Ebrahim Shaik & Ahmed, 2022; Y. Yang et al., 2021). Several studies have examined congestion patterns, providing valuable insights into traffic conditions (D'Andrea & Marcelloni, 2017; Noland & Quddus, 2005; Pasidis, 2019; Sánchez González et al., 2021a). Research studies demonstrated a substantial reduction in traffic volumes and congestion levels during Covid 19 period as well as reported changes in the temporal distribution of congestion, with less pronounced peak hours and more dispersed traffic patterns (Sánchez González et al., 2021a). Studies have observed shifts in peak hours and the overall dispersion of traffic patterns. A study by Cats et al. (Strzelecki, 2022) examined the impacts of the COVID-19 pandemic on mobility and transportation in European cities found that during the pandemic, there were less pronounced peak hours and more dispersed traffic patterns compared to pre-pandemic conditions. This was attributed to altered travel behaviour, reduced commuting demand, and the implementation of remote work practices. Several factors contributed to the observed changes in congestion patterns during and after the COVID-19 pandemic(Y. Yang et al., 2021). Studies identified reduced commuting demand, increased remote work practices, and limited recreational and leisure travel as primary factors leading to decreased traffic volumes (Ebrahim Shaik & Ahmed, 2022; Strzelecki, 2022).

The reduced traffic volumes and congestion during the pandemic resulted in improved travel speeds and shorter travel times for commuters. Yang et al. (Y. Yang et al., 2021) found that during the pandemic, travel speeds increased significantly on highways due to reduced traffic volumes and congestion. As a result, travel times were reduced, benefiting those who still needed to commute. The COVID-19 pandemic had a notable impact on highway congestion patterns, leading to noticeable differences in congestion levels, and overall traffic flow. On the other side, studies conducted after the COVID-19 provided insights into the changes left behind this disturbed period, and patterns returned to the one existing before. Indeed, Xu et al. (P. Xu et al., 2022) analysed six months of data from January to June 2020 to have three periods type related to covid: before, during and post first lockdown. Although the pandemic was not finished in June 2020, they observed that traffic returned to pre-pandemic levels and even exceeded them in certain areas.

Very few studies if not none have analysed and compared data from pre-pandemic levels to post-pandemic levels, however as the trends show a gradual return to pre-pandemic levels this research explored the relationship between traffic incidents and congestion from 2019 for a case study of a UK motorway. Several statistical models used to explore this relationship as much as accurate it could.

7.3 Discussion on Traffic Incident Detection

The need for a safer and sustainable transport system has driven both the public and private sectors to enhance network performance (Great Britain. Department for Transport. & Stationery Office (Great Britain), 2007). CVs provide valuable data, such as real-time driving behaviour, trajectory, origin and destination information, and traffic data, which were previously inaccessible (Abdelkader et al., 2021). These data can be transmitted through Vehicle-to-Vehicle (V2V) and Vehicle-to-

Infrastructure (V2I) communication, enabling precise monitoring and evaluation of system performance (Ghiasi et al., 2017; Nezafat et al., 2018).

As stated, CVs technologies enable communication with each other and the surroundings. Current navigation systems already incorporate CV capabilities like dynamic route guidance (Adegoke et al., 2019). The concept of CVs revolves to provide valuable information to drivers, empowering safer decisions (Outay et al., 2021). It's important to note that CVs do not make decisions for drivers but offer road condition data and help avoid hazards like incidents. In the coming years, CVs will be widespread on roads with higher adoption rates (Fu et al., 2019b).

CVs' superior performances in driverless navigation and V2V communication, have made them critical in the global automotive industry (Montanaro et al., n.d.). Compared to human-driving vehicles (HVs), CVs collect more accurate traffic data and implement precise traffic changes (Jiang et al., 2021), leading to safer and more efficient traffic flows (Yao et al., n.d.)(Yao et al., n.d.). However, transitioning from pure HV to mixed or pure CV traffic may take time, during which HVs and CVs will share the road (Bhavsar et al., 2017b). Mixed traffic flows from these vehicles may exhibit unique characteristics that not seen in pure HV traffic flows (Dodson et al., 2021). Researchers use computer simulations with traffic models and scenarios to explore mixed traffic dynamics and capabilities (Yu et al., 2021).

Until today CV dynamics in mixed traffic are not adequately analysed compared to HV dynamics. Machine learning algorithms (Mahbub & Malikopoulos, 2021) are essential to model CVs in mixed traffic accurately, reproducing their car-following and lane-changing behaviour (X. Li et al., 2023). Due to the limitation of CVs mixed with HVs, especially on motorways, further investigation into CV algorithms is needed.

In general, CVs create data-rich environments with numerous services to enhance road safety, reduce congestion, and improve the overall trip's productivity and enjoyment (Abdelkader et al., 2021). The growing demand for an "always connected" paradigm has motivated researchers and automakers to focus on safer and innovative software for connectivity (Abdelkader et al., 2021; Datta et al., 2016). Integrating connectivity into CVs requires reliable and functional technologies for the ITS(Z. Xu et al., 2017). These technologies enable also seamless and real-time data transmission between smartphones and in-vehicle networks (Aquino Santos et al., 2012). Currently, the combination of wireless CVs' communication technologies includes dedicated short-range communications (DSRC), Wi-Fi, and V2X communication (Abdelkader et al., 2021) can enhance the connectivity capabilities. To establish a reliable and secure connectivity for V2V services, viable connectivity solutions are essential (Abboud et al., 2016).

One of the key objectives of V2V technologies, is the early detection of traffic incidents via algorithms (Choudhury et al., 2016). Incident detection models aim to provide real-time traffic information before and during the transition phase leading to incident(Pettigrew et al., 2018). The effective use of V2V, can not only reduce secondary crashes but also decrease incident duration and fuel consumption (Farag & Hashim, 2017). Gathering diverse datasets like delays, driver behaviour, travel time, and using them to inform drivers for proactive actions (adjusting vehicle speed, executing lane change manoeuvres) is crucial. (Toledo et al., 2003c). Various technologies have been employed to transmit traffic information to drivers, including Advisory Radio and Variable Message Signs (VMS), but has limitations (Tian et al., 2017). CVs with wireless communication are promising alternatives (V. Singh & Kumar, 2010), enabling seamless interactions and data exchange in V2V context (Tian et al., 2017).

Although many approaches have been reported, the performance of incident detection models using CVs depends on their deployment context (F. Ahmed & Hawas, 2015) . The UK's Strategic Road Network, spanning 4,300 miles, witnesses around 0.5 million incidents annually, causing disruptions, safety concerns, and delays (DfT). While these models are being explored and implemented globally, no proper attempts have been made in the UK context.

In this part of research, to address the abovementioned weakness, a smart Traffic Incident Detection algorithm by leveraging the use of V2V connectivity technologies developed, enhancing further the C2X algorithm provided from PTV VISSIM, and explore possible improvement in the communicational range, distance communication of the message distributed and most critically its effectiveness at incident detection. The research demonstrates the effectiveness of V2V connectivity in simulating mixed traffic flows and their behavioural characteristics during motorway incidents. The incident detection and mitigation model are applied on a section of the M1 Motorway in the UK. Due to the lack of real-world CV data, especially on motorways, a simulation platform was vital to analyse HV-CV interactions during incidents. To address this gap, this study proposed an optimised CV algorithm model that incorporates HV-CV drivers' behavioural characteristics and interactions in simulating mixed traffic flows during motorway incidents. The proposed CV V2V communication protocol allows detailed simulations, leading to a better understanding of their mechanisms.

Chapter 8: Conclusions

This chapter provides a summary of the research undertaken, highlighting how the research objectives were met, the novel insights gained, recommendations for the transport and Intelligent Mobility sector, limitations encountered, and suggestions for future research aimed at achieving the last objective.

8.1 Summary

Recent breakthroughs in technology, autonomy, connectivity, dynamic mapping, and big data computing will transform how we plan, undertake, interact, make decisions, and use our built environment and transport infrastructure for the movement of people and goods. Future mobility will primarily be based on human-centred, connected, intelligent, sustainable, and resilient transport systems that will make more efficient use of current and new infrastructures, can always create ubiquitous mobility on demand, and will address the needs of rapidly growing traffic congestion and safety concerns as a result of exponentially increasing in traffic demand on our networks. Intelligent mobility, enabled by vehicle connectivity and automation, cloud computing, artificial intelligence, simulation, and the Internet of Things (IoT), will allow the unprecedented capability to collect, exchange and analyse large volumes of data for mitigating, for example, the impact of traffic incidents on the network performance and will therefore increasingly be revolutionised our economy and society over the next decade.

Current transport systems need to be more economically efficient, environmentally benign, and safe. One key reason for this is the 'human element'. As mentioned, human error is recognised as the primary cause of 94% of road traffic collisions (Naciones Unidas & Bull, 2004). Recent advancements in artificial intelligence, sensor fusion, connected capability, vehicle technology, and software algorithms have brought about the introduction of connected vehicles (CVs) closer to reality. CVs can learn, adapt, make decisions, and act independently of human control and are, therefore, envisaged to impact safety, mobility, and society profoundly (Jadaan et al., 2017). Nonetheless, the most important advantage CVs offers relates to improved road safety, which researchers and manufacturers promise. For instance, once a traffic incident (in the form of vehicle breakdowns, accidents, fires, and obstacles on the road) occurs on a network, CV technology has the potential to detect the incident quickly and mitigate its impact on traffic efficiency and safety.

Several attempts have been made to simulate on-demand mobility, MaaS, and CVs to assess their applications in detecting unusual traffic dynamics and how they influence road safety (Adler et al., 2013; Chin & Quddus, 2003; Lord et al., 2005a; Noland & Quddus, 2005; Quddus, 2008; Samant & Adeli, 2000a; Sánchez González et al., 2021b; Snelder et al., 2013). However, there is a dearth of studies on mitigating the consequences of traffic incidents using CV technology. CV technology proposes new tools to approach the traffic incident detection problem using V2V technologies provided by IoT. Although V2V connectivity technologies focus on efficient traffic information dissemination (Pasidis, 2019) and route guidance (Christidis & Rivas, 2012), they have not been evaluated in depth in situations where a traffic incident is likely to happen. By using their potentially advantageous route choice coordination system (Christidis & Rivas, 2012) and the online environment (C. Wang et al., 2009), they will manage to cope with this problem by relying, for instance, on link travel time prediction in case of incident detection. Therefore, a robust wireless communication network is the foundation for connected transport systems (Cutrell & ACM Digital Library., 2012), as trustworthy and seamless V2V connectivity is vital to CVs technologies applications. CVs can exchange traffic data among each other and with their surroundings to provide a more suitable vehicle awareness, decrease traffic jams and road fatalities, and provide a convenient and, most importantly, safe experience.

Detecting traffic incidents on a high-speed road network such as motorways is a systematic endeavour to locate, react to, and eliminate traffic incidents and re-establish safe traffic capacity within satisfactory timeframes (Cui et al., 2021). The research gap of this work is identified as there is a need to quantify the impact of CVs in case of an incident through the formulation of a traffic simulation framework capable of modelling connected vehicles along with traditional vehicles in a variety of pre-defined scenarios, with regards to maximising the traffic performance and road safety on highways.

Therefore, the main contribution to this research is to evaluate the effectiveness of using V2V technologies of CVs, as an intelligent incident detection and mitigation method, under representative incident scenarios. This will enable decision-makers to define the circumstances under which it is better to operate this technique when dealing with motorway incidents.

The increased urbanisation and the escalating Intelligent Mobility (IM) improvements can bring significant costs and prominent emerging externalities. More motorised road users and improved mobility options contribute to challenges such as traffic congestion and incidents. Innovations in artificial intelligence, like big data analysis, image recognition, machine learning, route optimisation, and capacity allocation, have revolutionised the vehicle industry. Nowadays, vehicles aren't just mechanical; they interact with drivers, surroundings, and infrastructure in new ways. Connected Vehicle (CV) technology relies on wireless data transmission, encompassing both vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication. Assessing the efficacy of different network options for V2V and V2I communication is essential for designing robust wireless networks tailored for CV technology applications, ensuring optimal resource utilisation.

Two significant challenges in transport are traffic congestion and traffic incidents, which often go hand in hand. Detecting incidents can be critical in addressing both issues, especially with advancements like V2V connectivity and enhancing IM systems. Road traffic congestion not only has environmental implications but also negatively impacts commuter safety and the performance of transport networks. To mitigate this issue, traffic Incident Detection (ID) algorithms needd to be implemented by utilising emerging technologies that enable connectivity. However, conducting comprehensive studies to evaluate how these technologies integrate with existing traffic management systems, infrastructure, and vehicle types while ensuring their operational effectiveness under real-world conditions is crucial. Such studies include assessing interoperability with current communication protocols, analysing scalability in diverse traffic scenarios, and validating performance through simulations and field trials replicating real-time conditions.

This study developed and evaluated an incident detection algorithm that leverages V2V technologies to alert road users in real-time when approaching an incident zone. The algorithm's effectiveness was measured using mobility and safety indicators, including average total vehicle delay, queue length, macroscopic fundamental diagrams (MFDs), and the number of conflicts. Real-time traffic conditions on a section of a UK motorway were replicated using traffic microsimulation software called VISSIM, which included data from Inductive Loop Detectors (ILDs). The results were verified using ground truth data collected by an instrumented vehicle. The research used traffic microsimulation software to examine diverse scenarios involving a mixture of regular vehicles, Heavy Goods Vehicles (HGVs), and CVs with varying penetration rates from 0% to 100%.

In today's world of innovative and interconnected transportation systems, CV technology has become increasingly important in Incident Detection, changing how we handle traffic management and safety. By integrating CV technology, there is a revolution in real-time communication and data exchange between vehicles, infrastructure, and transport authorities. This integration has greatly improved detecting, responding to, and mitigating incidents. As vehicles become seamlessly interconnected, this technological advancement promises to revolutionise incident management practices. It highlights an era of increased awareness, quick responses, and improved safety in the rapidly evolving field of mobility transport systems.

The V2V-enabled CVs demonstrated optimised behaviours, such as adaptive speed and lane changes, based on real-time incident alerts. The results analyse results both with and without CVs, highlighting the impact of incident detection system activation and increasing CV market penetration during incidents. Simulations with activated incident detection systems revealed significant improvements in network performance, particularly at higher CV penetration rates. For example, with 100% MPR, average delays decreased by 50%, and safety conflicts dropped by 55-70%, depending on the incident duration. Various incident configurations and vehicle compositions are considered to evaluate the system's performance across five diverse scenarios, providing a comprehensive assessment of its impact.

Five incident scenarios with varying durations and lane closures were simulated, revealing the impact of market penetration rates (MPRs) of V2V-equipped CVs using a traffic microsimulation platform, VISSIM. The results demonstrate that the impact range varies depending on the market penetration rate (MPR) of vehicles equipped with V2V capabilities. These findings highlight the role of CVs in maintaining efficient traffic flow and reducing the disruption caused by incidents. The study offers a robust framework to assist network operators in promptly detecting incidents and disseminating information to road users, roadside infrastructure, and operational centres, thereby minimising traffic disruptions and enhancing safety impacts.

To effectively address critical issues like incident detection, it is compulsory to fully understand the interlink between traffic incidents and traffic congestion. The analysis employs data collected on M1, a major UK motorway. Exploratory data analysis assessed the traffic congestion patterns and traffic incidents in 2019. The results highlighted notable differences in traffic congestion and incident occurrence, indicating pattern changes. This study contributed to a better understanding of the complex relationship between incidents and traffic variables, providing insights into traffic characteristics changes by detecting incidents in real-time. The findings can inform transport planners and policymakers to improve road safety and reduce incidents with congestion management strategies.

8.2 Research Objectives

This thesis addressed six research objectives, which were addressed as follows:

1. **To identify existing traffic management systems and traffic incident management services and their characteristics with respect to network performance:** The first objective of the thesis was to identify existing traffic management systems and traffic incident management services, along with their characteristics concerning network performance. This objective was addressed through an extensive literature review focused on traffic management and traffic incident literature, forming Chapter 2 of the thesis. The review encompassed academic and grey literature sources, as well as publications from commercial publishers and input from relevant stakeholders. The outcome of this objective was the compilation of a comprehensive set of intelligent mobility services, shedding light on their features and functionalities in the context of network performance.
2. **To investigate existing techniques for incident modelling and Vehicle-to-Vehicle Connectivity for real-time traffic incident management:** The second objective of the thesis aimed to explore current methodologies for incident modeling and V2V connectivity for real-time traffic incident

management. This investigation was conducted through a thorough literature review encompassing topics related to intelligent mobility, incident modeling and simulation, and V2V simulation. Chapter 2 of the thesis was dedicated to this review process. Academic and grey literature sources, along with publications from commercial publishers and insights from stakeholders, were consulted to gather relevant information. The outcome of this objective was to identify the impact of intelligent mobility on highways traffic performance, providing insights into the effectiveness of incident management techniques and V2V connectivity in real-time traffic management scenarios.

3. **To assess underlying factors affecting the occurrence of traffic incidents:** The third objective of the thesis was to evaluate the underlying factors influencing traffic incident occurrences. This involves descriptive analysis capable of explaining the complex relationship between traffic incidents and various traffic variables, with a particular focus on congestion indices. Chapters 3, 4, and 5 of the Ph.D. thesis, were dedicated to this task. Real-world data was utilised for this analysis. The outcome of this assessment was a descriptive exploration of connection between incidents and congestion, providing network operators with insights for conducting sensitivity analysis when designing real-time traffic control strategies. This approach aimed to enhance the effectiveness of traffic detection efforts by better understanding the incident location, duration and frequency in specified location of the examined network.
4. **To build an integrated simulation platform, which combines a microscopic traffic simulation model with an External Driver Model that can incorporate connected vehicles (CVs) and mixed traffic:** The fourth objective of the thesis was to construct an integrated simulation platform that merges a microscopic traffic simulation model with an External Driver Model capable of accommodating connected vehicles (CVs) and mixed traffic scenarios. This involved the development of an integrated CV simulation algorithm, which was subsequently implemented in a calibrated traffic microsimulation environment. Chapters 3 and 5 of the thesis were dedicated to achieving this objective, with real-world data being utilised throughout the process. The outcome of this endeavour was the creation of an adaptable simulation platform, empowering network operators to conduct sensitivity analyses when designing real-time traffic control strategies. By integrating CVs and mixed traffic into the simulation framework, this platform aimed to provide a more comprehensive understanding of traffic dynamics and facilitate more effective traffic management decisions in dynamic traffic environments.
5. **Construct traffic incidents within the integrated simulation and develop an incident detection method using Vehicle-to-Vehicle Connectivity:** The fifth objective of the thesis was to generate traffic incidents within the integrated simulation framework and to devise an incident detection method leveraging V2V Connectivity. This task involved developing a simulation technique to generate incidents and crafting a novel incident detection approach. Chapters 3 and 5 of the thesis were dedicated to accomplishing these goals. Simulated data from VISSIM was used for this purpose. The outcome of this effort was the creation of traffic flow models capable of identifying optimal scenarios for introducing future mobility services involving fleets of CVs. By integrating incident generation and detection capabilities into the simulation framework, this approach aimed to enhance traffic management strategies and optimise the deployment of future mobility services in dynamic traffic environments.
6. **To recommend a number of specific scenarios where the mobility and safety benefits of CVs would be maximised, during the transition period and after:** The final objective of the thesis was to recommend specific scenarios where the mobility and safety benefits of CVs would be maximised, both during the transition period and in the long term. This involved estimating the mobility and safety benefits associated with each simulation scenario to provide actionable recommendations for the real-world implementation of CVs. Chapter 6 of the thesis synthesised

key findings from the literature review and scenarios development and testing. The outcome of this objective was a set of recommendations aimed at optimising traffic operations and leveraging new mobility services effectively. By identifying scenarios where the advantages of CVs are most pronounced, this approach aimed to guide decision-makers in prioritising initiatives that enhance mobility and safety in transport systems.

8.3 Contribution to Knowledge

In this Ph.D. thesis, firstly, various methodological and statistical approaches were employed to model traffic incidents, focusing particularly on evaluating the relationship between incidents and traffic KPIs, with a specific emphasis on congestion levels across a major UK motorway. The aforementioned analysis conducted through these traffic models, holds potential to enhance motorway safety by predicting incident occurrence based on examined traffic variables. A substantial volume of data was gathered through a developed data integration system, utilising inductive loop detectors, and multiple factors were collected and estimated for analysis.

Additionally, this Ph.D. research involved the creation of a large and comprehensive traffic simulation model for the same UK motorway, examined in the first section. This model was accurate calibrated and validated using real-world data, collected by from inductive loop detectors, and its accuracy was further confirmed by comparing simulated results with data collected from instrumented vehicle. Given the absence of real-world data on CVs, it was imperative to calibrate the driving behaviour of CVs. This was achieved by integrating V2V connectivity algorithm into the simulation platform, enabling specification of CVs' driving behaviour within the W99- Car Following Model. Furthermore, this V2V connectivity algorithm was developed and refined through experimentation with various distance distributions for message transfer during motorway incidents. Finally, the efficiency of incident detection simulations utilising V2V connectivity was evaluated through the implementation of several scenarios in high-risk areas identified based on traffic and incident data analysis.

Furthermore, the simulation platform's integration of V2V connectivity facilitated a better understanding of how connected vehicles respond to incidents on the motorway. By simulating different scenarios and adjusting parameters using real-world data insights, the study aimed to improve incident detection and response strategies. This comprehensive approach enabled the refinement of CV driving behaviour models, which contributed to developing and validating effective V2V communication algorithms specific to incident detection scenarios.

This research investigated the factors that can improve traffic incident detection by implementing accurate and sensitive V2V connectivity on a motorway at various levels of CV market penetration rates. There are limited regulations on verifying the reliability of CV driving behaviour despite the importance of evaluating the outputs from such systems. Therefore, this study significantly contributes by integrating a novel algorithm into a virtual network using an integrated simulation framework. The key contributions to knowledge in this thesis is the Contribution to Incident Detection through V2V technologies

8.3.1 Contribution to Incident Detection through V2V connectivity

The objective of this research was to implement and evaluate representative scenarios using VISSIM to assess the effectiveness of Vehicle-to-Vehicle (V2V) technologies in mitigating the impact of traffic incidents. This involved real-time incident detection using V2V communication and determining the optimal simulation approach to evaluate different MPR of CVs in terms of capacity, average total vehicle delays, queue length, and conflicts. The study addressed the unique challenges of simulating incidents in the CV environment, considering the limited availability of CV data on motorways worldwide, particularly in UK motorways.

The simulation provided promising results, indicating improved mitigation of traffic and safety impacts through CV technology. The observed shapes of the MFD in different scenarios validated the theoretical relationship between speed and density, affirming the accurate calibration of the simulation incident model.

The findings demonstrated that the consequences varied based on the MPR of CVs with V2V capabilities and the traffic volume on the motorway. MPRs exceeding 75% showed reductions in average total vehicle delays and queue length compared to the baseline scenario by a lot. Moreover, higher MPRs of CVs resulted in a significant decrease in total conflicts. The safest scenario was 100% MPR of CVs, followed by 75% MPR, while the scenario without any connectivity exhibited the least safety.

The study showcased that incident detection utilising V2V communication led to improved message reception rates and enhanced safety efficiency across different CV penetration rates. The research methodology assumed that CVs are equipped with V2V communication technologies, allowing them to interact with each other. Stopped vehicles transmit notifications to nearby vehicles, which receive the message and adapt their driving behaviour accordingly.

To evaluate the proposed analytical method for mixed traffic corridors with varying CV penetration rates, simulation tests were conducted using VISSIM due to the absence of real-world CVs on UK motorways. The simulation results aligned with the trends observed in the analytical results concerning the variation of corridor capacity with CV penetration rate. Future research should consider incorporating V2V communication technologies for HGVs and test these scenarios in areas with higher traffic congestion.

In summary, this research successfully integrated knowledge from various domains to develop a framework for evaluating incident detection using V2V technologies with VISSIM and API COM Interface. Future expansions could include integrating the incident control algorithm into a more complex re-routing environment at a network level, allowing the simulation of CVs within a mixed traffic flow and incorporating dynamic assignment for vehicle rerouting in the event of an incident.

The algorithm developed in this study offers potential benefits for network operators in enhancing motorway safety during incidents. It can aid traffic authorities in addressing motorway traffic conditions and devising traffic demand management strategies for mixed flows. The findings have the potential to enable instantaneous identification of traffic incidents, facilitating the transmission of information to drivers, road-side infrastructure, and traffic control centres, thereby reducing traffic and safety impacts and minimising disruptions.

8.4 Study Limitations and Assumptions

This section outlines the limitations of the study concerning the data and each aspect of the methodology employed, including traffic incident identification and assessment of traffic incident management. Identifying and addressing these limitations is important as it provides insights into potential areas for improvement, which could ultimately enhance the accuracy and robustness of real-time traffic incident management systems.

8.4.1 Traffic data

Firstly, concerning data limitations, this Ph.D. research may have been constrained by the quality and completeness of the available data sources. Inaccuracies or inconsistencies in the incident data, such as missing or accidentally incident reports, could have introduced biases or uncertainties into our analysis. Additionally, the temporal and spatial resolution of the data might have been insufficient to capture all relevant incidents or adequately assess their impact on congestion levels. Additionally, the ControlWorks data presents several challenges that need to be addressed in the future. One significant issue is the occurrence of false alarms, particularly concerning stopped vehicles. These false alarms can inflate the recorded incident count, leading to potentially misleading conclusions about the frequency of incidents. It's essential to address these challenges to ensure the accuracy and validity of the data used for analysing traffic incidents and implementing effective management strategies.

Secondly, as concerns the traffic data, the process its collection includes various challenges, including missing data, communication disruptions, and the occurrence of spurious data due to hardware or software anomalies. Specifically, in loop detector data, a notable concern arises from instances of "no-flow" data, where no vehicles are detected during a given minute. This issue can affect the accuracy of traffic flow measurements, although where it was noticed, it was neglected from the analysis. Moreover, errors may manifest as unrealistic values within the collected data, further complicating its reliability and usability. Addressing these challenges is crucial to ensure the quality and integrity of the collected data for accurate analysis and decision-making in transportation management.

Thirdly, in assessing traffic incident management strategies, the methodology employed may have been subject to certain limitations. For instance, the effectiveness of incident response measures could have been influenced by various factors such as response times, resource allocation, and coordination among stakeholders. Failure to account for these factors comprehensively could limit the validity and generalisability of the findings regarding the efficacy of different management approaches.

By addressing these limitations, future research endeavours can strive to improve the accuracy and reliability of real-time traffic incident management systems. This may involve enhancing data collection processes, refining incident detection algorithms, and adopting more comprehensive methodologies for evaluating management strategies. Ultimately, by overcoming these challenges, we can work towards developing more effective and responsive solutions for mitigating the impact of incidents on traffic congestion and ensuring the safety and efficiency of transportation networks.

8.4.2 Traffic simulation

The validation section of this thesis relies on the microscopic simulator VISSIM. Despite the thorough calibration and validation of VISSIM's traffic simulation model using real-world data, it's essential to recognise that certain results could be influenced by the assumptions embedded in the software. Additionally, it's crucial to highlight the safety risks associated with mixed traffic scenarios, where both intelligent and driver-operated vehicles coexist. For instance, the behaviour of CVs is not extensively studied compared to autonomous vehicles, and there are uncertainties regarding how they interact with their surroundings. Furthermore, while intelligent vehicles utilise onboard sensors to perceive their environment, they still face limitations, especially in challenging driving conditions such as inclement weather or unexpected behaviors of other road users. Moreover, malfunctions in the vehicle's technology can also include safety concerns. It's worth noting that these challenges were not addressed in this study, indicating potential areas for future research and development in the field of intelligent transport systems.

Despite its benefits, the integrated simulation framework comes with high computational demands. To mitigate these demands, minimised parameter variations in each scenario developed.

However, a single simulation, when it comes to a simulation of five hours, including an incident, run still requires approximately 2 hours to complete. To ensure robustness, each of the five scenarios was executed 10 times using different random number seeds, resulting in a total of 250 simulations for all five cases in total. Additionally, the evaluation V2V script generated after each test run took an average of 60 seconds to compute. While this process may not be highly efficient, it's important to note that computational efficiency was not the primary focus of this study.

8.5 Recommendations for Future Research

The research provides several key recommendations, as outlined in Section 9.3:

1. Utilisation of Real-world Driving Data: Incorporating both microscopic real-world driving data and disaggregated traffic data into proactive safety systems can enhance incident detection capabilities. This approach offers more comprehensive insights into network efficiency and enables real-time detection of incidents such as stopped vehicles.
2. Optimal Modelling Strategy: Employing deep learning methods on large real-time datasets can optimise the prediction of traffic incidents. These methods are adept at extracting complex and nonlinear patterns, particularly with the emergence of digital twins, which simulate real-world environments.
3. Addressing Uncertainties in V2V Algorithms: Traffic incident detection algorithms leveraging V2V connectivity must account for uncertainties, especially in scenarios beyond simple 'car-following'. Estimating conflicts in two-dimensional space based on relative vehicle motion is critical, particularly for CVs.
4. Integrated Simulation Framework: Developing an integrated simulation framework is vital for virtually evaluating and validating incident detection algorithms. This framework makes it easier to model and simulate important scenarios, helping to test connected driving technologies more efficiently.
5. Expanding V2V Connectivity: Implementing V2V connectivity in both Human Good Vehicles (HGVs) and autonomous vehicles can yield positive outcomes. Additionally, dynamic rerouting systems can be explored to manage incidents requiring road closures effectively.

These recommendations provide actionable insights for enhancing incident detection systems, optimising modelling strategies, addressing uncertainties in V2V algorithms, leveraging integrated simulation frameworks, and expanding V2V connectivity to improve overall traffic safety and efficiency.

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Appendix

A. Publication related to this research

Conferences papers:

Paraskevi Koliou, Léah Camarcat, Mohammed Quddus, Paraskevi Michalaki (2023) Does Traffic Congestion Impact Traffic Incidents?: A case study of a Major United Kingdom Motorway in: Transportation Research Board 103rd Annual Meeting, Washington D.C., USA, January 2024.

Paraskevi Koliou, Léah Camarcat, Mohammed Quddus, Paraskevi Michalaki (2024) Estimating the impact of vehicle breakdown on traffic performances: V2V simulation study of UK Motorways in:

Transportation Research Arena, 10th conference, Dublin, Ireland, April, 2024

Journal papers:

Two papers: a)one under the V2V connectivity in real-time traffic incident detection theme and b)one concerning incident modelling are prepared for journal submission at Accident Analysis & Prevention Journal

B. V2V Incident detection algorithm

This V2V example demonstrates how to model communication between vehicles.

```
At simulation second 5400, there is a breakdown of a vehicle. At the time of breakdown,
the vehicle sends out a warning message. This is varying depending on the incident time and
duration
Vehicles receiving this message will drop their speed and adjust their driving behavior
until they passed the incident.
"""

def Initialization():
    # Global Parameters:
    global distDistr
    global Vehicle_Type_ V2V_no_message
    global Vehicle_Type_ V2V_HasCurrentMessage
    global speed_incident

    distDistr = 1 # number of Distance distribution used for sending out a V2V message
    Vehicle_Type_V2V_no_message = '101' # number of V2V vehicle type (no active message) has
to be a string!
    Vehicle_Type_ V2V _HasCurrentMessage = '102' # number of V2V vehicle type with active
message has to be a string!
    speed_incident = 80 # Speed of vehicles receiving the V2V message in kph
def toList(NestedTuple):
    """
    function to convert a nested tuple to a nested list
    """
    return list(map(toList, NestedTuple)) if isinstance(NestedTuple, (list, tuple)) else NestedTuple
```

```
def Main():
    """
    Main control
    """
    # Get several attributes of all vehicles:
    Veh_attributes = Vissim.Net.Vehicles.GetMultipleAttributes(('RoutDecType', 'RoutDecNo',
'VehType', 'No'))

    if Veh_attributes: # Check if there are any vehicles in the network:

        # Filter by VehType V2V:
        Veh_ V2V _attributes = [item for item in Veh_attributes if item[2] == Vehicle_Type_ V2V
_no_message or item[2] == Vehicle_Type_ V2V _HasCurrentMessage]

        # For all V2V vehicles: check if there is an incident | incident is modeled as parking routing
decision #1
        for cnt_ V2V _veh in range(len(Veh_ V2V_attributes)):
            if Veh_ V2V _attributes[cnt_ V2V _veh][0] == 'PARKING' and Veh_ V2V _attributes[cnt_
V2V _veh][1] == 1: # vehicle has an incident (parking routing decision #1)
                Veh_sending_Msg = Vissim.Net.Vehicles.ItemByKey(Veh_ V2V _attributes[cnt_ V2V
_veh][3])
                Coord_Veh = Veh_sending_Msg.AttValue('CoordFront') # reading the world coordinates
(x y z) of the vehicle
                PositionXYZ = Coord_Veh.split(" ")

                Pos_Veh_SM = Veh_sending_Msg.AttValue('Pos') # relative position on the current link
                Veh_sending_Msg.SetAttValue(' V2V _HasCurrentMessage', 1)
                Veh_sending_Msg.SetAttValue(' V2V _SendingMessage', 1)
                Veh_sending_Msg.SetAttValue(' V2V _MessageOrigin', Pos_Veh_SM)

                # Getting vehicles which receive the message:
                Veh_Rec_Message = Vissim.Net.Vehicles.GetByLocation(PositionXYZ[0], PositionXYZ[1],
distDistr)
                #print('type(Veh_Rec_Message)  ',type(Veh_Rec_Message))
                # Reading Attribute of all Vehicles who are receiving the V2V message (Note: all vehicle
classes involved, also non V2V vehicles)
                Attributes = ('Pos', 'VehType', ' V2V _HasCurrentMessage', ' V2V _MessageOrigin', ' V2V
_Message', 'DesSpeed', ' V2V _DesSpeedOld','Lane')
                Veh_attributes_Rec_Message =
toList(Veh_Rec_Message.GetMultipleAttributes(Attributes))

                # Adjusting the attributes of the V2V vehicles because of this message:
                for cnt_Veh_Rec_Message in range(len(Veh_attributes_Rec_Message)):
                    atts_current = Veh_attributes_Rec_Message[cnt_Veh_Rec_Message]
                    pos_cur = atts_current[0]
                    veh_type_cur = atts_current[1]
                    pos_ V2V_cur = atts_current[3]
                    des_speed_cur = atts_current[5]
```

```
            des_speed_old_cur = atts_current[6]
            lane_old_cur = str(atts_current[7])
            if lane_old_cur in ['8-1','8-2','8-3','8-4']:

              # check if vehicle has V2V & position of V2V message is downstream & there is no
other further downsteam message active
              if veh_type_cur in (Vehicle_Type_ V2V _no_message, Vehicle_Type_ V2V
_HasCurrentMessage) \
              and pos_cur < Pos_Veh_SM \
              and (pos_ V2V _cur is None or Pos_Veh_SM > pos_ V2V _cur):
                if des_speed_cur == speed_incident:
                  # if the attribute 'DesSpeed' was already set to 'speed_incident', don't
overwrite ' V2V _DesSpeedOld' with with current 'DesSpeed' = 'speed_incident'
                  Veh_attributes_Rec_Message[cnt_Veh_Rec_Message] =
tuple([int(Vehicle_Type_ V2V _HasCurrentMessage), 1, Pos_Veh_SM, 'Breakdown Vehicle
ahead!', speed_incident, des_speed_old_cur])
                else:
                  Veh_attributes_Rec_Message[cnt_Veh_Rec_Message] =
tuple([int(Vehicle_Type_ V2V _HasCurrentMessage), 1, Pos_Veh_SM, 'Breakdown Vehicle
ahead!', speed_incident, des_speed_cur])
              else:
                Veh_attributes_Rec_Message[cnt_Veh_Rec_Message] = atts_current[1:7] # no
changes, vehicle has no V2V or is not affected due to the position
            else:
              Veh_attributes_Rec_Message[cnt_Veh_Rec_Message] = atts_current[1:7]
          # Giving back the adjusted attributes to Vissim (note: attribute 'Pos' is read-only)
          Veh_Rec_Message.SetMultipleAttributes(Attributes[1:7],
Veh_attributes_Rec_Message)

    # Check if vehicles with active message passed the position of the warning message:
    Attributes = ('Pos', 'VehType', ' V2V _HasCurrentMessage', ' V2V _MessageOrigin', ' V2V
_Message', 'DesSpeed', ' V2V _DesSpeedOld')
    Veh_attributes = list(Vissim.Net.Vehicles.GetMultipleAttributes(Attributes))

    for cnt_Veh in range(len(Veh_attributes)):
      atts_current = Veh_attributes[cnt_Veh]
      pos_cur = atts_current[0]
      veh_type_cur = atts_current[1]
      V2V _msg_active_cur = atts_current[2]
      pos_ V2V _cur = atts_current[3]
      des_speed_old_cur = atts_current[6]
      # if the vehicle has an active V2V message AND the position is larger than the V2VPosition
      if V2V _msg_active_cur == 1 and pos_cur > pos_ V2V cur:
        Veh_attributes[cnt_Veh] = [int(Vehicle_Type_ V2V _no_message), 0, '', '',
des_speed_old_cur, '']
      else:
        Veh_attributes[cnt_Veh] = atts_current[1:] # no changes
    # Returning the adjusted attributes to Vissim (note: attribute 'Pos' is read-only)
```

```
Vissim.Net.Vehicles.SetMultipleAttributes(Attributes[1:], Veh_attributes)
```

C. Glossary

The following is a list of definitions for terms appearing throughout this report:

Term	Definition
Accident	An accident pertains to an unanticipated and unintentional occurrence resulting in vehicular collisions, property damage, or bodily injuries. These events are typically characterized by a confluence of factors, such as human error, mechanical malfunction, adverse weather conditions, or a combination thereof. Despite its widespread usage, the term "accident" has faced scrutiny due to its implication of an absence of intent, prompting advocacy for alternatives such as "collision" to underscore the preventable nature of such incidents.
Advanced Driver Assistance Systems (ADAS)	Vehicle-based intelligent systems developed to automate / adapt / enhance vehicle systems for safety and better driving.
Autonomous / Automated Vehicles (AV)	‘Autonomous (or Automated) Vehicles’ are those in which operation of the vehicle occurs without direct driver input to control the steering, acceleration, and braking and are designed so that the driver is not expected to monitor constantly the roadway while operating in self-driving mode.
Connected Vehicles (CV)	‘Connected vehicles’ are vehicles that use any of a number of different communication technologies to communicate with the driver, other vehicles on the road, roadside infrastructure, and to other systems and services via the Cloud.
Incident	In the context of road safety, an incident is a comprehensive term encompassing any event, whether intentional or unintentional, that disrupts the normal progression of vehicular activities. Road incidents extend beyond collisions and include breakdowns, vehicle fires, spills, and various unforeseen circumstances affecting traffic flow or safety. This broader classification acknowledges a spectrum of occurrences, some of which may not lead to direct harm. Management of road incidents typically involves coordinated efforts by emergency services and traffic authorities to ensure public safety and mitigate disruptions.
Intelligent Mobility (IM)	Encompassing everything from autonomous vehicles to seamless journey systems and multi-modal modelling software, Intelligent Mobility uses emerging technologies to enable the smarter, greener and more efficient movement of people and goods around the world.
Intelligent Transport Systems (ITS)	ITS is the deployment, operation, on-going maintenance and renewal of roadside infrastructure such as cable networks, CCTV and traffic detectors, gantry signals, VMS and information travellers via web services, smartphone apps, news feeds, social media and radio broadcasts.
Internet of Things (IoT)	The inter-networking of physical devices, vehicles, buildings and other items – embedded with electronics, software, sensors, actuators and network connectivity that enable these objects to collect and exchange data.

Light Detection and Ranging (LIDAR)	An instrument which detects the position and/or motion of objects and which operates similarly to a radar, but which uses laser radiation rather than microwaves.
Mobility as a Service (MaaS)	Various forms of transport services integrated through digital mobility service platform(s), accessible by users on demand. MaaS has the potential to change the way people travel from A to B by providing more comprehensive travel planning and retail options, addressing the 'missing mile' issue.
Original Equipment Manufacturer (OEM)	Nominal parlance for Tier 1 Automotive manufacturers which integrate products, components and services to deliver a finished vehicle to the market

D. Intelligent mobility definitions

The table below presents the definition of Intelligent Mobility as described by different governmental and industrial sources (The definitions and the scope of each one has been taken through their annual reports, cc in each one). .

Source	What is IM? Target/Stakeholders – Issues – Goals – Tools
Highways England's definition based on: Automotive Council/Transport Systems Catapult	A concept which focuses on the ultimate goal of 'mobility', **rather than the provision of independent and specific modes of transport** such as road, rail, and air. The delivery of Intelligent Mobility relies on **harnessing the 'intelligence' of modern electronic devices** and **communications systems** and using that capability to **control** and **optimise the performance of the overall system**. Pursuing this concept requires a different mind-set to that which has underpinned all previous generations of transport planning; one which recognises the roles that public transport systems, private cars, **freight vehicles**, **commercial fleet operators**, **infrastructure providers**, and **government** must play in delivering improved mobility for all. The common goal is to develop **future transport systems** that are: • **User-focused**, to meet the needs of an ever-connected world and an ageing population. • **Integrated**, to maximise the capacity of transport. • **Efficient**, to meet global resource demands; and • **Sustainable**, to address global social, environmental, and economic risks. In order to meet these massive and multiple challenges, Intelligent Mobility has to cut across and **go beyond the traditional transport sector**.
1. Transport Systems Catapult	Encompassing everything from **autonomous vehicles** to **multi-modal modelling software and seamless journey systems** Intelligent Mobility uses emerging technologies to enable the smarter, greener, and more efficient movement of **people** and **goods** around the world. Intelligent Mobility is all about taking a different approach to the challenges that have traditionally beset the transport sector, whether it be **pollution, congestion,** or the **lack of "joined up" thinking between different means of transport**. It goes further than that, however, by also helping the transport industry to address **wider societal trends** – including a **climate change**, **growing, and ageing global population**, the **rapid depletion of our traditional energy resources**, and **increasing urbanisation**.

	In order to meet these massive and multiple challenges, Intelligent Mobility has to cut across and **go beyond the traditional transport sector**. Intelligent Mobility focuses instead on **new** and **emerging technologies** that make it possible to achieve more for less. The Transport Systems Catapult and its partners are taking advantage of developments in **integrated systems, web connectivity**, state of the art **modelling and visualisation**, and the emerging **Internet of Things** to change how we think about the movement of **goods and people**. Their mission is to **drive global leadership in Intelligent Mobility, promoting sustained economic growth and well-being through integrated, efficient and sustainable transport systems.** (Catapult, 2018) Intelligent Mobility is the future of transport. It is about harnessing innovation and emerging technologies to create more integrated, efficient, and sustainable transport systems. It marks an exciting meeting point between traditional transport and the new products and services that are emerging as we start to exploit vast amounts of multi-layered data. As such it offers us a remarkable opportunity to make much more efficient use of networks and to revolutionise transport, all driven by the needs of the end user. Market segments where the UK should focus its efforts include: **intermodal smart ticketing**; **security**, **resilience**, **safety** and **cyber security**; **Internet of Things asset management**; **monitoring and management systems**; **data analysis and management**; **data collection; autonomous vehicles** and **communication platforms** (Transport Systems Catapult, 2016)
2. Innovate UK	**Intelligent Mobility** attempts to meet user needs through efficient and seamless journeys, with a **broader perspective than focusing on specific transport modes or infrastructure**. Instead, the focus is on what **people** and **businesses** value, enabling commercially attractive solutions to be developed for effective, efficient, and reliable use of networks, vehicles, and transport services. Intelligent Mobility is characterised by: • **Understanding of the preferences, needs** and **behaviours** of **people** and **businesses**. • **The exploitation of data**. • **Capitalising on advances in technology** in areas like the **sensors, Internet of Things**, and **autonomous systems**. • **Transport networks operating reliably and freely at optimal capacity with seamless interchange**. A vibrant **commercial market** that encourages business innovation and can **learn from experience beyond the transport world**. (Innovate UK, 2019)(Innovate UK, 2019)
3. Automotive Council	Their concept focuses on the ultimate goal of 'mobility', rather than the provision of independent and specific modes of transport such as road, rail, and air. The delivery of Intelligent Mobility relies on **harnessing the 'intelligence' of modern electronic devices** and **communications systems** and using that capability to control and optimise the performance of the overall system. Pursuing this concept requires a different mind-set to that which has underpinned all previous generations of transport planning; one which recognises the roles that **public transport systems**, **private cars**, **freight vehicles**, **commercial fleet operators**, **infrastructure**

	providers, and government must play in delivering improved mobility for all. (Automotive council UK, 2018)
4. British Vehicle Rental and Leasing Association (BVRLA)	Intelligent Mobility refers to any optimised form of transporting **people** and **goods** that **increases mobility**, **improves safety,** and **enhances user benefits** whilst simultaneously **reducing pollution**, **consumption,** and **congestion**. Intelligent mobility technologies such as **connected vehicles**, **smart motorways** and **big data** are beginning to have a major impact on the road transport sector. The **use and storage of data** has become one of the most important issues facing global business. Business models within the **fleet** and **automotive industries** are likely to be re-shaped by the **magnitude of customer, driver and vehicle data** that will be generated in coming years. This **data will be varied, come at incredible velocity**, and will need to be **stored**, **processed,** and **analysed within both existing and future regulations**. While these new data systems offer benefits for both industry and consumers, it also presents significant challenges in the **control and storage of personal and/or commercially sensitive information**. Innovations and developments in vehicle and mobile technologies are presenting a huge opportunity to **tackle road safety, congestion, emissions, affordability and other transport challenges.** (BVRLA, 2018)
5. The Institution of Engineering and Technology (IET)	They champion travel and transport for people by air, sea, rail, and road. They focus on **opportunities for engineering and technology.** Bringing together experts from industry, academia, and government, they deliver programmes of activity, inspired by issues of the day and innovation around the transport from autonomous vehicles to integrated systems and beyond. Innovation will significantly improve the **efficiency** and **experience of the end-to end journey** for **people** and **freight**. Working with the ICT and Built Environment sectors, the Transport Sector will be developing thought leadership in **connected vehicles**, **intelligent logistics**, **monitoring and data**, **smart systems**, **urban mobility**, **passenger information** and **intermodal transport**. (IET, 2019)
6. IMPART (Intelligent Mobility Partnership)	Their vision of Intelligent Mobility is that it is not a new version of transport infrastructure but a **service** that places the **traveller** at the heart of the mobility process and seeks to implement measures that provide the **greatest choice and efficiency of travel**. There are a variety of definitions, but the Automotive Council offers the following objectives: • **Improve safety.** • **Increase mobility.** • **Enhance user benefits.** whilst simultaneously reducing **pollution**, **consumption**, and **congestion** (Mandžuka, 2020)
7. Horiba-Mira (Motor Industry Research Association)	Intelligent mobility is the convergence of **transport infrastructure**, digital **industries**, **vehicles,** and **users** to provide **innovative services relating to traffic management and different modes of transport**. Their **goal** is to improve lives by making journeys safer, cleaner and smarter. (HORIBA-MIRA, n.d.-b)(HORIBA-MIRA, n.d.-b) Horiba-Mira has been involved in the development of Connected and Autonomous Vehicles (CAV) for over 15 years, delivering pioneering research programmes, developing purpose-built test facilities around the world, and supporting development of vehicles and highly automated

	systems from concept through to verification. They help customers to define, design, build, test and validate their CAV solutions. (HORIBA-MIRA, n.d.-a)
8. CCAV (Centre for Connected and Autonomous Vehicles)	They are providing **over £250 million in funding,** matched by industry, to position the UK at the forefront of CAV studies, development, and use. **This will contribute to UK economic growth and help industry to develop safe, efficient systems to move goods and help people get around.** Their Future of Mobility Minister, Jesse Norman, supported that "As vehicles get smarter, major opportunities for the future of mobility increase" and also said that "The government is supporting the safe, transparent trialling of this pioneering technology, which could transform the way we travel". **They are trying to ensure we take the public with us as we move towards having self-driving cars on our roads by 2021.** **CCAV** aims to take advantage of **the extraordinary innovation in UK engineering and technology** to make journeys **cleaner, safer, cheaper, and more reliable.** (GOV.UK, 2017, 2018a, 2018b, 2019)
9.GATEway (Greenwich Automated Transport Environment) **Innovate UK**	**Their goal is to conduct a number of different trials to figure out how people respond, engage with and accept automated vehicles as well as explored the potential impact this technology could have in our cities.** To this end, **to understand how automated vehicles can fit into the future urban mobility needs and the barriers people must overcome before these vehicles become a reality on our roads**. (Innovate UK, 2020) The GATEway Project builds on more than 50 years of research into automated vehicles by TRL and operates within the Smart Mobility Living Lab: London a world-class test bed and real-world environment for the development and validation of new mobility solutions enabled by connected and automated vehicle technology. (Innovate UK, 2014)
10. TRL – The future of transport	**1.Smart Mobility Living Lab (SMLL – Building the Future of Mobility in London)** aims to become the place to go for advanced real-world CAV and mobility testing – a place where technology and service providers can look at the entire connected mobility environment and get their products and services market-ready faster. SMLL is open to any organisation interested in the future of mobility and will offer testing opportunities on both open and closed routes in London. SMLL also include a bespoke shared research programme (SRP) in the autonomous, connected, electric and shared (ACES) domain. **SMLL will seek to match the government's ambition and ensure the UK can offer a coherent proposition in the future mobility arena.** (TRL, 2018) **2.Enabling connected autonomous vehicle environments** TRL was commissioned to identify and assess the benefits of safety use case scenarios that would be best supported by the development and implementation of Vehicle to Infrastructure (V2I) communications and cloud-hosted data storage (TRL, 2019) . **3.MOVE_UK – Connected Validation of Advanced Driver Assistance Systems (ADAS) Systems** • Develop applications for autonomous vehicle data in the 'smart city', including new ways to improve safety, services and information for residents and managing environmental impact.

	• help our project partners to predict how driverless technologies will change their businesses in the future, providing insight to respond to these challenges. Ultimately, the MOVE_UK project is seeking to bring new technology to market in a more efficient manner, with a lower cost and improved safety. (TRL, 2017)
11. Navigant Research (market for smart city)	Their goal is to present an **unbiased, objective view of market opportunities across dozens of industry verticals**. Navigant Research is not beholden to any special interests and is thus able to offer clear, actionable advice to help clients navigate the energy transformation, unfettered by technology hype, political agendas, or emotional factors that are inherent in emerging technology markets. **The Mobility Research Service focuses on the emerging services, technologies, and business models that redefine the roles of personal and commercial vehicles in enabling sustainable multimodal mobility.** The markets covered include car-sharing and ridesharing, connected vehicles, autonomous vehicles, electric vehicle mobility, intelligent transportation services, smart parking, and smart street management. The service analyses the changing roles of automakers, the emergence of mobility as a service, and communications and analytics that are seamlessly connecting individuals to the most appropriate mode of transportation. (Navigant Research, 2019a)(Navigant Research, 2019a) **The Transport Logistics Innovations Research Service focuses on the emerging technologies, service models, and business models in good transportation, both on-road and off-road**. Topics covered include drones/unmanned vehicles, connectivity, vehicle automation for commercial vehicles, first and last mile delivery, and other new service models. The service analyses the opportunities related to new technologies and fuels as well as innovative service models that enable goods and logistics transportation that is efficient, sustainable and less costly.) (Navigant Research, 2019b)
12. SMMT Driving the motor industry	SMMT is the voice of the UK motor industry, supporting and promoting its members' interests, at home or even abroad, to stakeholders, government, and the media. SMMT represents more than 800 automotive companies in the UK, providing them with a forum to voice their views on issues affecting the sector, helping to guide strategies and build positive relationships with government and regulatory authorities. **The Challenges** **1.** Innovative solutions for intelligent fleets **2.** Creating value from mobility data and generating insights **3.** Urban mobility solutions for cities: **Make cities more attractive places to work, live, and play through creating affordable and deliverable urban mobility solutions**. **4.** New on-demand mobility models and ownership shared: While some customers will continue to own cars in the traditional way, others may wish would explore new models of ownership or opt for access to a flexible service. There are yet others who prefer car-sharing, ridesharing, or ride-hailing services. They are therefore looking for solutions and new business models that can help us become a single platform for existing and prospective customers' mobility needs.

	5. Beyond the car: creating new services and delivering superior customer experiences. 6. New connected and in-car services: The majority of new cars sold today are 'connected' in some form. It wouldn't be a stretch to say that the market is quite saturated with connected car apps and services of various types, serving various purposes. They are looking for something new, ideally something **out of the box.** They may include the following but should not be an offering already in the market: Location-based services; Infotainment and content services; Real-time traffic information; Journey management; In-car productivity tools; On-demand mobility services integration; Remote services including one-time access, diagnostics and predictive maintenance; Monetizable telematics services. Additionally, **how can vehicle cabin comfort and passenger health and wellbeing be improved**. 7. Automated driving technologies for on-road and off-road vehicles: **without vehicles there is no mobility.** Some vehicles will be privately owned, others will operate in shared fleets. They are likely to include increasing levels of automation. They are looking for automated driving technology solutions in the following areas that are new or innovative, and not already common in the market: High-resolution near-field sensors with high environmental resistance; High-accuracy, high-definition positioning technology; Advanced vision and imaging technology; Advanced vehicle safety technology; Innovative cyber security solutions and quantum computing. 8. E-mobility solutions: An important measure in driving market uptake of electric vehicles is addressing the concerns of prospective and new EV users. Common concerns include range anxiety, inadequate charging infrastructure, the lack of clarity on charging costs, upfront and running costs of an EV, and how EVs may suit people's mobility needs. They are looking for solutions that utilise data generated by EVs to clearly demonstrate the technology's benefits and help users make informed usage decisions. (SMMT, 2019)
13. Westminster Forum Projects (WFP) (energy environment & transport forum)	**The aim is to provide policymakers with context for arriving at whatever decisions they see fit, and for all delegates to have the opportunity to lobby, learn, exchange views and network**. Each WFP forum is structured to facilitate the formulation of 'best' public policy by providing policymakers and implementers, and those with an interest in the issues, with a sense of the way different stakeholder perspectives interrelate. **England's road network - infrastructure delivery, finance and RIS2** Policymakers and stakeholders assessed the priorities for the Draft Road Investment Strategy 2, including: its relationship with local and combined authorities regarding the setting of priorities and delivery of key projects; and key issues for meeting the intended objectives of **delivering a network which supports the economy that is safer and more reliable, greener, more integrated, and smarter.** Sessions also examined the future finance of road projects and included discussion on alternative approaches to funding, include road user

	charging; and what more is needed to encourage long-term investment, reduce delivery costs and mitigate the environmental impact of the Strategic Road Network. (Westminster Energy, 2020)(Westminster Energy, 2020)
14. Atkins	Intelligent Mobility is about innovating and thinking differently, based on the new opportunities' technology brings. An end-user and outcome-focused approach to connecting **people**, **places,** and **services** – **reimagining infrastructure across all transport modes**, enabled by **data**, **technology** and **innovative ideas**. It will transform **people**'s journeys and the **movement of goods**, whilst **increasing the efficiency**, **sustainability** and **safety** of our transport systems and cities worldwide. (Atkins, 2016, 2019b) **Benefits** 1. **Safety** –Improving access to safe and secure walkways and cycle ways, making it easier and more attractive for people to choose. 2. **Environmental** – reducing emissions, improving air quality, and reducing the environmental impact through innovative transport options. 3. **Travel modes** – providing new, innovative, or alternative options for commuters and road users. 4. **Transforming towns and cities** – as great places to work, visit and travel: offering well connected travel and transport options including CAVs. 5. **Improving choice and customer satisfaction** – connecting all modes of travel with the latest technology and data to bring additional benefits to passengers. 6. **Smart transport** – Making the most of existing assets (park and rides, car parks, motorways, trains, trams, airports, walking, cycling.) **Solutions** 1. **Mobility as a Service** – Focusing on the customer-centric approach to mobility and how to deliver a fully integrated transport system. 2. **Journey management** – Investigating ways to deliver a seamless customer experience across the whole journey, regardless of the mode of travel. 3. **Cyber resilience and security** – Delivering a safe, secure, and trusted environment to both the operator and the travelling public. 4. **CAVs** – The development and implementation of new solutions for CAVs for ports, airports, railways, and roads. 5. **Big Data and analytics** – Collecting, aggregating, and analysing data to improve strategic decision making and operational network performance.
15. Frost & Sullivan	Frost & Sullivan definition of Intelligent mobility includes **Automation of vehicles**, **connected car**, **sustainability & environment** and most importantly **new business models**. (Frost & Sullivan, 2017) Their Growth Partnership Services and interactive workshops help their clients identify the top Mega Trends impacting the market and build innovative business models in the areas of Mobility, Vehicle Technology,

	Autonomous Driving and Connected Cars, Car Retailing and Aftermarket, Commercial Vehicles, Transport and Rail. **Future of Automotive Retail & Aftersales** (Frost & Sullivan, 2018) The business of selling cars, parts, and services is undergoing tremendous disruption at every level and the downstream automotive eco-system is expected to be completely transformed over the next 10-15 years. Mega Trends like urbanization, pollution, congestion, connectivity, and globalization are powering the shift away from private vehicle ownership to new business models like car sharing, carpooling, ride-hailing, integrated mobility, and dynamic shuttles. Technology enabled devices can now deliver real-time, door-to-door, multi-modal travel encompassing pre-trip, in-trip and post-trip services that yield convenience, time and cost savings.
16. Sopra Steria	**Transport providers** have something of a roadblock facing them. How to make **services more available** against a backdrop of **dwindling budgets**, **increasing passenger numbers** and **transport networks that are in many cases already at, or even over, capacity**. But is the problem of **availability** the right problem for them to be solving? As users of transport networks, which do we really care more about – whether a particular mode of transport is 100% operational or whether our **personal objectives are satisfied** e.g., getting to work, not being late for an interview or delivering goods before they perish? Sopra Steria aims to address both these challenges. They **integrate systems** and **exploit data** to **optimise the availability**, **reliability,** and **security** of transport networks, as well as implementing solutions that ensure users – **passengers** or **freight** – are given the **information they need to make optimum, or alternative, transport choices**. (Sopra Steria, 2015, 2019b, 2019a)

Below it is presenting the perspective of four major car companies regarding Intelligent Mobility and how they are going to encourage it in the future (The definitions and the scope of each one has been taken through their annual reports, cc in each one).

Car Companies	Intelligent Mobility Program
17. Nissan	At Nissan, Intelligent Mobility encompasses three core areas of innovation that inspire how cars are powered, driven, and integrated into society. From cars that drop you off and park themselves to highways that charge your EV as you drive along, it's all in the very near future. 1. **Together we ride – Nissan Intelligent Driving**: Their goal is to provide a car that takes the stress out of driving and leaves only the joy, by pick you up, navigate heavy traffic and find parking all on its own. It can even communicate with other cars and pedestrians. 2. **Together we electrify – Intelligent Power:** As the world's best-selling electric vehicle, Nissan LEAF is redefining the power you crave behind the wheel. LEAF beats just about any car off the line with 100% instant torque – and zero emissions. Nissan's leadership position in EVs means we're committed to expanding our range of **zero emission vehicles**, bringing the unique pleasures of clean, quiet power to more and more people worldwide.

	3. **Together we empower – Intelligent integration:** A connected ecosystem of drivers, cars, and communities is key to a cleaner and safer world. At Nissan, we're playing a central role in defining what the roads of the future will look like, from **traffic management systems** to **public charging** to **car sharing,** whilst they are committed to make this infrastructure accessible to everyone. (NISSAN, 2020)
18. Jaguar	Jaguar Land Rover has built a reputation for developing breakthrough innovations and world firsts and must keep pace with the fast-moving technology industry. **They are investing in autonomous, connected, electrified, and shared future.** They have already successfully tested their vehicles on complicated inner-city roads. Collaborations with leading tech companies enables them to better understand how humans will trust self-driving vehicles in the near future. 1. **Autonomous** They have partnered with Waymo to bring the first premium self-driving electric vehicle, the Jaguar I-PACE, to the Waymo fleet. Through the long-term strategic partnership with Waymo, they exchange learning and expertise about autonomy and are integrating Waymo self-driving technology into Jaguar I-PACE vehicles. 2. **Connected**. They are testing the Green Light Optimal Speed Advisory (GLOSA) system, a new vehicle-to-everything technology designed to communicate with traffic lights to find the optimum driving speed that minimises the need for vehicles to stop at junctions. Reducing harsh acceleration and sudden braking brings positive environmental benefits, improving air quality. 3. **Electrified** Creating a better world today, with a choice of mild and plug-in hybrid electric options, while they continue to research and invest into alternative propulsion technologies for future vehicles. The Jaguar I-PACE embodies the innovation that puts Jaguar Land Rover at the forefront of the electric vehicle revolution. **Jaguar Land Rover** created a fleet of more than 100 research vehicles, to develop and test a wide range of Connected and Autonomous Vehicle (CAV) technologies. The first of these research cars had been driven on a new 41-mile test route on motorways and urban roads around Coventry and Solihull throughout 2016. The initial tests involved vehicle-to-vehicle and vehicle-to-infrastructure communications technologies that will allow cars to not only talk to each other, but also roadside signs, overhead gantries, and traffic lights. Ultimately, data sharing between vehicles would allow future connected cars to co-operate and work together to assist the driver and make lane changing and crossing junctions easier and safer. The research project test a number of technologies including; **Safe Pull away**, a technology that uses a stereo camera to monitor the area immediately in front of the vehicle, helping to limit low speed collisions, avoid getting too close to the vehicle in front in traffic jams and prevent drivers hitting walls, garage doors or parked cars because they mistakenly put the vehicle into drive instead of reverse when attempting to pull

	away. If objects such as vehicles or walls are detected, and the system receives signals from throttle pedal activation or from gear selection that could lead to a collision, the vehicle brakes are automatically applied and the driver receives an audible warning. (Jaguar, 2019)
19. Ford	Ford Mobility designs, grows, and invests in emerging mobility services and connectivity solutions. **Their aim** is to deliver new transport initiatives and address urban transportation challenges. (Ford, 2020)(Ford, 2020) **Helping the world move smarter:** Ford Mobility designs, grows and invests in emerging mobility services and connectivity solutions. **Their aim** is to deliver new transport initiatives and address urban transportation challenges. Using technology, innovation, and a collaborative approach, we want to improve the way people and goods move. **Business Solutions** Ford Mobility is contributing to building the future sustainable urban logistics with a new generation of cleaner vehicles, new mobility goods delivery initiatives and fleet management tools. **City Solutions** With an increasing population concentrated in cities, mobility has become increasingly complex with rising congestion and pollution. Ford Mobility is exploring innovative initiatives that aim to integrate connected vehicles, city data and infrastructure. Their aim is to deliver a cohesive and efficient urban transportation system. **Citizen Solutions** Ford Mobility is committed to addressing mobility challenges for people across the world. This includes finding and creating solutions for everyone- whether or not they have a car. Modern technology is evolving at an unprecedented speed. That's why Ford Mobility is developing the products of tomorrow today. **Autonomous Vehicles** They envision a city of tomorrow that could be holistic, organic, inter-connected system powered by a transportation operating system and shaped by total multimodal mobility including autonomous vehicles. (Ford, 2019)
21. Porsche	Driven by digitalization and automation, the consumption of mobility is experiencing a historical caesura. It is no longer (only) about fast and effective travel from A to B, as long as it's a new, multi-mobile age. It is no longer exclusively about spatial locomotion, forms of propulsion or the use of means of transport. Sustainability, new energies, networked cities, intelligent transport systems, car-to-car communication, smart transport systems and unprecedented mobility concepts in combination with future technologies determine four major megatrends (electrification, connectivity, autonomous driving, new digital services) in todays and tomorrow's road, rail, air and beyond. *"Digitization, 5G technology, electrification, connectivity — all these are happening simultaneously and, if you like, at full speed."* (Porsche, 2019) Porsche E-Performance includes a new mobility concept is only innovative if it extends beyond the vehicle and therefore the entire infrastructure: an optimally integrated vehicle charge port and intelligent charging equipment for daily use at home and on the road (Porsche, 2020) **Porsche plans to invest more than six billion euro in electromobility by 2022.**

	The decision was made by the Porsche as they are doubling their expenditure on electromobility from around three billion euro to more than six billion euro. Alongside development of their models with combustion engines, they are setting an important course for the future with this decision. The plans have been bolstered significantly to include around three billion euro of investment in material assets, and slightly more than three billion euro in development costs. (Porsche, 2018)